California Partners for Advanced Transit and Highways (PATH)
UC Berkeley

Title:
Anonymous Vehicle Tracking for Real-Time Freeway and Arterial Street Performance Measurement

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Publication Date:
03-01-2005

Series:
Research Reports

Publication Info:
Research Reports, California Partners for Advanced Transit and Highways (PATH), Institute of Transportation Studies (UCB), UC Berkeley

Permalink:
http://escholarship.org/uc/item/50c6z6zh

Abstract:
This research involved an important extension of existing field-implemented and tested PATH research by the authors on individual vehicle reidentification, to develop methods for assessing freeway and arterial (and transit) system performance for the Caltrans PeMS (Performance Measurement System). PeMS has been adopted by Caltrans as the standard tool for assessing freeway system performance, but lacks capabilities for assessing arterial and transit system performance, and strategies that combine freeways, arterials and/or transit and commercial vehicle fleets. It was shown that the research methodology of this project could directly address these limitations in PeMS. A systematic investigation was conducted of anonymous vehicle tracking using existing inductive loop detectors on both freeway and arterial street facilities combined with new, low-cost high-speed scanning detector cards (that were utilized by the authors in PATH TO 4122) to meet the needs of PeMS. Both field data and microscopic simulation were utilized in a major travel corridor setting, using the Paramics simulation model and field sites that were part of the California ATMS (Advanced Transportation Management Systems) testbed network in Irvine, California. The experience and insights of the research team obtained from extensive previous and current PATH research on vehicle reidentification techniques for single roadway segments and signalized intersections was used to investigate and develop methods for tracking individual vehicles (including specified classes of vehicle such as buses and trucks) across multiple detector stations on a freeway and an arterial street network to obtain real-time performance measurements (including dynamic or time-varying origin-destination (OD) path flow

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information such as path travel time and volume). This study presented a framework for studying the feasibility of an anonymous vehicle tracking system for real-time freeway and arterial traffic surveillance and performance measurement. The potential feasibility of such an approach was demonstrated by simulation experiments for both a freeway and 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 freeway and arterial network. It is also 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 realtime congestion monitoring, traveler information, control, and system evaluation. Furthermore, the automatic vehicle classification system developed in this study showed very encouraging results.

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Anonymous Vehicle Tracking for Real-Time Freeway and Arterial Street Performance Measurement

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California PATH Research Report
UCB-ITS-PRR-2005-9

This work was performed as part of the California PATH Program of the University of California, in cooperation with the State of California Business, Transportation, and Housing Agency, Department of Transportation; and the United States Department of Transportation, Federal Highway Administration.

The contents of this report reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the State of California. This report does not constitute a standard, specification, or regulation.

Final Report for Task Order 4159

March 2005

ISSN 1055-1425

CALIFORNIA PARTNERS FOR ADVANCED TRANSIT AND HIGHWAYS

California PATH
(Partners for Advanced Transit and Highways)
Task Order 4159 Final Report

Anonymous Vehicle Tracking for Real-Time Freeway and Arterial Street Performance Measurement

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January, 2005

ACKNOWLEDGEMENT

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The authors gratefully acknowledge the assistance of Steven Hilliard, Inductive Signature Technologies, Inc., and Fred Yazdan, California Department of Transportation, in conducting this research.

ABSTRACT

This research involved an important extension of existing field-implemented and tested PATH research by the authors on individual vehicle reidentification, to develop methods for assessing freeway and arterial (and transit) system performance for the Caltrans PeMS (Performance Measurement System). PeMS has been adopted by Caltrans as the standard tool for assessing freeway system performance, but lacks capabilities for assessing arterial and transit system performance, and strategies that combine freeways, arterials and/or transit and commercial vehicle fleets. It was shown that the research methodology of this project could directly address these limitations in PeMS. A systematic investigation was conducted of anonymous vehicle tracking using existing inductive loop detectors on both freeway and arterial street facilities combined with new, low-cost high-speed scanning detector cards (that were utilized by the authors in PATH TO 4122) to meet the needs of PeMS. Both field data and microscopic simulation were utilized in a major travel corridor setting, using the Paramics simulation model and field sites that were part of the California ATMS (Advanced Transportation Management Systems) testbed network in Irvine, California. The experience and insights of the research team obtained from extensive previous and current PATH research on vehicle reidentification techniques for single roadway segments and signalized intersections was used to investigate and develop methods for tracking individual vehicles (including specified classes of vehicle such as buses and trucks) across multiple detector stations on a freeway and an arterial street network to obtain real-time performance measurements (including dynamic or time-varying origin-destination (OD) path flow information such as path travel time and volume). This study presented a framework for studying the feasibility of an anonymous vehicle tracking system for real-time freeway and arterial traffic surveillance and performance measurement. The potential feasibility of such an approach was demonstrated by simulation experiments for both a freeway and 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 freeway and arterial network. It is also 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. Furthermore, the automatic vehicle classification system developed in this study showed very encouraging results.

Keywords: vehicle signature, detector, sensor, inductive loop, vehicle classification, vehicle reidentification, testbed, freeway, signalized intersection, level of service, detector card, search space reduction, microscopic simulation

EXECUTIVE SUMMARY

A new generation of Advanced Transportation Management and Information Systems (ATMIS) is now widely under development, for applications in traveler information, route guidance, traffic control, congestion monitoring, incident detection, and system evaluation, across extremely complex transportation networks. However, the limitations, and often large errors, inherent in present point-based vehicle surveillance systems greatly diminishes the ability of public agencies to effectively control, manage and evaluate the performance of highway and transit systems, and to provide useful, timely and accurate travel information to users. New types of travel data, in real-time, are essential for effective implementation and performance assessment of ATMIS. In the past, such data were extremely difficult to obtain. To address this need, there has recently been substantial interest in Europe and the United States, and particularly in California, in implementing vehicle reidentification systems. Interest has initially focused on using the extensive existing inductive loop infrastructure in California, while recognizing that some emerging technologies such as video and laser detectors, the Global Positioning System (GPS) of satellites, and automatic vehicle identification (AVI) systems involving on-board vehicle sensors/tags/transponders and wireless vehicle-to vehicle and vehicle to roadside communications, may transition into practice in the future.

Regardless of the traffic sensor technologies used, the California Department of Transportation (Caltrans) has identified real-time travel time and origin-destination (OD) information as particularly important outputs of such systems. Relatively inexpensive, anonymous individual vehicle tracking systems based on the existing infrastructure of inductive loop detectors on freeway and arterial streets could be a particularly cost-effective, immediately implementable solution, for the medium term and beyond. The vehicle reidentification system developed by the authors in recent and current PATH research provides real-time freeway and signalized intersection and arterial section or link traffic performance data, and potentially network OD information such as vehicle paths and OD path travel times and volumes. Data such as these, derived from individual vehicle tracking, form the basis for numerous real-time traffic performance measures that can meet and exceed the needs of PeMS for assessment of freeway and arterial and transit system performance.

However, all applications to date by the authors of the vehicle reidentification approach have been to individual freeway, arterial or signalized intersection sites with only one upstream and downstream station (and in the intersection case with three downstream stations for left, through and right vehicles). No substantive studies have been undertaken of the ability of the system to operate effectively in a freeway or arterial network, nor of the accuracy of OD information it would generate (except for the three destinations represented by the left, through and right turn movements at an individual intersection). Although the

potential for extension of this approach to network applications is very high, further feasibility study is necessary before investing in actual network-wide implementation. This research conducted such a study, using both field data and microscopic simulation of sites in the California ATMS Testbed in Irvine, California.

A systematic investigation was conducted of anonymous vehicle tracking using existing inductive loop detectors on both freeway and arterial street facilities combined with new, low-cost high-speed scanning detector cards (that were utilized by the authors in PATH TO 4122) to meet the needs of PeMS. Both field data and microscopic simulation were utilized in a major travel corridor setting, using the Paramics simulation model and field sites that were part of the California ATMS (Advanced Transportation Management Systems) testbed network in Irvine, California. The experience and insights of the research team obtained from extensive previous and current PATH research on vehicle reidentification techniques for single roadway segments and signalized intersections was used to investigate and develop methods for tracking individual vehicles (including specified classes of vehicle such as buses and trucks) across multiple detector stations on a freeway and an arterial street network to obtain real-time performance measurements (including dynamic or time-varying origin-destination (OD) path flow information such as path travel time and volume).

This study presented a framework for studying the feasibility of an anonymous vehicle tracking system for real-time freeway and arterial traffic surveillance and performance measurement. The potential feasibility of such an approach was demonstrated by simulation experiments for both a freeway and 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 freeway and arterial network. It is also 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. Furthermore, the automatic vehicle classification system developed in this study showed very encouraging results.

The findings of this study could be invaluable to Caltrans and other operating agencies interested in real-time performance assessment of freeway and arterial street systems, and the implementation of such capabilities in PeMS.

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Task Order 4122 - Anonymous Vehicle Tracking for Real-Time Freeway and Arterial Street Performance Measurement

CHAPTER 1 INTRODUCTION

1. Introduction

1.1 Background

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 report presents a new framework for anonymous vehicle tracking that is capable of tracking individual vehicles by utilizing the state – of – the art in detector technology. A systematic simulation investigation of the performance and feasibility of anonymous vehicle tracking on freeways and signalized arterials using the PARAMICS (PARAllel MICroscopic Simulation) simulation model is performed. Extensive study 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 will serve as a logical and necessary precursor to possible field implementation of vehicle reidentification techniques

1.2 Report Outline

In chapter 2, the analysis of real world vehicle signature data is discussed. This section will serve as basis for the vehicle feature generation module in the microscopic simulation model. Chapter 3 presents enhanced vehicle tracking algorithms for freeway and arterial sections. A multi-section vehicle tracking scheme and possible elements for performance measurements are also discussed in this section. Simulation settings, as well as each individual module inside the simulation, are presented in Chapter 4. Experimental simulation design and results are described in chapter 5. An enhanced approach to vehicle classification is presented in Chapter 6 . Finally, Chapter 7summarizes the conclusions of this research and directions for future research.

CHAPTER 2 SIGNATURE DATA ANALYSIS

2.1 Introduction

Prior to using the simulation models for vehicle tracking, analysis of vehicle signature data should be performed. This procedure is essential to obtain the input data for the simulated vehicle reidentification system. Therefore, in this section, detailed analysis of vehicle signature data using a real world dataset collected from Detector Testbed site was conducted for synthetic vehicle signature feature data generation. Such analysis includes spatial repeatability and the error distribution of vehicle signature feature vectors. This section will help to generate the input data for the vehicle reidentification algorithm that will be implemented in the simulation model. The vehicle reidentification system and simulation model settings will be discussed further in the following chapters.

2.2 Data Collection / Ground Truthing

The California ATMS Testbed has been an ongoing testing ground for ITS strategies since 1991. The Testbed uses an integrated approach to the development and deployment of advanced technologies in the operation and management of transportation systems.

The Testbed has the capability to perform real-time, computer-assisted traffic management and communication. The real-time information system collects both arterial and freeway data from the Testbed area of Orange County, California. The Testbed communications network links the Transportation Management Centers (TMC's) of the City of Irivine, City of Anaheim, Caltrans District 12, and University of California at Irvine (UCI) Institute of Transportation Studies. Figure 2.1 summarizes the major functions and current communication system of the Testbed with the real world TMC and the field.

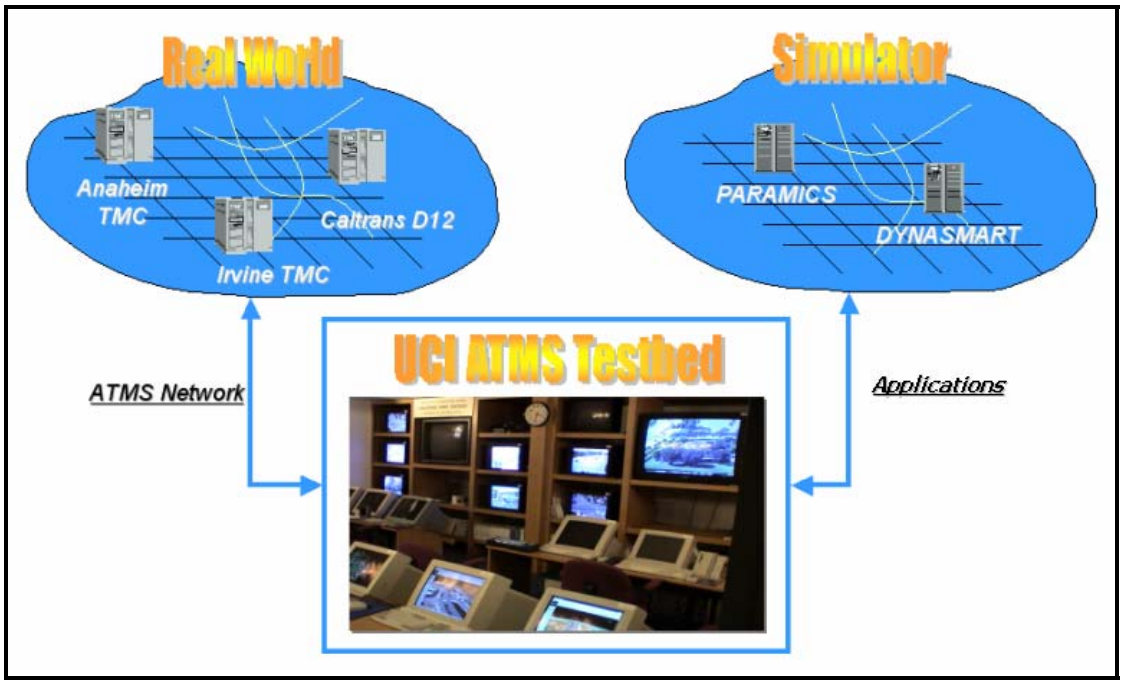


Figure 2.1. Testbed Communication

In addition to the existing multi-jurisdictional and multi-agency operated surveillance and communications infrastructure, the Testbed features an 0.7 mile freeway section on northbound I-405 and a major signalized intersection in Irvine that are both fully instrumented with the latest detector technologies for advanced traffic control and surveillance. The Traffic Detector and Surveillance Sub-Testbed (TDS^2), one of the study sections in this research, consists of two contiguous sites on the seven-lane I-405 freeway, south of Irvine, between Laguna Canyon and Sand Canyon. The section is about 0.7 mile long and is equipped with different traffic sensors in both upstream and downstream. The overall purpose of the TDS^2 is to provide a real-world laboratory for the development and evaluation of emerging traffic detection and surveillance technologies. As illustrated in Figure 2.2, double inductive loops are implemented for all lanes, and special cameras, that capture the horizontal images of each single vehicle passing over the detection zone, are installed on top of each lane. Other detectors such as radar detector and acoustic detectors are installed on the adjacent wireless antenna pole. There are seven lanes upstream, at Laguna Canyon, and one that merges with the adjacent lane within the section. The left most lane is an HOV lane. At the downstream, Sand Canyon, there are two HOV lanes, four mainstream lanes and one off-ramp lane. Poles adjacent to the mainline also permit side mounting of detectors. A number of traffic cabinets to house computers, communications, and video image processing equipment were also installed for the research purposes.

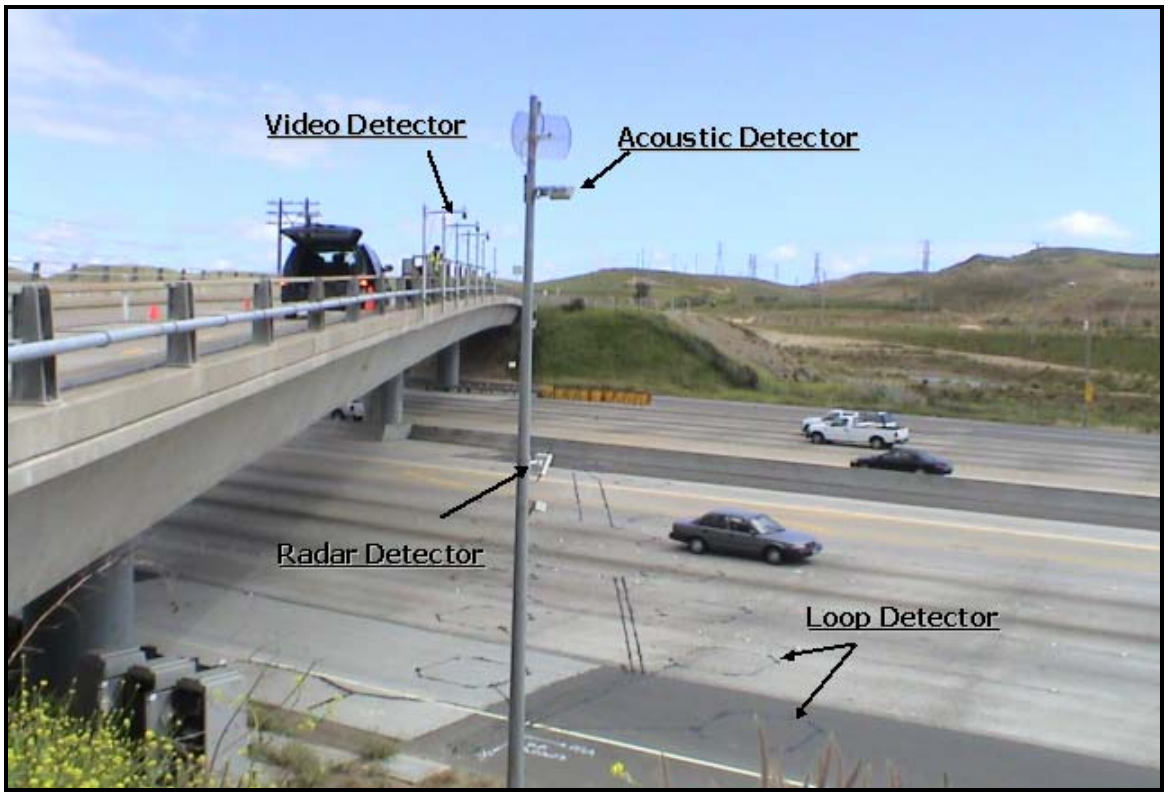


Figure 2.2. Detector Testbed

The signature dataset used in this study was obtained from 15:00 to 15:20 PM on July 23rd, 2002. Detailed description of the vehicle signatures can be found in many research studies by the authors (MOU 3008, TO 4122, Park et al 2004, Oh, S. et al 2002). Each upstream vehicle was manually matched to the corresponding vehicle at downstream along with the corresponding vehicle class information. The dataset contains about 2500 vehicles at each detection station. This data reduction result will serve as initial step toward further analysis, such as feature repeatability test as well as feature difference distribution analysis that are key issues for the error generator in simulation.

2.3 Signature Data Analysis

2.3.1 Feature Repeatability Analysis

Vehicle reidentification is a pattern recognition process based on the vehicle feature vectors from different sites. Therefore, if signature variations that result in significant discrepancies between up and downstream vehicle feature vectors do not exist, the algorithm would be capable of producing perfect vehicle signature matching. However, in practice, because of the exogenous effects of environmental elements such as physical loop installation, and entrance angle of a vehicle into the inductive field, vehicle signatures vary

from different detection stations. Therefore, investigation of such variations should be conducted to build the basis for the synthetic vehicle signature generator in the simulation model. Detailed description on vehicle feature vectors, vehicle specific feature vectors and traffic specific feature vectors, can be found from previous PATH project report by same authors (MOU 3008, TO 4122). In this study, degree of symmetry (DOS) was added as one of the vehicle feature vectors. DOS captures the upper part signature symmetry whereas shape parameter is more dedicated to represent the overall signature symmetry. Table 2.1 and Figure 2.3 summarize the signature feature vectors.

Table 2.1. Signature Feature Vectors

Feature Vector	Feature Description
Maximum Magnitude	Maximum absolute magnitude value (a)
Shape Parameter (SP)	Degree of Symmetry ((b)/(b+c))
Electronic Vehicle Length	(d)
Degree of Symmetry (DOS)	Degree of Symmetry e : median Sum of the distance from median g, to each point that is above “0.5” y value
Number of High Magnitude (NHM)	Sample number above “0.5” y value after x,y normalization

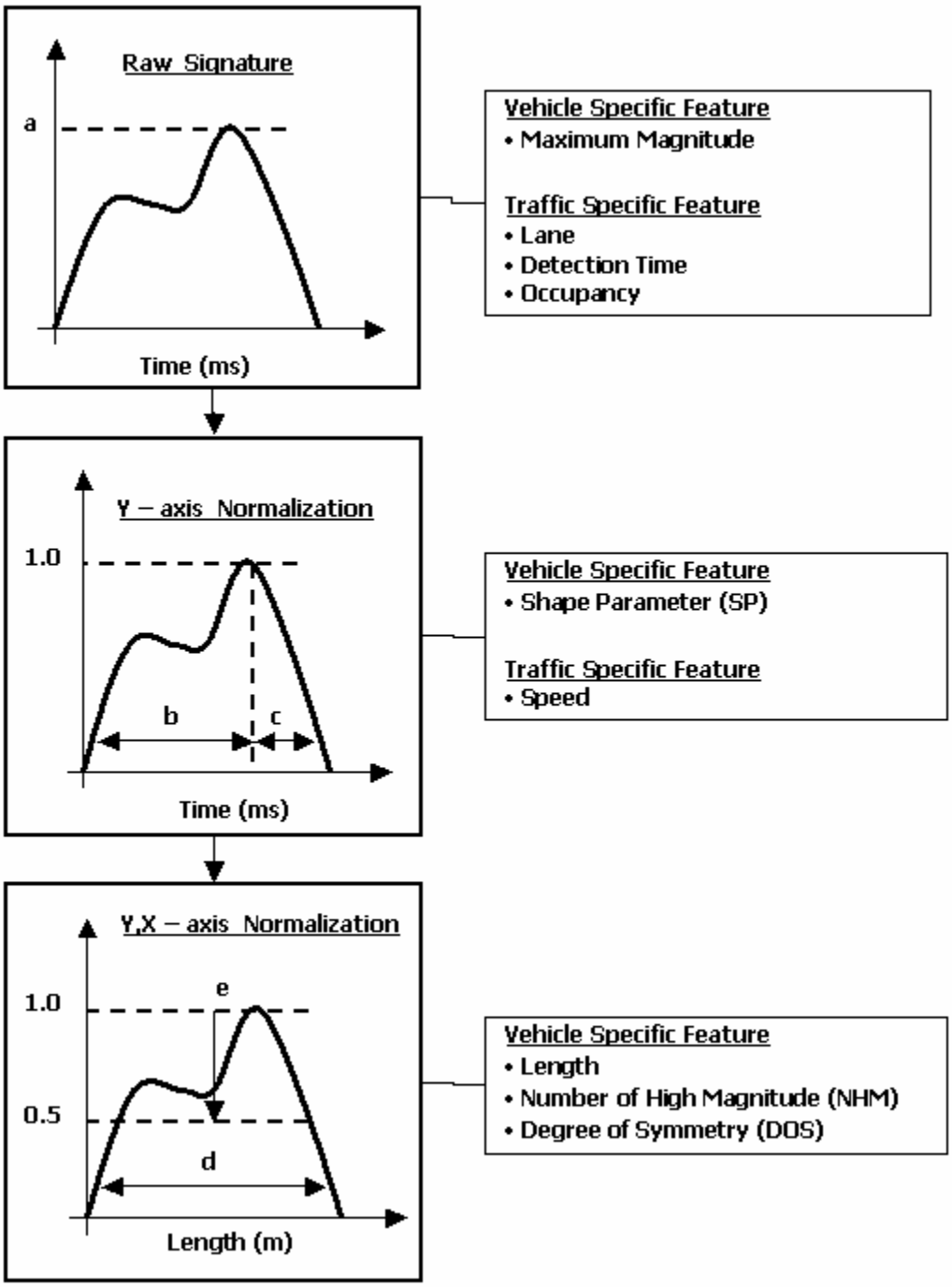


Figure 2.3. Signature Feature Vector Extraction

For the vehicle signature repeatability analysis, the average percentage error (APE) of each feature vector was chosen as the criterion. Derivation of such index is as following:

$$APE_i = \text{Average}\left(\left(\frac{abs(FV_i^{up} - FV_i^{down})}{FV_i^{down}} \right) * 100 \right)$$

where

APE_i: Average Percentage Error for Feature i

FV_i^s : Feature i at station s

Analysis results are presented in Table 2.2, and among all the feature vectors analyzed, it is clear that the vehicle length is the most reliable and repeatable one with the lowest average percentage error. This also implies that the length feature will be the critical element to determine the system performance in the reidentification model.

Table 2.2. Average Percentage Error

Feature	**Percentage Error in Feature Difference**
Maximum Magnitude	22.97
Electronic Length	1.34
Shape Parameter (SP)	4.02
Number of High Magnitude (NHM)	2.09
Degree of Symmetry (DOS)	23.08

Scatter plots of each feature are described in Figure 2.4 – 2.8 . Vehicle length and NHM are the feature vectors that follow close to the 45-degree line. This again explains the low average percentage error for both feature vectors. SP also shows promising vehicle specific feature characteristics, invariability over space. Maximum magnitude and DOS are the ones that show wide range of variation. From the above analysis, we can conclude that vehicle length is the most prominent feature vector that show reliable repeatability and therefore should be the most important parameter for vehicle reidentification algorithm.

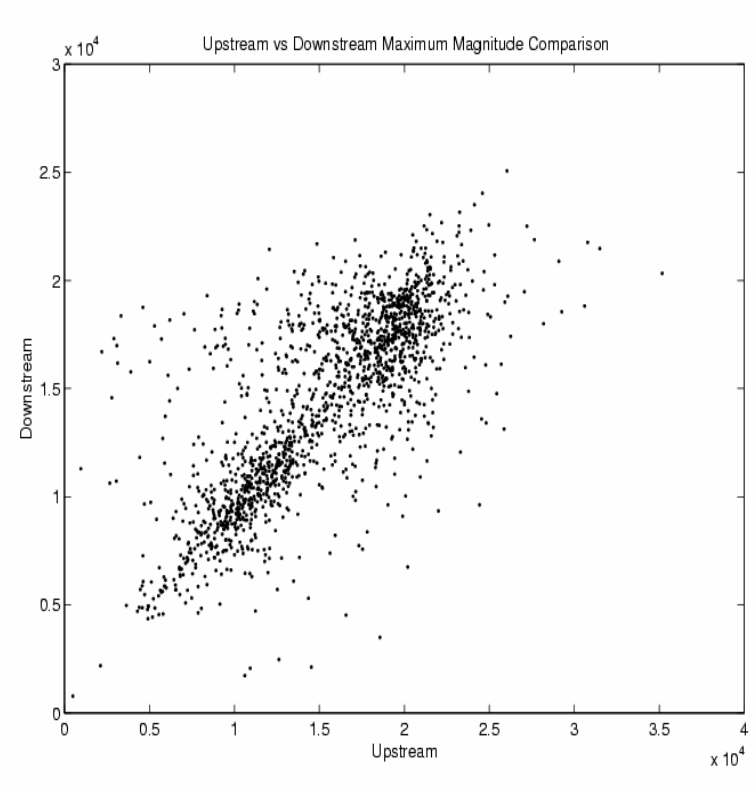


Figure 2.4. Maximum Magnitude Scatter Plot

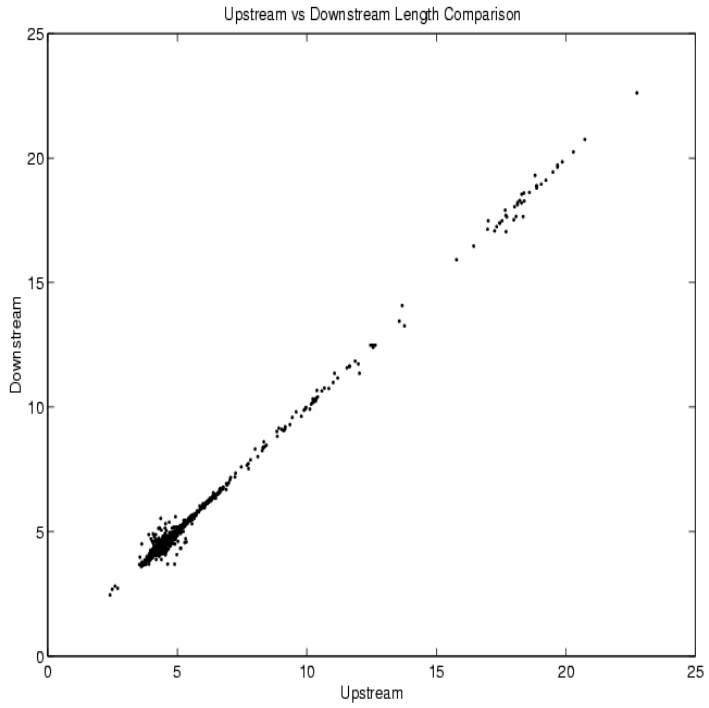


Figure 2.5. Electronic Length Scatter Plot

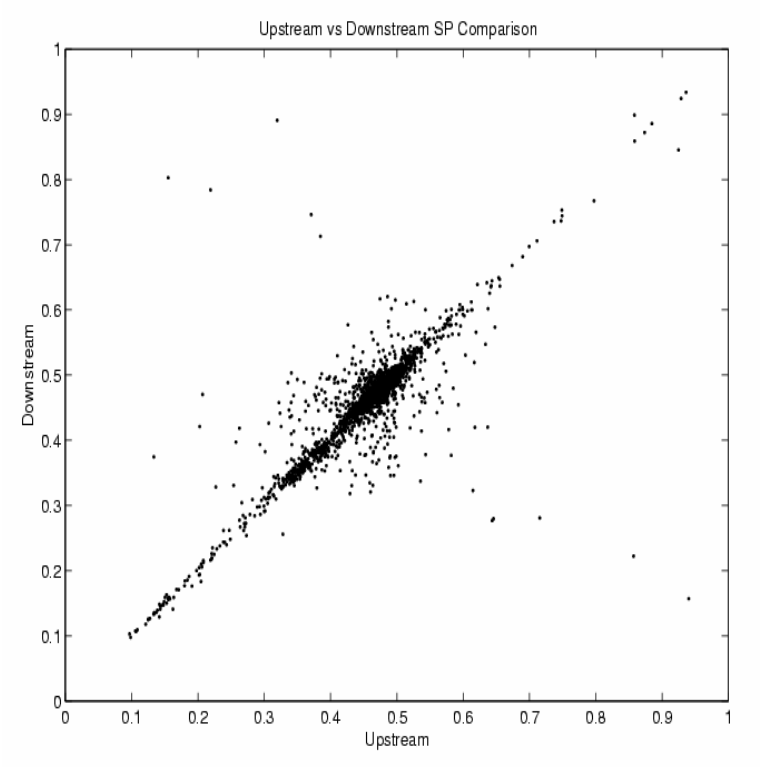


Figure 2.6. SP Scatter Plot

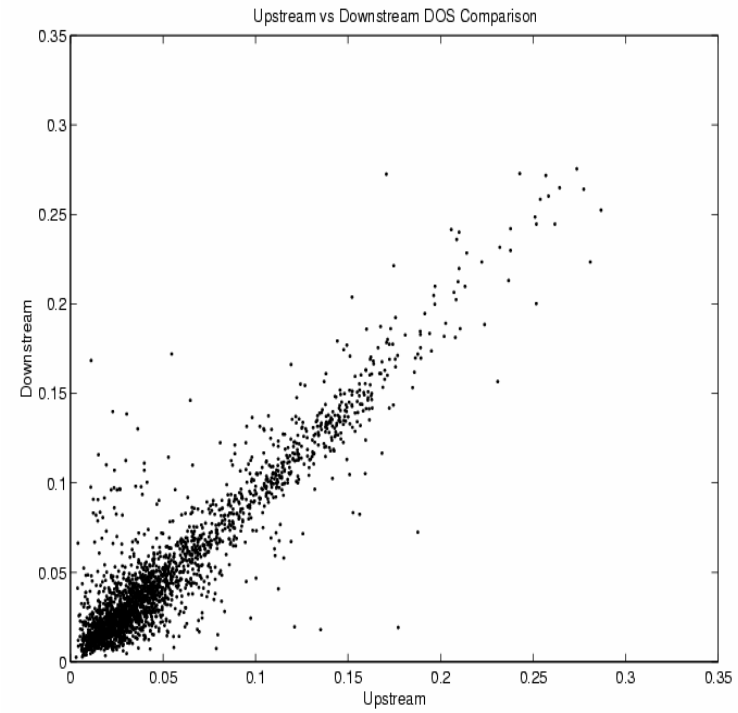


Figure 2.7. DOS Scatter Plot

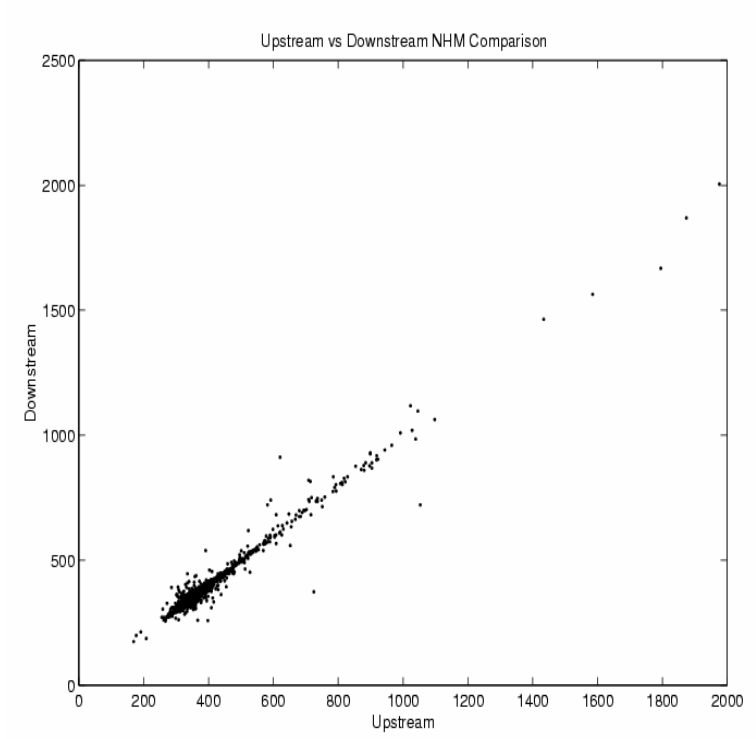


Figure 2.8. NHM Scatter Plot

2.3.2 Statistical Analysis on Feature Difference Distribution (K-S, chi-Square Testing)

The core part of the simulation logic is to generate the inputs for the vehicle reidentification module, based on the vehicle signature feature difference from upstream and downstream. Therefore, the distribution of each vehicle feature should be tested before the feature vector difference generation.

One procedure for testing the hypothesis that a random sample size n of the random variable X follows a specific distributional form is the chi-square goodness-of-fit test. Goodness of fit tests provide helpful guidance for evaluating the suitability of a potential input model. This test formalizes the intuitive idea of comparing the histogram of the data to the shape of the candidate density or mass function. The test is valid for the large sample sizes, for both discrete and continuous distributional assumptions, when parameters are estimated by maximum likelihood. The test statistic is given by the following formula.

$$\chi_0^2 = \sum_{i=1}^{k}\left(\frac{(O_i - E_i)^2}{E_i}\right)$$

$$E_i = n\,p_i$$

where

χ_0^2 : Chi – Square Statistics

O_i: Observed frequency in the *i*th class interval

E_i: Expected frequency in the *i*th class interval

p_i: Theoretical, hypothesized probability associated with the *i*th class interval

n : obsevation, sample size

k : analysis class interval

It can be shown that χ_0^2 approximately follows the chi-square distribution with *k-s-1* degree of freedom, where *s* represents the number of parameters of the hypothesized distribution estimated by the sample statistics. The hypotheses are :

H_0 : the random variable, *X*, conforms to the distributional assumption

H_1 : the random variable, *X*, does not conform

The null hypothesis, H_0, is rejected if $\chi_0^2 > \chi_{\alpha,k-s-1}^2$

In this study, in order to test the normal distribution, two parameters, mean and variance, should be investigated with a degree of freedom of *k-2-1*, where *k* represents the analysis interval. Table 2.3 shows the chi-square statistics and the results for five feature vectors. As presented in the Table, each feature vector difference distribution cannot reject the null hypothesis at the five percent at level of significance, and therefore, can be regarded as a normal distribution.

Table 2.3. Chi-Square Test (* $\chi_{0.05,5}^2 = 11.1$)

Feature Vector	Chi-Square Statistics (Hypothesis Testing)
Maximum Magnitude	9.33 (Cannot reject the H_0)
Length	9.91 (Cannot reject the H_0)
Shape Parameter (SP)	10.98 (Cannot reject the H_0)
Number of High Magnitude (NHM)	8.45 (Cannot reject the H_0)
Degree of Symmetry (DOS)	3.62 (Cannot reject the H_0)

2.3.3 Vehicle Clustering

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, it is impractical to estimate each single error distribution for each individual vehicle. 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 distinct from those of other vehicles in different clusters.

The vehicle signatures in the dataset were clustered 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 feature differences extracted from individual vehicles passing between upstream and downstream detectors were used. The number of clusters corresponds to the number of vehicle types specified in PARAMICS. However, the number of clusters to use is an issue because it 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 in the freeway has attained about 70 ~ 80% of correct matching rate based on the previous studies (Sun et al, 1999; TO 4122).

CHAPTER 3 REIDENTIFICATION SYSTEM DEVELOPMENT

3.1 Introduction

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. (1999) 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.

Vehicle reidentification is the pattern recognition procedure based on a set of vehicles. For each detected vehicle at downstream, the system tries to capture possible matching vehicles from the corresponding upstream station. To reach higher performance rate in vehicle matching, the search for optimal upstream candidate set for each downstream vehicle is critical. This selecting procedure is called optimal candidate searching and several levels of restriction are applied to obtain the final optimal candidate set. Figure 3.1 shows multi - level restriction for the vehicle reidentification system. The restriction can be divided into two categories. Vehicle specific feature restriction and traffic specific restriction. In vehicle specific feature restriction, the elimination of most unlikely identical upstream vehicles is processed based on the vehicle's physical attributes. Traffic specific feature restriction includes the possible upstream set searching as well as time window setting. The first step of this restriction is to reduce the spatial search space, which identifies the upstream origin of each vehicle. The next step of the search space restriction is temporal search space reduction, which establishes a lower and upper bound for feasible travel time, called a 'time window'. For both freeways and arterials, this procedure is more complicated than vehicle specific feature restriction because it involves time/flow variant traffic dynamics. In arterial case, because of the signal interruption, this step is more challenging part. The following sections will discuss the complications and resolution points.

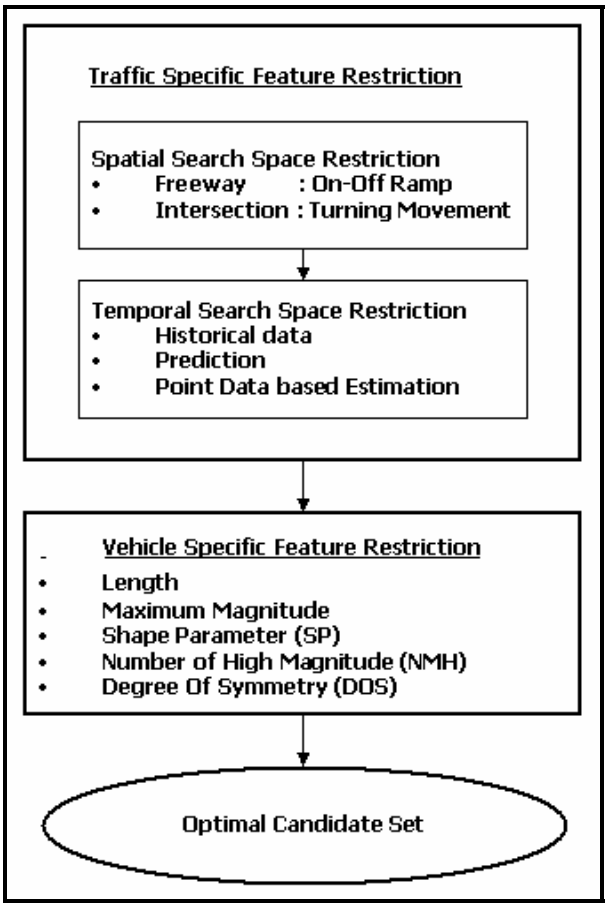


Figure 3.1. Multi Level Restriction

3.2 Freeway Search Space Restriction

For accurate vehicle tracking, accurate upstream and time window settings need to integrate traffic changes. Efforts to achieve this concept are carried in the following steps. The future task includes finding the dynamic optimal time window with the prediction model involved.

3.2.1 Spatial Search Space Restriction

In freeway cases, the upstream corresponds to the immediate adjacent section or the on-ramp, if there is any. Therefore, identification of appropriate upstream is an issue when the on-ramp is present. Depending on the on-ramp distance from the downstream, lane information is used to restrict the spatial space searching procedure. Further investigation on driver's lane changing behavior will contribute to the effective searching space reduction. This investigation will also help to build accurate microscopic simulation model by integrating improved driver's behavior, and to provide safety guideline as lane changing, speed variance and traffic safety are all connected.

3.2.2 Temporal Search Space Restriction

Based on each vehicle's detection time at downstream, downstream point speed data, and the estimated upstream detection time, appropriate time window for each vehicle is derived. Followings show the detailed steps for time window setting and flow chart is summarized in Figure 3.2.

Step I : Downstream Vehicle Detection

DT_v: *Downstream Detection Time of Vehicle v*

S_v : *Downstream Speed of Vehicle v*

L_i : *Length of Section i*

Step II : Travel Time Estimation

$$TT_v = \frac{L_i}{S_v}$$

TT_v: *Estimated Travel Time of Vehicle v*

Step III : Upstream Detection Time Estimation

$$EUT_v = DT_v - TT_i$$

EUT_v: *Estimated Upstream Detection Time of Vehicle v*

Step IV : Lower and Upper Bound Setting

1. From the estimated upstream detection time, get the previous t seconds vehicle speed
2. Find the minimum and maximum speed within the analysis interval, *t*
3. Maximum Speed : gives minimum travel time, TT_{min}
4. Minimum Speed : gives maximum travel time, TT_{max}

Step V : Time Window Setting

$$DT_v - TT_{\max} \le TW_v \le DT_v - TT_{\min}$$

TW_v : *Time Window for Vehicle v*

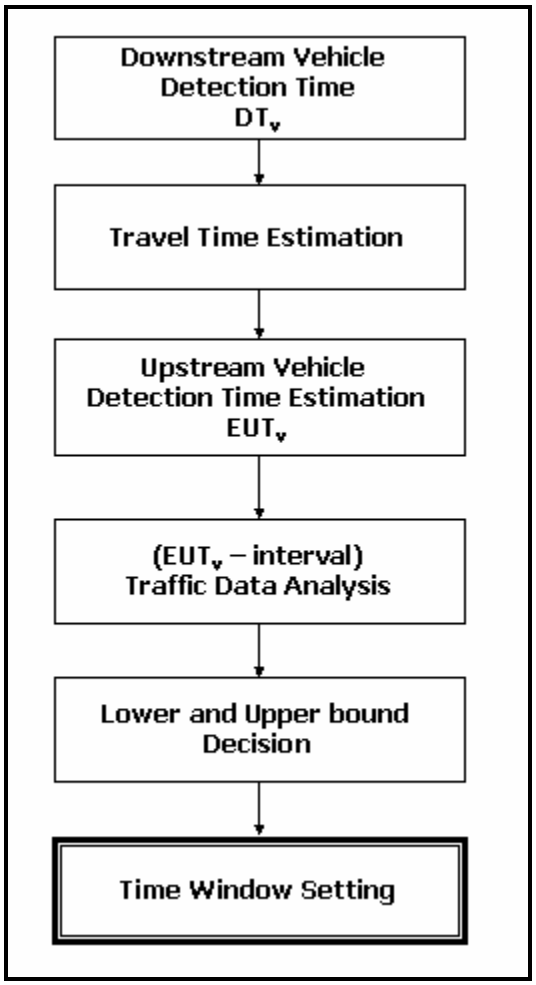


Figure 3.2. Freeway Time Window Setting Flow Chart

3.3 Arterial Search Space Restriction

Unlike the freeway case, the intersection traffic flow is interrupted by vehicle-actuated signal control, resulting in highly variable travel times. A new search space reduction algorithm is developed for more general use of the proposed vehicle reidentification technique at signalized intersections utilizing midblock system detector and signal phase information. Figure 3.3 presents a schematic of general loop detector configurations on signalized arterials including upstream detector, mid-block system detector, and actuated signal control detector. This section presents search space reduction algorithm utilizing mid-block system detectors with signal phase information. Delay mechanism at signalized intersections including arterial travel time is the basis of developing the algorithm.

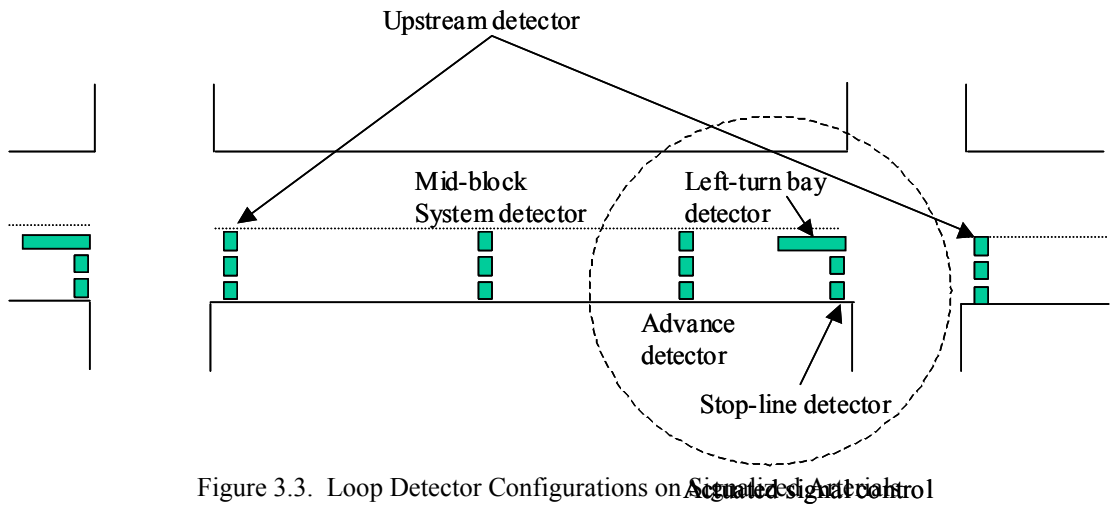


Figure 3.3. Loop Detector Configurations on Signalized Arterials

3.3.1 Background

Unlike freeway case, estimating travel time on signalized arterials is a much more challenging problem due to the presence of signal control, resulting in highly fluctuated travel times. Since the purpose of this study is to use loop detector data as inputs of travel time estimation algorithm, relevant literature were reviewed. Reviewed studies include British model (Gault and Taylor, 1977), Illinois model (Sisiopiku and Rouphail, 1994), Iowa model (Zhang, 1998), and Singapore model (Xie et al., 2001). The models are briefly introduced in the following.

• *The British model* (1977)

$$T = ao + b, \left\{ \begin{array}{l} a = \alpha_0 + \alpha_1 \left(\dfrac{L}{v_f} \right) + \alpha_2 \left(\dfrac{qC}{sg} \right) + \alpha_3 \left(\dfrac{P_d}{P_u} \right) \\ b = \beta_0 + \beta_1 \left(\dfrac{L}{v_f} \right) + \beta_2 + \beta_3 \left(\dfrac{P_d}{P_u} \right) \end{array} \right\}$$

where

T : Average link travel time

o : Average detector occupancy

L : Link length

v_f : Free flow speed

q : Flow (obtained from detector)

C : Cycle length

g : Green time

P_d : Downstream green time

P_u : Upstream green time

α, β : Regression coefficient

• *The Illinois model* (1994)

$$T = \frac{L}{v_f} + b_1 + b_2 \det loc + b_3 o + b_4 grnrat$$

where

$\det loc$: Ratio of detector setback from the stopline over link length

$grnrat$: Effective green ratio (g / C)

b : Regression coefficient

• *The Iowa model* (1999)

$$u = \gamma u_{v/c} + (1-\gamma) u_{q/o}, \begin{cases} u_{v/c} = u_f - \alpha \exp\left(\beta X'\right) \\ u_{q/o} = 0.379\left(\dfrac{q}{o}\right) \end{cases}$$

where

u : Journey speed

X : Critical V/C ratio $= \max\limits_{i=1,\ldots,n}\left(\dfrac{q_i C}{s_i g_i}\right)$

γ : Weight factor, $(0 \le \gamma \le 1)$

u_f, α, β : Model parameter to be calibrated

• *The Singapore model* (2001)

$$T = \frac{L}{u_{\text{det}}} + 0.9\phi\left[\frac{C(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2q(1-x)}\right]$$

where

u_{det} : Maximum speed of the downstream and upstream detector stations

ϕ : Downstream queue factor (more details of ϕ can be found in the literature)

It has been identified that proposed models in the literature are based on statistical modeling using regression analysis. Travel time model for signalized arterials can be viewed as the combination of running time and signal delay. The major factors affecting running time are free flow speed and link length defined by upstream and downstream detector stations. On the other hand, signal delay is a function of signal control parameters such as cycle length and green time. Of course, traffic volume provides a significant impact on both running time and signal delay. This study develops an arterial travel time model that will be used for establishing time window based on these findings.

Estimating travel time is a basis for establishing time window, which reduces upstream candidate vehicles. Travel time between detection stations for vehicle reidentification at signalized intersections consists of three components. These components include stopped delay (t_D), time spent from upstream detector location to the end of the queue (t_2), and time spent from stopline to downstream detector location (t_1) as shown in Figure 3.4. Minimum and maximum travel times of vehicle k are derived from the delay process at signalized intersections, and further utilized for time window.

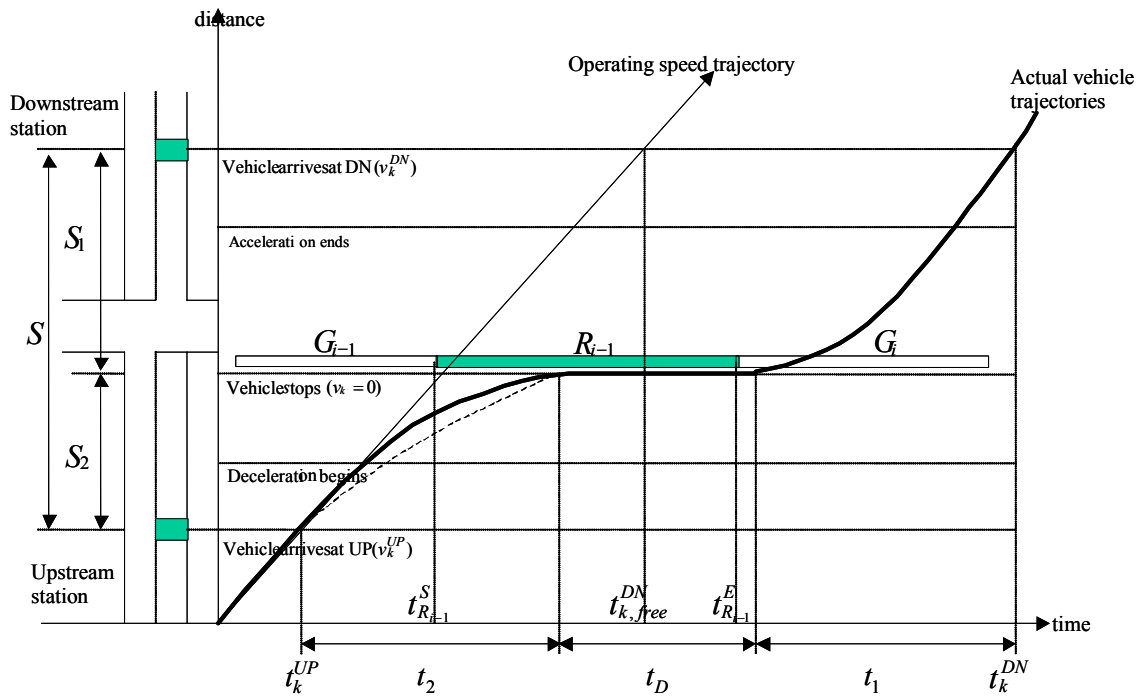


Figure 3.4 Delay process at signalized intersections

3.3.2 Spatial Search Space Restriction

Once t_1 is estimated as presented above, the upstream origin of a certain vehicle can be readily identified by checking signal phase information with $t_k^{DN} - t_1$. Figure 3.5 shows the proposed search space reduction procedure to perform vehicle reidentification at signalized intersections.

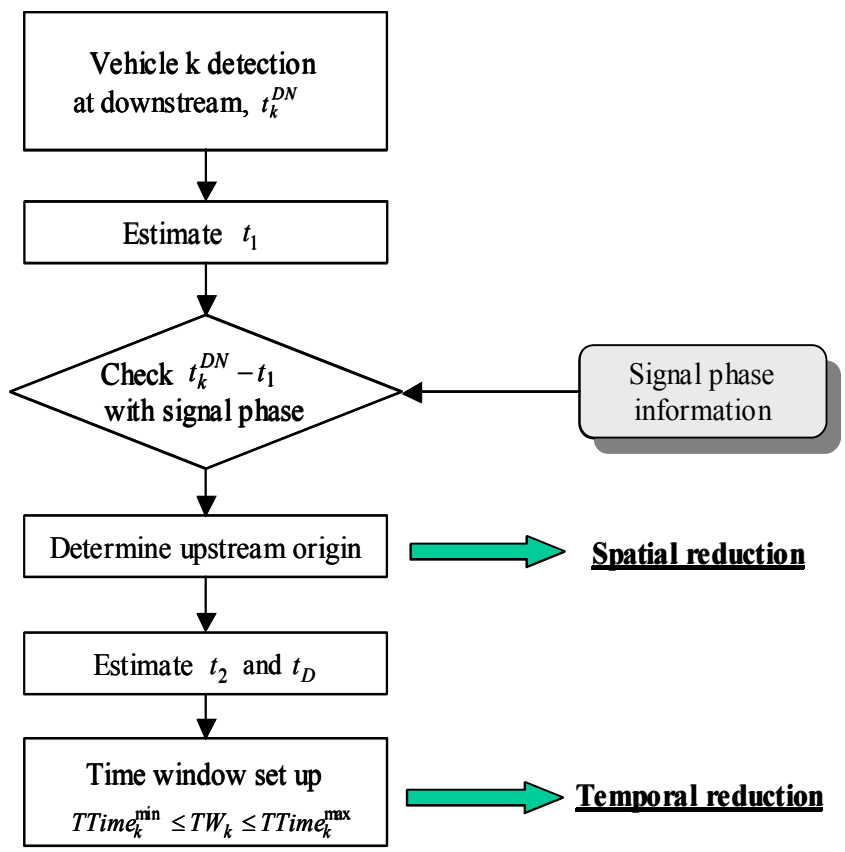


Figure 3.5 Procedure for Signalized Arterial Spatio-Temporal Search Space Reduction

3.3.3 Temporal Search Space Restriction

Temporal search space reduction is performed by establishing a time window, which is based on the delay mechanism at signalized intersections. When a certain vehicle is observed at a downstream detector station, the time window of the vehicle is established by minimum and maximum travel times. The time window of vehicle k can be described as

$$t_k^{DN} - TTime_k^{\min} \le TW_k \le t_k^{DN} - TTime_k^{\max}.$$

Figure 3.6 – 3.8 illustrate the flow chart for distance calculation to determine the time window. The algorithm embedded in simulation first checks if the vehicle is transferring the link as well as the detector configuration setup for proper distance calculation. Each time segment, such as t_1, t_2, and t_D in Figure 3.4, is derived according to the detector position, and signal phase information.

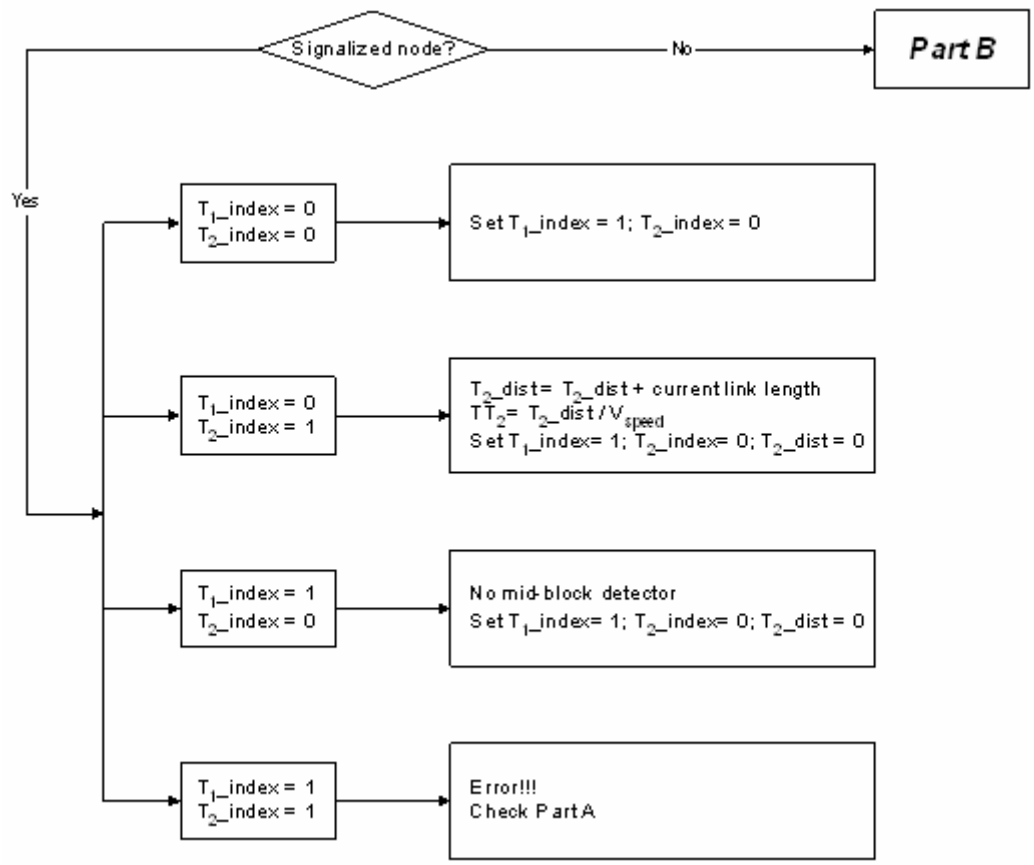


Figure 3.6 Arterial Time Window Setting : Part A

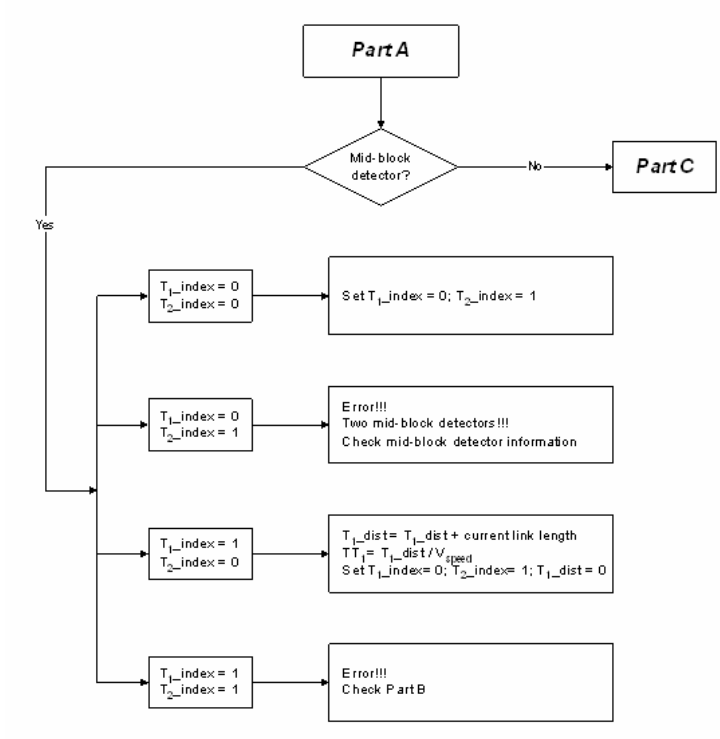


Figure 3.7 Arterial Time Window Setting : Part B

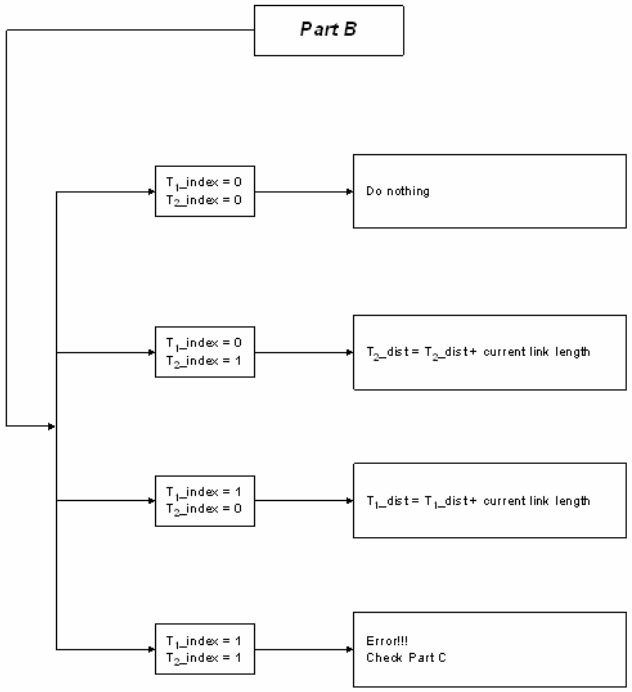


Figure 3.8 Arterial Time Window Setting : Part C

3.4 Multi – Section Reidentification

Vehicle tracking along the multi section will be performed based on the combination and integration of single section tracking results. Each vehicle keeps single section reidentified information that gives the starting/ending node of each link. The path information, multi – section reidentification algorithm result, is then obtained by updating each link's ending node as the starting node for the next adjacent link. In this study, simple and straightforward updating procedure is applied. Future research area should involve further investigation on single section result updating scheme. Figure 3.9 describes the multi-section reidentification result derivation concept.

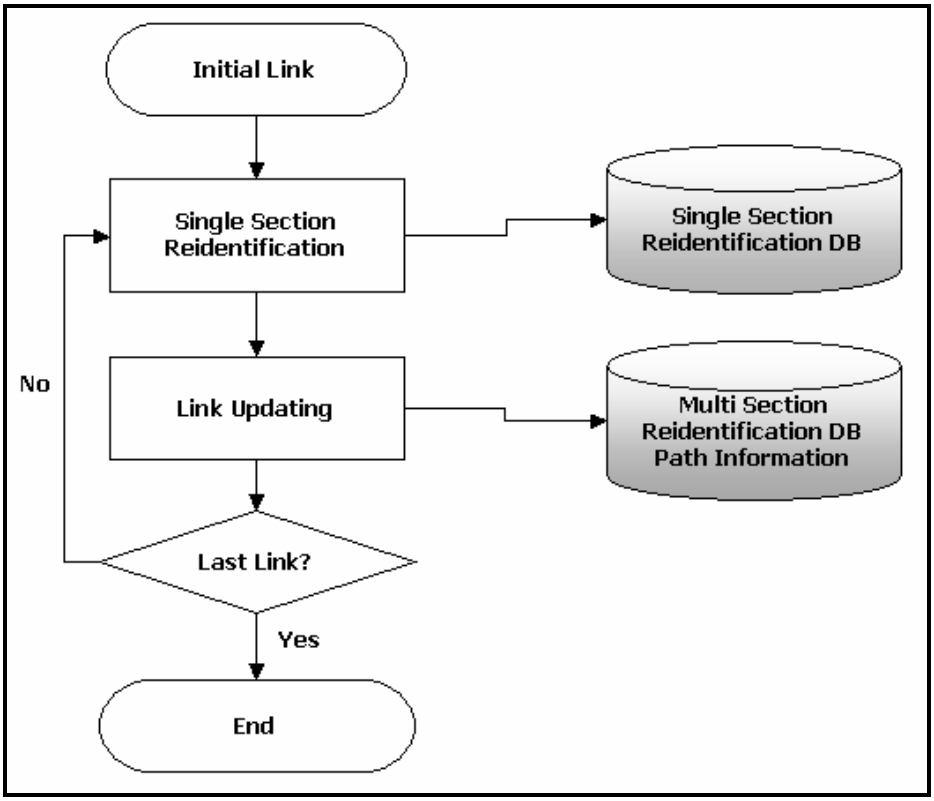


Figure 3.9 Multi Section Concept

3.5 Performance Measurements (PeMS)

The performance measurements (PeMS) that have been developed in this study based on anonymous vehicle tracking provide a breakthrough in traffic performance measurement accuracy and versatility. Previous performance measure studies relied on point-based traffic information either from single or double loop data. As these methodologies provide performance measures based on point data, they cannot provide an accurate reflection of entire sections. In fact, these section-related performances are obtained from

extrapolations from a single point in the network. Since traffic movement represents a dynamic compressible flow, it is not possible to assume uniform conditions across an entire section based on measurements from a single point. While point measurements may be accurate at the immediate vicinity of the detector station, they would provide erroneous estimates for street or freeway sections, which typically span between one and three quarters of a mile.

With the critical need for a comprehensive performance measurement system and the limitations of the present systems, it is imperative to develop new performance measures that are able to provide traffic information representative of piecewise continuous road sections. Through the implementation of the anonymous vehicle tracking system, vehicles can be tracked across freeway sections, street sections and even street intersections. Hence, accurate section travel times and speeds can be obtained without compromising the privacy of vehicle occupants. Besides, this system can be readily expanded to track vehicles across multiple sections to obtain performance measures of not just individual road segments, but origin-destination paths in extensive road networks. The following table summarizes the performance measurement details that can be obtained at information and network levels and data applications.

Table 3.1 Summary of PeMS

	PeMS	Information Source	Application
Station (Point)	- Flow, volume, intersection turning volume - Occupancy - Speed - Vehicle class	Basic Traffic Point Data	- Performance evaluation based on point measurements - Vehicle Classification
Link (Section)	Algorithm Evaluation - Detection Rate (= B/A) - Correct Matching Rate (= C/A) - System Reliability Rate (= C/B) Link Travel Time - Accuracy - Variation - Delay OD Information - Lane based OD Matrix	Single Section Vehicle Reidentification Total vehicle at downstream = A Algorithm declared matching vehicle = B Correctly matched vehicle from algorithm = C Origin : upstream lane Destination : downstream lane	- Performance evaluation based on section measurements - Congestion monitoring - Travel time reliability - Real time traveler information - Driver's behavior analysis - Safety - LOS Analysis
Network (Path)	Algorithm Evaluation - Detection Rate (= B/A) - Correct Matching Rate (= C/A) - Total System Reliability Rate (= C/B) - Individual Vehicle System Reliability Rate (= (C/B)*(L_m/L_t)) OD Information - Volume accuracy - Travel time accuracy - Travel time variation - Travel time delay	Multi-Section Vehicle Reidentification Total vehicle at destination Z_d from origin Z_o = A Algorithm declared at destination Z_d with origin Z_o = B Correctly tracked vehicle from algorithm (correct Z_o) = C Missing Link from algorithm in predefined path= L_m Total Link in predefined path= L_t	- Time-varying OD matrix estimation - Dynamic traffic assignment - Route guidance - Coordinated traffic control - Real-time traveler information

CHAPTER 4 SIMULATION FRAMEWORK

4.1 Introduction

The proposed evaluation framework employs PARAMICS microscopic traffic simulator. To date, various simulation models have been used for evaluating ATMIS strategies. Traffic simulation models can be broadly classified into two groups: 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 better 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. The overall simulation flow chart is described in Figure 4.1 and each module is mentioned in detail respectively in the following sections.

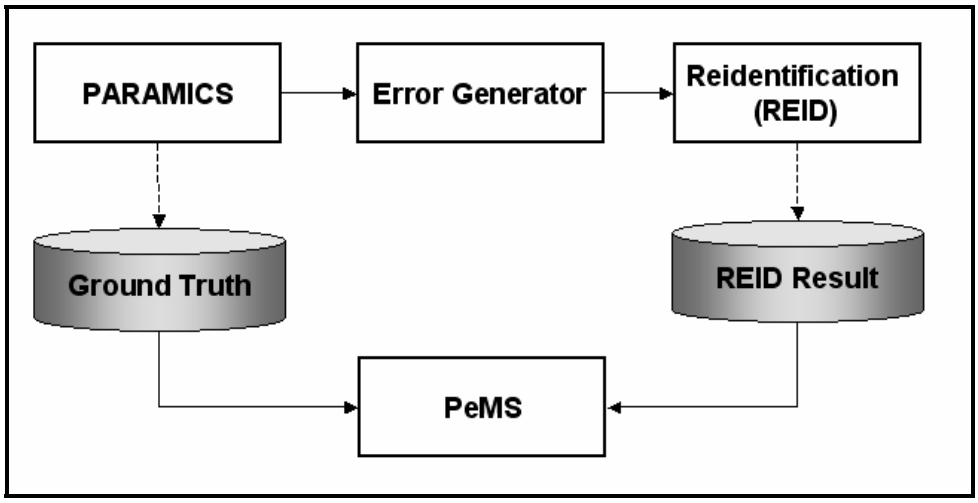


Figure 4.1. Overall Simulation Framework

4.2 PARAMICS

PARAMICS (PARAllel MICroscopic Simulation) is a parallel, microscopic, scalable, user programmable and computationally efficient traffic simulation model (Duncan, 1995; Quadstone Ltd., 2003) that has been used for many applications in the ATMS Testbed. Individual vehicles are modeled in fine detail for the duration of their entire trip, providing comprehensive traffic characteristics and congestion information, as well as enabling the modeling of the interface between drivers and Intelligent Transportation Systems facilities and strategies.

The Testbed network (for Orange County) coded into PARAMICS consists of 5,400 nodes, 12,160 links and 420 zones, and provides a highly detailed 3-dimensionally and geographically correct representation for traffic and ITS simulations. This network is coded for over 200,000 vehicle trips across both freeways and major arterials in the 4-6pm afternoon peak period. This network is also calibrated based on UCI Testbed archived real world dataset. At ITS-Irvine, PARAMICS currently operates on an SGI Origin2000 mutiprocessor workstation. With this system, over 90,000 vehicles can be simulated in real-time (or fewer vehicles in faster than real-time) (Lee, 1998).

A notable feature of PARAMICS is its scalability. A large network, such as that for the California ATMS Testbed, can be decomposed into regions where each is simulated on a processor in a parallel machine. This scalability enables development to start off small and then grow, and provides the potential for achieving faster than real-time, multi-scenario simulations. Another major feature of PARAMICS is its Application Programming Interface (API). The API allows the user to customize many features of the underlying simulation model, and to link PARAMICS to other applications developed by the user. Moreover the API allows additional functionality by adding more external modeling routines. Additional PARAMICS key features include:

- A fully integrated and interactive graphical network editor and manager
- A highly detailed definitions of roadway network, travel demand, driver, vehicle, and traffic control devices
- ITS-capability, featuring integrated simulation of ITS components, including a variety of traffic management, information and control strategies
- Capability of modeling pre-timed and actuated signal control mechanisms
- Capability of modeling vehicle emissions, incident, bus, and car parking
- A fully integrated visualization tools to display simulation results

4.3 Network Setting and Tracking Module

The initial step to build the simulation framework is discussed in this section. Parameters setting, network scope decision and API module implementation for vehicle tracking are the major tasks. The inter-relation among those factors is illustrated in Figure 4.2.

A central control module in PARAMICS is connected with both arterial and freeway vehicle tracking API module. Detector ID information will contribute to identify the network attribute to set the corresponding reidentification algorithm. In PARAMICS, users are able to 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 chapter, we pre-defined vehicle types and vehicle proportions in PARAMICS prior to running the simulation. The calibrated parameters, such as reaction time and headway, were set according to the previous studies (Chu et al 2003, 2004).

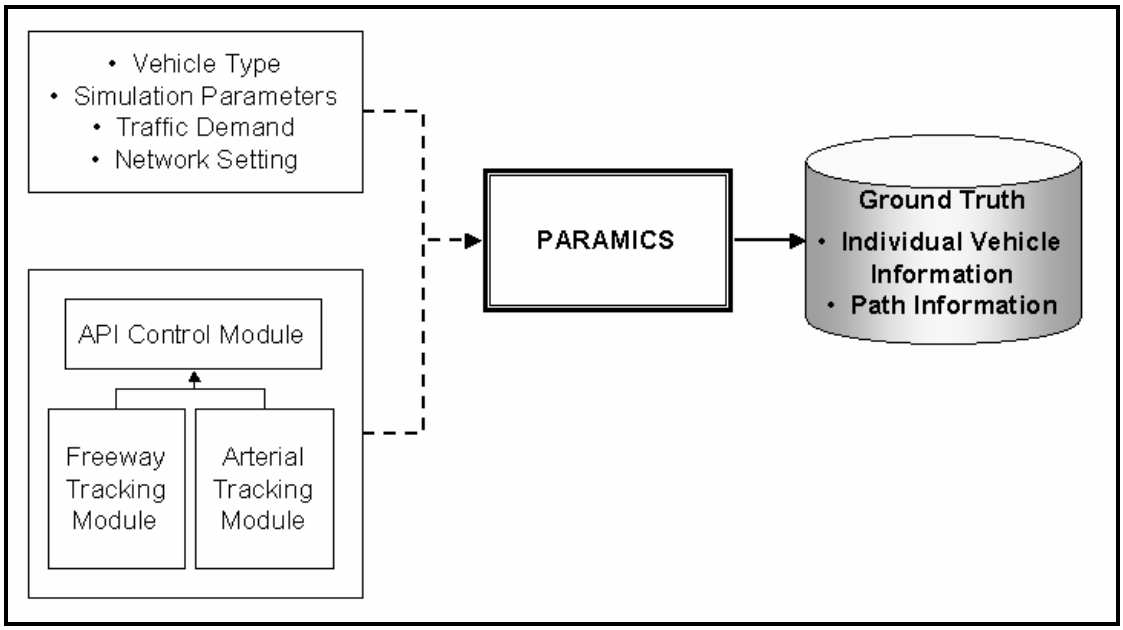


Figure 4.2 PARAMICS Modeller

The network site for the proposed study covers the I-405 corridor and 36 arterial intersections in southern California. The entire study site network is presented in Figure 4.3.

In freeway setting, I-405 and SR-133 were the major freeway corridors with five consecutive interchanges. The interested five interchanges are:

1. I-405 and Jeffrey
2. I-405 and Sand Canyon

3. I-405 and SR-133
4. I-405 and Irvine Center Dr.
5. SR-133 and Barranca

A total 115 detector stations were coded including on-ramp detectors, off- ramp detectors, and mainline detectors. The freeway was configured with six lanes and a speed limit of 65 mph, while on-ramps had a speed limit of 40 mph. A total of five zones were connected with the freeway traffic demand.

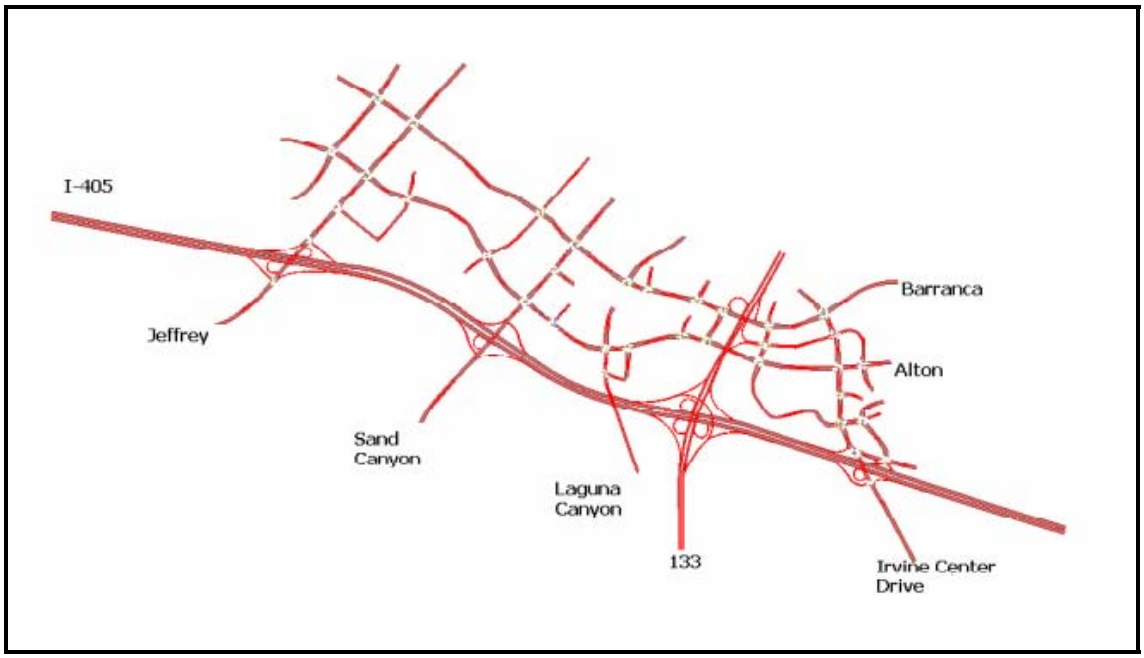


Figure 4.3 Proposed Study Site

In the arterial network, 36 intersections in city of Irvine were included. They were coded with a three - lane configuration and a speed limit of 40 mph. A total of 156 detection stations and 30 zones were implemented. Table 4.1 lists the 36 intersections coded in the simulation network.

Table 4.1 Intersection List

Intersection Number	Road Name	
1	Barranca Parkway	East Yale Loop
2	Alton Parkway	East Yale Loop
3	Barranca Parkway	Jeffery Road
4	Alton Parkway	Jeffery Road
5	Jeffery Road	Quailcreek Road
6	Jeffery Road	Northbound 405
7	University Drive	Southbound 405
8	Alton Parkway	Royal Oak Drive
9	Barranca Parkway	Valley Oak Drive
10	Alton Parkway	Valley Oak Drive
11	Barranca Parkway	Sand Canyon Avenue
12	Sand Canyon Avenue	Hospital
13	Alton Parkway	Sand Canyon Avenue
14	Alton Parkway	Hospital
15	Barranca Parkway	Laguna Canyon Road
16	Alton Parkway	Laguna Canyon Road
17	Laguna Canyon Road	Pasteur
18	Barranca Parkway	Telemetry
19	Alton Parkway	Jenner
20	Barranca Parkway	Herchel
21	Alton Parkway	Telemetry
22	Barranca Parkway	Banting
23	Alton Parkway	Banting
24	Barranca Parkway	Pacifica
25	Pacifica	Gateway
26	Alton Parkway	Pacifica
27	Barranca Parkway	Irvine Center Drive
28	Irvine Center Drive	Gateway Boulevard
29	Alton Parkway	Irvine Center Drive
30	Irvine Center Drive	Spectrum
31	Irvine Center Drive	Pacifica
32	Irvine Center Drive	Enterprise Drive
33	Irvine Center Drive	Southbound 405
34	Alton Parkway	Gateway Boulevard
35	Gateway Boulevard	Fortune Drive
36	Enterprise	Freeway 133

4.4 Error Generator Module (EG)

In this module, the input data for reidentification algorithm will be generated based on vehicle statistics analysis performed in the previous chapter. Vehicle types, their traffic pattern, and their proportion in traffic stream are predefined from the PARAMICS module. Major API coding was also performed for the Error Generator module.

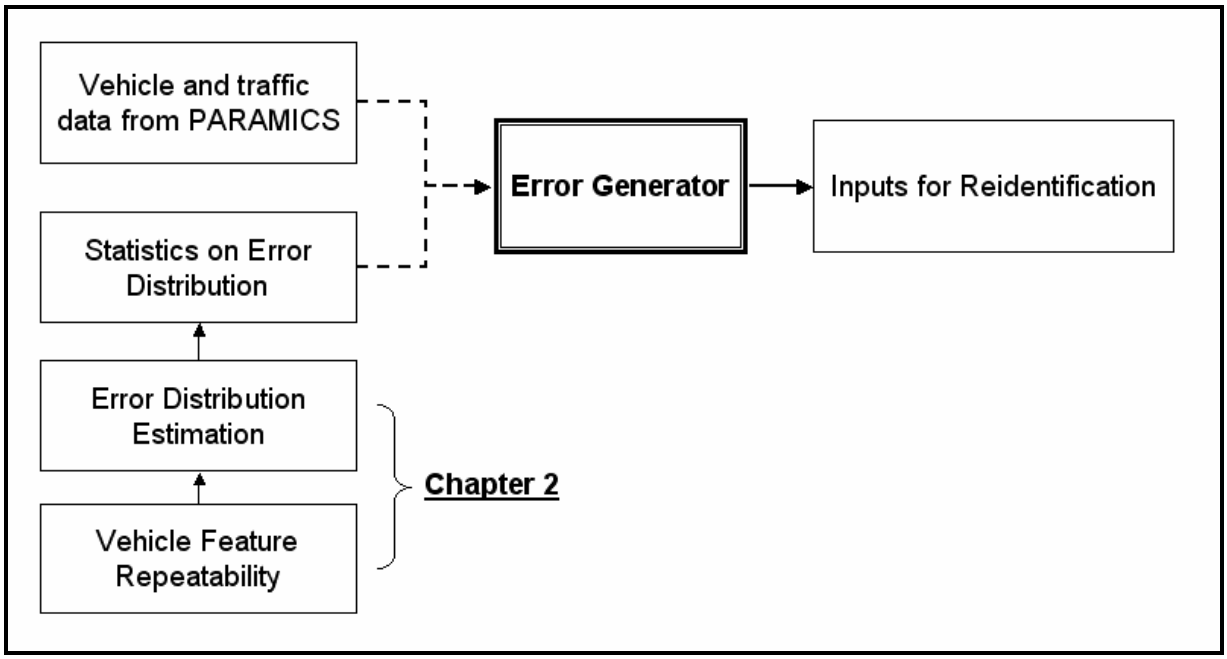


Figure 4.4 Error Generator Module

4.5 Reidentification Module (REID)

In the Reidentification Module (REID), a lexicographic reidentification algorithm was implemented and examined by applying the input data from EG Module. The path information was then derived through integration of single section reidentification results.

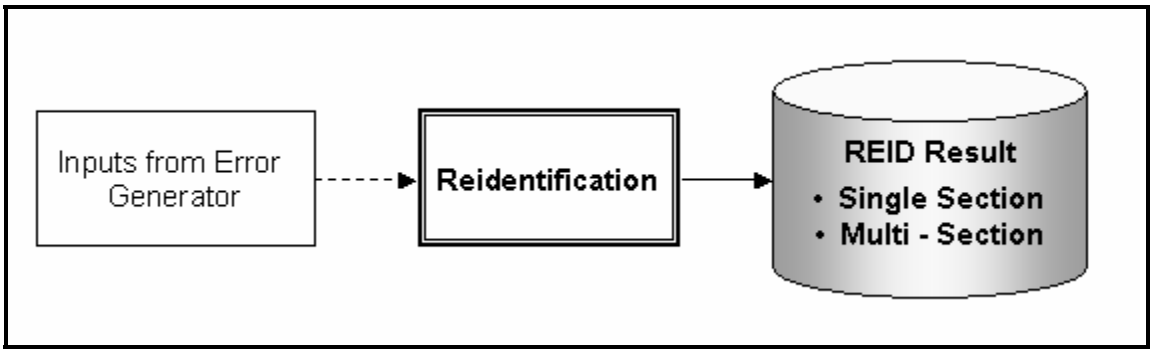


Figure 4.5 Reidentification Module

4.6 PeMS Module

As discussed in the earlier chapter, performance measurements are obtained by comparing the ground truth data with reidentification results. The investigation on defining the optimal aggregation interval for accurate traffic parameters derivation is also a future study area.

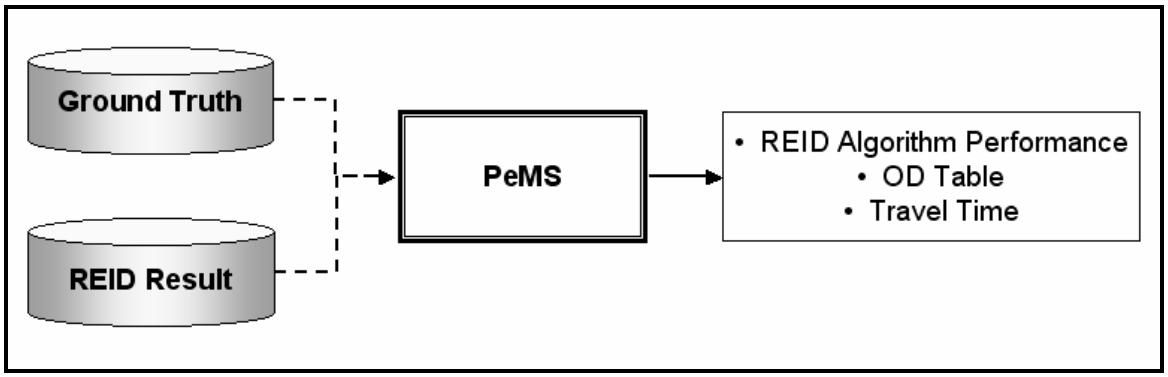


Figure 4.6. PeMS Module

CHAPTER 5 PARAMICS EXPERIMENTAL DESIGN AND RESULT ANALYSIS

5.1 Introduction

Invaluable section-related traffic information can be obtained by tracking individual vehicles. In this section, travel time is chosen as the main analysis component since it is one of the most important traffic measurement parameters for successful and efficient traffic operations and control. The search for an optimal aggregation interval was conducted based on the assessment of travel time percentage error. In this section, five different aggregation intervals were used. Furthermore, three types of path, with different road geometry compositions, were also selected for expanded research scope. The following subsections will explain each analysis step in detail.

5.2 PARAMICS Setting

Traffic demand was set to be moderate flow throughout the simulation running. The simulation duration, which consisted of a total of 45-minute simulation running time, with 20-minute warmup time, was deployed due to limitations of computer processors. The warmup time served to ascertain stable traffic flow conditions before executing the vehicle re-identification algorithm. The vehicle-releasing pattern followed the normal distribution and a total of 30 simulation runs with different seed numbers were performed. In average, there were 4470 vehicles that were released after the warm-up time period and therefore, were subject to the REID API running. Among those 4470 vehicles, about 1500 vehicles were declared as reidentified by the implemented REID API. Details on REID module results will be mentioned in the following section.

In this study, three different paths that varied with road type were selected for further analysis. Path 1 was mainly composed of I-405 freeway sections. Arterial links were the main components for path 2. In path 3, freeway and arterial sections were mixed. With this setup, the effect of vehicle re-identification results on estimated travel time accuracy at different locations and paths can also be examined. Figure 5.1 explains the overall study site as well as three different paths.

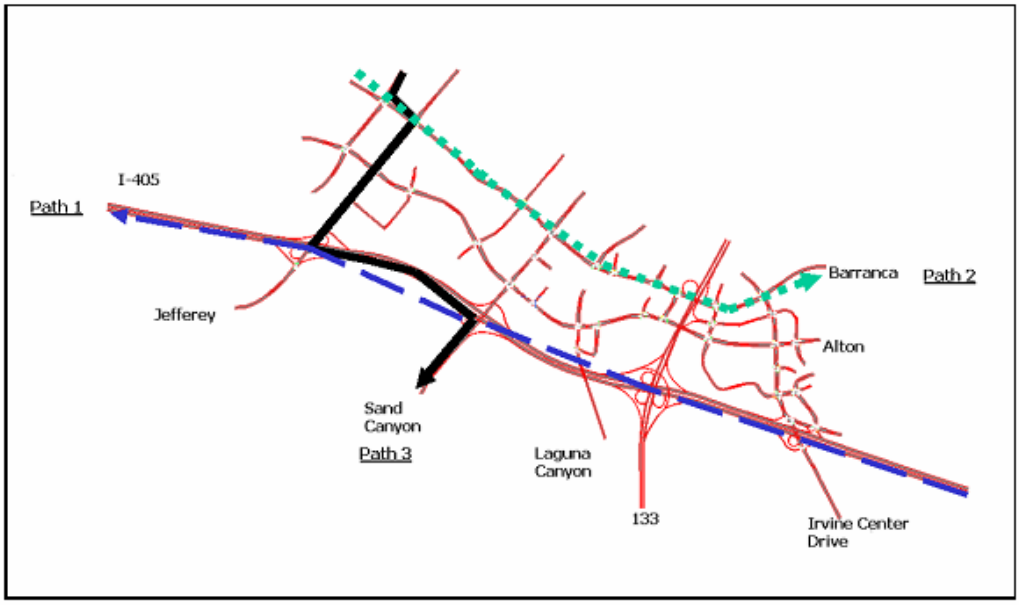


Figure 5.1 Three Different Paths

5.3 REID Module Analysis

A total of 17 vehicle types were generated to ensure average correct matching rate of 70% for single section REID. The mixture of vehicles types is set to represent or replicate closely the real world traffic composition. Motorcycles and short vehicles that include passenger cars, SUVs, and vans were categorized as vehicle type from one to twelve. Trucks and trailers were categorized as vehicle types from 13 to 17 depending on vehicle feature vectors. In this study, short vehicles refer to vehicle types from one to twelve and the rest as long vehicles.

The average Correct Matching Rate (CMR), as defined in previous section, across all the single sections in the network were 70.12%. Table 5.1 describes analysis of multi-section REID module results. As illustrated in this table, CMR for long vehicles are higher compared to the CMR of short vehicles in all three different paths. Outstanding signature feature vectors of long vehicles are contributing to the resulting high CMR. Another element that affects multi s-section CMR is number of single sections in the corresponding path; in this case, path 1, 2, and 3.

Table 5.1 Multi-Section REID Module Results per Vehicle Type

Vehicle Code	Vehicle Description	Composition %	CMR (%)		
			Path 1 (*14)	Path 2 (*10)	Path 3 (*15)
1 - 12	Short Vehicles - Motorcycle, PC, SUV, Van, Small Pickup etc	72.02	10.65	5.25	6.30
13 - 17	Long Vehicles - Truck, Trailer etc	27.98	11.61	5.28	6.43

(*) Number of single section in corresponding path

5.4 Travel Time Analysis

5.4.1 Travel Time Validation, Hypothesis Test

The investigation on validation of estimated travel time needs to be processed prior to the analysis of estimated travel time. Hence, two hypothesis analysis techniques were applied for this purpose, depending on the sample numbers, which in turn are also highly related to the aggregation interval.

KS Test

The Kolmogorov-Smirnov test (K-S Test) is applied to examine the significance of the difference between travel time from reidentified travel time and ground truth travel time. The K-S test is non-parametric and is based on the largest absolute difference between the observed and the expected (or theoretical) cumulative distributions. An attractive feature of this test is that the distribution of the K-S test statistic itself does not depend on the underlying cumulative distribution function being tested. In other words, the KS-test has the advantage of making no assumption about the distribution of the dataset of interest. Another benefit of the K-S test is that it is an exact test, unlike the chi-square goodness-of-fit test, which depends on the availability of an adequate sample size for the approximations to be valid. Due to the small sample number at the aggregation level of 30 seconds, the K-S test was deployed for the travel time hypothesis analysis.

t-test

t-test is used when comparing the differences between two sample means. Depending on sample size and sample variance characteristics, there exist three types of *t-test*. In this study, Type 2 *t-test* was applied since the sampling size was less than 30 at the aggregation interval of 60, 90, 120, and 150-second. It

should be noted that the vehicle- releasing pattern follows the normal distribution and therefore samples satisfy one of the requirement of a Type 2 *t-test*.

Table 5.2 shows the two hypotheses test procedure mentioned in this study.

Results

Both KS test and *t-test* results show that the estimated travel time does conform to the true travel time for all paths and at all aggregation intervals. The results demonstrate that the re-identification system is capable of producing accurate estimates of travel time information

Table 5.2 Hypothesis Procedure

Step I : Hypothesis Definition H_0 : Reidentified travel time distribution conforms to the real travel time distribution H_1 : Reidentified travel time distribution does not conform to the real travel time distribution Or $H_0: \bar{X}_1 = \bar{X}_2,\ H_1: \bar{X}_1 \neq \bar{X}_2$	
Step II : Level of significance Definition α =0.05	
Step III : Statistics Calculation	
KS test *KS* = Max(difference value between theoretical cumulative curve and sample cumulative curve)	***t-test*** $T = \dfrac{(\bar{X}_1 - \bar{X}_2)}{S_p\sqrt{(1/n_1)+(1/n_2)}}$ n_1 : Sample Size of Group 1 n_2 : Sample Size of Group 2 $S_p^2 = \dfrac{(n_1-1)S_1^2+(n_2-1)S_2^2}{n_1+n_2-2}$ (Pooling variance)
Step IV : Degree of Freedom Definition	
KS test $\nu = n - \rho + 1$ n : sample number ρ : number of estimated parameter	***t-test*** $\nu = n_1 + n_2 - 2$
Step V : Decision Making – Rejection Area	
KS test $KS > KS_\alpha$	***t-test*** $T < -t_{\alpha/2}$ $T > t_{\alpha/2}$ Two-tailed test.

5.4.2 Estimated Travel Time Analysis

The preceding analysis on travel time validation has shown that it was safe to conclude that the estimated travel time represents the true travel time at all five different aggregation levels. Identifying the optimal travel time aggregation intervals for generating useful traffic information accounting for the real-time performance of transportation systems is an important issue in the field of traffic surveillance and information systems. In this section, estimated travel time accuracy was assessed at five different aggregation intervals.

Analysis Index

Total travel time percentage error (TotTTPE) was applied as the index for accuracy analysis and the following formula shows the TotTTPE calculation procedure. At each step, the travel time accuracy is evaluated based on the comparison between the system declared travel time and ground-truthed travel time. TotTTPE is the average of these step-by-step percentage errors. Five different aggregation intervals are applied in this study.

$$TTPE^k = 100 \times \left(\frac{abs\left(\frac{\sum_{i=1}^{N^k} GTT_i^k}{N^k} - \frac{\sum_{j=1}^{RN^k} RTT_j^k}{RN^k} \right)}{\frac{\sum_{i=1}^{N^k} GTT_i^k}{N^k}} \right)$$

where

$TTPE^k$: Travel time percentage error at interval k

GTT_i^k : Ground truth travel time for individual vehicle i within interval k

RTT_j^k : REID travel time for individual vehicle j within interval k

RN^k : REID volume during interval k

N^k : Ground truth volume during interval k

k : analysis time step

$$TotTTPE = 100 \times \left(\frac{\sum_{k=1}^{INT} TTPE^{k}}{INT} \right)$$

where

$TotTTPE$: Total travel time percentage error

$TTPE^{k}$: Travel time percentage error at interval k

INT : number of total analysis interval

In addition to TotTTPE, the effect of aggregation interval on travel time accuracy was investigated by the percentage error changing rate (PE_CR) index shown as follows.

$$PE_CR_{l}^{k} = 100 \times \left(\frac{\left| TotTTPE_{k} - TotTTPE_{l} \right|}{TotTTPE_{l}} \right)$$

where

$PE_CR_{l}^{k}$: Changing rate of percentage error from interval l to k second

$TotTTPE_{l}$: Total travel time percentage error at interval of l

$l \neq k$

Travel Time Result Analysis

Figure 5.2 describes average TotTTPE from 30 different simulation runs at five different aggregation intervals. PE_CR is also presented in Table 5.3. It is obvious that the aggregation interval size is an important issue for designing real-time traffic management and information strategies. As described from the above results analysis, different aggregation intervals produce different levels of accuracies. In addition, shorter aggregation intervals have bigger travel time variations than those of the longer intervals.

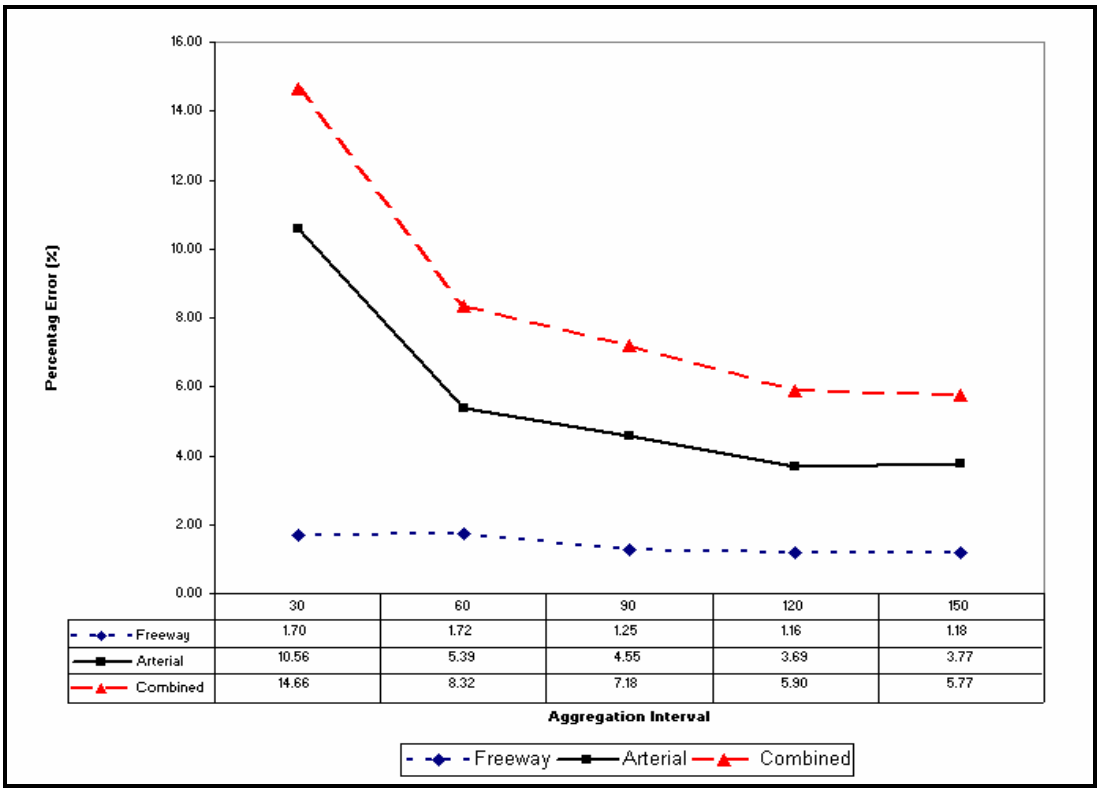


Figure 5.2 Average TotTTPE at Different Aggregation Intervals

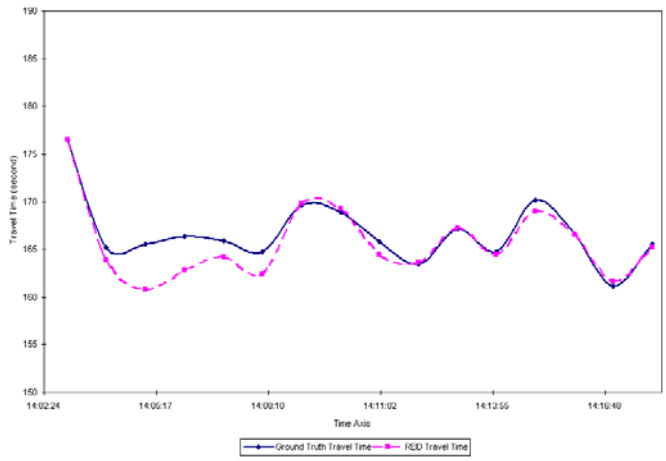
Table 5.3 PE_CR Analysis Results

Analysis Intervals (second)	Freeway	Arterial	Combined
30-60	1.284	96.090	76.134
60-90	37.663	18.312	15.840
90-120	7.239	23.409	21.813
120-150	1.288	2.244	2.179
Average	11.869	35.014	28.991

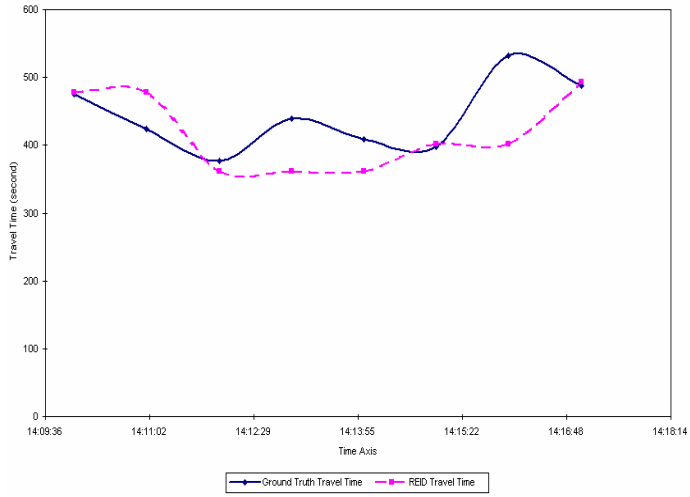
In path 1 (freeway only), the biggest TotTTPE change occurs between the aggregation intervals of 60 seconds and 90 seconds, yielding highest PE_CR. However, the TotTTPE values at all intervals were lower than two percent and therefore, the high PE_CR was not significant enough for further investigation. It is of interest to note that in path 2 (arterial only), aggregation levels above 60 seconds yield TotTTPE with less than five percentage error rate. Considering the traffic signal cycle used in PARAMICS, 60-90 seconds depending on the intersection size, these results suggest that aggregation interval close to the corresponding signal cycle timing is prone to generate lower travel time estimation error. For path 3, all TotTTPE values were higher than the rest two paths at all aggregation intervals. In the case of PE_CR, the

highest value was observed between aggregation intervals of 30 and 60 seconds. Comparison between estimated and true travel times at the 60-second aggregation interval is depicted in Figure 5.3.

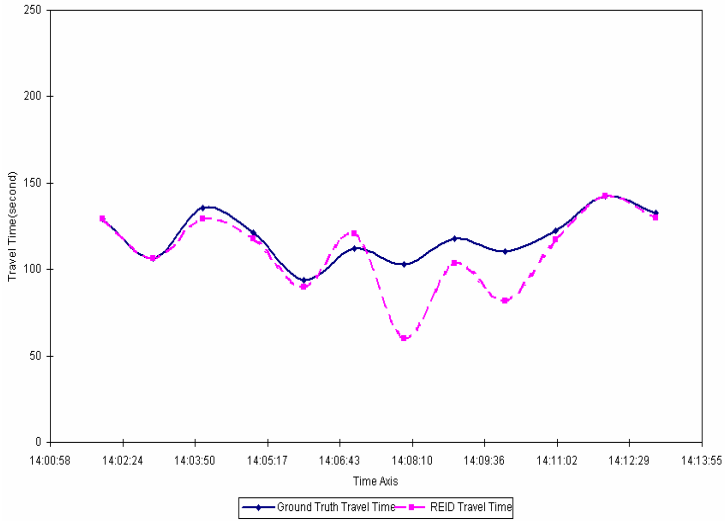
For all paths, the PE_CR between aggregation interval of 120 seconds and 150 seconds was the smallest and lower than value of three. The arterial-only path yields the highest average PE_CR compared to the other paths. It is also a remarkable point that for all paths at above the aggregation interval of 90 seconds, the TotTTPE was less than 10 percent. Based on the above analysis, once the traffic measurements' acceptable error ranges are defined by TMC operators, the corresponding aggregation intervals can also be determined. For instance, if the pre-defined travel time error range is less than seven percent, then for freeway-only case, the suggested five aggregation intervals are all suitable. However, in the case of arterial all intervals are acceptable with exception of the 30-second aggregation interval. Moreover, for combined path case, only 120-second and 150-second aggregation intervals satisfy pre-defined error rate. This also suggests that optimal aggregation intervals differ for different path types.



(a). Freeway Path



(b). Arterial Path



(c). Combined Path

Figure 5.3 Travel Time Analysis

5.5 Findings and Discussions

This section has demonstrated a framework for simulated network evaluation based on vehicle re-identification results. Unlike most other simulation models, where vehicle tracking or re-identification is based on individual vehicle unique ID, this study has shown an API module that enables the re-identification of vehicles based on feature vectors. This approach also facilitates the testing and evaluation of developed vehicle re-identification algorithms. Travel time analyses from three different paths also suggest significant results with low estimation errors. Furthermore, this study also aims to provide optimal aggregation interval selection depending on path characteristics and TMC's operator viewpoint – such as acceptable error rate.

This study needs to extend its scope by applying and implementing enhanced and more robust vehicle re-identification algorithms for better traffic measurements estimation. Comparison among different vehicle tracking algorithms is also an area of future study

CHAPTER 6 VEHICLE CLASSIFICATION

6.1 Introduction

Complete and accurate traffic information is becoming more and more available with the advance in transportation surveillance technology. Especially, vehicle classification information can contribute to many transportation related fields such as road pavement management, estimation of polluted emission etc. In previous sections and chapters, it was shown that vehicle signature is function of vehicle type and traffic conditions. By exploiting this concept, the algorithm development in vehicle classification is investigated and corresponding results are presented

Vehicle classification is the process of vehicle type recognition based on given vehicle characteristics. Accurate vehicle classification has many important applications in transportation. One example is road maintenance, which is highly related to the monitoring of heavy vehicle traffic. Because trucks and oversized vehicles exhibit distinctly different performance characteristics from passenger cars, the continuous updating of those vehicles with respect to their share in daily traffic will help estimate the life of current road surface and assist in the scheduling of road maintenance. Design of a toll system can also use the same information. Moreover, by obtaining the heterogeneity of traffic flow, vehicle classification information can lead to more reliable modeling of vehicle flow. Incorporating the information of vehicle classification in the analysis of environmental impact is also highly desirable since different vehicle types have different degree of airborne and noise emission. The class of vehicle is one of most important parameters in the process of road traffic measurement. Improvement of highway safety can also benefit from vehicle classification information, knowing that the severity of traffic accidents is highly correlated with vehicle types. This will be discussed more in detail in the following section. To summarize, an area-wide assessment of the component of vehicle classes in traffic is essential for more reliable and accurate traffic analysis and modeling.

6.2 Background

Since early 1970s, vehicle classification has been an interested study area by many agencies and researchers because of its importance as mentioned earlier. Especially Federal Highway Administration (FHWA) focuses in differentiating trucks by axle counting for better road and pavement maintenance. Davies (1986) summarized a review on early vehicle detection technologies and vehicle classification systems. Various traffic sensors including inductive loop detector, video detector, acoustic detector, range sensor, and infrared detector were applied in many vehicle classification studies. Inductive loop data, most widely implemented detector system, was used by Wang et al (2001) to classify three vehicle types: heavy vehicles, small cars, and motorcycles. Lu et al (1989) conducted k-nearest neighbor method for categorizing vehicles into four classes using infrared detector. Video detector is also one of major detectors used by many researchers for vehicle classification (Yuan et al, 1994; Wei et al, 1996; Gupte et al, 2002; Avery et al, 2004). However, setting an optimal camera angle and selecting appropriate camera calibration parameters remain issues when exploiting video data. Nooralahiyan (1997) applied signature data from acoustic sensor and neural network method to derive four vehicle categories. A laser sensor, that returns vehicle range and intensity information, was deployed and examined by Harlow et al (2001) for vehicle detection and classification. However, most of the listed studies focus on detecting and distinguishing long vehicles such as trailer and trucks from passenger cars and little consideration was paid in short vehicle categories. In an effort to broaden study prospect on non-truck vehicle categories, Pursula et al (1994) and Sun et al (2001, 2003) have applied loop signature data.

The proposed study aims to develop an automated vehicle classification system that can not only detect trucks from non-truck vehicles but also can categorize small vehicles into more detailed classes. Considering the real-time algorithm implementation in the future, the study also suggested a simple but powerful and robust algorithm that is based on heuristic decision tree method. Especially, the multi-level decision tree method expedites the classification system by applying selected most distinguishable vehicle feature vectors at each step. Furthermore, a large dataset from I-405 freeway was applied to test developed algorithm transferability. Another innovative part of this study lies in deriving vehicle classification results in conjunction with single loop speed estimation model mentioned in earlier section. This approach will also help to enhance the use of single loop for vehicle classification. Comparison between current FHWA vehicle classification methods is also one of the focal points of this study.

6.3 Methodology

As shown in Table 6.1, three different vehicle classification schemes are introduced. Two categories are based on FHWA classification. FHWA classification scheme is separated into categories depending on whether the vehicle carries passengers or commodities. Non-passenger vehicles are further subdivided by

number of axles and number of units, including both power and trailer units. The difference between FHWA I and FHWA II category is in class 2 and 3. Because automatic vehicle classifiers have difficulty distinguishing class 3 from class 2, these two classes may be combined into class 2, which is FHWA II category. The last category, UCI category, dedicates more to differentiate FHWA I class 3, two axle four-tire vehicles that contains pickup truck, van and SUV. However, the signature similarity among vehicle type in class 3 leads to classification error and therefore more sophisticated classification procedure is required at this stage.

Heuristic decision tree method, comparable to sequential screening approach, is deployed for vehicle classification model development. The advantage of suggested model is its simplicity, which is one of the most important elements for fast algorithm computation process. This feature will also contribute on possible future real-time algorithm implementation. This is very significant from both practice and research aspects. Sequential splitting approach is based on threshold values selected from corresponding feature vector distribution of each vehicle class. This sequential approach helps to reduce the dimension of possible vehicle classes and therefore minimize the misclassification rate. At each step different vehicle features, which will most distinguish one vehicle class from others, were deployed. It was shown that vehicle length is the most dominant factor in distinguishing vehicle classes. Similar to vehicle grouping module in previous section, DOS and SP are then used for further classification among similar vehicle length groups. Other variables such as maximum magnitude and entropies are all applied for detailed classifications. Figure 6.1 depicts above mentioned classification process.

Table 6.1 Vehicle Class Category

Vehicle Type	UCI Category	FHWA I	FHWA II
Motorcycle	1	1	1
Passenger Car	2	2	2
Pickup Truck	3	3	
Van	16		
Sport Utility Vehicle (SUV)	17		
Buses	4	4	4
Two-Axle 6 Tire Single Unit Truck	5	5	5
Three-Axle Single Unit Truck	6	6	6
Four or More Axle Single Unit Truck	7	7	7
Four or Less Axle Single Trailer	8	8	8
Five Axle Single Trailer	9	9	9
Six or More Axle Single Trailer	10	10	10
Five or Less Axle Multi Trailer	11	11	11
Six Axle Multi Trailer	12	12	12
Seven or More Axle Multi Trailer	13	13	13
Class2 + Trailer	14	-	-
Class3 + Trailer			
Class5 + Trailer			
Class6 + Trailer			
Auto Carrier, Moving Trailer	15	13	13

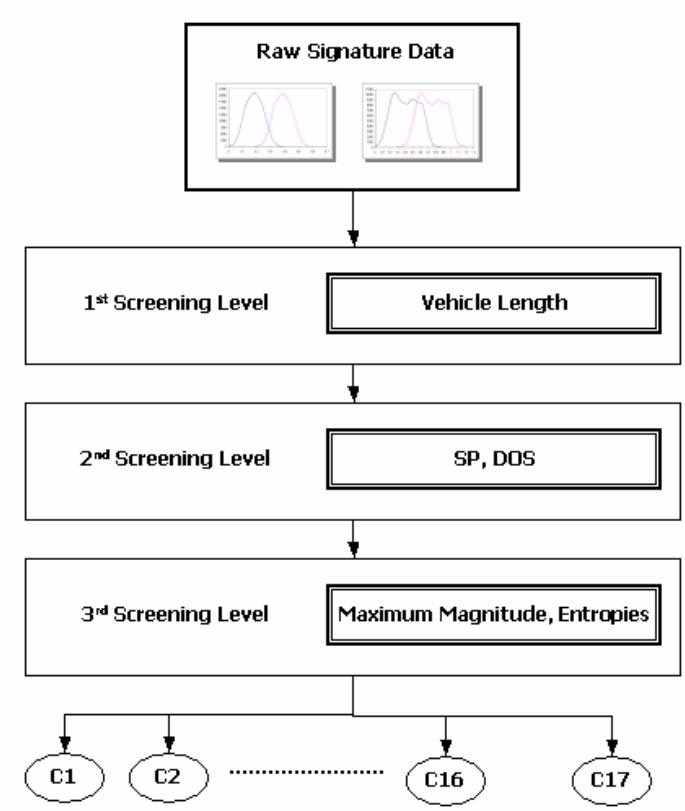


Figure 6.1 Vehicle Classification Flow Chart

6.4 Result Analysis

6.4.1 Dataset Description

In this study, two datasets, calibration and testing, were used and manually verified for vehicle classification. The calibration dataset consists of vehicle signature data collected from 14:00 to 14:30 PM on I-405 at Sand Canyon and Laguna Canyon. Data from Laguna canyon at morning peak period was applied for testing dataset. This will satisfy for model transferability testing at different time of the day. In addition, because double loop configuration was used, single loop speed estimation can also be verified. Datasets used in this study are illustrated in Table 6.2.

Table 6.2 Dataset Description

	Dataset	
	Training	**Testing**
Location	Sand Canyon, Laguna Canyon	Laguna Canyon
Lane	7 lanes	7 lanes
Time Period	July 23rd, 2002, 14:00 – 14:30 PM	July 23rd, 2002, 8:05 – 9:15 AM
Loop Configuration	Square Double Loop	Square Double Loop
Sample Rate	1200 Hz	1200 Hz
Dataset Traffic Count	3836	6001

Both datasets were manually ground truthed using side-view video from UCI research team for vehicle classification purpose. Because of installed video angle and vehicle occlusion problem, not all the vehicles were identified and therefore some vehicles were excluded from study datasets. Morning peak hour data from Laguna Canyon shows that about 5.8% from total traffic volume fits into this category. Moreover, due to the heavy traffic volume during the morning peak period, some signatures were not in the format that could be processed and consequently were not considered for further investigation.

6.4.2 Model Result Analysis

The algorithm is tested under two loop conditions: double loop and single loop. In case of single loop configuration, vehicle length is attained using speeds from speed estimation model in previous section. Two datasets, calibration and test, are applied for model evaluation.

Calibration Results

Table 6.3 summarizes calibration dataset classification results under different classification categories using different loop configurations. Double loop configuration classification yield better results compared to single loop configuration case. The results are very promising in that proposed algorithm not only separates small vehicles from long vehicles such as truck or multi trailer but also generates comprehensive differentiation within small vehicles, such as SUV and passenger cars.

Table 6.4, 6.5, and 6.6 present the algorithm results in-detail according to the three proposed classification schemes. Table 6.4 shows UCI vehicle classification category. It is obvious that the misclassification rate is high among passenger cars, SUVs, pickup trucks and vans. For trucks and trailers, the misclassification occurs when the signatures are similar but only differs in axle number. For instance, in case of category 8

and 9 the axle count differs by one but because of signature similarities, the misclassified category vehicle 8 are all assigned as category 9. Same pattern is observed for category 5 and 6. Recently developed traffic detector, blade detector, can be used to overcome these limitations by addressing vehicle axle number counting. However, these detectors were not available to be fully implemented at the time of this study and integration with these blade detectors for enhanced and robust vehicle classification system is an area of future study. It is also remarking point that classification results based on single loop are also encouraging. Especially, in FHWA I and II categories classification outcomes are very encouraging with over 90% correct classification rate. It should also be noted that for some vehicle classes, such as multi trailer, even under single loop configuration, classification results show almost perfect classification rate because of unique vehicle signatures.

Table 6.3 Vehicle Classification Result Summary (Calibration Dataset)

	Double Loop	**Single Loop**
UCI Code	3358 (87.54%)	3286 (85.66%)
FHWA Code Version I	3555 (92.67%)	3438 (89.62%)
FHWA Code Version II	3809 (99.30%)	3787 (98.72%)

Table 6.4 UCI Category Classification Result (Calibration Dataset)

Vehicle Category	Vehicle Count	Loop Configuration	
		Double Loop	Single Loop
1	1	1 (100%)	1 (100%)
2	1933	1818 (94.05%)	1797 (92.96%)
3	607	515 (84.84%)	511 (84.18%)
16	217	152 (70.04%)	115 (52.30%)
17	888	703 (79.16%)	716 (80.63%)
4	6	6 (100%)	6 (100%)
5	81	73 (90.12%)	50 (61.73%)
6	10	8 (80%)	8 (80%)
7	-	-	-
8	12	6 (50%)	6 (50%)
9	50	45 (90%)	45 (90%)
10	1	1 (100%)	1 (100%)
11	-	-	-
12	-	-	-
13	-	-	-
14	24	24 (100%)	24 (100%)
15	6	6 (100%)	6 (100%)
Total	3836	3351 (87.36%)	3277 (85.43%)

Table 6.5 FHWA I Category Classification Result (Calibration Dataset)

Vehicle Category	Vehicle Count	Loop Configuration	
		Double Loop	Single Loop
1	1	1 (100%)	1 (100%)
2	1933	1818 (94.05%)	1797 (92.96%)
3	1712	1567 (91.53%)	1494 (87.27%)
4	6	6 (100%)	6 (100%)
5	81	73 (90.12%)	50 (61.73%)
6	10	8 (80%)	8 (80%)
7	-	-	-
8	12	6 (50%)	6 (50%)
9	50	45 (90%)	45 (90%)
10	1	1 (100%)	1 (100%)
11	-	-	-
12	-	-	-
13	-	-	-
14	24	24 (100%)	24 (100%)
15	6	6 (100%)	6 (100%)
Total	3836	3555 (92.67%)	3438 (89.62%)

Table 6.6 FHWA II Category Classification Result (Calibration Dataset)

Vehicle Category	Vehicle Count	Loop Configuration	
		Double Loop	Single Loop
1	1	1 (100%)	1 (100%)
2	3645	3639 (99.84%)	3640 (99.86%)
4	6	6 (100%)	6 (100%)
5	81	73 (90.12%)	50 (61.73%)
6	10	8 (80%)	8 (80%)
7	-	-	-
8	12	6 (50%)	6 (50%)
9	50	45 (90%)	45 (90%)
10	1	1 (100%)	1 (100%)
11	-	-	-
12	-	-	-
13	-	-	-
14	24	24 (100%)	24 (100%)
15	6	6 (100%)	6 (100%)
Total	3836	3809 (99.30%)	3787 (98.72%)

Model Transferability

In order to perform model transferability assessment, dataset collected at different time period was applied. Classification results are illustrated from Table 6.7 to Table 6.10. Because the test dataset vehicle categories were mainly passenger cars, consisting about 81.053% of total volume, and considering the relatively high correct classification rate in this particular vehicle category, the total correct classification results in double loop configuration were better compared to calibration dataset. On the other hand, the single loop configuration case yields slightly lower correct classification rates in all vehicle categories. However, the results were still significant enough to conclude the reliable model transferability. In case of each vehicle category, classification result trends were similar compared to calibration dataset. In other words, misclassification pattern was observed among vehicle classes whose signatures are similar but differ only in vehicle axle count such as class 5 and class 6.

Table 6.7 Vehicle Classification Result Summary (Test Dataset)

	Double Loop	**Single Loop**
UCI Code	5384 (89.72%)	4893 (81.53%)
FHWA Code Version I	5543 (92.37%)	5051 (84.17%)
FHWA Code Version II	5937 (98.94%)	5864 (97.72%)

Table 6.8 UCI Category Classification Result (Test Dataset)

Vehicle Category	Vehicle Count	Loop Configuration	
		Double Loop	Single Loop
1	0	-	-
2	4891	4707 (96.24%)	4351 (88.96%)
3	133	82 (61.58%)	68 (50.94%)
16	638	328 (51.34%)	283 (44.32%)
17	42	20 (47.63%)	14 (32.89%)
4	9	9 (100%)	9 (100%)
5	112	87 (77.85%)	53 (46.88%)
6	24	13 (55.25%)	13 (55.25%)
7	4	2 (50%)	2 (50%)
8	8	3 (42%)	2 (26%)
9	100	95 (95.10%)	66 (65.78%)
10	1	1 (100%)	1 (100%)
11	9	8 (85%)	4 (42%)
12	2	1 (50%)	0 (0%)
13	0	-	-
14	20	20 (100%)	20 (100%)
15	8	8 (100%)	8 (100%)
Total	6001	5384 (89.72%)	4893 (81.53%)

Table 6.9 FHWA Category Classification Result (Test Dataset)

Vehicle Category	Vehicle Count	Loop Configuration	
		Double Loop	Single Loop
1	0	-	-
2	4891	4707 (96.24%)	4351 (88.96%)
3	813	589 (72.39%)	522 (64.26%)
4	9	9 (100%)	9 (100%)
5	112	87 (77.85%)	53 (46.88%)
6	24	13 (55.25%)	13 (55.25%)
7	4	2 (50%)	2 (50%)
8	8	3 (42%)	2 (26%)
9	100	95 (95.10%)	66 (65.78%)
10	1	1 (100%)	1 (100%)
11	9	8 (85%)	4 (42%)
12	2	1 (50%)	0 (0%)
13	0	-	-
14	20	20 (100%)	20 (100%)
15	8	8 (100%)	8 (100%)
Total	6001	5543 (92.37%)	5051 (84.17%)

Table 6.10 FHWA II Category Classification Result (Test Dataset)

Vehicle Category	Vehicle Count	Loop Configuration	
		Double Loop	Single Loop
1	0	-	-
2	5704	5690 (99.75%)	5687 (99.7%)
4	9	9 (100%)	9 (100%)
5	112	87 (77.85%)	53 (46.88%)
6	24	13 (55.25%)	13 (55.25%)
7	4	2 (50%)	2 (50%)
8	8	3 (42%)	2 (26%)
9	100	95 (95.10%)	66 (65.78%)
10	1	1 (100%)	1 (100%)
11	9	8 (85%)	4 (42%)
12	2	1 (50%)	0 (0%)
13	0	-	-
14	20	20 (100%)	20 (100%)
15	8	8 (100%)	8 (100%)
Total	6001	5937 (98.94%)	5864 (97.72%)

6.5 Findings and Discussions

This section has shown the application of vehicle signatures in vehicle classification field. Accurate vehicle classification not only contributes on efficient road maintenance but also on many transportation perspectives including accurate traffic modeling. Future tasks include integration with new detector, blade detector, for robust classification system development. Furthermore, an algorithm that enables to train real time data automatically and adaptively should be investigated for straightforward model transferability.

CHAPTER 7 CONCLUSION AND FUTURE RESEARCH

7.1 Summary of Findings

Although a variety of sensor technologies have been developed and tested for tracking individual vehicles on transportation networks, the proposed anonymous vehicle tracking system utilizing vehicle feature vectors provides significant advantages since it uses existing field equipment and is free from privacy concerns. Moreover, the use of existing loop infrastructure harnesses the full potential of investments already made and facilitates the ability for immediate field implementation. Field investigation of the vehicle reidentification systems for a single roadway intersection and a freeway section on I-405 detector Testbed 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 freeway and arterial traffic surveillance and performance measurement. The potential feasibility of such an approach was demonstrated by simulation experiments for a freeway and 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 freeway and arterial network. It is also 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. Furthermore, the automatic vehicle classification system developed in this study showed very encouraging results.

7.2 Future Research

To fully exploit the benefits of the new generation of Intelligent Transportation Systems now widely under development, including applications for performance measurement and homeland security, more accurate and appropriate real-time traffic data need to be collected from the urban highway transportation network and communicated to traffic management centers, traffic operations personnel, travelers, and other agencies. Future research should now deploy and investigate at a corridor level the anonymous vehicle tracking techniques that have been pioneered by the authors in previous PATH research. The objective of such deployment would be to investigate and demonstrate real-time freeway and arterial performance measurement in a major real-world setting. This research under TO 4159 emphasized microscopic

simulation in conjunction with individual intersection and freeway segment field implementations to develop and assess methods for tracking vehicles across multiple detector stations in a traffic network, based on real-time acquisition of vehicle inductive signatures, in order to provide improved freeway and arterial (and transit) performance measures to the Caltrans PeMS. Ultimately, however, the utility and effectiveness of such new network-based methods can only be judged through large-scale field implementation.

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