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Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies - Phase 2

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Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies – Phase 2

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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.

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ABSTRACT

This report presents the results of Phase 2 of a multi-year research effort on "Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies." Phase I of this research was conducted under PATH MOU 3008. Phases I and II of this research extended previous PATH research by the authors on MOU 336 "Section-Related Measures of Traffic System Performance: Prototype Field Implementation." Phase II of this research continued development, field investigation and assessment of the latest technologies available for traffic detection and surveillance, for collecting more accurate traffic characteristics and traffic data necessary for Intelligent Transportation Systems (ITS) applications. The focus of Phase II of this research was to utilize fully instrumented freeway and signalized intersection sites in the California Advanced Transportation Management Systems Testbed in Southern California for field investigation of several emerging traffic sensor and detector technologies for vehicle reidentification (REID) purposes and real-time traffic performance measurement. As part of this project, a traffic detector and surveillance sub-testbed (TDS^2) on North I-405 in Irvine became operational in August 2002, and the ability to perform REID-based real-time traffic performance measurement in TDS^2, developed as part of this research, and including section travel times, traffic origins and destinations, and vehicle classification, was demonstrated on-line at the PATH Annual Meeting in October 2002. The very encouraging results obtained to date by developing and applying a vehicle reidentification approach for real-time traffic performance measurement suggest that further development, implementation and testing of this approach would clearly be of value.

Keywords

vehicle signature, detector, sensor, inductive loop, single loop speed estimation, vehicle classification, vehicle reidentification, testbed, freeway, level of service, detector card, data fusion, web-site

EXECUTIVE SUMMARY

California PATH has been leading research in the field of vehicle reidentification for the purpose of real-time traffic performance measurement. The research reported here builds on and extends previous PATH research by the authors on "Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies, Phase I" (PATH MOU 3008), and "Section-Related Measures of Traffic System Performance: Prototype Field Implementation" (MOU 336).

This research continued development, field investigation and assessment of the latest technologies available for traffic detection and surveillance, for collecting more accurate traffic characteristics and traffic data necessary for Intelligent Transportation Systems (ITS) applications. The focus of Phase II of this research was to utilize fully instrumented freeway and signalized intersection sites in the California Advanced Transportation Management Systems Testbed in Southern California for field investigation of several emerging traffic sensor and detector technologies for vehicle reidentification (REID) purposes and real-time traffic performance measurement. These technologies included the IST-222 high-speed scanning detector card from IST, Inc. for capturing vehicle signatures from conventional inductive loops, V^2SAT video detection system from Loragen Corporation, and the innovative new Embedded Differential Inductance Scanning (EDIS) or "Blade" loop detector from IST, Inc.

This study also implemented real-time vehicle reidentification and traffic performance measurement in the traffic detection and surveillance sub-testbed (TDS^2) on North I-405 in Irvine, which became operational in August 2002. Based on the research and the improved algorithms developed in this study, real-time traffic performance measurement in TDS^2 (including section travel times, traffic origins and destinations, and vehicle classification) was demonstrated on-line at the PATH Annual Meeting in Richmond, California in October 2002.

This study also explored the vehicle reidentification problem based on vehicle signatures collected from different types of detection technologies, including conventional square inductive loops and the newly developed blade inductive loop sensors. A lexicographic optimization algorithm together with a genetic algorithm was introduced to solve the vehicle reidentification problem. Goal programming approaches for search space reduction in the vehicle reidentification algorithm both improved the algorithm matching performance and the computational burden. The algorithm performed well. For example, less than 10 % travel time error was achieved with a 5-minute travel time aggregation period. Although the number of vehicles for which data could be collected in this specific comparative study was small, encouraging results were obtained for vehicle reidentification performance in a system of mixed traffic detection technologies. In future large-scale applications of vehicle reidentification approaches for real-time traffic performance

measurement, management and control, it would be most beneficial and practical if heterogeneous as well as homogeneous detection systems could be supported. This initial study yielded many useful insights about this important issue, and demonstrated on a small scale the feasibility of vehicle reidentification in a system with heterogeneous detection technologies.

Overall, the very encouraging results obtained to date by developing and applying a vehicle reidentification approach for real-time traffic performance measurement suggest that further development, implementation and testing of this approach would clearly be of value.

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CHAPTER 1 INTRODUCTION

1.1 Background

Research in Intelligent Transportation Systems (ITS) addresses various transportation needs such as efficiency, safety, environmental protection, mobility, and economic viability. Different agencies on different levels try to utilize ITS for improving the transportation system. These agencies range from day-to-day operators and managers of the transportation system to long term designers and planners of the transportation infrastructure. In order to fully exploit the advantages of ITS strategies, accurate and appropriate data need to be collected from the transportation network. Therefore it is vital to develop advanced surveillance systems that can properly support the objectives of ITS.

In the United States and Europe, and particularly in California, there is increasing interest in investigating methods for obtaining trip travel times and other measures, such as density and origin/destination demands, that can be derived from vehicle reidentification systems. By using non-obtrusive and anonymous tracking methods, individual vehicles can be identified and correlated over numerous identification stations, and very specific real time data can be obtained for any vehicle.

California PATH has been leading research in the field of vehicle reidentification. The actual physical sensor for these reidentification systems can be from a variety of different sensor technologies. It can also consist of a combination of technologies. This research builds on and extends previous PATH research by the authors on MOU 336 "Section-Related Measures of Traffic System Performance: Prototype Field Implementation." The research investigates the use of the latest technologies available for traffic detection for collecting more accurate traffic characteristics and traffic data necessary for ITS applications, but which are difficult to obtain. The primary traffic characteristic that this research attempts to measure more accurately is section (or trip) travel time. Travel time has been identified by Caltrans as particularly important for assessing traffic system performance. Travel times are also important because they are inputs to Advanced Traveler Management and Information Systems (ATMIS). The direct measurement of travel times via vehicle reidentification avoids the inaccuracies associated with estimation methods using local or point speeds obtained from point detectors (such as individual loop or other detector stations). In addition, real-time traffic measures such as dynamic origin/destination demand fractions, lane changing, and section densities can be obtained with a vehicle reidentification approach.

The research reported here builds on and extends previous PATH research by the authors on "Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies, Phase I" (PATH MOU 3008), and "Section-Related Measures of Traffic System Performance: Prototype Field Implementation" (MOU 336). The multi-year research effort, of which Phase II (this report) represents the final part, consists of three major components, based on fully instrumented signalized intersection and freeway sites in the California Advanced Transportation Management Systems Testbed in Southern California.

The first component, which was the focus of Phase I, involved major expansion of an ILD (inductve loop detector)-based vehicle reidentification system (that was implemented in MOU 336) at a major signalized intersection in Irvine, California, to address reidentification of turning vehicles in addition to through vehicles, develop techniques for on-line real-time intersection level of service estimation, develop a capability for communicating real-time traffic performance data to operators in the City of Irvine Transportation Management Center (TMC), conduct initial testing of a new state-of-the-art detector card (IST-222) from our research partner IST, Inc., and develop a prototype real-time web-site for internet-based access to performance data from the study intersection (and other sites in the future). In addition, a study was undertaken to derive improved estimates of fundamental real-time traffic parameters such as speed, volume and vehicle class from single loop detectors and inductive signatures. Obtaining accurate estimates of vehicle speed from single ILD's (as opposed to dual loop speed traps) enables the vehicle reidentification approach developed by the authors to be widely applied in practice, and not limited by the existence of double loops.

Phase II of the research (this report) addressed the second and third components. The second component involved a field investigation of several emerging and advanced freeway detector technologies developed by the PATH program, including the V2SAT video detector, and a particularly promising new detector named the Embedded Differential Inductance Scanning (EDIS) or "Blade" detector. The Blade detector has a resolution several orders of magnitude greater than regular ILD's and addresses many of the shortcomings of ILD's. In addition, this study implemented real-time vehicle reidentification and traffic performance measurement in the traffic detection and surveillance sub-testbed (TDS^2) on North I-405 in Irvine, which became operational in initial form in August 2002. Based on the research and the improved algorithms developed in this study, real-time traffic performance measurement in TDS^2 (including section travel times, traffic origins and destinations, and vehicle classification) was demonstrated on-line at the PATH Annual Meeting in Richmond, California in October 2002.

The third component involved an investigation of the fusion of the various advanced detection systems noted above that have been developed by the PATH program, for the purpose of vehicle reidentification (or tracking vehicles from one site to another). Until now, each advanced surveillance system has been researched independently and vehicle reidentification has been studied using feature vectors from a single type of detector.

1.2 Traffic Detection and Surveillance Sub-testbed (TDS^2)

The growing popularity of the Caltrans PeMS (Performance Measurement System), traveler information, and other ITS functions have placed an increased emphasis on data validity and the detection systems upon which the "intelligence" in ITS is based. The need to have data of known quality, and the increasing number of available roadway detector technologies, provided the motivations for the development of a unique new Traffic Detection and Surveillance Sub-Testbed (TDS^2) facility on the Northbound I-405 freeway, located within the Southern California ATMS Testbed Network in Caltrans District 12. 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 relative to: appropriateness for ITS operations and performance measurement, data quality and consistency, ease of use, ease of installation, and overall cost.

The TDS^2 consists of two contiguous sites on a 7-lane freeway (I-405), each pre-wired for power and communication for the mounting of any type of detector. When complete, the TDS^2 overhead cameras will automatically take a picture of every passing vehicle at both the upstream and downstream sites and re-identify it between the two (V^{2}SAT system). This will provide not only an absolute ground truth upon which other detectors can be compared, but will also allow the same detector to be set up at each site to evaluate reproducibility as a function of speed, lane, headway, vehicle type, lighting, or other types of environmental or traffic conditions which may effect detection accuracy.
The TDS^2 has a number of unique capabilities optimized for detector evaluation, which in aggregate, are not duplicated anywhere else in the nation. When the TDS^2 is completed, these high tech capabilities will include:

1. The video "ground truth" system which will take a picture of each vehicle and automatically re-identify it downstream independent of its lane or speed.
2. Inductive loops with detectors that will output the unique waveform or "signature" of each vehicle and then use this information to re-identify each vehicle downstream. This will provide independent automatic confirmation of the video re-ID system above. These loop detectors will also output the more conventional bivalent data compatible with 170 and 2070 controllers, only with much greater accuracy than that produced by loops at other freeway sites.
3. Three streaming PTZ video cameras that can be accessed and controlled through any web browser connected to the internet.

4. Wireless broadband communication allowing all types of information to be available real-time across the internet. The data passes through the City of Irvine, UCI, and Caltrans communication hardware on its way to the web, in a remarkable institutional synergy of interagency cooperation.

Additionally, the TDS^2 has two overcrossings with overhead mounting and wiring systems, which can allow detectors to be installed over traffic lanes without shutting down lanes. This in itself is a unique capability not available anywhere else in California. Moreover, the TDS^2 is equipped with poles pre-wired for installation of side-fire detectors on the outside shoulder of both sites. One site has also a pole and wiring on the inside shoulder to evaluate HOV detectors and/or duel side-fire detectors.

In conjunction with this project, the TDS^2 became operational in August 2002 in initial form. In fact, this project contributed directly to the development of some V^{2}SAT capabilities. For example, the V^{2}SAT video detection system was implemented with project funding via subcontract in prototype form, and the design and implementation of field computer hardware and communications was guided in part by the vehicle reidentification concepts and algorithms developed in this research.

1.3 Report Outline

Chapter 2 describes a study of TDS^2 freeway inductive loop signature and V^{2}SAT video detection feature extraction, for purposes of vehicle reidentification via fusion of loop and video data. Chapter 3 presents an analysis of point traffic data in TDS^2 including inductive loop volume accuracy analysis, speed analysis and single loop speed estimation. Chapter 4 presents an analysis of freeway section data in TDS^2 including ground truthing, vehicle reidentification using loops only and vehicle reidentification based on fusion of loop and video data. Chapter 5 describes data communication and real-time traffic information provision via a project web-site. Chapter 6 presents the results of an initial study of the EDIS or Blade detector, including feature extraction and analysis, and a new technique for vehicle reidentification with the blade detector. Finally, Chapter 7 summarizes the conclusions of this research and directions for future research.

CHAPTER 2 FEATURE DATA EXTRACTION

2.1. Introduction

This section presents feature derivation from the sensors used in this project. Loop signature data and video data are described. In both cases, feature vectors are categorized into two categories: vehicle specific feature vectors and traffic specific feature vectors. Vehicle specific feature vectors represent the features that are unique according to a vehicle itself, therefore they are invariant over time or location. Vehicle length is a good example for this category. Traffic specific feature vectors indicate the features that could describe either traffic condition or road geometry. Speed and lane information fall into this category. Correlation between feature vectors and repeatability analysis are also presented.

2.2. Loop Signature Data

The advanced IST-222 loop detector card enables capture of the inductance change over the loop at high scan rate when a vehicle is present. These inductance changes are vehicle loop signatures and many feature vectors are available by processing the signatures. Feature description and the correlation among feature vectors are mentioned in the following paragraphs.

2.2.1. Vehicle Specific Feature Vector

As mentioned earlier, vehicle specific features represent the "unique" characteristics of vehicles such as vehicle length. In this study, four vectors were chosen as candidates for vehicle specific feature vectors. Figure 2.1 and Table 2.1 explain these four features: maximum magnitude, vehicle electronic length, shape parameter (SP) and number of high magnitude (NHM).

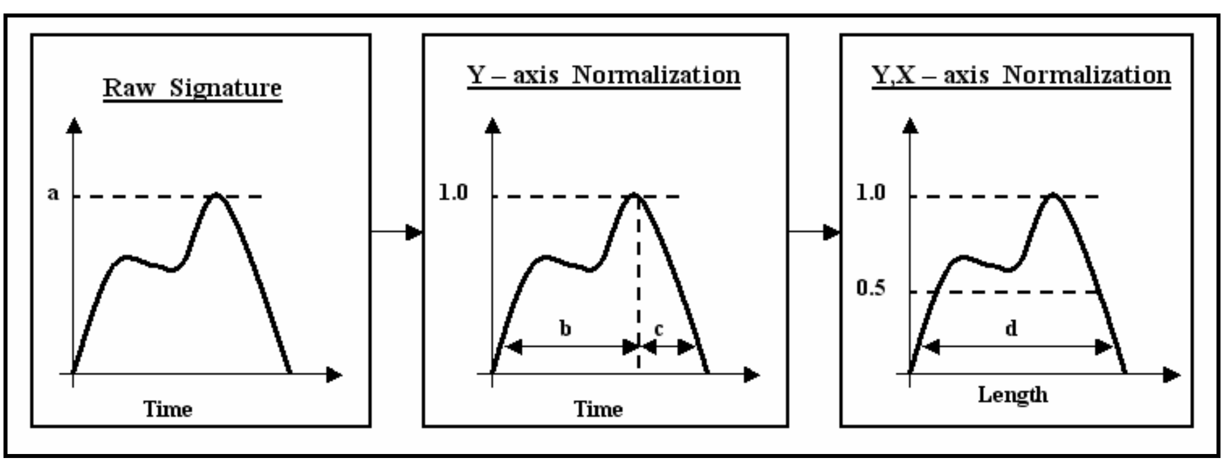


Figure 2.1. Signature Feature

Table 2.1. Signature Feature

Feature Vector	Feature Description
Maximum Magnitude	Maximum absolute magnitude value (a)
Electronic Vehicle Length	(d)
Shape Parameter (SP)	Degree of Symmetry ((b)/(b+c))
Number of High Magnitude (NHM)	Sample number above “0.5” y value after x,y normalization

Because vehicle length is the most salient feature vector in representing vehicle type, the correlation analysis between vehicle length and other features was investigated. The main purpose of this study is for the vehicle grouping and classification module inside the single loop speed estimation algorithm, which will be discussed in Chapter 3.

Based on Figure 2.2 ~ 2.4, the SP and NHM have high correlation with the vehicle electronic length. Especially, the SP and vehicle length has a clear “U” curve, 2nd order parabola, relationship.

For the vehicle signature repeatability analysis, feature vectors differences for identical vehicles at different locations were investigated. Figure 2.5. ~ Figure 2.8. show the relationship of the same vehicle features at different locations. It is clear that vehicle length and NHM follow the 45 degree line, which implies the reliable feature repeatability. SP also shows promising vehicle specific feature characteristics, invariability over space. But it is obvious that maximum magnitude doesn’t meet this standard and therefore, was eliminated from the vehicle specific feature vector set. The percentage error for each feature vector difference is illustrated in Table 2.2. According to this table, maximum magnitude yields the highest percentage error compared to other 3 feature vectors. Again this supports the selection of vehicle length, SP and NHM for vehicle specific feature vectors.

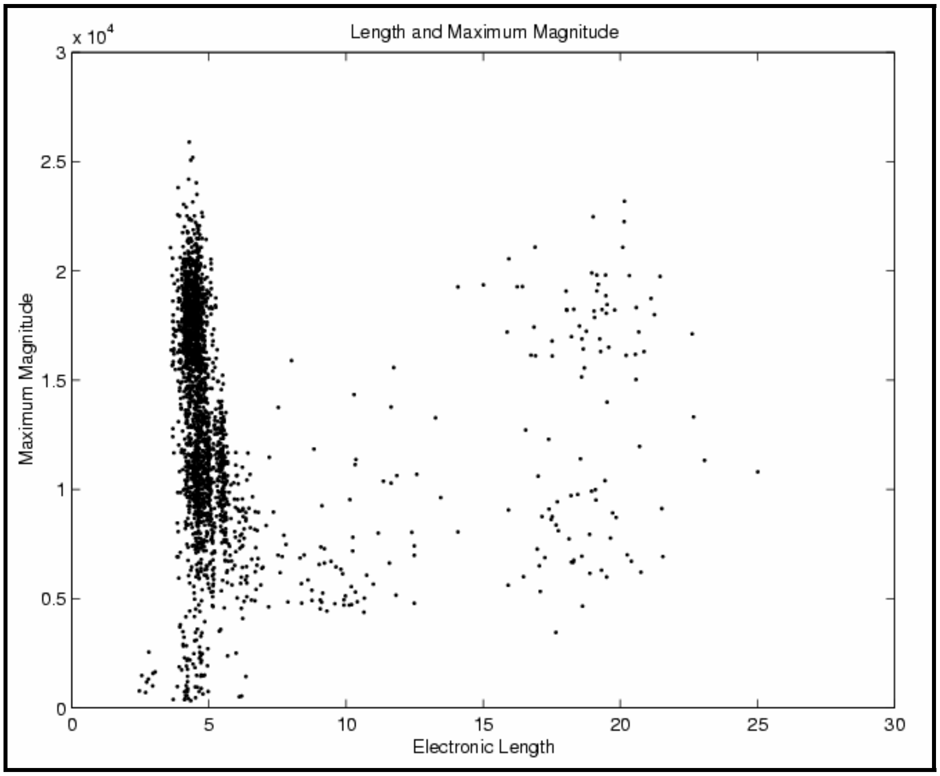


Figure2.2. Vehicle Length vs Maximum Magnitude

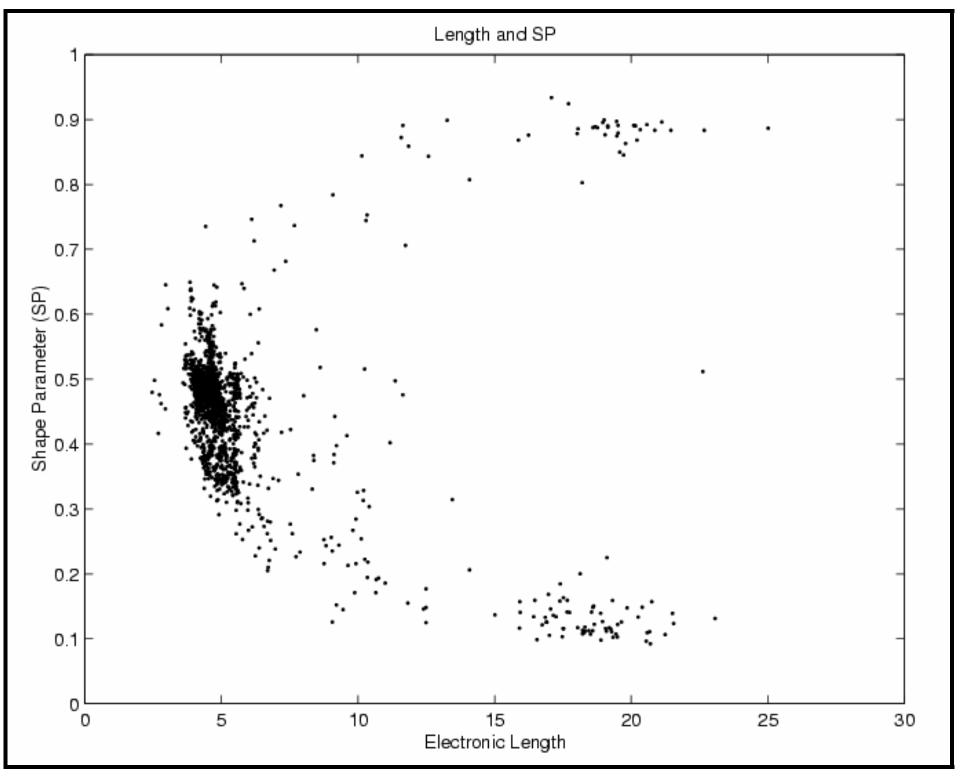


Figure 2.3. Vehicle Length vs SP

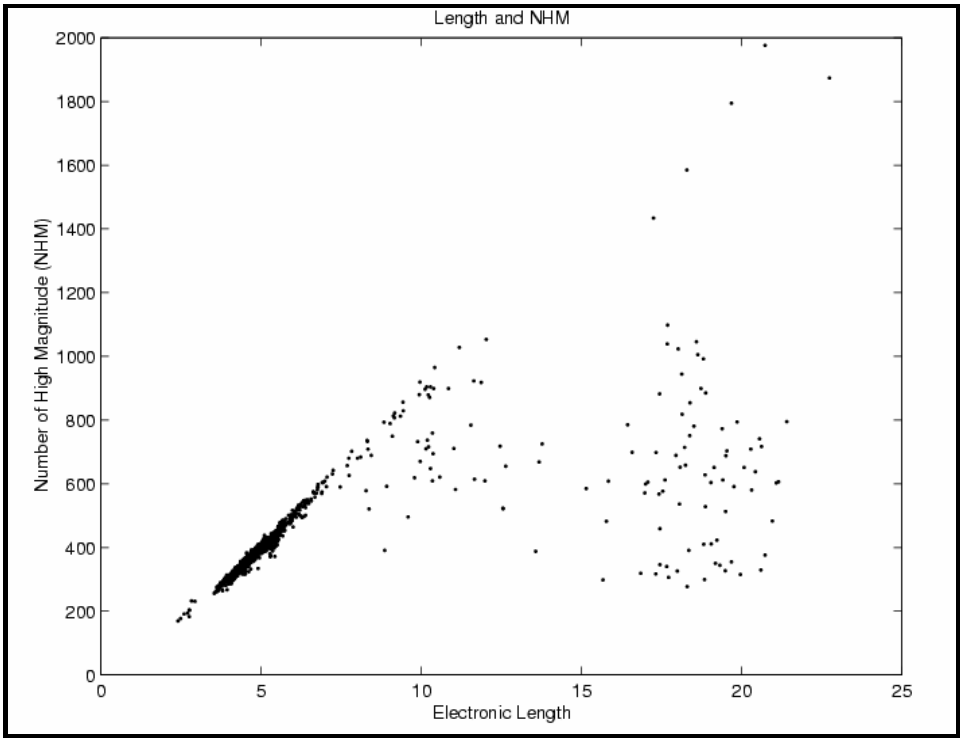


Figure 2.4. Vehicle Length vs NHM

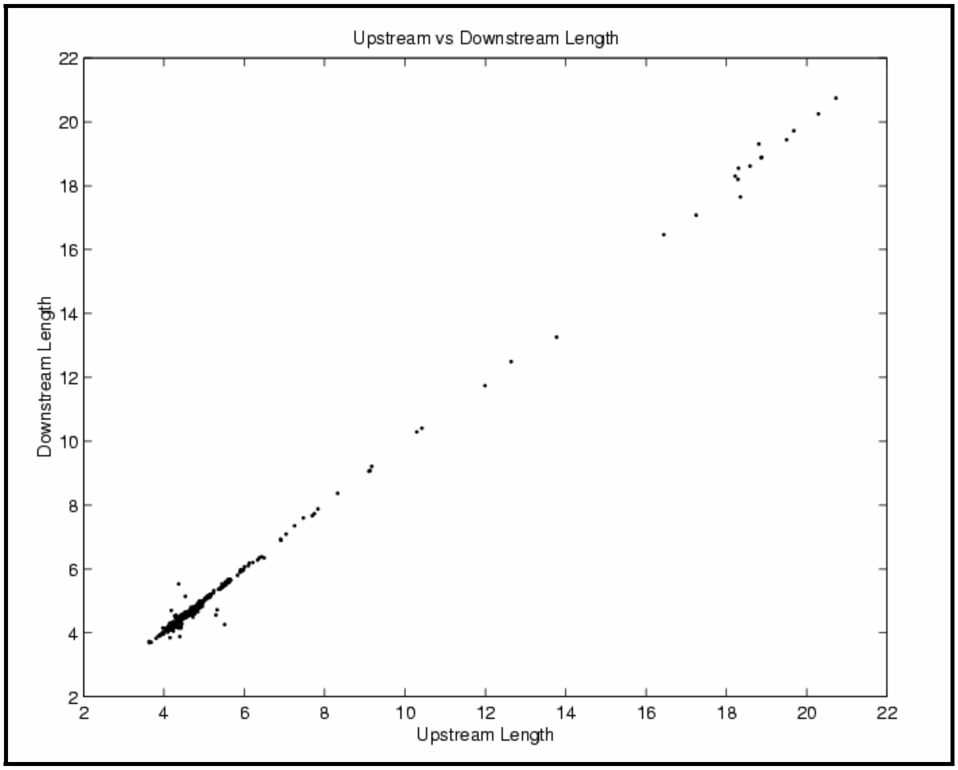


Figure 2.5. Vehicle Length at Different Locations

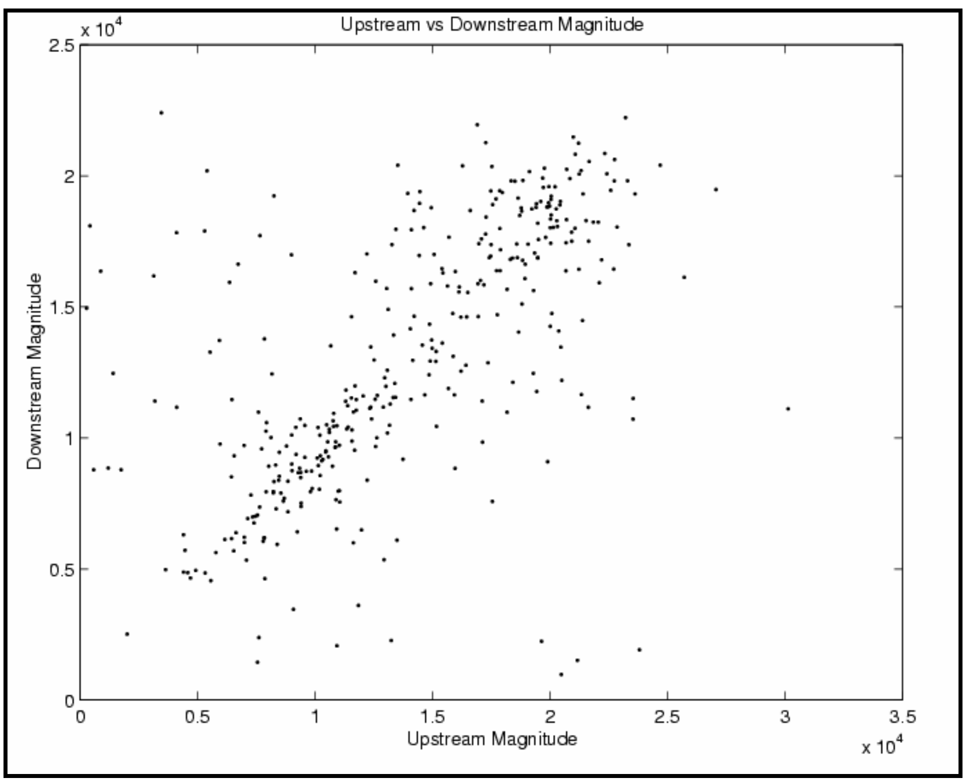


Figure 2.6. Maximum Magnitude at Different Locations

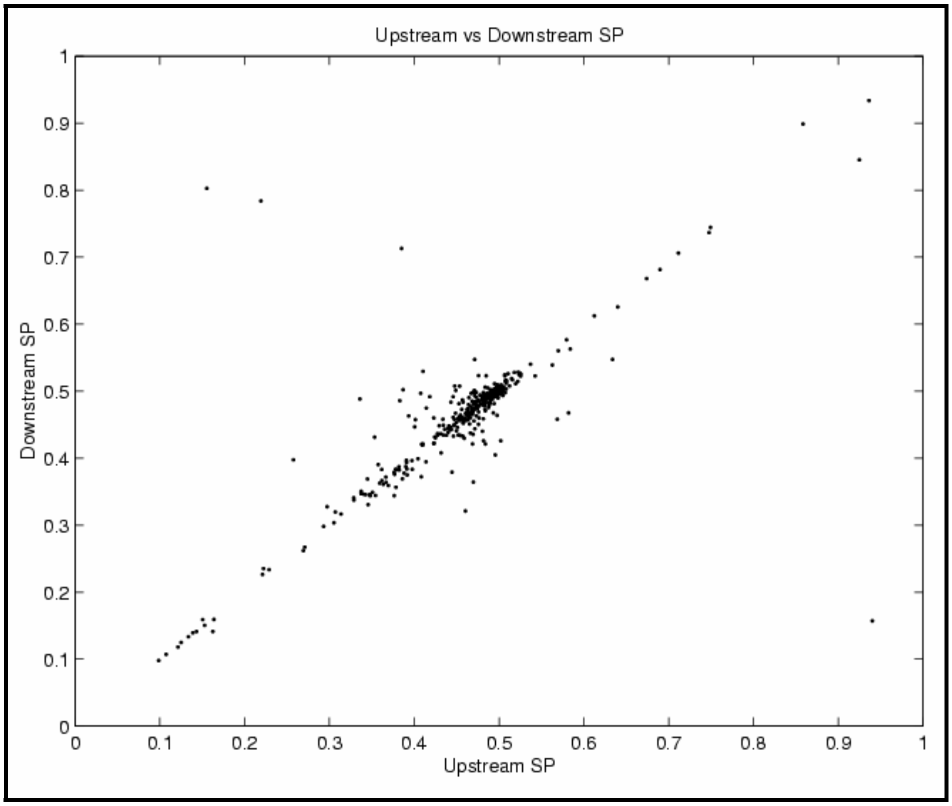


Figure 2.7. Shape Parameter at Different Locations

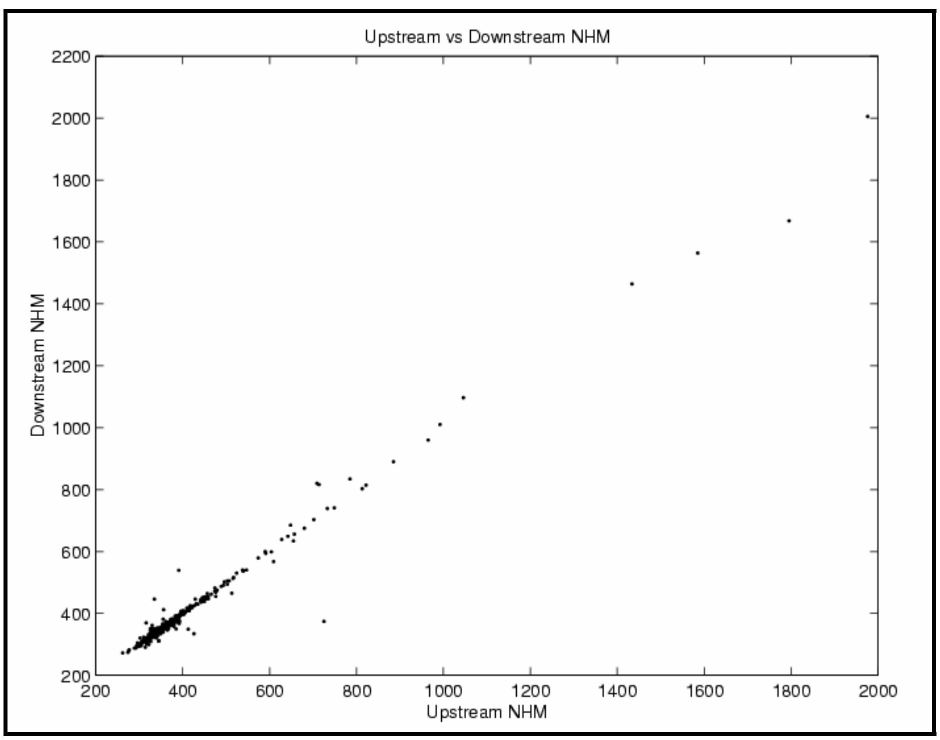


Figure 2.8. NHM at Different Locations

Table 2.2. Percentage Error of Feature Vectors Difference

Feature Vector	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

In summary, three vehicle specific feature vectors, vehicle electronic length, SP, and NHM were chosen.

2.2.2. Traffic Specific Feature Vector

Speed, occupancy, lane information and station detection time were classified as traffic specific features. In this study, speed was generated using the double loop speed trap.

2.3 V^{2}SAT Data

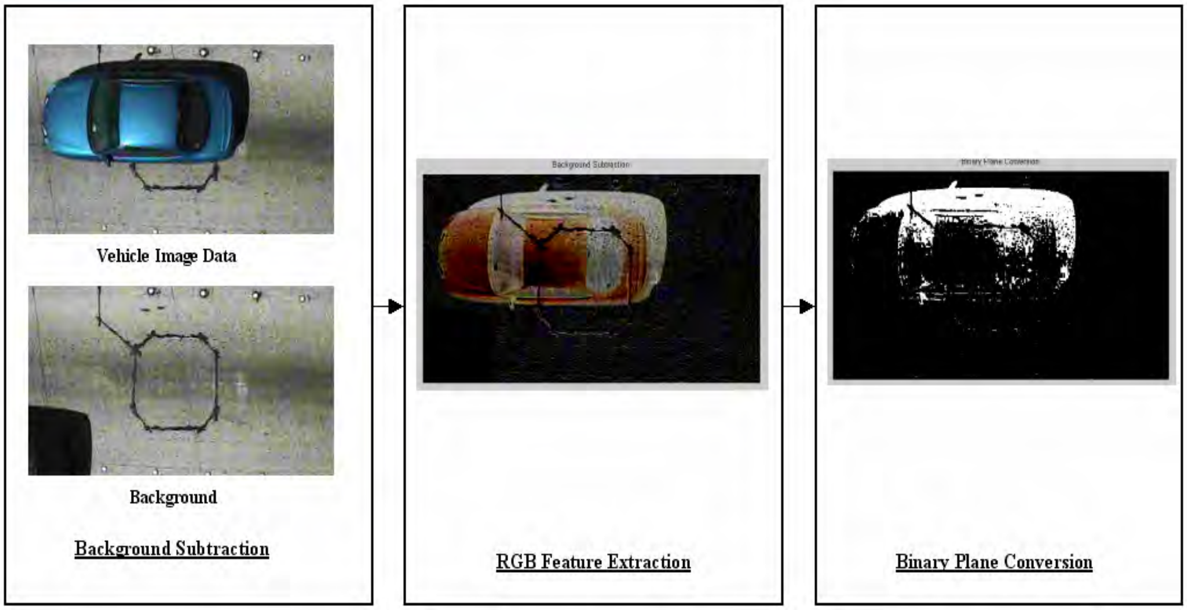
Video images were generated using the V^{2}SAT system, which was presented in the previous chapter. From the cameras installed right above each traffic lane, the image profile for each individual vehicle was captured. Figure 2.9 shows a sample V^{2}SAT image. In this section image processing and video feature derivation steps are discussed.

Figure 2.9. Sample V2SAT image

In order to derive image feature vectors, the following steps were processed.

- Background subtraction

- Color information extraction
- Conversion into binary plane

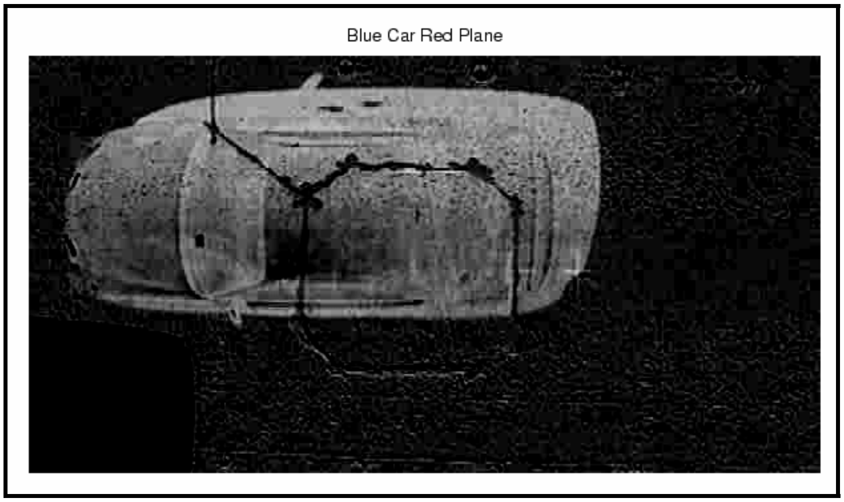


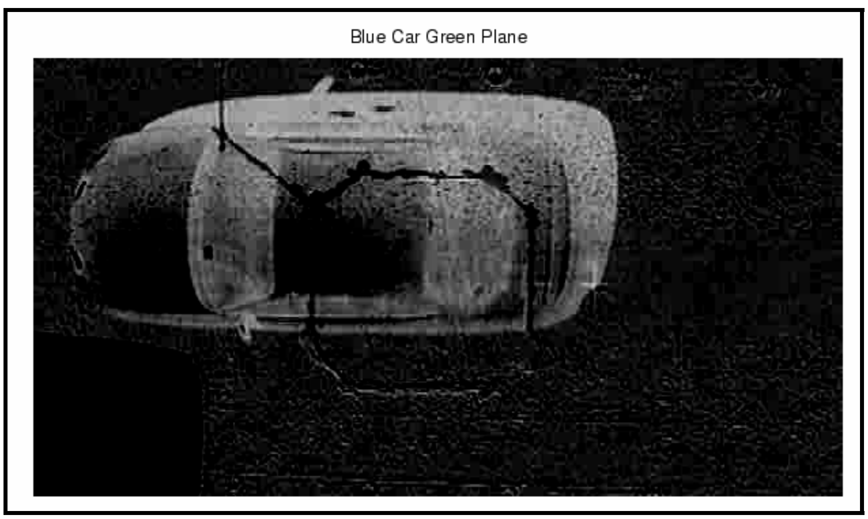
2.3.1 Vehicle Specific Feature Vector

One of the salient feature vectors in image data is the color information, which is usually described as RGB planes (Red-Green-Blue). In this study Matlab was used for RGB extraction. In Matlab, an image is stored in red, green and blue planes and each part of image is determined by the combination of those planes' intensities. The intensity value range for each plane is from 0 to 1. The combination of "0" intensities at each RGB plane shows black. In contrast, the combination of "1"'s displays as white image. The following two figures show the difference in RGB planes from two different color vehicles, blue and red vehicle. As is clear in the figures, for the blue car the blue plane is the darkest whereas in case of red car the red plane presents the darkest one. This feature difference will help to distinguish vehicles that have similar signatures but different colors and contribute to the higher correct matching rate for vehicle reidentification algorithm.

The number of pixels (NP) that falls between an upper and lower intensity threshold value at each color plane is also a good vehicle specific feature. The selection of optimal upper and lower threshold value was examined and based on an extensive analysis, 0.9 and 0.1 were chosen as upper and lower threshold values respectively. The repeatability of NP at each color plane for the same vehicles at different location is shown in Figure 2.12.

Image conversion from RGB planes to binary planes was performed to obtain vehicle length and width. Binary planes differ from RGB planes in that the plane intensity value is either 0 or 1 according to the specified conversion threshold value. Figure 2.13 describes vehicle image change at different threshold level. In this study, 0.3 was set as threshold value.





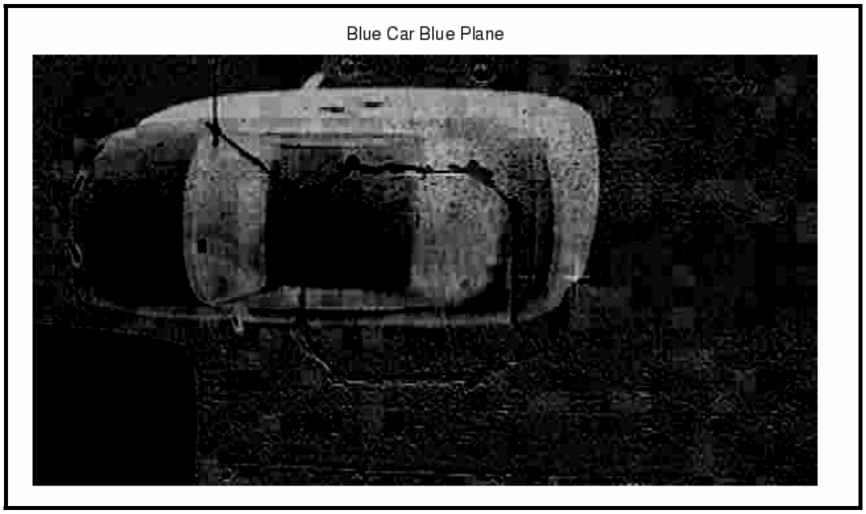


Figure 2.10. RGB planes for Blue Car

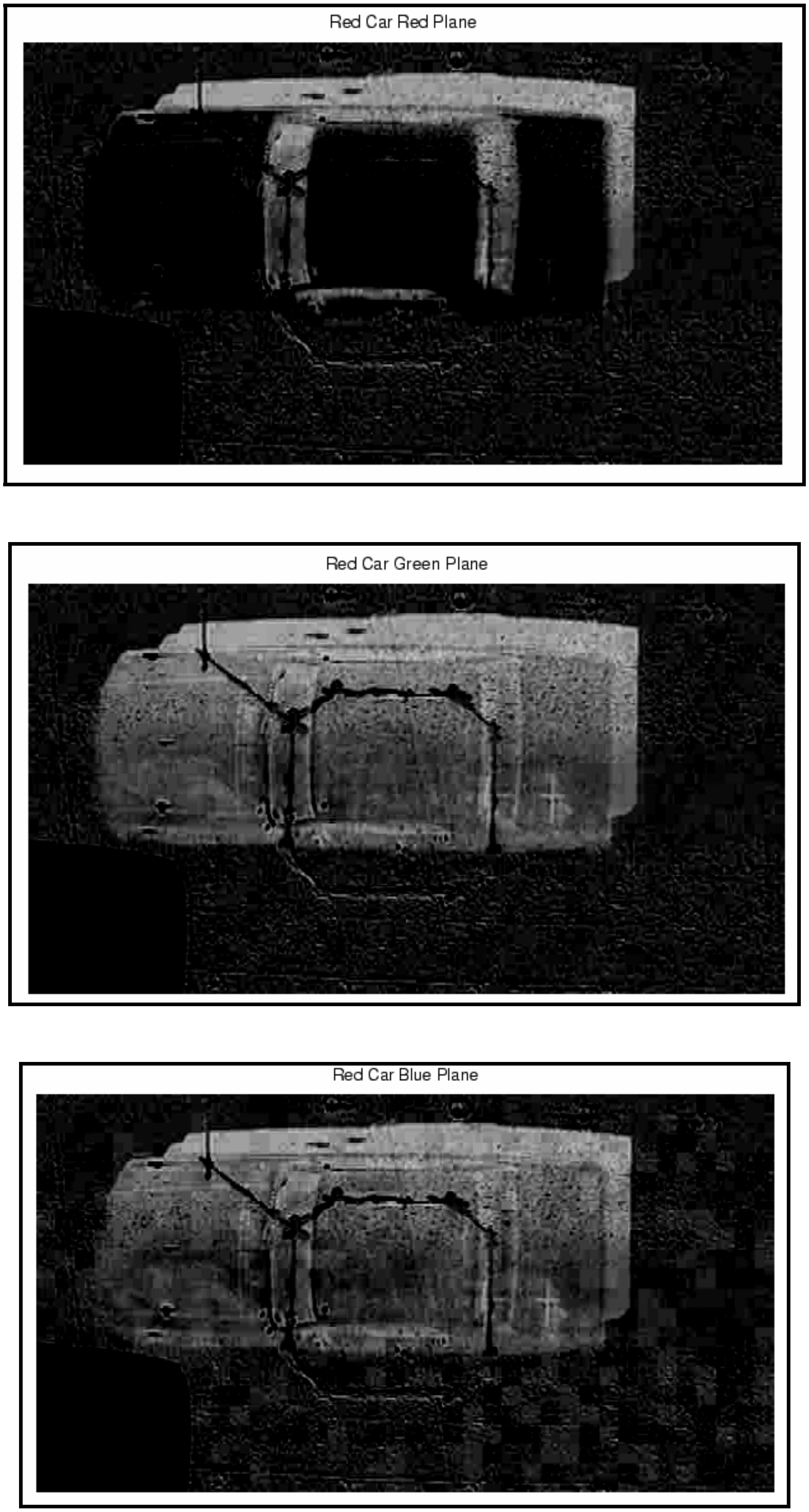
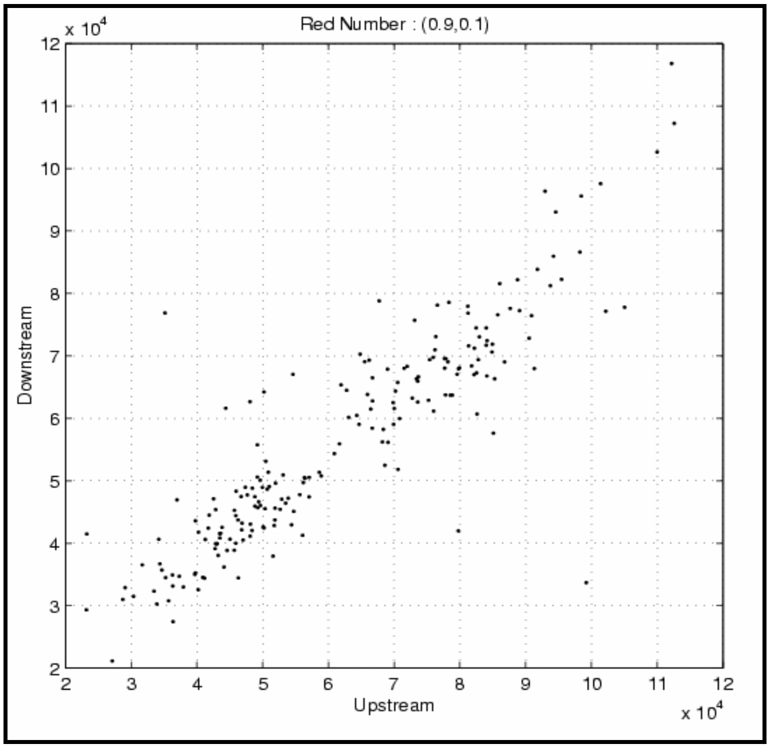
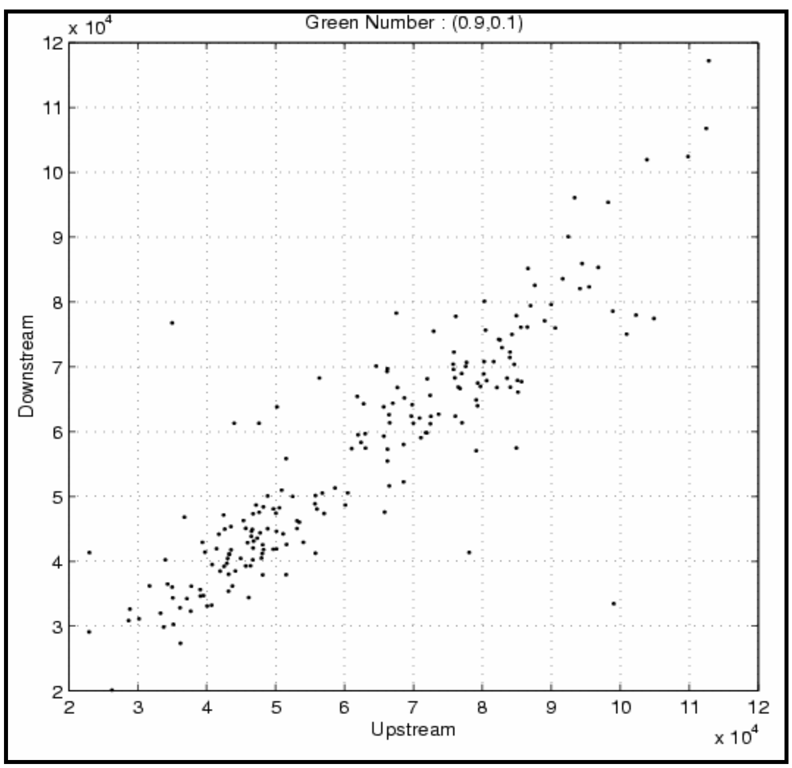


Figure 2.11. RGB planes for Red Car


Red Number : (0.9,0.1)
x 10^4
Downstream
Upstream
x 10^4
2
3
4
5
6
7
8
9
10
11
12


Green Number : (0.9,0.1)
x 10^4
Downstream
Upstream
x 10^4
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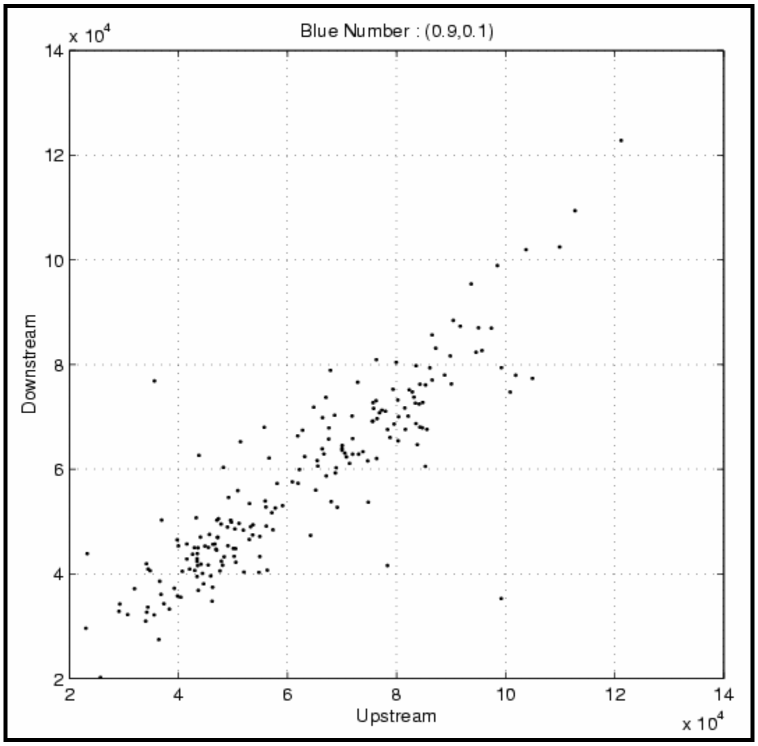


Figure 2.12. NP for identical vehicles at different locations

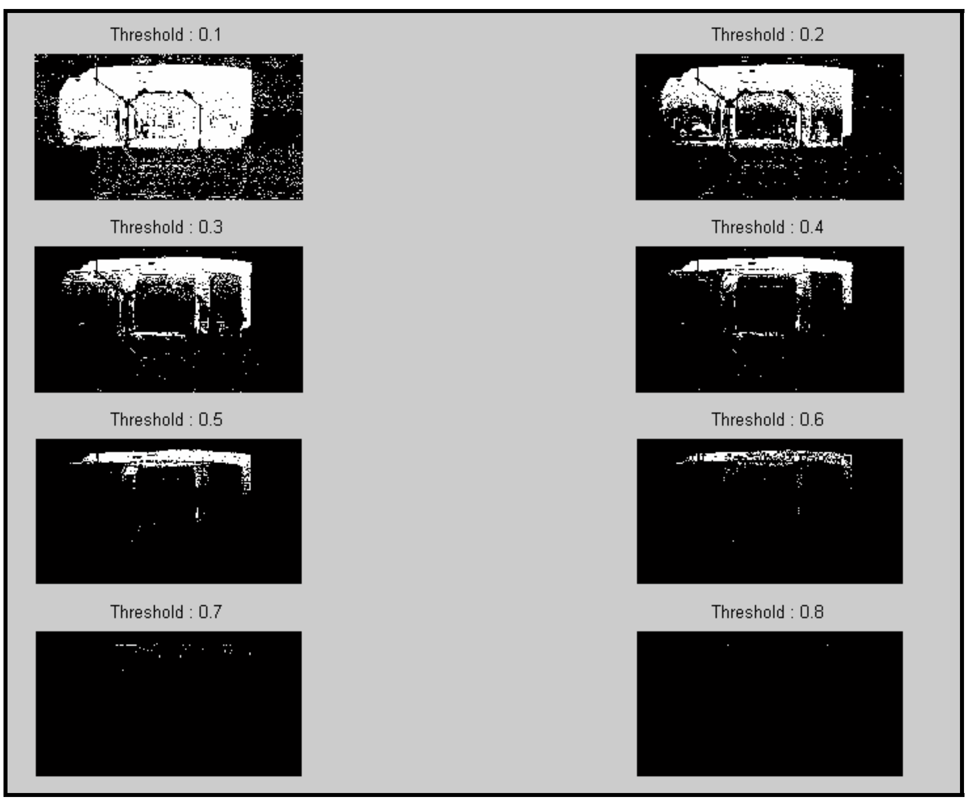


Figure 2.13. Binary Image Conversion

2.3.2 Traffic Specific Feature Vector

As for traffic specific feature vectors, station detection time and lane information were selected.

Table 2.3. Feature Summary

	Loop Signatures	Video Images
Vehicle Specific Features	Vehicle Length Shape Parameter NHM	RGB Vehicle Width Vehicle Length
Traffic Specific Features	Lane Time stamp Speed	Lane Time Stamp

2.4 Concluding Comment

In this section, the derivation and selection of salient feature vectors from two different sensors was discussed. Analysis of feature vector correlation and repeatability was also presented.

CHAPTER 3 TDS^2 FREEWAY POINT DATA ANALYSIS

3.1 Loop Volume Accuracy Analysis

3.1.1 Background

The objective of this analysis was to obtain a preliminary volume accuracy estimate of the IST-222 loop detectors. This was achieved through matching of data collected through the IST-222 loop detectors with video images obtained from the V^{2}SAT system.

3.1.2 Data

The study data were obtained from a field site on the northbound I-405 freeway at Laguna Canyon on July 23, 2002. Two data acquisition stations were instrumented with video and loop waveform data loggers. Standard 6 ft × 6 ft (1.82 m × 1.82 m) loops were used. Several hours of data were collected, but a smaller portion of the data was chosen, when there was sustained data logging in both systems for all lanes
The period of the analysis was between 1505hrs and 1550hrs on July 23 2002, as it provided optimal lighting conditions for the V^{2}SAT video cameras. In addition, IST-222 and V^{2}SAT equipment were in operation for all lanes during this period.

The loop signatures used in this study were obtained using the IST-222 Loop Detectors. These detectors are triggered by the change in inductance of loops embedded in the pavements by ferrous properties of passing vehicles. The subsequent change of inductance as the vehicle passes through is stored as a loop signature. Each signature has an associated date and time stamp and is grouped by lane. The parameter used in this study was the time stamp of the signatures. There were a total of 5556 loop signature records during the analysis period.

All video images obtained from the V^{2}SAT system were stored as JPEG files, and had an associated date and time stamp in the file name. These vehicle images were captured by video cameras mounted over each lane. The date and time stamps were extracted from each file and saved as the dataset for volume accuracy analysis. A total of 5340 V2SAT events were recorded during the analysis period.

A summary of the number of IST and V^{2}SAT events for each lane is shown in Table 3.1. In all lanes with exception of lanes 2 and 3, there were more recorded IST events than V^{2}SAT events. This is because the V^{2}SAT system was generally less sensitive than the IST system, which resulted in some missed vehicle events.

Table 3.1 Summary of IST and V^2SAT events by lanes

Lane	1	2	3	4	5	6	7	Total
IST	614	1317	1289	952	773	339	272	**5556**
V^2SAT	534	1330	1295	886	754	280	261	**5340**

However, in higher traffic volumes, the IST system suffered from undercounting errors caused by a higher incidence of tailgating vehicles, where several single loop events contained more than one vehicle signature. Hence, lanes 2 and 3, which also happened to be the highest volume lanes, had higher volume counts from the V^2SAT system than the IST system.

3.1.3 Methodology

Validation of V^2SAT data

The purpose of the study was to ground truth the IST data against V^2SAT data. Hence, the first task was to remove erroneous video events from the V^2SAT data. These are empty video events triggered by vehicles in adjacent lanes, or duplicate video events, such as additional records of the rear of trailers or other long vehicles.

Synchronizing IST and V^2SAT data

The next challenge in the study was to synchronize the times between the IST and the V^2SAT system. The IST system used a common time reference for all lanes, while the V^2SAT used an individual time stamping system for each lane. This caused a time discrepancy not only between the IST and V^2SAT system, but also between lanes within the V2SAT system. In addition, data buffering within the V^2SAT system also resulted in a small variation between detection time and time stamping.

A program was written in MATLAB to analyze the IST data sequentially and identify a possible match in the V^2SAT data within the proximity of the offset between the systems. The proximity window could be relaxed to increase the possibility of finding a vehicle within the window, or shrunk to reduce the likelihood of a mismatch.

With the randomness of traffic flow, there would only be one true offset value between the IST and V^2SAT data that would produce the highest match rate, i.e., the highest number of data points in the IST dataset with a corresponding V^2SAT data point within their corresponding time windows. These optimum offsets for each lane are established by varying the offset values in small incremental values, and finding the value with the highest match rate.

In order to improve the accuracy of matches, the dataset was sub-divided into 5 minute intervals, for a more precise offset to be obtained. It was found that the offset for each lane was not a constant throughout the analysis period. In fact, the offset varied with each subsequent time interval, and had a general tendency to increase with time. The linearity of the increase in offset with time could not be established with the limited number of interval periods.

Analysis of Volume Accuracy

The final step is the analysis of volume accuracy of the IST with the V^2SAT data. A time window of 2 seconds was used in this analysis to obtain matches with the V^2SAT data. Although a larger time window always increases the matching rate, it would also increase the possibility of matching to a wrong vehicle. Hence, with consideration of realistic car following time gaps, a time window of 2 seconds was determined to be the optimal value.

From the analysis, 3 values are obtained. They are the matched IST and V^2SAT events, unmatched IST events and unmatched V2SAT events. Considering that most of the IST events are likely true events missed by the V^2SAT system and that there are still some positive matches within the unmatched IST and V^2SAT events missed by the analysis, a lower bound estimate of the volume accuracy the IST system would be as follows:

$$\text{IST Volume Accuracy} = \left[\frac{\text{Matched Events} + \text{Unmatched IST Events}}{\begin{array}{c}\text{Matched Events} + \text{Unmatched IST Events}\\ + \text{Unmatched V2SAT Events}\end{array}}\right] \times 100\% \qquad \textbf{(3.1)}$$

Also, since a significant number of the unmatched IST events are true events, it is reasonable to assume that an upper bound estimate of the false or erroneous events in the IST system can be represented by the following equation:

$$\text{IST False Event Rate} = \left[\frac{\text{Unmatched IST Events}}{\text{Matched Events} + \text{Unmatched V2SAT Events}}\right] \times 100\% \qquad \textbf{(3.2)}$$

Such false events are usually double counts caused by lane changing vehicles that pass over inductive loops on both lanes.

3.1.4 Results

First, a time window of 0.6 seconds was set to capture some of the variability in the time stamping within the V^2SAT system due to data buffering. From preliminary investigations, it was found that the offset between the IST and V^2SAT datasets was between 120 and 180 seconds. Hence, the offset was ranged between 120 and 180 seconds, and unique matches with V^2SAT data within the time window of each IST data were recorded. The initial offset values obtained are shown in Table 3.2. As shown in Figure 3.1, the percentage of matches peaked only at a unique offset value for each lane due to the randomness of traffic flow.

Table 3.2 Initial offset values for entire analysis period

Lane	1	2	3	4	5	6	7
Offset (seconds)	170.0	162.9	146.2	154.7	170.1	167.1	147.7

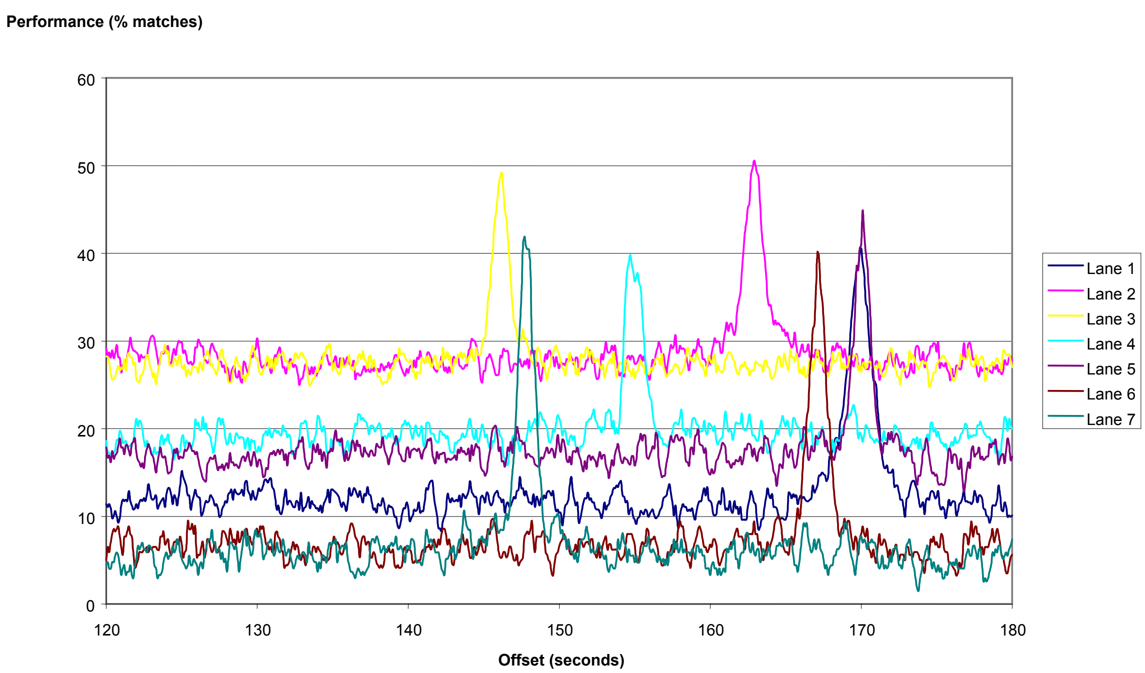


Figure 3.1 Initial Offset Analysis between IST and V^2SAT datasets

With the initial offsets determined, the dataset was sub-divided into 5-minute intervals to obtain more accurate offset values that reflect the time drift between the IST and V^2SAT system. The results from this offset analysis at 5-minute intervals is summarized in Table 3.3. It can be observed that there is a general increasing trend in offset times with time.

Table 3.3 Offset Analysis at 5-minute Intervals

Interval	Lane 1	Lane 2	Lane 3	Lane 4	Lane 5	Lane 6	Lane 7
1505 - 1510	169.3	162.5	145.5	154.5	169.6	166.7	147.0
1510 - 1515	169.4	162.7	145.6	154.5	169.5	166.7	147.4
1515 - 1520	169.7	162.8	145.9	154.7	169.9	166.9	147.5
1520 - 1525	169.5	162.9	146.2	154.6	170.1	167.1	147.6
1525 - 1530	169.9	162.7	146.1	154.9	170.2	167.3	147.7
1530 - 1535	169.8	162.9	146.2	155.1	170.2	167.5	148.1
1535 - 1540	170.3	163.3	146.2	155.2	170.1	167.4	148.0
1540 - 1545	170.3	163.2	146.4	155.1	170.3	167.3	148.2
1545 - 1550	170.3	163.2	146.6	155.6	170.6	167.6	148.0

Using a time window of 2 seconds, there were a total of 5051 matched events between the IST and V^2SAT datasets. This resulted in a lower bound IST volume accuracy of 95.06% and upper bound IST false event rate of 9.46%, obtained using equations 3.1 and 3.2. The summary of the volume accuracy analysis for all lanes is shown in Table 3.4.

Table 3.4 Summary of volume accuracy analysis across all lanes

Lane	IST	V^2SAT	Matches	Unmatched IST	Unmatched V^2SAT	L.B. Volume Accuracy	U.B. False Event Rate
1	614	534	518	96	16	97.46%	17.98%
2	1317	1330	1277	40	53	96.13%	3.01%
3	1289	1295	1242	47	53	96.05%	3.63%
4	952	886	813	139	73	92.88%	15.69%
5	773	754	687	86	67	92.02%	11.41%
6	339	280	267	72	13	96.31%	25.71%
7	272	261	247	25	14	95.10%	9.58%
Overall	**5556**	**5340**	**5051**	**505**	**289**	**95.06%**	**9.46%**

3.1.5 Concluding Comments

From the results obtained, the performance of the IST loop detectors gives a volume accuracy of at least 95%. The maximum false event rate of the IST loop detectors is about 9.5%, although this would be an extreme overestimate, since it assumes that all unmatched IST events are false events.

Overall, the results from the volume accuracy analysis provide a reasonable estimate to the reliability of IST data. This method is inherently limited by the accuracy of the V^2SAT data, which the IST data is compared to. Hence, for an improved volume accuracy analysis, the V^2SAT system must be made more sensitive to capture 100% of traffic events. In addition, the variability of the time stamp as well as the time drift within the V^2SAT system must be addressed. This would allow for the use of a much smaller time window, which would further eliminate possible error matches between the IST and V^2SAT datasets, further improving the reliability of the analysis.

3.2 Speed Analysis

The speed of each lane at each station is illustrated in Figure 3.2 and Figure 3.3. As expected, the HOV lanes showed relatively high speed compared to other lanes. The speed difference between fastest and slowest lane was about 10 ~ 20 mph at both stations.

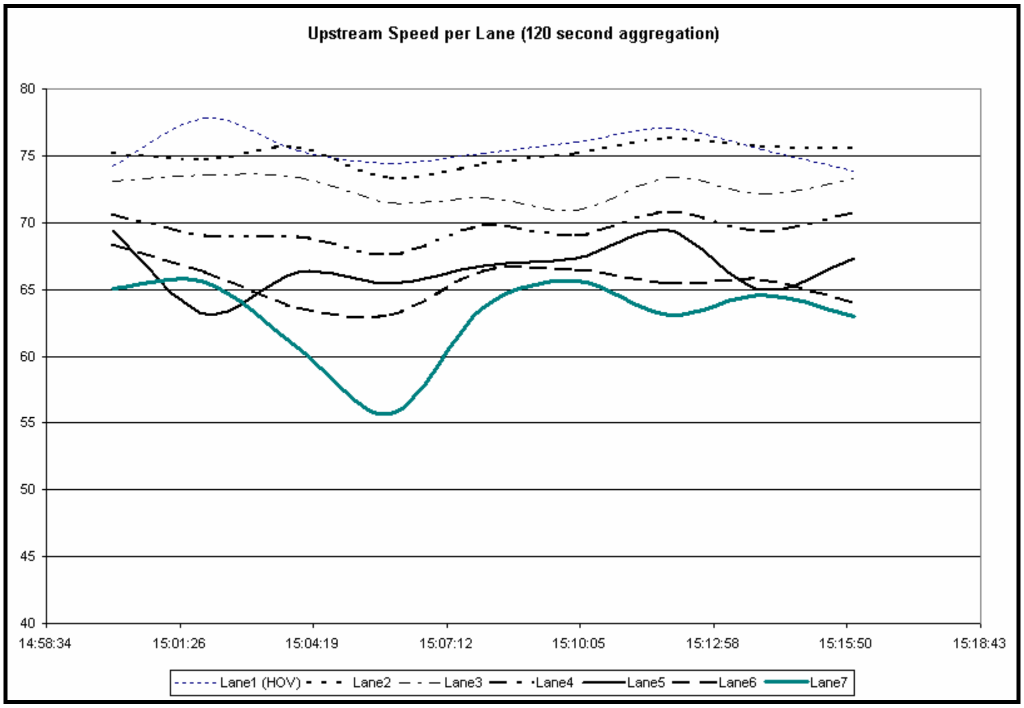


Figure 3.2. Upstream Speed Distribution according to the lane

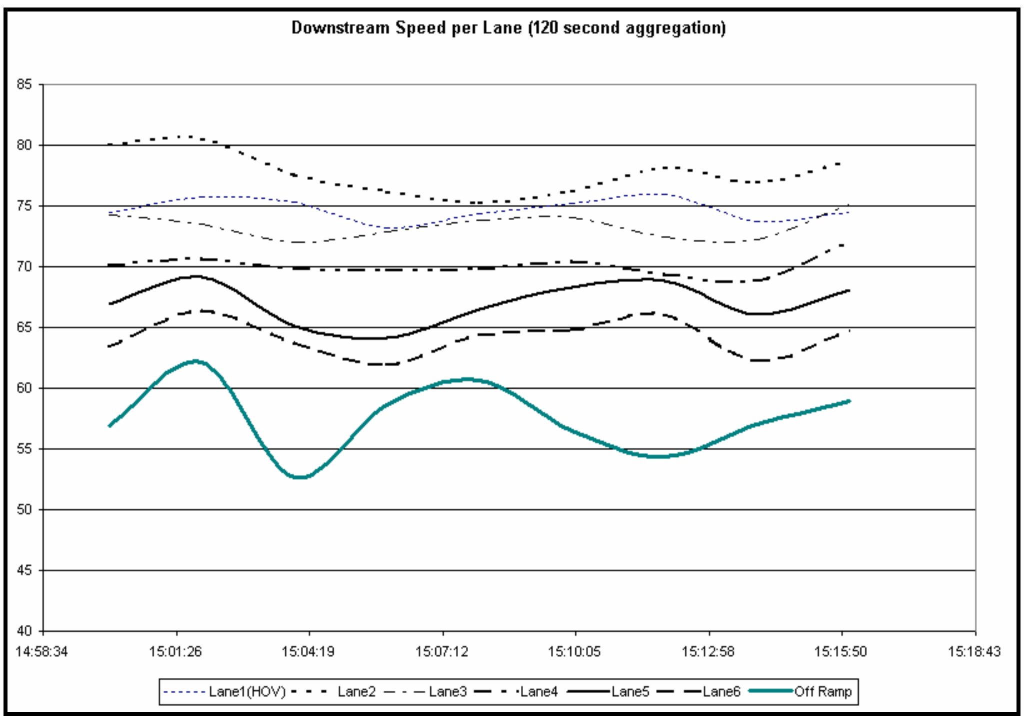


Figure 3.3. Downstream Speed Distribution according to the lane

Tables 3.5 and 3.6 show the average and standard deviation of vehicle length and speed in each lane. In case of lanes 5 and 6 at both stations, the standard deviations of vehicle length were high because of high truck and trailer volumes. In those cases, the standard deviations of speed were also large compared with other lanes. This indicates the correlation between vehicle composition and speed variation exists. The investigation on the effect of vehicle type heterogeneity on speed variance is one of the interesting future studies.

Rather than the vehicle length distribution, special road geometry was the main cause of high value in speed standard deviation at upstream lane 7 (merging lane) and downstream off ramp.

Table 3.5 Upstream Vehicle Length and Speed Statistics

	Length		Speed	
	Average	STD	Average	STD
Lane1 (HOV)	4.667444	0.565347	75.35151	4.567755
Lane2	4.947038	2.105771	75.26212	4.281101
Lane3	5.173064	2.678814	72.79188	4.528061
Lane4	5.695	3.637672	70.06944	5.256258
Lane5	5.798704	3.470313	67.33424	6.281174
Lane6	5.164232	2.232747	65.17844	6.005204
Lane7	5.186757	2.192707	63.56187	7.310732

Table 3.6 Downstream Vehicle Length and Speed Statistics

	Length		Speed	
	Average	STD	Average	STD
Lane1 (HOV)	4.758947	1.147045	74.08277	4.986483
Lane2 (HOV)	4.881813	1.883141	75.62387	4.622439
Lane3	5.103941	2.481683	73.49872	4.327911
Lane4	5.287474	3.054583	70.14197	4.416055
Lane5	5.983259	3.88531	67.13084	5.794152
Lane6	5.878609	3.51793	64.21106	6.140121
Off Ramp	5.023153	1.642307	60.44909	6.813628

3.3 Single Loop Speed Estimation

A more robust and enhanced single loop speed estimation algorithm was developed based on more than 50,000 vehicles over 7 hours during AM peak and PM. Vehicle classification study was also performed as part of single loop speed investigation.

3.3.1 Vehicle Grouping

The assumption of same effective vehicle length for single loop speed estimation is a major element contributing to speed estimation error. Therefore, differentiating vehicles into different groups according to vehicle length is the first step to improve single loop speed estimation. Because vehicle length can only be derived after speed calculation another vehicle specific feature, shape parameter (SP) was used for vehicle grouping. The correlation analysis between vehicle length and shape parameter was discussed in the previous chapter. Figure 3.4 depicts the vehicle length distribution of each vehicle group. Vehicle length variance was the highest for group II and this resulted in higher speed estimation error as shown in Table 3.7.

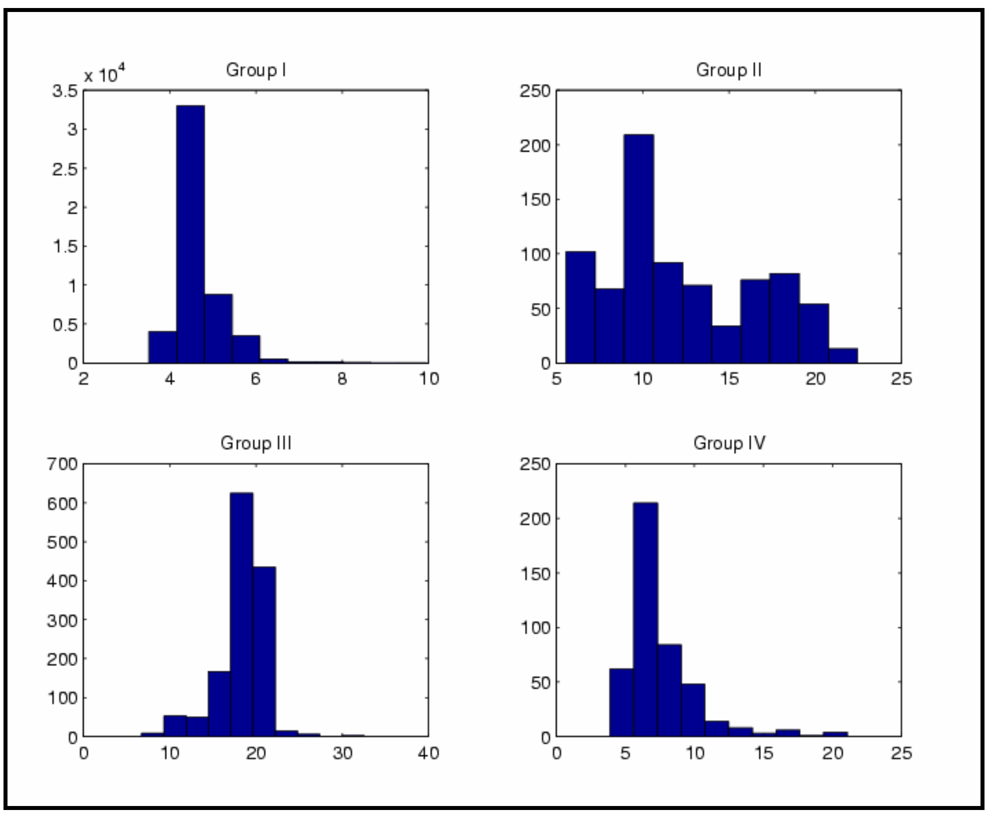


Figure 3.4 Length Distribution for each Vehicle Group

3.3.2 Statistical Module

Detailed description of the statistical module can be found in the previous PATH report (Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies – Phase I, UCB-ITS-PRR-2002-15) by the authors. Each different statistical model was applied for each vehicle group. Table 3.7 presents the estimation dataset as well as the estimation result using the test dataset. Speed from double loop speed trap was used as ground truth.

Table 3.7 Single Loop Speed Estimation Model Summary

	Vehicle Length		Estimation Model Dataset			Estimation Result (with Test Dataset)		
	Average	STD	Total	Calibration	Test	Error (mps)	Error (mph)	Error (%)
Group1	4.66	0.51	50,080	25,000	25,080	1.29	2.89	4.90
Group2	12.31	4.22	786	400	386	1.95	4.37	7.67
Group3	18.41	2.70	1,356	622	734	1.85	4.15	6.75
Group4	7.55	2.55	440	200	240	2.02	4.54	8.16

mps : meter per second

mph : mile per hour

3.3.3 Estimation Result

Table 3.8 shows the single loop speed estimation result when applied to the whole dataset according to the different interval. Because the speed variation was not high at PM period, the estimation error was relatively small compared to the AM case. In all cases, the percentage average error was less than 4% even though the speed fluctuation was high in AM peak period. Figures 3.5 and 3.6 graphically depict the true and estimated speeds during the AM and PM periods, respectively, for the three different aggregation intervals.

Table 3.8 Single Loop Speed Result

Aggregation Interval (second)	AM		PM	
	Error (mph)	Error (%)	Error (mph)	Error (%)
30	1.88	3.55	0.92	1.29
60	1.78	3.33	0.83	1.17
300	1.45	2.66	1.22	1.07

Figure 3.5 a) AM Speed Analysis – 30 second interval

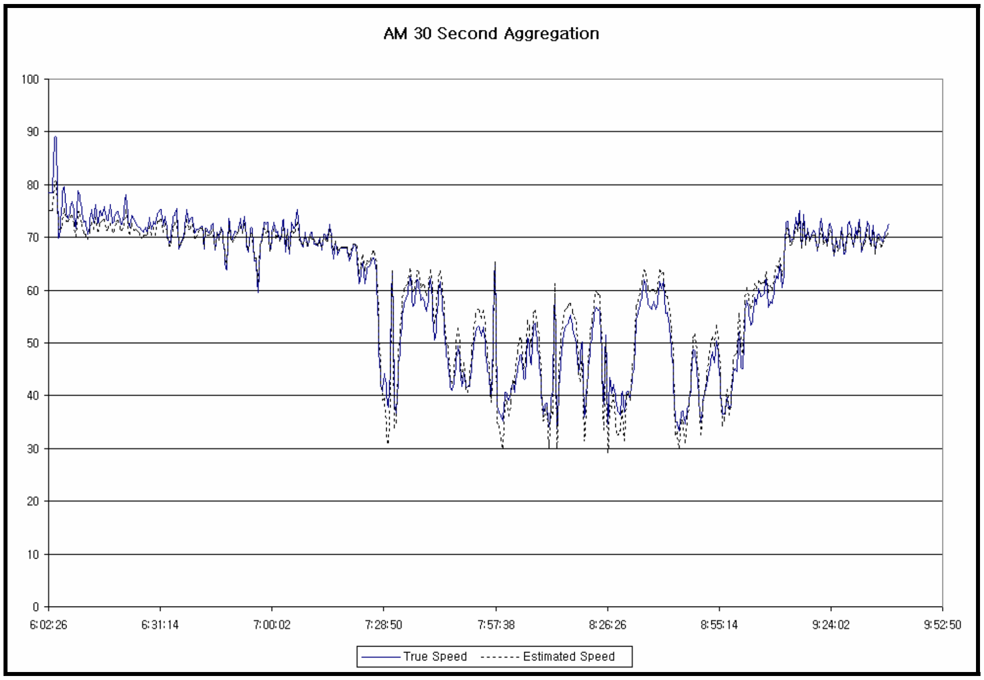


Figure 3.5 b) AM Speed Analysis – 60 second interval

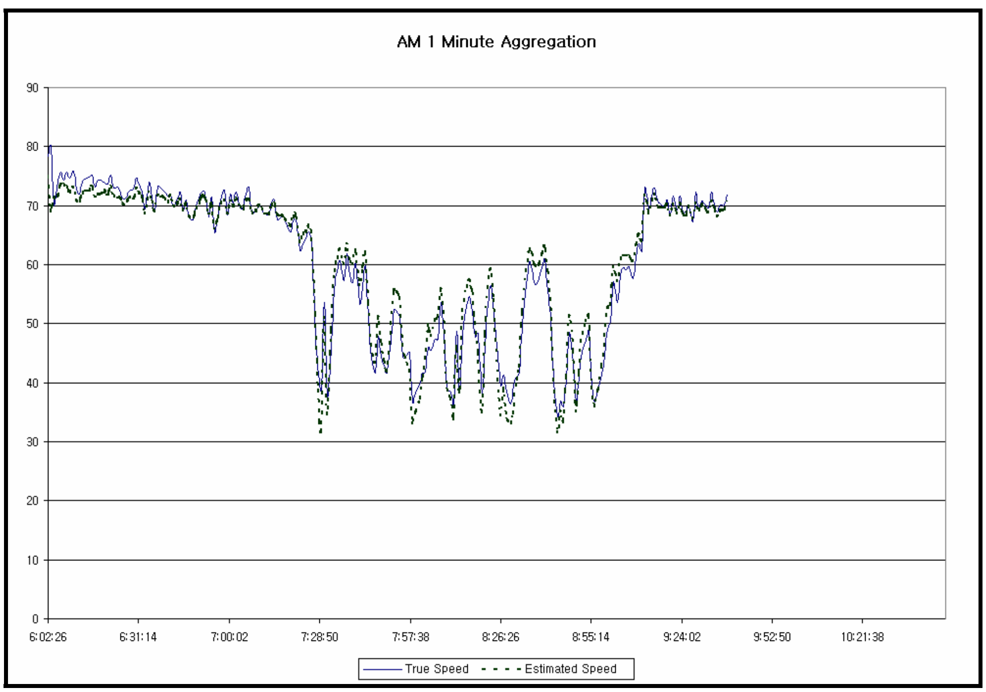


Figure 3.5 c) AM Speed Analysis – 300 second interval

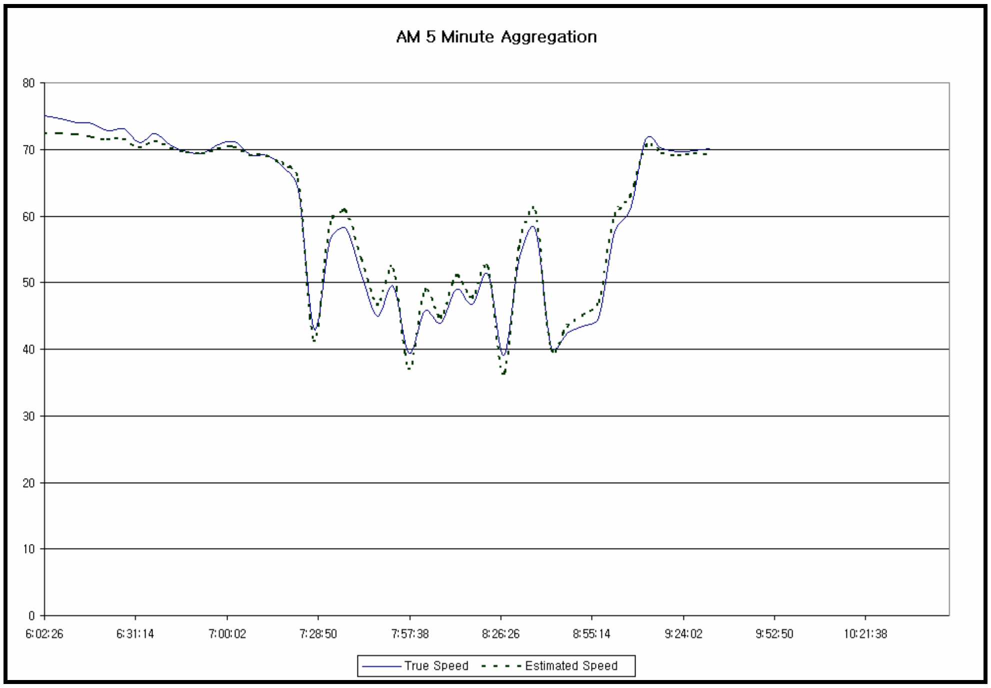


Figure 3.6 a) PM Speed Analysis – 30 second interval

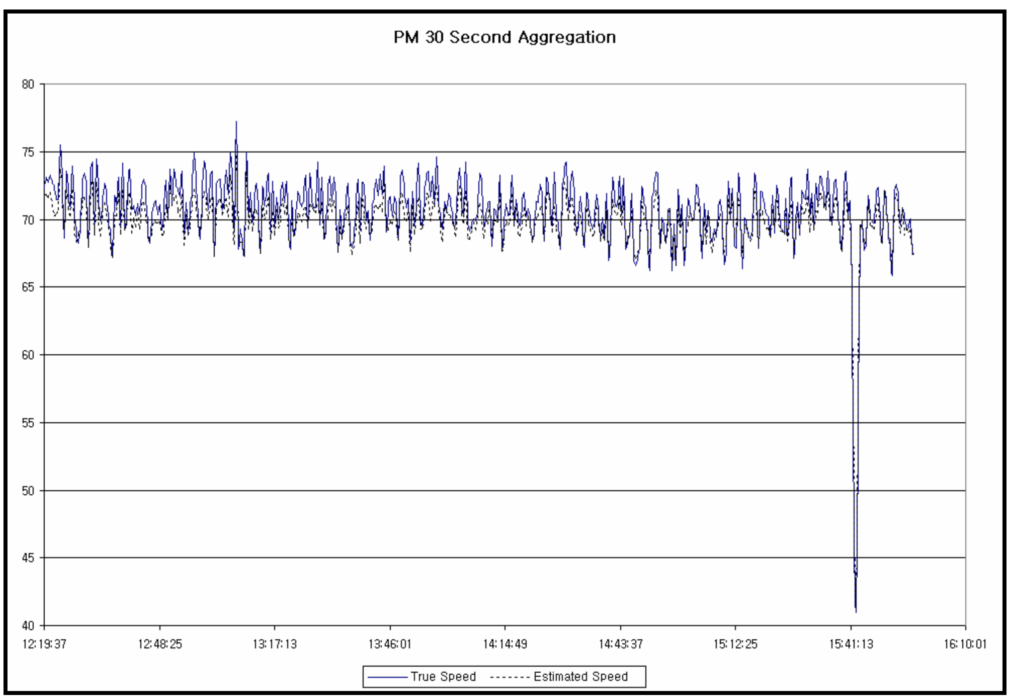


Figure 3.6 b) PM Speed Analysis – 60 second interval

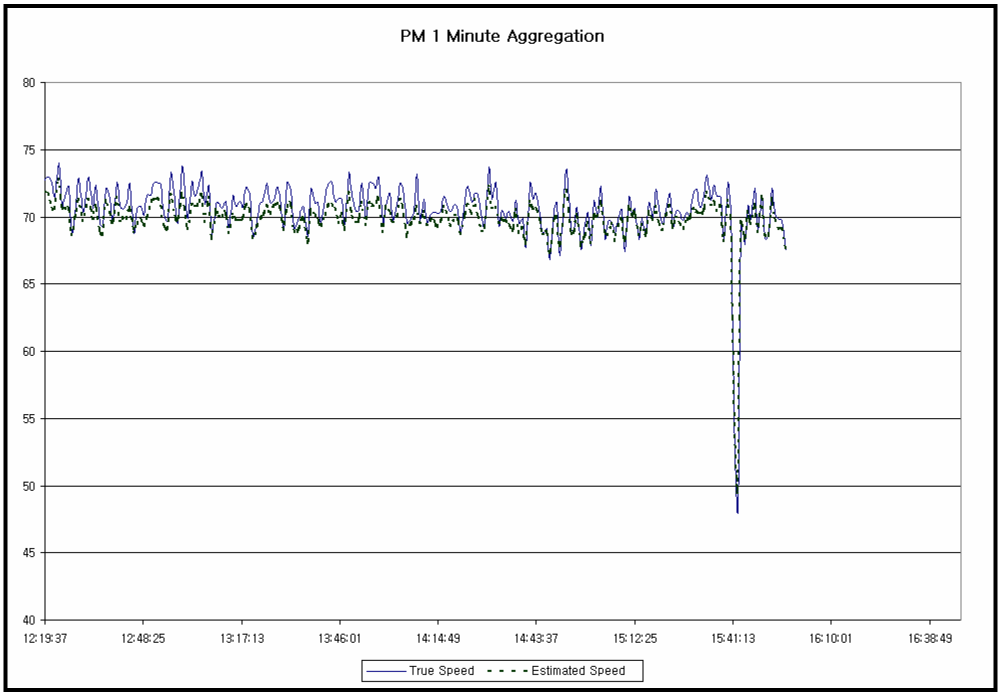
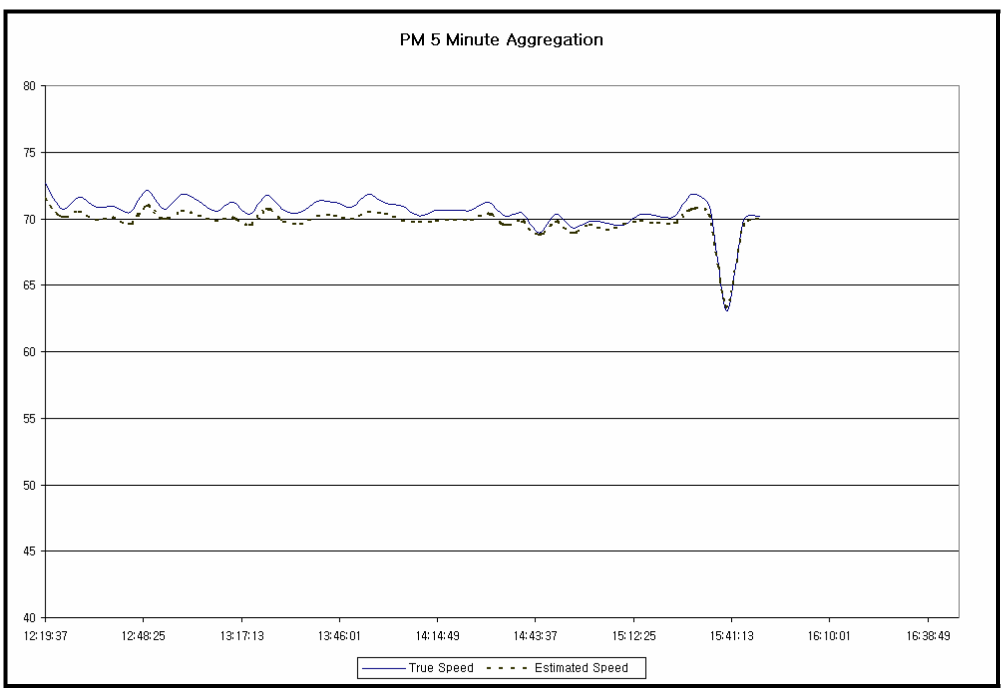


Figure 3.6 c) PM Speed Analysis – 300 second interval



3.3.4 Concluding Comments

Improvement in vehicle grouping will enhance the overall single loop speed estimation result. Only one vehicle specific feature, shape parameter, was used in this vehicle grouping even though the NHM was highly correlated to the vehicle length. This is because NHM can be only obtained once the speed is calculated, meaning this feature is not available for the proposed speed estimation algorithm input. Investigation on vehicle specific features finding will enhance the vehicle grouping accuracy. Moreover, vehicle classification can be automatically achieved while vehicle grouping is performed. This is a very encouraging result considering that vehicle length, the core element for vehicle classification, is not directly obtainable in single loop configuration.

CHAPTER 4 TDS^2 FREEWAY SECTION DATA ANALYSIS

4.1. Introduction

Vehicle reidentification using the TDS^2 N I-405 freeway data is discussed in this section. Travel time estimation and origin destination matrix estimation are identified as useful outputs from the vehicle reidentification algorithm. Sensitivity analysis between reidentification performance and signature feature restriction is also investigated. The last section suggests future vehicle reidentification algorithm enhancement by fusing data from multiple sensors. Initial investigation based on a small dataset indicates encouraging results.

4.2. I-405 Freeway Vehicle Reidentification (REID)

4.2.1. Vehicle Reidentification Result

Vehicle reidentification algorithm was tested using the same July 23rd, 2002 dataset mentioned in earlier chapters. Figure 4.1 illustrates the proposed vehicle reidentification algorithm procedure. The results are presented in Table 4.1 and 4.2. As defined in Table 4.1, the system reliability rate represents the confidence level of the reidentification algorithm result. The likelihood of having higher matching rate will probably increase if the total algorithm declared matching volume (B) is high. However, this could also yield in high mismatched vehicle pairs and yielding high error in traffic parameters estimation. Therefore, rather than mainly focusing on high correct matching rate, the balance between correct matching rate and system reliability rate should be considered. It is recommendable to set a predefined and acceptable system reliability rate that would generate accurate traffic parameters.

Table 4.1. Reidentification Result

Total Volume (A)	2257
REID Algorithm Declared Matching Volume (B)	1844
REID Correct Matching Volume (C)	1626
Correct Matching Rate (=C/A)	**72.04**
System Reliability Rate (=C/B)	88.18

Table 4.2. Reidentification Result by Vehicle Type

Vehicle Type	Actual Volume	Correct Matching volume	Correct Matching Rate %
Motorcycle	4	3	75
Passenger Car	1127	735	65.22
SUV/Van	637	470	73.78
Truck/Trailer	132	118	89.40
Pickup	352	296	84.09
Bus	5	4	80
Total	**2257**	**1626**	**72.04**

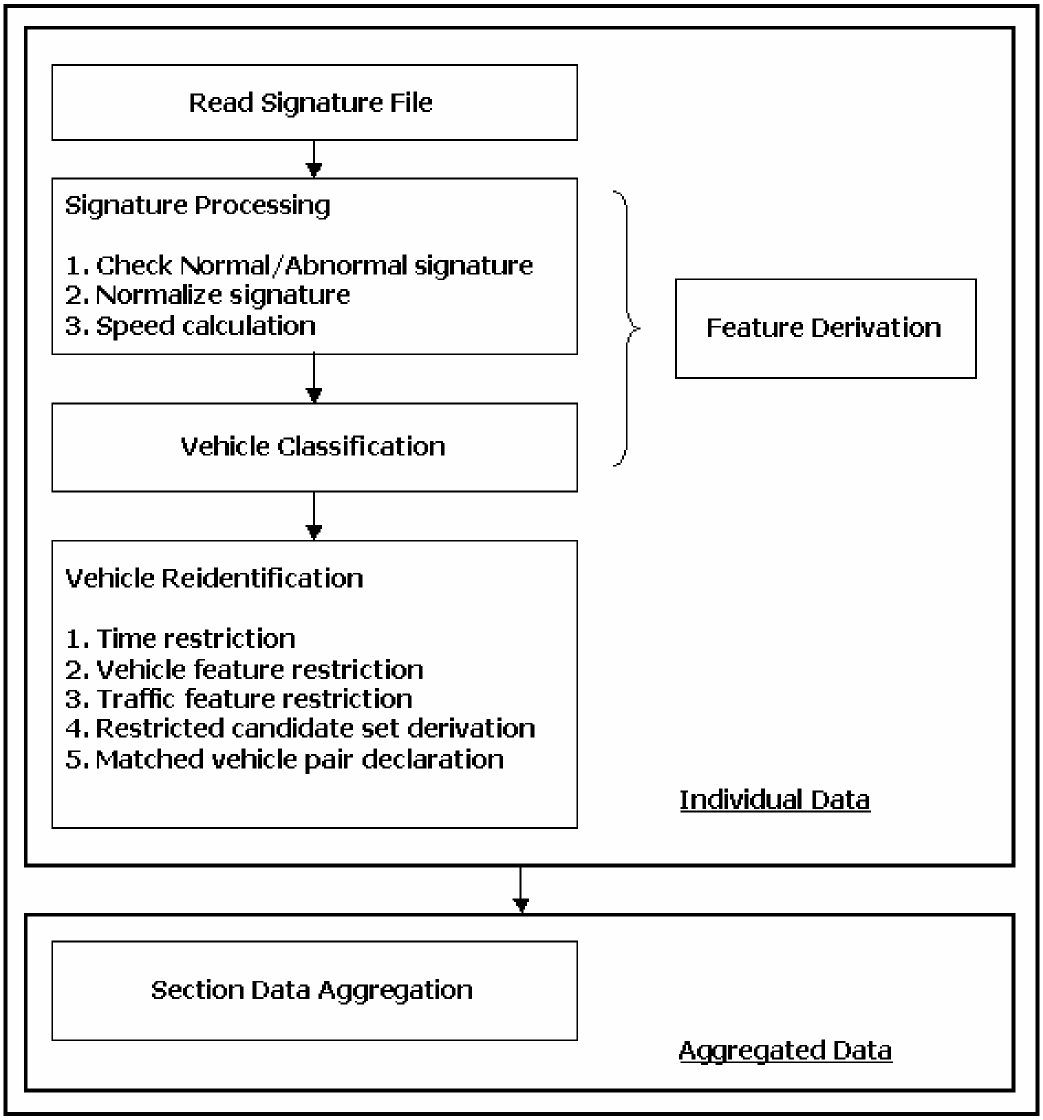


Figure 4.1. Vehicle Reidentification Algorithm Procedure

Table 4.2 describes the reidentification result by vehicle types. Because the signatures of motorcycle, bus, truck, and trailer are so unique, the correct matching rates were relatively higher than that of passenger car. In order to improve the correct matching rate of passenger car, the data fusion methodology will be presented later in this chapter.

Table 4.3 shows the sensitivity analysis among algorithm correct matching rate, system reliability and signature length restriction threshold. As we can see when the length restriction value is “0.7”, the algorithm outputs the highest correct matching rate. But it is clear that the system reliability rate is lower in this case compared to the case of length restriction “0.5”. Because it is also important to derive more accurate traffic parameters and section data with higher system reliability rate, the threshold value “0.5” was selected in this research.

Table 4.3. Sensitivity Analysis I

Length Restriction	Correct Matching Rate (%)	System Reliability Rate (%)
0.1	69.16	88.34
0.2	71.69	88.36
0.3	71.82	88.10
0.4	71.90	88.16
0.5	**72.04**	**88.18**
0.6	72.04	88.04
0.7	72.13	88.09
0.8	72.13	88.05

4.2.2. Origin Destination Estimation

Origin-Destination matrix is one of the useful section data from the vehicle reidentification algorithm. Table 4.4 and Table 4.5 present the estimated O-D matrix and true O-D matrix respectively. Because not all the vehicles were matched in the reidentification algorithm, the O-D matrix was estimated by multiplying by a weighting factor. The following formula explains O-D estimation in this research.

$$OD\_Flow_i^j(k) = \frac{\mathrm{Re}id\_Flow_i^j(k)}{\sum_{i=1}^{n} \mathrm{Re}id\_Flow_i^j(k) \Big/ Total\_Flow^j(k)}$$

where,

$OD\_Flow_i^j(k)$: Origin - Destination flow traveling from origin i to destination j over time period k

$\mathrm{Re}id\_Flow_i^j(k)$: Reidentified flow traveling from origin i to destination j over time period k obtained from vehicle reidentification

$Total\_Flow^j(k)$: Total flow observed at destination j over time period k obtained from point detection

n : Number of origins

The estimated O-D matrix error was examined using two criteria. One is the correlation analysis as well as the linear relationship analysis. Figure 4.2 shows the linear relationship between estimated and true OD pairs. The line slope in this figure is 45 degree and it is clear that the estimated OD result follows closely the true OD values. The correlation between the two matrices shows 0.99, which indicates high linear correspondence.

A misclassified OD pair percentage was used as the second criterion to evaluate estimated OD matrix. In this research, using the following formula, the error was 9.22%. This means that about 9.22 percent out of total OD pairs were assigned on wrong paths.

$$OD\ \ Error = \left(\frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \text{abs}(\text{OD}_{\text{ijTRUE:}} - OD_{ijREID})}{\sum_{i=1}^{m} \sum_{j=1}^{n} \text{OD}_{\text{ijTRUE}}} \right) * 100$$

where

n : *nmber of origin*

m : *number of destination*

OD_{REID} : *OD volume from reidentification algorithm*

OD_{TRUE} : *True OD volume*

Table 4.4. Origin Destination Matrix from Vehicle Reidentification

	1 (HOV)	2 (HOV)	3	4	5	6	Off Ramp
1 (HOV)	255	12	6	0	0	0	0
2	10	17	460	60	1	0	0
3	3	5	63	357	47	1	0
4	0	4	14	64	311	38	4
5	0	0	14	19	52	209	29
6	0	48	3	29	34	0	12
7	0	0	0	0	18	50	8

Table 4.5. True Origin Destination Matrix

	1 (HOV)	2 (HOV)	3	4	5	6	Off Ramp
1 (HOV)	263	11	1	0	0	0	0
2	2	22	468	52	11	1	0
3	0	4	60	347	49	10	1
4	1	3	11	68	283	43	5
5	2	3	8	23	57	191	27
6	0	43	11	30	40	0	14
7	0	0	1	9	23	53	6

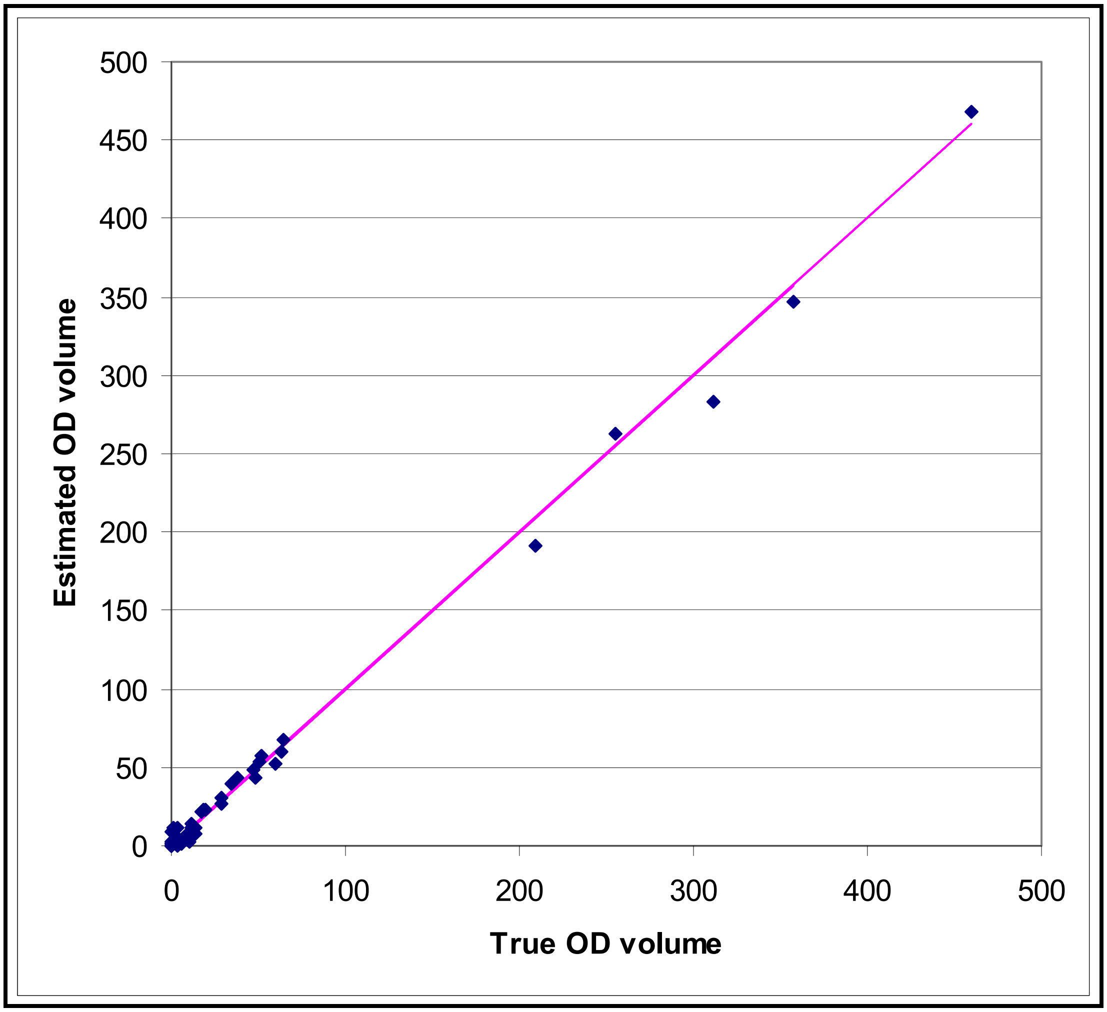


Figure 4.2. Estimated OD and True OD

4.2.3. Section Travel Time Estimation

Section travel time is one of the most important parameters for ATMIS and efficient traffic control. Travel time can also serve as an index for traffic variation as well as traffic stability. Table 4.6 illustrates the estimated section travel time error from vehicle reidentification at different aggregation intervals.

Table 4.6. Travel Time Error

Aggregation Interval (second)	Average % Error
30	1.67
60	0.87
90	1.03

In all cases, the percentage error was less than 1.7%. The estimated travel time tends to be overestimated. This can be explained from the lower correct matching rate for passenger car, which is in general a high-speed vehicle type. In contrast the slow vehicle such as trailer shows high correct matching rate and this is also one factor contributing to the travel time overestimation.

Figures 4.3, 4.4 and 4.5 illustrate the derived section travel time at different aggregation intervals along the analysis time period.

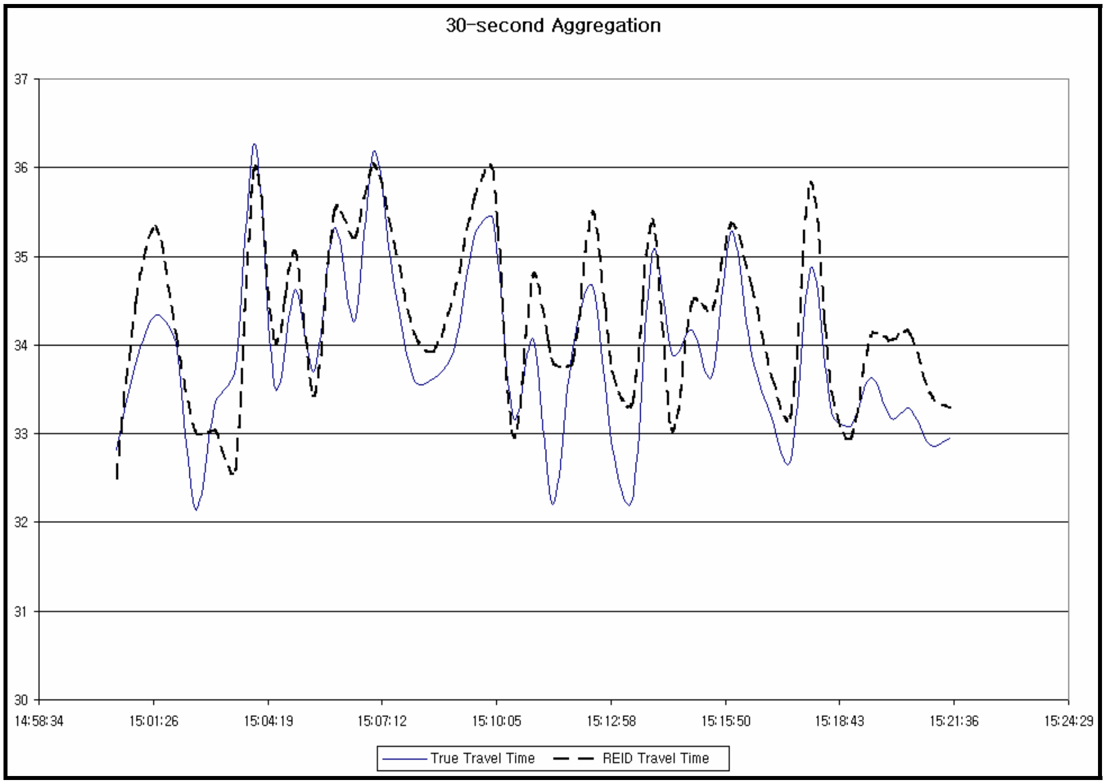


Figure 4.3. Travel Time at 30 second Aggregation Interval

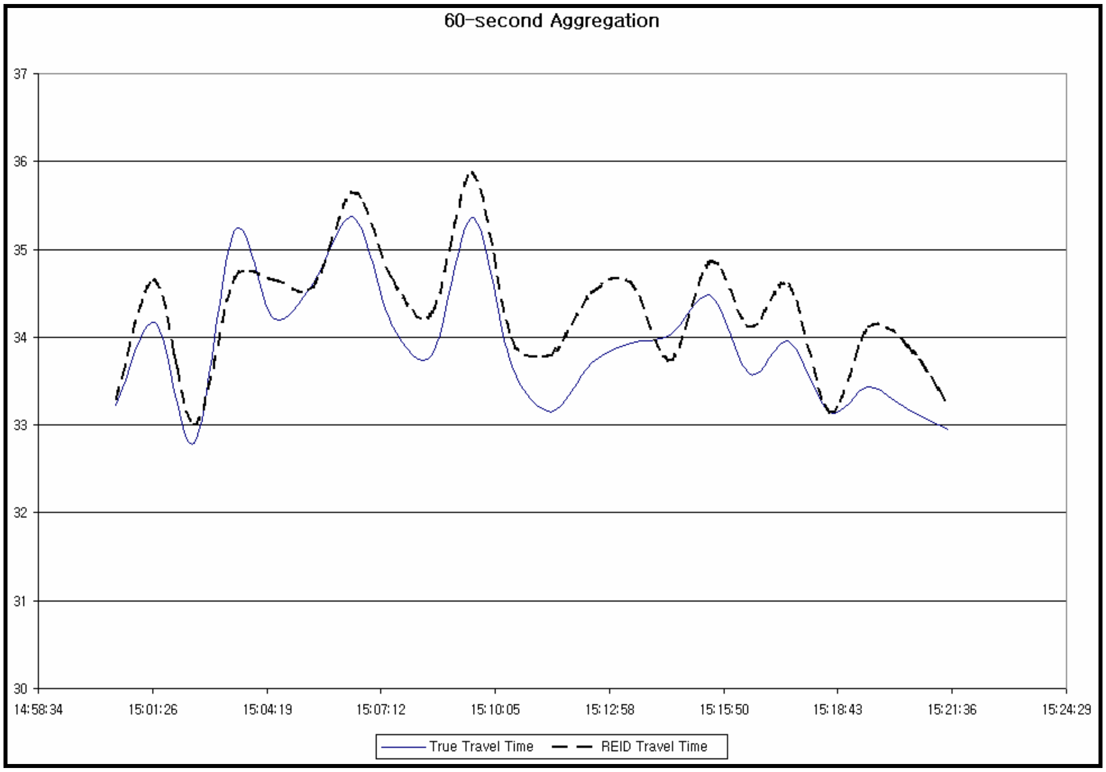


Figure 4.4. Travel Time at 60 second Aggregation Interval

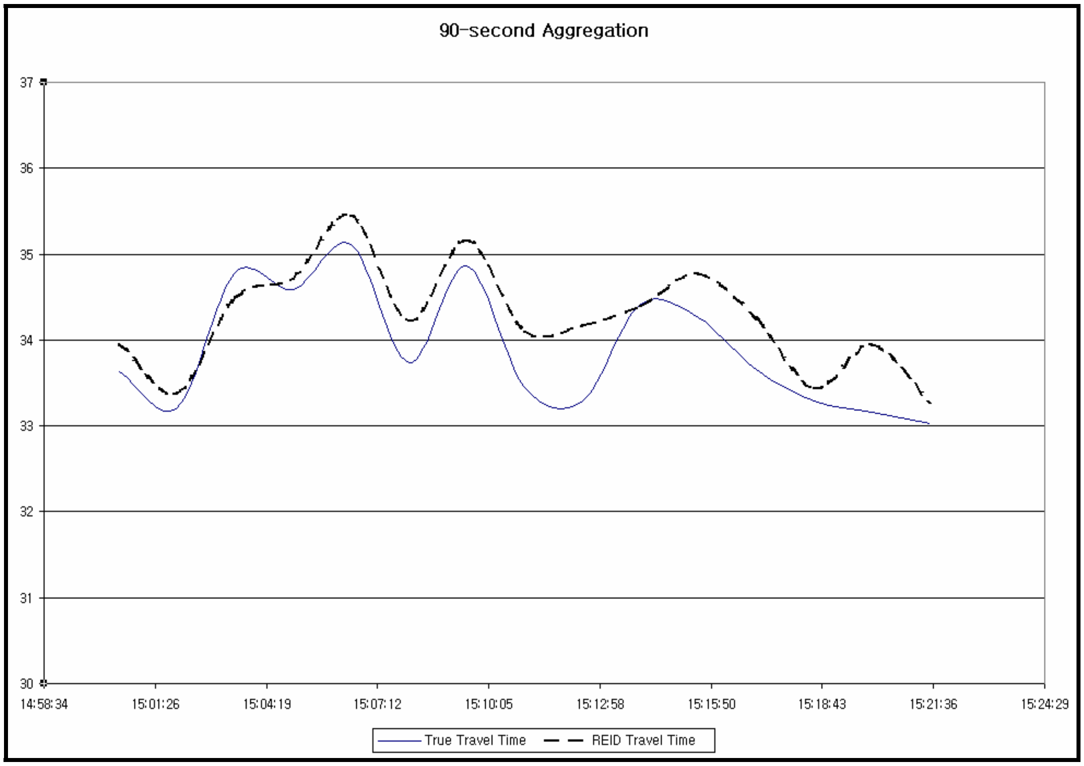


Figure 4.5. Travel Time at 90 second Aggregation Interval

4.3. Vehicle Reidentification Enhancement Using Data Fusion

In order to enhance vehicle reidentification algorithm performance, fusion with the V^2SAT video image dataset was investigated. Only a small dataset from the HOV lane was tested for this initial research. It was assumed that the additional vehicle color information from these video images would improve the vehicle reidentification algorithm, especially in case of passenger cars where the signature feature vectors are quite similar.

Comparison of vehicle reidentification algorithm performance using different datasets is presented in Table 4.7. Even though the improvement rate was not high, the system reliability rate increased significantly, being close to 100 percent. The system reliability enhancement yields a low incorrect matching rate, which also reduces errors in traffic parameter estimation. Once again, this confirms the importance of system reliability.

Table 4.7. Vehicle Reidentification Result Comparison

Data	Total Volume (A)	Algorithm Result			REID Correct Matching Rate (%, B/A)	REID Reliability Rate (%, B/C)
		Correct Matching (B)	Incorrect Matching	Total Matching (C)		
Loop Signature Data	204	184	6	190	**90.2**	**96.8**
Loop Signature and Video Data	204	187	1	188	**91.7**	**99.5**

Table 4.8 illustrates the reidentification result by vehicle type. As expected, the correct matching rate in the passenger car group was improved by fusing the loop signature data and video image data. Figure 4.6 shows an example of a passenger car that was matched incorrectly when only loop signature data was applied but correctly matched when the fused dataset was used. It is clear that the signature data for both vehicles are similar. But from the video data, the two vehicles show a different color pattern and this additional information increased the correct matching rate.

Table 4.8. Vehicle Reidentification Result by Vehicle Type

Vehicle Type	Total Volume	Signature Data	Signature and Video Data
Passenger Car	93	80	83
Pickup Truck	73	67	67
Van/ SUV	37	36	36
3 – Axle Single Unit Truck	1	1	1
Total	204	184	187

This data fusion approach is very helpful in deriving a high correct matching rate, especially in the case of passenger cars, which usually occupies the largest vehicle category both in freeways and arterials. Also, the reduced number of incorrectly matched vehicle pairs can yield more accurate estimation of traffic parameters.

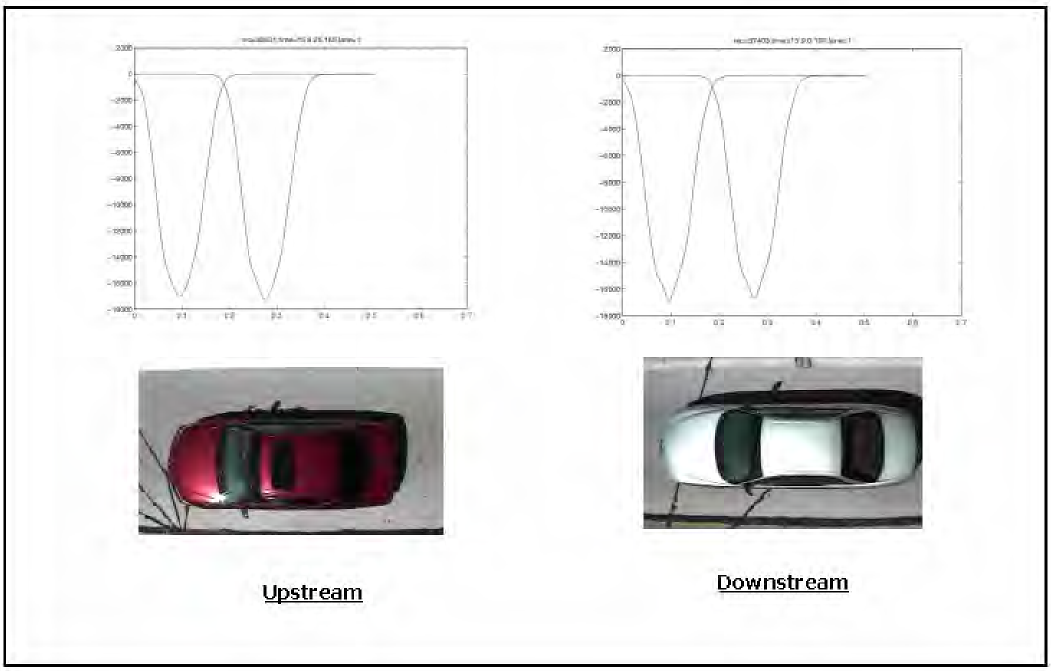


Figure 4.6. Vehicle Signature and Video Data Comparison

4.4. Conclusion

Vehicle reidentification algorithm result based on loop signature data and fused dataset with video images is presented. The importance of system reliability rate is discussed. It was also proven that the fused dataset contributes on the increase of system reliability rate. Consequently, this will improve the accurate traffic parameter estimation.

CHAPTER 5 DATA COMMUNICATION AND REAL-TIME TRAFFIC INFORMATION PROVISION VIA WEBSITE

5.1 Introduction

A website for providing real-time traffic performance data obtained from the vehicle reidentification system to users on-line has been operated, and is connected by an existing UCI/City of Irvine network to an industrial PC in the controller cabinet running the vehicle reidentification algorithms. This chapter presents the communication method between Traffic Detection and Surveillance Sub-testbed (TDS^2) on the I-405 northbound freeway and the website. The ability to obtain valuable real-time traffic information through the vehicle reidentification results displayed on the website is also introduced.

5.2 Data Communication

The TDS^2 comprises two contiguous sites 1 km apart along the Northbound I-405 freeway in Irvine – at I-405 and Laguna Canyon Road (Figure 5.1), and at I-405 and Sand Canyon Avenue. It was instrumented with double inductive loops in all lanes (including HOV lanes and the off-ramp at Sand Canyon). In addition, overhead vertical-mount video cameras were installed over each lane of traffic (including the Sand Canyon off-ramp) and were connected to a ground-truthing video image processing system. A number of traffic cabinets to house computers, communications, and video image processing equipment were also installed (Figure 5.2).

Communications between the upstream and downstream sites is by dedicated high-speed wireless Ethernet, with fiber optic cable between the downstream mainline cabinets and the Sand Canyon cabinet. Wireless Ethernet is also used to communicate from the downstream site to a City of Irvine cabinet where data enters the City network and is sent to the UCI testbed labs and a UCI data and web server, as well as the internet.

An on-line version of the freeway vehicle reidentification algorithm was implemented on the industrial PCs in traffic cabinets upstream and downstream and reidentified section data (such as travel time, speed, vehicle-hours, vehicle-miles, and lane by lane OD flows and travel times) was aggregated into regular time intervals, in most cases acceptable minimum intervals such as 60 seconds, at the remote sites. Aggregated data was sent to the data center at UCI and received by the data collection server located at the data center. The collection server receives data and posts records into the database server. The web server queries data from the database, performs more aggregation if needed and presents data in tables and graphs to users. The database is also designed to address future data from different and multiple detectors. For efficient and high speed algorithm operation on-site, the aggregated data is sent continuously, and the processed individual raw vehicle signatures are stored on-site during the day. The stored signature data are transmitted at night when both freeway traffic and the website load are relatively light. Currently, the data collection, database, and web services are integrated into a single server that is an Intel-based dual processor running Windows 2000. These services could be distributed over multiple servers in the future. In terms of software, the data collection server uses Java, the database server uses Microsoft SQL server, and the web server uses ColdFusion.

Figure 5.1 Upstream of TDS^2 on Northbound I-405 freeway (Laguna Canyon)

Figure 5.2 Field traffic cabinets

5.3 Real-time Traffic Information Provision Via Web-site

Both point traffic data and section traffic data are provided by the website in real time. Various aggregation intervals specified by users can be employed to represent dynamic traffic characteristics.

5.3.1 Point Data

Fundamental traffic parameters obtained from individual detector stations are presented by tables and graphs. Figure 5.3 presents an example of point volume and speed data aggregated over 2 minutes. Vehicle classification information is also produced by the vehicle reidentification algorithm and displayed through the website. Vehicle classification is the process of vehicle type recognition based on given vehicle characteristics. Accurate vehicle classification has many important applications in transportation. Those applications include highway maintenance that is highly related to the monitoring of heavy vehicles and traffic safety focusing on identifying the relationship between the accident severity and vehicle types. Figure 5.4 presents the website page of real-time vehicle classification information.

5.3.2 Section Data

Section data such as travel time, section speed, and reidentified volume are obtained from the reidentified data between upstream and downstream locations. One of the nicest features of this study is the ability to provide real-time origin destination (OD) information. Lane by lane OD information including travel time and volume is also presented through the website as shown in Figure 5.5. Real-time OD traffic volume is derived as follows.

$$OD\_Flow_i^j(k) = \frac{\mathrm{Re}id\_Flow_i^j(k)}{\sum_{i=1}^{n} \mathrm{Re}id\_Flow_i^j(k) \Big/ Total\_Flow^j(k)}$$

where,

$OD\_Flow_i^j(k)$: Origin - Destination flow traveling from origin i to destination j over time period k

$\mathrm{Re}id\_Flow_i^j(k)$: Reidentified flow traveling from origin i to destination j over time period k obtained from vehicle reidentification

$Total\_Flow^j(k)$: Total flow observed at destination j over time period k obtained from point detection

n : Number of origins

5.3.3 Real-time Level of Service (LOS)

According to Highway Capacity Manual (HCM), traffic density is the parameter used to define Level Of Service (LOS) criteria for basic freeway sections. Unlike speed, density increases as flow increases up to capacity, resulting in a measure of effectiveness which is sensitive to a broad range of flows. Under this project, the vehicle reidentification system produces the section density as one of the useful traffic parameters. Therefore, the direct measurement for freeway LOS is available. Figure 5.6 shows an example of real-time LOS information.

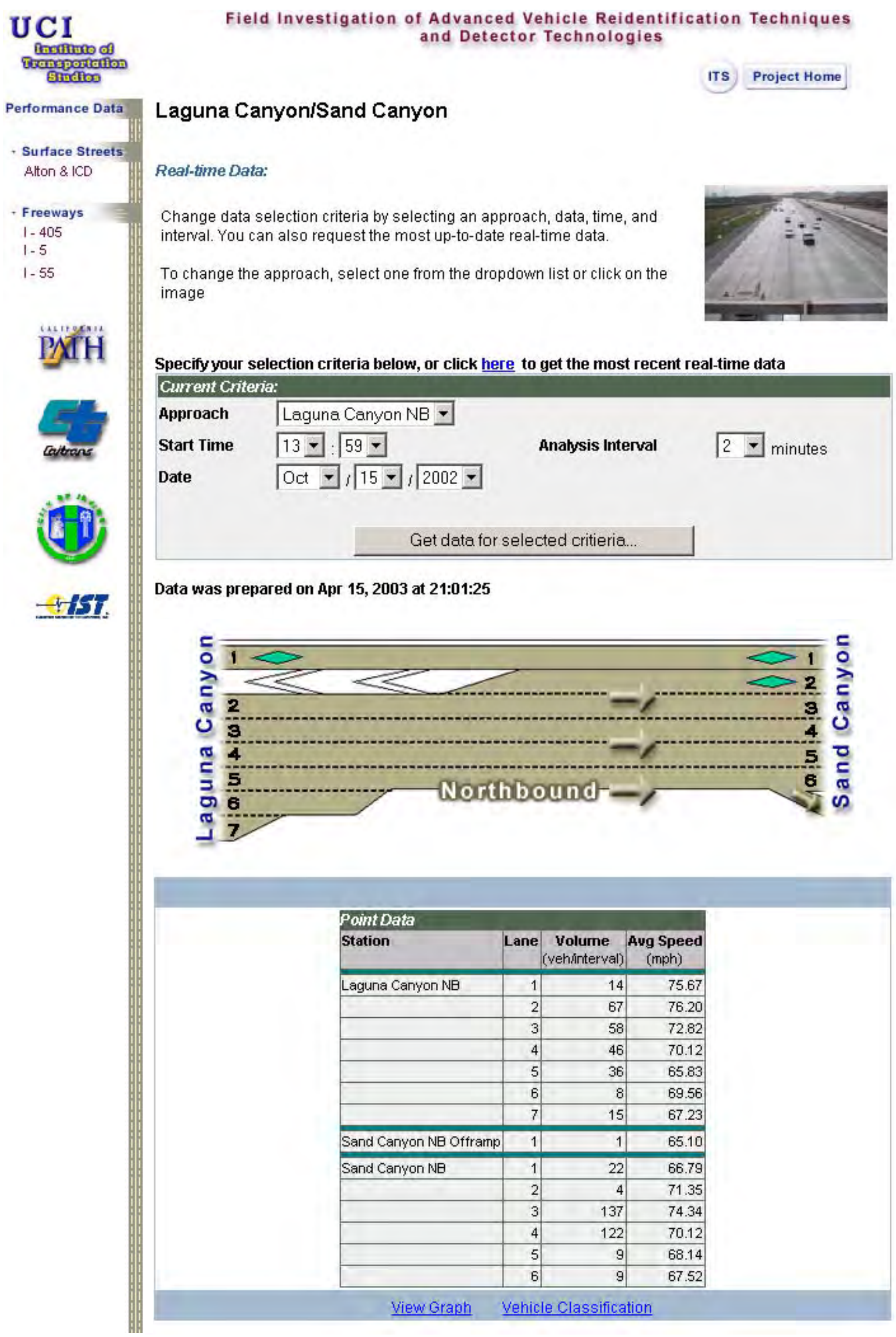
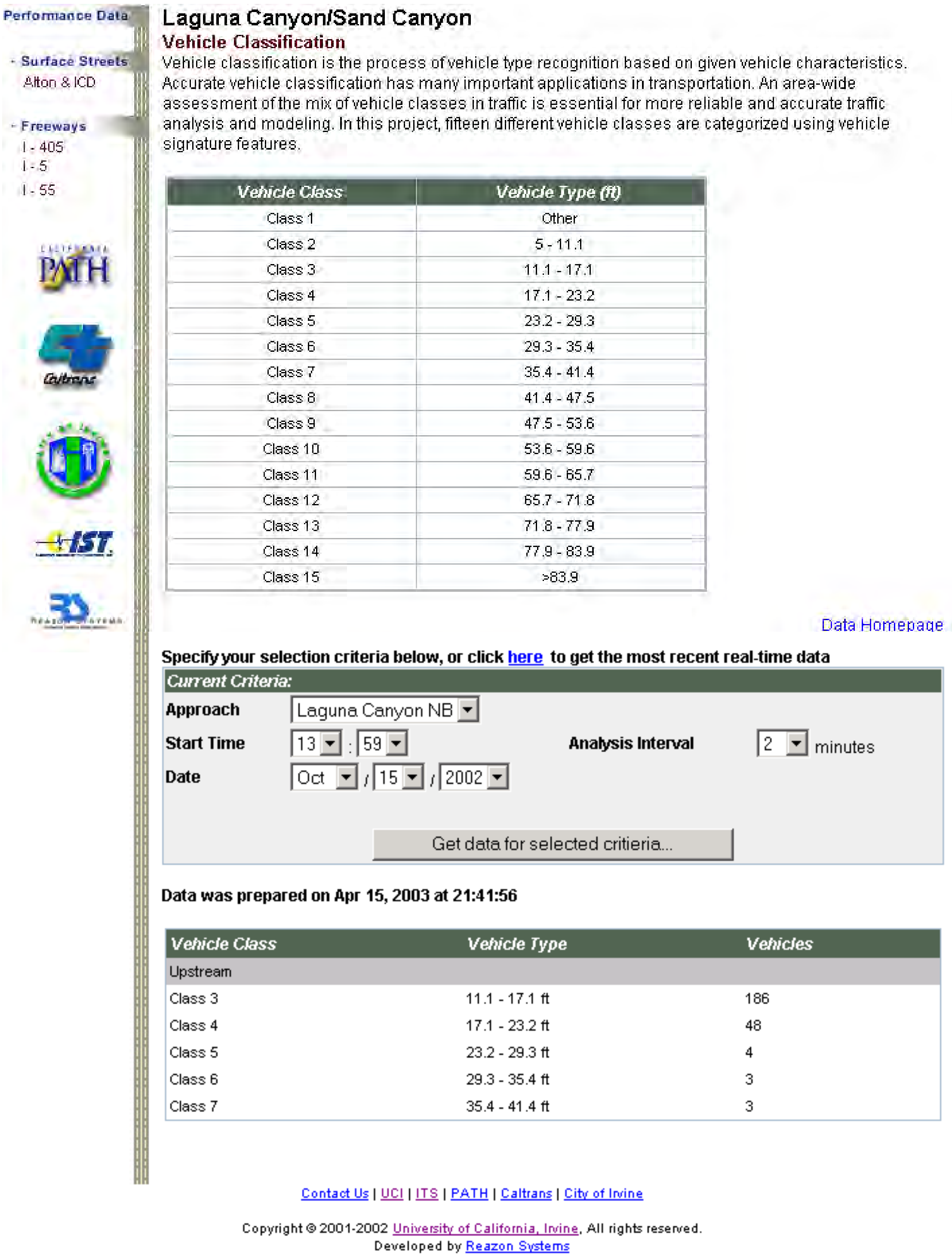


Figure 5.3 Point data example



Performance Data

- Surface Streets
  Alton & ICD
- Freeways
  I - 405
  I - 5
  I - 55

Laguna Canyon/Sand Canyon

Vehicle Classification

Vehicle classification is the process of vehicle type recognition based on given vehicle characteristics. Accurate vehicle classification has many important applications in transportation. An area-wide assessment of the mix of vehicle classes in traffic is essential for more reliable and accurate traffic analysis and modeling. In this project, fifteen different vehicle classes are categorized using vehicle signature features.

Vehicle Class	Vehicle Type (ft)
Class 1	Other
Class 2	5 - 11.1
Class 3	11.1 - 17.1
Class 4	17.1 - 23.2
Class 5	23.2 - 29.3
Class 6	29.3 - 35.4
Class 7	35.4 - 41.4
Class 8	41.4 - 47.5
Class 9	47.5 - 53.6
Class 10	53.6 - 59.6
Class 11	59.6 - 65.7
Class 12	65.7 - 71.8
Class 13	71.8 - 77.9
Class 14	77.9 - 83.9
Class 15	>83.9

Data Homepage

Specify your selection criteria below, or click here to get the most recent real-time data

Current Criteria:

Approach Laguna Canyon NB

Start Time 13 : 59 **Analysis Interval** 2 minutes

Date Oct / 15 / 2002

Get data for selected critieria...

Data was prepared on Apr 15, 2003 at 21:41:56

Vehicle Class	Vehicle Type	Vehicles
Upstream		
Class 3	11.1 - 17.1 ft	186
Class 4	17.1 - 23.2 ft	48
Class 5	23.2 - 29.3 ft	4
Class 6	29.3 - 35.4 ft	3
Class 7	35.4 - 41.4 ft	3

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Figure 5.4 Real-time vehicle classification information

Section Data					
Upstream	Downstream	Downstream Lane	Reid Volume (veh/interval)	Travel Time (sec)	Avg Speed (mph)
Laguna Canyon NB	Sand Canyon NB Offramp	1	10	35.71	61.29
	Sand Canyon NB	1	51	34.24	79.29
		2	10	33.55	72.25
		3	121	33.96	73.46
		4	132	34.63	71.85
		5	99	39.01	67.89
		6	64	36.82	70.63

View Graph   Level of Service (LOS)

Origin-Destination Table								
Volume (veh/interval) **Travel Time** (sec)		**Downstream**						
		Offramp	**Lane 1 HOV**	**Lane 2 HOV**	**Lane 3**	**Lane 4**	**Lane 5**	**Lane 6**
Upstream	**Lane 1 HOV**	-	97 veh 34.41 sec	16 veh 32.85 sec	12 veh 38.54 sec	7 veh 56.09 sec	-	-
	Lane 2	-	-	-	197 veh 33.74 sec	19 veh 30.43 sec	-	-
	Lane 3	-	24 veh 35.73 sec	2 veh 39.91 sec	4 veh 30.58 sec	151 veh 34.45 sec	27 veh 32.70 sec	5 veh 26.97 sec
	Lane 4	-	-	-	-	1 veh 29.52 sec	121 veh 41.53 sec	-
	Lane 5	9 veh 24.20 sec	3 veh 20.99 sec	-	-	16 veh 31.98 sec	15 veh 31.48 sec	64 veh 36.12 sec
	Lane 6	9 veh 63.31 sec	8 veh 37.83 sec	-	-	-	3 veh 32.43 sec	33 veh 39.03 sec
	Lane 7	12 veh 23.64 sec	5 veh 25.81 sec	-	-	-	-	3 veh 43.07 sec

Figure 5.5 Section based traffic information

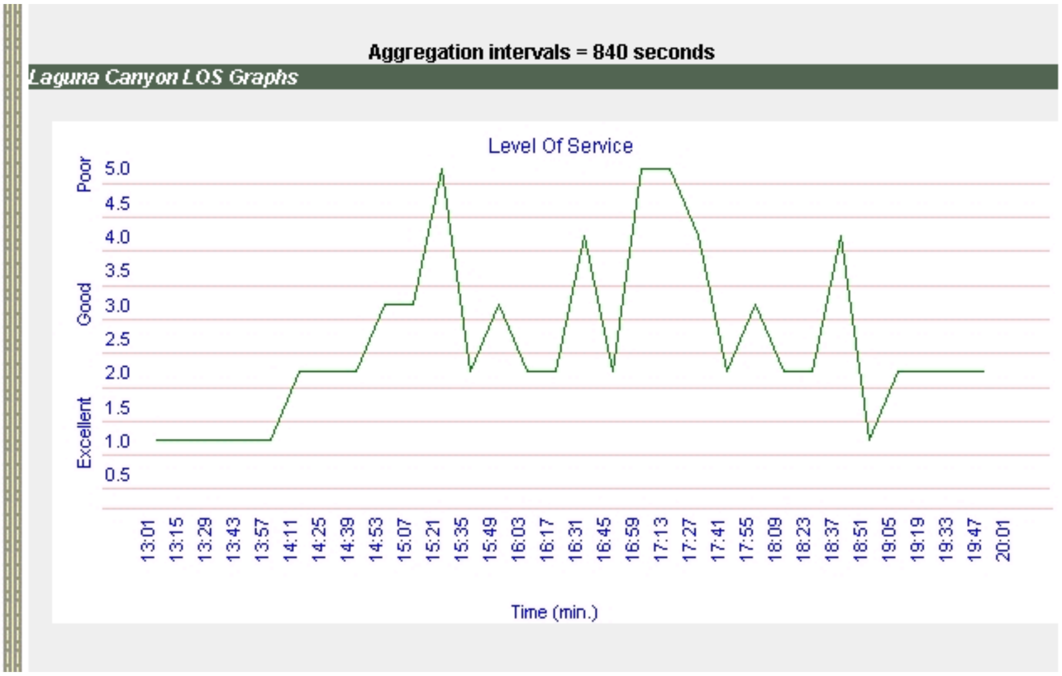


Figure 5.6 Real-time LOS information

CHAPTER 6 VEHICLE REIDENTIFICATION USING HETEROGENEOUS DETECTION SYSTEMS

6.1 Introduction

Travel time has been identified as a particularly important traffic parameter for evaluating the performance of dynamic traffic systems by transportation researchers and engineers. It is also important because it is an input to advanced transportation management and information systems (ATMIS) to alleviate traffic congestion and its associated impacts.

A promising approach to obtain travel times is tracking vehicle to identify their locations and arrival times, so that travel times can be readily collected. A variety of sensor technologies have been developed and tested for tracing individual vehicles on transportation networks. Use of global positioning system (GPS) and in-vehicle tag-based automatic vehicle identification (AVI) technologies have been successfully used for obtaining accurate travel times. However, privacy issues still remain with such systems, and a limited market penetration does not yet allow us to measure wide-area transportation performance. As a result, it would be advantageous if individual vehicles could be traced without any privacy concerns on wide-area transportation networks.

In order to meet the aforementioned requirement, there has recently been substantial interest in implementing vehicle reidentification systems that anonymously trace vehicles in a network. Examples include license plate matching (1), use of existing loop detectors with high speed scanning detector cards to generate inductive signatures (2-8), laser-based detection systems (9) providing vehicle length, and video-based vehicle signature generation (10) using video image processing technology.

Previous studies performed by the authors (2-8) have proven that accurate travel times can be obtained from inductive signature-based vehicle reidentification using new detector card technology. Because inductive loops are still the dominant surveillance system in the U.S. and many other countries, use of such loops for vehicle reidentification is potentially quite cost-effective.

This paper investigates the feasibility of real-time vehicle reidentification algorithm development at a signalized intersection where different traffic detection technologies were employed at upstream and downstream locations. Previous research by the authors on vehicle reidentification has utilized the same traffic sensors (e.g. conventional square inductive loops) and detectors (e.g. high speed scanning detectors cards) at both locations. In this study, an opportunity arose for the first time to collect a downstream dataset from a temporary installation of a prototype innovative inductive loop sensor, known as a “blade” sensor, in conjunction with conventional inductive loops upstream. At both locations advanced high speed scanning detector cards were used.

The following section of the paper introduces the blade sensor that is able to produce unique vehicle signatures. Data collection and vehicle feature extraction for blade signature is presented in the third section. The next section describes an algorithm for vehicle reidentification with the heterogeneous detection system used in this study. An analysis of travel times using the outputs of the algorithm is then presented. Finally, conclusions including comments and findings are provided.

6.2 Blade sensor

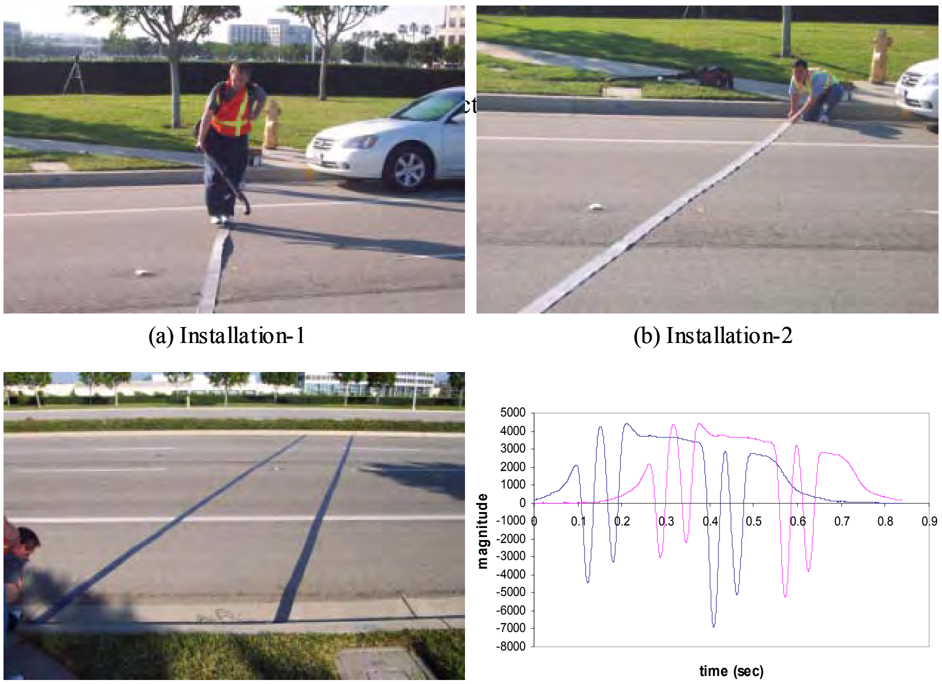
Traditional applications of inductive loop sensors have focused on counting vehicles or detecting the presence of vehicles. For such purposes, the ideal loop should approximate the vehicle's periphery (11). A physical configuration of $6^{'} \times 6^{'} (1.8m \times 1.8m)$ is a commonly used size for inductive loops that measure counts and presence. More recently, inductive loops have been utilized for outputting inductive signatures for vehicle reidentification purposes. The standard $6^{'} \times 6^{'} (1.8m \times 1.8m)$ loop configuration is not ideal for this purpose since the square geometry results in the integration of the inductive signature over the traversal distance. Therefore, if this smoothing effect, which can remove distinctive features from the inductive signature, can be eliminated it may make vehicle reidentification more effective. The blade sensor addresses the loop configuration problem and incorporates additional improvements to the inductive loop detection system through use of a high-speed scanning detector card.

The blade is a new remote vehicle sensor technology. The physical embodiment of this concept uses two matched oscillating LRC circuits whose induction coils are oriented contained within a single, solid 'sensor blade' that is then embedded in a 3/16 inch wide pavement slot (for a permanent installation). The sensing coil is oriented toward the surface of the pavement and the reference coil is oriented toward the base of slot. Because the sensing coil is positioned nearer overpassing vehicles, it responds more strongly to this stimulus than the reference coil. Data collection is initiated by simultaneously charging both circuits to a threshold voltage using an impulse function and then allowing them to rapidly decay to a base line asymptote. This differential signal is amplified and digitized using an A/D converter.

A continuous stream of signed integers is generated by the blade sensor, which can be monitored by a dedicated on-board microprocessor. The resulting measurement data produce the vehicle's inductive signature. Figure 6.1 shows the temporary surface installation of blade sensors as deployed in this study and an example of a blade vehicle signature.

In its present configuration, the blade sensor collects data from two parallel sensor blades separated by a distance of 6 feet and oriented at an angle of 20º to the direction of the traffic flow. This orientation allows for a significant amount of valuable data to be generated including speed, the number of axles, and wheel based-vehicle length. The prominent peaks shown in Figure 6.1-(d) represent the wheels passing over the sensors. A clearer view of the composite metallic profile of the vehicle, which allows us to differentiate the vehicle wheel part from the vehicle body part, can also be seen.

The temporary surface mounted version of the blade sensor is an out-of-pavement installation that does not require pavement cutting. This version is particularly useful for short-term studies.



(a) Installation-1 (b) Installation-2

(c) Installation-3 (d) Blade signature example

Figure 6.1 Blade sensors and blade vehicle signature

6.3 Vehicle signature analysis and feature extraction/selection

Vehicle signature analysis for vehicle reidentifiction can be generally separated into two components: feature extraction and classification. The first component seeks to extract salient and parsimonious features from raw detector output, while the second component classifies or matches the vehicles using feature vectors.

6.3.1 Data collection

In this study, blade sensors were installed next to existing conventional square inductive loop stations upstream and downstream on westbound Irvine Center Drive at the intersection of Alton Parkway and Irvine Center Drive in

Irvine, California on January 21, 2003. Vehicle inductive signatures were generated from each type of loop sensor using high speed scanning detector cards.

Each of the detector cards being used to collect the blade signatures had a 40GB hard-drive. The signatures were recorded to the local hard-drives. A laptop computer was used to start the data collection, set the time, etc., and to download the signatures from the cards. Figure 6.2 shows the blade signature data collection layout.

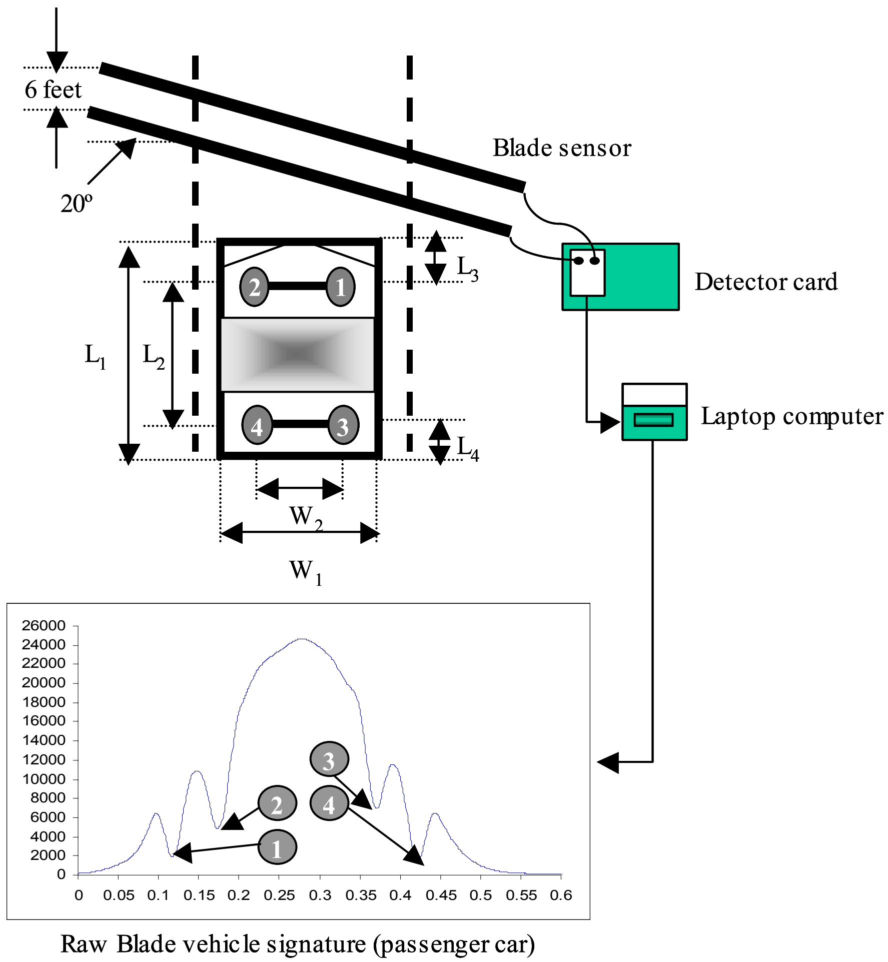


Figure 6.2 Data collection layout for blade vehicle signature

One-hour of data collected from 11:40 am to 12:40 pm constituted the available data set for both conventional loop and blade loop data. In addition, 140 blade vehicle signatures collected in the right-most lane of the downstream detector station and upstream conventional loop signatures constituted the valid signature data set that could be used for feature analysis and algorithm development for vehicle reidentification. The vehicle reidentification algorithm was developed and tested based on the different detector systems: the conventional inductive loops upstream and blade sensors downstream. Therefore, a vehicle reidentification algorithm was developed with the first 70 vehicle pairs, and the other 70 vehicle pairs were used for algorithm testing. Table 6.1 presents the through movement vehicles including vehicle types and volumes collected in the right-most lane at the downstream station.

Camcorders were also installed at each station for the purpose of video ground truthing. The video ground truthing was performed based on visual inspection identifying an upstream vehicle on a monitor, and then searching for matching the corresponding vehicle downstream on another monitor. True travel times were obtained by comparing the time stamps of each vehicle at both upstream and downstream stations.

Table 6.1 Blade vehicle classification data for downstream lane 3 (through movement)

Vehicle type	# vehicles	%
Motorcycle	1	0.69
Bus	1	0.69
Passenger car	71	51.724
Pickup	17	11.724
SUV	33	23.448
Trailer	2	1.379
Truck	2	1.379
Van	13	8.966

6.3.2 Vehicle feature extraction from Blade sensor signatures

Vehicle feature extraction is one of the major tasks for accomplishing vehicle reidentification because it seeks to extract salient components of vehicle images that would sufficiently differentiate vehicles. As mentioned in the previous section, blade loops are more sensitive than existing inductive loops, and are capable of capturing vehicle wheel locations in a signature. Use of vehicle wheel information is expected to improve the performance of vehicle reidentification. In this paper, we focus on developing a new method for vehicle signature feature extraction for blade sensors. Detailed information on feature extraction from conventional loops can be found elsewhere (3,8).

Figure 6.3 shows the feature extraction scheme for vehicles signatures produced by blade loops. Because a blade vehicle signature consists of two vehicle parts, namely, the wheel part and the vehicle body part, each part of a vehicle signature provides different vehicle features as shown in Figure 6.3. Figure 6.4 presents both conventional inductive loop vehicle signatures and blade loop vehicle signatures for different types of vehicles.

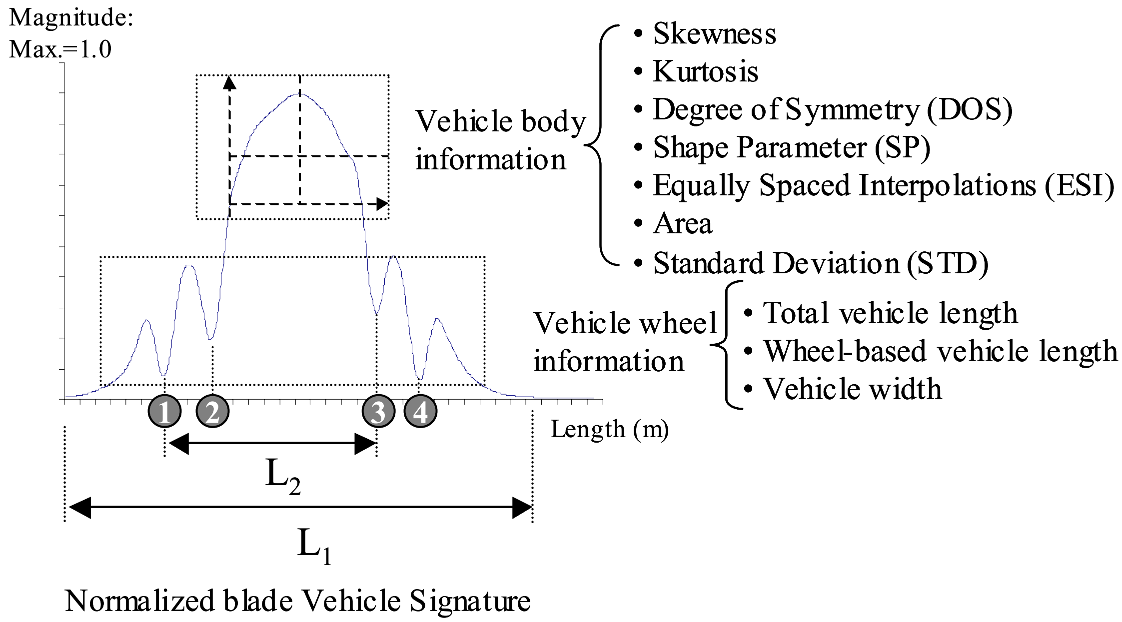


Figure 6.3 Feature extraction scheme

6.3.3 Vehicle feature analyses

This section focuses on the selection of vehicle features that will be used for vehicle reidentification. In this study, four vehicle types including passenger car, pickup truck, sport utility vehicle, and van were analyzed.

The feature selection seeks to select the salient features extracted from the vehicle signature that would sufficiently differentiate vehicle types. To select salient features, we used Bayes decision theory, which minimizes the probability of classification error for feature selection. As shown in Figure 6.5, the overlapping areas, Φ_i for the probability density functions for each vehicle type represent the probability that could be misclassified. Therefore, vehicle features showing the minimum overlapping area can be regarded as salient features that are capable of classifying vehicle types more effectively, and can be used for vehicle reidentification.

It was found that seven features were salient features based on Bayes decision theory. Those features are lane, vehicle length, maximum magnitude of inductance change, standard deviation for whole vehicle signature, shape parameter for whole vehicle signature, degree of symmetry for the body part of the signature, and standard deviation for the body part of the signature. Figure 6.6 shows the examples of the comparison of the probability density functions for vehicle features obtained from different vehicle types.

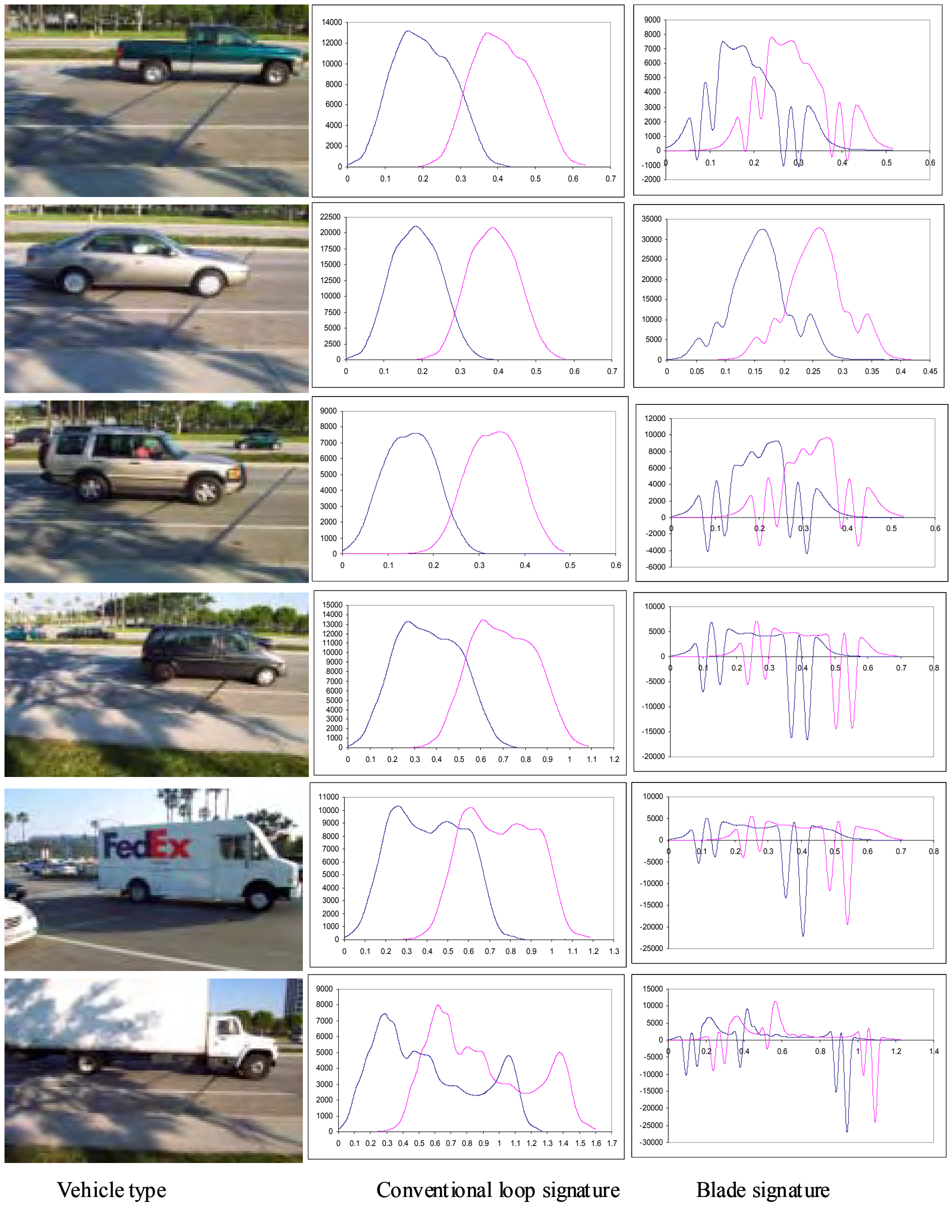


Figure 6.4 Conventional inductive loop vehicle signatures vs. blade loop vehicle signatures

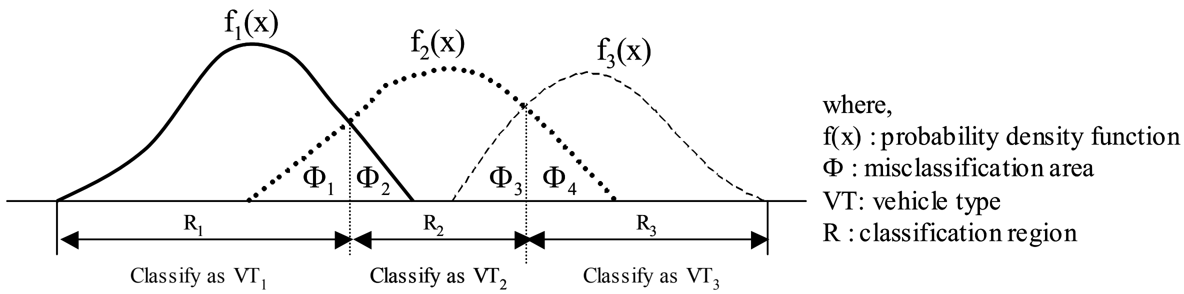
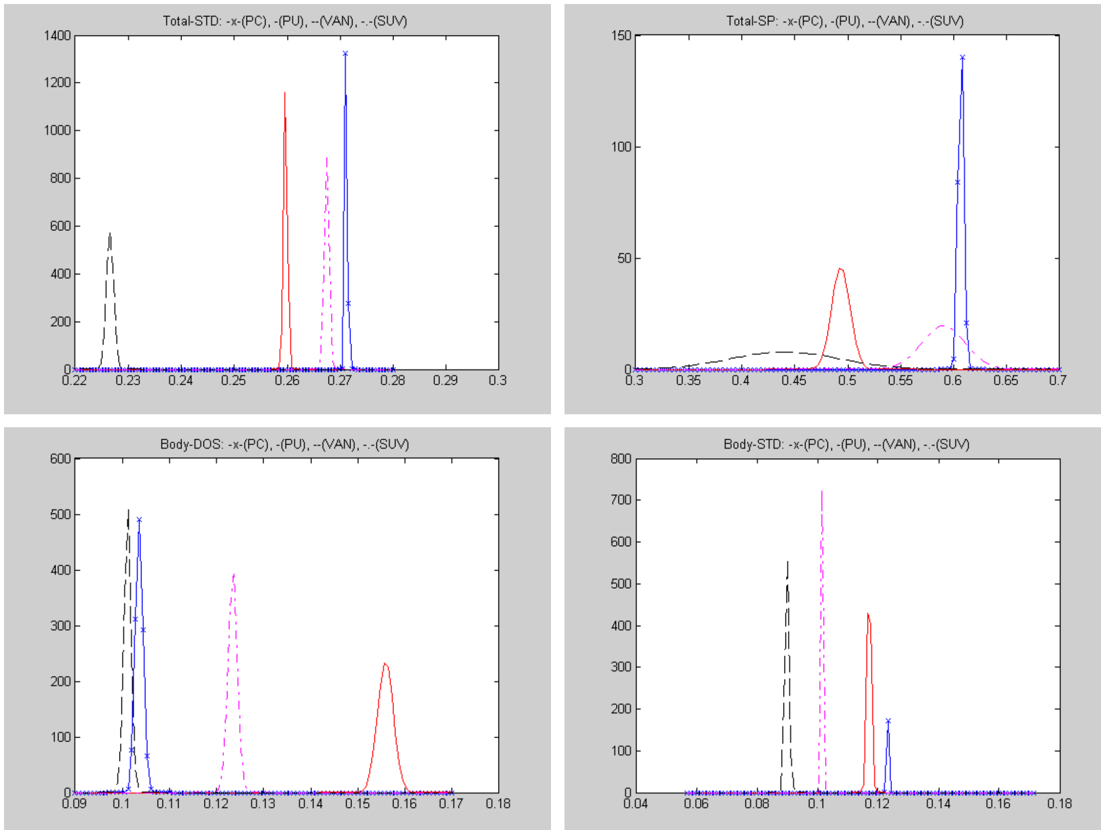


Figure 6.5 Misclassification probabilities for hypothetical vehicle classification regions



• STD: Standard Deviation, SP: Shape Parameter, DOS: Degree of Symmetry
• PC: Passenger Car, PU: Pickup Truck, VAN: Van, SUV: Sport Utility Vehicle

Figure 6.6 Vehicle feature distribution analyses

6.4 Genetically enhanced lexicographic optimization algorithm for vehicle reidentification

The vehicle reidentification problem with heterogeneous detection systems is much more challenging compared to the case of using homogeneous detection systems. It is because each detector system has unique characteristics for representing vehicle images, resulting from the different level of a detection sensitivity. In order to develop a robust vehicle reidentification algorithm that can be successfully used with heterogeneous detector system, both a mapping procedure for input features and a genetic algorithm (GA) were incorporated into a lexicographic optimization based vehicle reidentification algorithm for enhancing the matching capability.

The lexicographic method is a sequential approach to solve the multi-objective optimization problem. The vehicle reidentification problem was formulated as a lexicographical optimization problem consisting of two main components. The first component has several layers to reduce the search space by eliminating upstream vehicle signatures that are unlikely to match a given downstream vehicle signature. The second component computes discriminant scores to determine vehicle matching, which involves a multiple criteria decision-making process. The discriminant function of the second component has feature vectors as independent variables. More detailed algorithmic descriptions can be found in Sun et al. (4). The lexicographic optimization approach has the following benefits (12):

▪ multiple objectives can be addressed with different levels of priority
▪ sequential reduction of the feasible set from level to level enhances the computational efficiency
▪ sensitivity analysis can be conducted separately for each level

Search space reduction consists of four levels of optimization procedures with goal programs. The fundamental idea of goal programming is to establish a specific numeric goal for each objective and then search for a solution to minimize the weighted sum of deviations of objective functions from respective goals (12). The goal programs that can be used for search space reduction are described as follows.

$$\text{goal for 'time window'}: (f_1(x) = t(x) = z_1) \text{ such that } (z_1 \in [L_t, U_t]),\ \ x \in S,\ \ S^1 = [x \in S:\ f_1(x) = z_1]$$
$$\text{goal for 'lane'}: (f_2(x) = |d_l(x)| = z_2) \text{ such that } (z_2 < T_l),\ \ x \in S^1,\ \ S^2 = [x \in S^1:\ f_2(x) = z_2]$$
$$\text{goal for 'maximum magnitude'}: (f_3(x) = |d_m(x)| = z_3) \text{ such that } (z_3 < T_m),\ \ x \in S^2,\ \ S^3 = [x \in S^2:\ f_3(x) = z_3]$$
$$\text{goal for 'length'}: (f_4(x) = |d_{vl}(x)| = z_4) \text{ such that } (z_4 < T_{vl}),\ \ x \in S^3,\ \ S^4 = [x \in S^3:\ f_4(x) = z_4]$$
$$\vdots$$

where,
x: feature vector
f: objective function
z: objective value
$t(x)$: travel time between upstream and downstream vehicle arrival times for individual vehicle
L_t/U_t: lower and upper bound for feasible travel time
S: feasible set of vehicle pairs
T: threshold value for feature vectors
d: vehicle feature distance
l: lane
m: maximum magnitude
vl: vehicle length

This process can generally continue until all objectives considered, although this study used four objectives. These first four optimization levels reduce the search space of similar vehicle signature pairs.

The fifth level lexicographic optimization objective can be described as follows:

$$\min \ f_5 = p_a |d_a(x)| + p_b |d_b(x)| + p_c |d_c(x)| + p_d |d_d(x)| \cdots \qquad \text{s.t. } x \in S^4$$

where,

p : set of coefficients associated with the feature vector differences

Prior to applying lexicographic optimization for vehicle reidentification, input features should be adjusted since downstream vehicle features and upstream vehicle features are from the different detection systems. Adjustment factors (k_i, l_i) were employed for adjusting the feature differences between conventional inductive loop signatures and blade signatures. Therefore, the distance measure of vehicle feature i between an upstream loop vehicle feature (vf_{Loop}^{up}) and downstream blade vehicle feature (vf_{EDIS}^{dn}) is described by

$$d_i(vf_{Loop}^{up}, vf_{EDIS}^{dn}) = \sum_{n=1}^{q} \left| vf_{Loop}^{up}(n) - (k_i \times vf_{EDIS}^{dn}(n) + l_i) \right| ,$$

where n denotes the n^{th} element of the feature vector and q is the vector dimension.

In order to obtain an optimal set of parameters capable of maximizing vehicle reidentification performance, GA was applied. GA is an algorithm that searches the solution space of a function by emulating the mechanism of natural selection, that is, the survival of the fittest strategy. Optimization is performed on a set of strings, where each string is composed of a sequence of characters. Given an initial population of strings, a genetic algorithm produces a new population of strings according to a set of genetic rules. This constitutes one generation. The rules are devised so that the new generation tends to have strings that are superior to those in the previous generation. Successive generations of strings are produced, each of which tends to produce a superior population (13). The algorithms are not only robust but also simple, and do not require the assumption of knowledge of the search space. More detailed description of GA can be found in the literature (14).

GA was applied to solve the maximization problem for the vehicle reidentification system. The problem in this study was to maximize the Correct Matching Rate (CMR). The fitness function to be optimized by GA is the vehicle reidentification algorithm. A set of coefficients for feature vector differences ($\overline{P}$) that were used in computing discriminant scores were prepared by the GA optimizer. Output of the fitness function is the CMR. The maximization of CMR is defined as follows:

$$\max_{\Sigma} \ CMR$$

$where,$

$CMR = REID(\Sigma)$

$CMR =$ Correct Matching Rate

$REID =$ vehicle reidentification algorithm

$\Sigma =$ parameters to be optimized : coefficients for discriminant fucntion

The steps of the GA performed in this study can be summarized as follows.

Step 1: Initialization

Step 2: Retrieval of fitness (CMR) from vehicle reidentification algorithm

Step 3: Selection process

Step 4: Crossover and Mutation

Step 5: Repeat Step 2-4

Figure 6.7 shows the framework for obtaining the optimal set of parameters by GA for the vehicle reidentification algorithm.

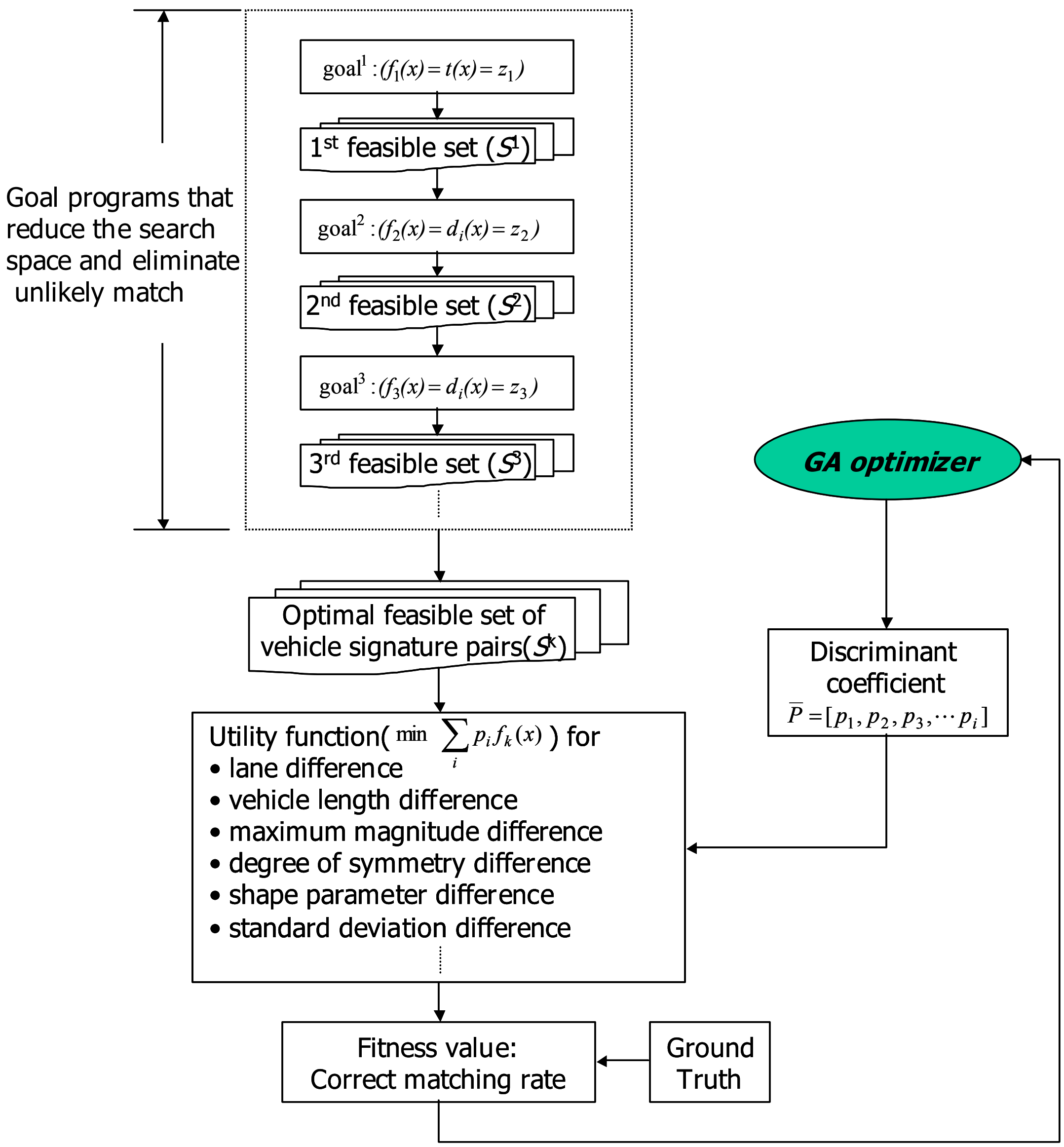


Figure 6.7 Framework for genetically enhanced lexicographic optimization algorithm for vehicle reidentification

6.5 Results

Performance measures for the vehicle reidentification algorithm evaluation included the total matching rate (TMR), the correct matching rate (CMR), the mismatching rate (MMR), and the matching reliability rate (MRR) were used. TMR is the percentage of the total number of matched vehicles declared by the algorithm. CMR is the percentage of individual vehicles that the algorithm is able to match correctly. On the other hand, MMR is the percentage of individual vehicles that algorithm matches incorrectly. MRR is the ratio of CMR to TMR, and proportion of matched vehicles that are correctly matched. Table 6.2 summarizes the vehicle reidentification performance. As shown in Table 6.2, the CMR of the training data set was 41.43 %, while the CMR of the testing data set was 50.00%.

Table 6.2 Vehicle reidentification performance measure

Data	TMR: total matching rate	CMR: correct matching rate	MMR: mismatching rate (TMR-CMR)	MRR: reliability Rate (CMR/TMR)
Training	97.14 %	41.43 %	55.71 %	42.65 %
Testing	97.14 %	50.00 %	41.43 %	51.47 %

Sensitivity analysis on the effect of the time window (the first goal program in the vehicle reidentification algorithm) was performed in terms of travel times between the upstream and downstream stations. When a large time window is applied, the algorithm includes many upstream candidate vehicles resulting in increasing the matching possibility of the corresponding vehicle. The computational burden and mismatching possibility then increase simultaneously. On the other hand, the algorithm can find the corresponding vehicle efficiently with a small time window, but the corresponding vehicle could be excluded from the set of candidate vehicles. In addition, since arterial traffic flow is interrupted by signal control highly variable travel times result and the effect of the aggregation period on travel time accuracy needs to be investigated. Figure 6.8 shows the relationship among time window sizes, aggregation periods, and travel time accuracies. In this study, 6.9 aggregation periods were ranging from 2-minute to 10-minutes. In order to evaluate travel time accuracy, the mean absolute percentage error (MAPE) was calculated.

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

where,

$TTime_{obs,n}$: Observed travel time at time step n (Ground truth)

$TTime_{est,n}$: Estimated travel time at time step n (Reidentification algorithm)

N : Total number of time step

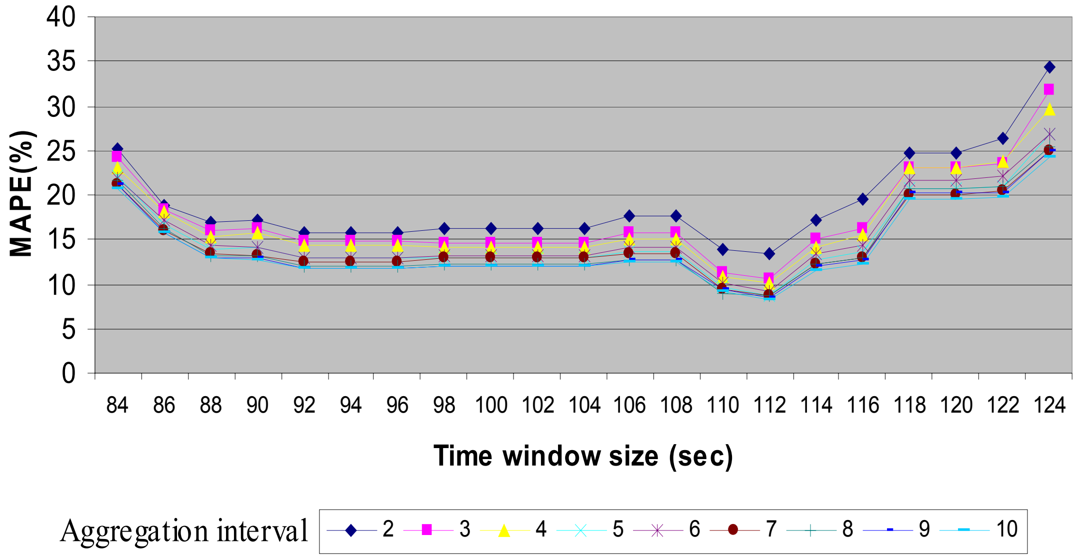
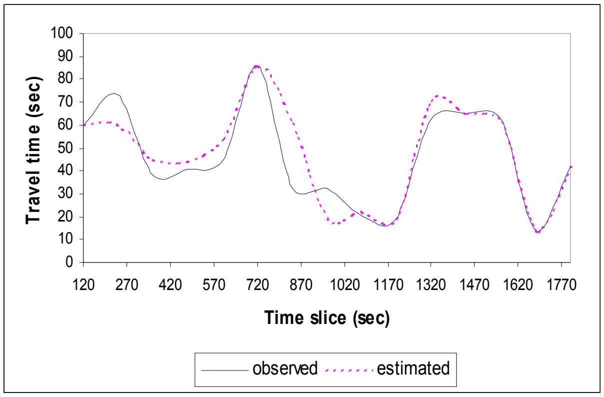


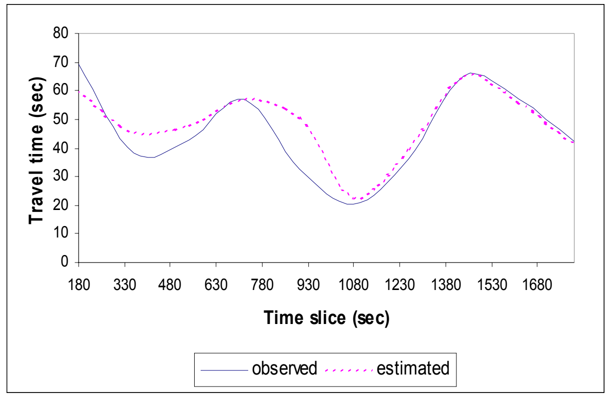
Figure 6.8 Travel time accuracy analysis

As shown in Figure 6.8, it is obvious that longer aggregation intervals yield smaller errors than those of shorter intervals. 112-second was identified as the best time window size to produce the highest travel time accuracy for most aggregation intervals. Less than 10% MAPE were achieved for 5-minute and longer aggregation periods. The shorter aggregation periods such as 2, 3, and 4-minutes were also able to produce less than 15% MAPEs when a 112-second time window was applied to derive travel times. Figure 6.9 shows comparisons of the estimated travel times obtained by the vehicle reidentification algorithm with the true travel times. It should be noted that results are quite encouraging despite the small size of the data set used.

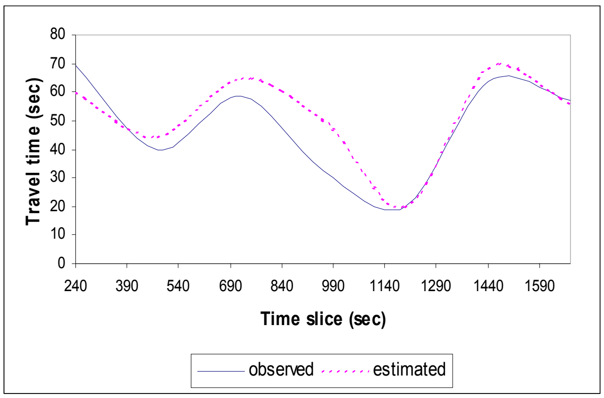
The size of aggregation interval is an important issue for designing real-time traffic management and information strategies. As shown in the evaluation results, different aggregation intervals produce different levels of accuracies. In addition, shorter aggregation intervals have bigger travel time variations than those of the longer intervals. Therefore, the use of rolling averages of travel times on the time horizon would be a possible way to reduce the travel time variations. Identifying optimal travel time aggregation intervals for generating useful traffic information accounting for the real-time performance of transportation systems is an important issue in the field of traffic surveillance and information systems.



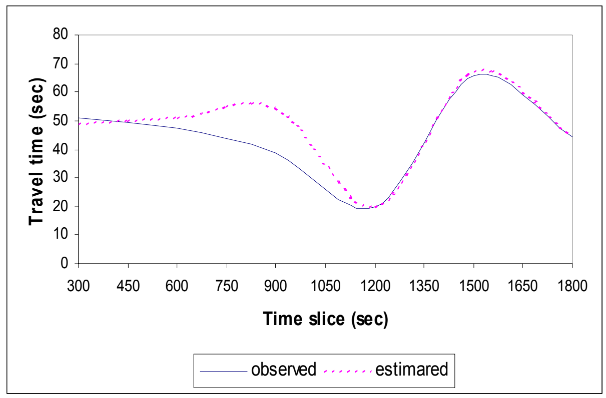
(a) 2-minute aggregation



(b) 3-minute aggregation



(c) 4-minute aggregation



(d) 5-minute aggregation

Figure 6.9 Comparison of travel times

6.6 Conclusions

This study explored the vehicle reidentification problem based on vehicle signatures collected from different types of detection technologies, including conventional square inductive loops and newly developed blade inductive loop sensors.

A lexicographic optimization algorithm together with a genetic algorithm was introduced to solve the vehicle reidentification problem. Goal programming approaches for search space reduction in the vehicle reidentification algorithm both improved the algorithm matching performance and the computational burden. The algorithm performed well. For example, less than 10 % travel time error was achieved with a 5-minute travel time aggregation period.

Although the number of vehicles for which data could be collected was small, encouraging results were obtained for vehicle reidentification performance in this system of mixed traffic detection technologies. In future large-scale applications of vehicle reidentification approaches for real-time traffic performance measurement, management and control, it would be most beneficial and practical if heterogeneous as well as homogeneous detection systems could be supported. This initial study yielded many useful insights about this important issue, and demonstrated on a small scale the feasibility of vehicle reidentification in a system with heterogeneous detection technologies.

6.7 References

1. Turner, S., W. Eisele, R. Benz, and D. Holdener. *Travel Time Data Collection Handbook*. FHWA-PL-98-035. Federal Highway Administration and Texas Transportation Institute. 1998.
2. Ritchie, S.G., and C. Sun. *Section Related Measures of Traffic System Performance: Final Report*. California PATH Research Report UCB-ITS-PRR-98-33. 1998.
3. Sun, C., S.G. Ritchie, and K. Tsai. Algorithm Development for Derivation of Section-Related Measures of Traffic System Performance using Inductive Loop Detectors. In *Transportation Research Record 1643*, TRB, National Research Council, Washington, D.C., 1998, pp. 171-180.
4. Sun, C., S.G. Ritchie, W. Tsai, and R. Jayakrishnan. Use of Vehicle Signature Analysis and Lexicographic Optimization for Vehicle Reidentification on Freeways. *Transportation Research*, Part C, Vol. 7, 1999, pp 167-185.
5. Sun, C., and S.G. Ritchie. Individual Vehicle Speed Estimation Using Single Loop Inductive Waveforms. *Journal of Transportation Engineering*, American Society of Civil Engineers, Vol. 125, No. 6, 1999, pp 531-538.
6. Oh, C., and S.G. Ritchie. Real-Time Inductive-Signature-Based Level of Service for Signalized Intersections. In *Transportation Research Record 1802*, TRB, National Research Council, Washington, D.C., 2002, pp. 97-104.
7. Oh, S., S.G. Ritchie, and C. Oh. Real-Time Traffic Measurement from Single Loop Inductive Signatures. In *Transportation Research Record 1804*, TRB, National Research Council, Washington, D.C., 2002, pp. 98-106.
8. Oh, C., S.G. Ritchie, S. Park. *Development A Real-Time Probabilistic Vehicle Reidentification Algorithm for Signalized Intersections*. Working paper, Institute of Transportation Studies, University of California, Irvine, 2002.
9. Larson, J.E. et al. *A Real-Time Laser-Based Prototype Detection System for Measurement of Delineation of Moving Vehicles*. MOU 263 Working paper to California PATH, University of California, Davis, 1998.
10. MacCarley, C.A. *Video-Based Vehicle Signature Analysis and Tracking System Phase 2: Algorithm Development and Preliminary Testing*. MOU 350 Final Report to California PATH, California Polytechnique State University, San Luis Obispo. 2001.
11. *Traffic Detector Handbook*. Institute of Transportation Engineers, Washington D.C., 1990.
12. Steur, R. *Multiple criteria optimization: Theory, computation, and application*. John Wiley & Sons, N.Y., 1986.
13. Wasserman, P.D. *Advanced Methods in Neural Computing*. Van Nostrand Reinhold, New York, 1993
14. Gen, M., and Cheng, R. *Genetic algorithms and engineering optimization*.Wiley, 2000

CHAPTER 7 CONCLUSIONS AND FUTURE RESEARCH

7.1 Conclusions

This report presents the results of "Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies, Phase II" and builds on and extends previous PATH research by the authors on "Field Investigation of Advanced Vehicle Reidentification Techniques and Detector Technologies, Phase I" (PATH MOU 3008), and "Section-Related Measures of Traffic System Performance: Prototype Field Implementation" (MOU 336).

This research continued development, field investigation and assessment of the latest technologies available for traffic detection and surveillance, for collecting more accurate traffic characteristics and traffic data necessary for Intelligent Transportation Systems (ITS) applications. The focus of Phase II of this research was to utilize fully instrumented freeway and signalized intersection sites in the California Advanced Transportation Management Systems Testbed in Southern California for field investigation of several emerging traffic sensor and detector technologies for vehicle reidentification (REID) purposes and real-time traffic performance measurement. These technologies included the IST-222 high-speed scanning detector card from IST, Inc. for capturing vehicle signatures from conventional inductive loops, V^2SAT video detection system from Loragen Corporation, and the innovative new Embedded Differential Inductance Scanning (EDIS) or "Blade" loop detector from IST, Inc.

This study also implemented real-time vehicle reidentification and traffic performance measurement in the traffic detection and surveillance sub-testbed (TDS^2) on North I-405 in Irvine, which became operational in August 2002. Based on the research and the improved algorithms developed in this study, real-time traffic performance measurement in TDS^2 (including section travel times, traffic origins and destinations, and vehicle classification) was demonstrated on-line at the PATH Annual Meeting in Richmond, California in October 2002.

The very encouraging results obtained to date by developing and applying a vehicle reidentification approach for real-time traffic performance measurement suggest that further development, implementation and testing of this approach would clearly be of value.

7.2 Future Research

An important extension of existing field-implemented and tested PATH research on individual vehicle reidentification would be 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. The proposed research could directly address each of these limitations in PeMS.

A systematic investigation could be 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 (as utilized in this project) to meet the needs of PeMS. Both field implementation and microscopic simulation could be utilized in a major travel corridor setting, using the Paramics simulation model and field sites that are part of the California ATMS testbed network in Irvine, California. The purpose would be 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). The findings of such a study should 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.