

Real Time Traffic Measurement from Single Loop Inductive Signatures

Seri Oh

serio@uci.edu

Stephen G. Ritchie

sritchie@uci.edu

Cheol Oh

cheolo@uci.edu

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

Submitted for presentation and publication
at the 81st Annual meeting of the Transportation Research Board
January 13-17, 2002, Washington D.C.

Real Time Traffic Measurement from Single Loop Inductive Signatures

Seri Oh, Stephen G. Ritchie, and Cheol Oh

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

ABSTRACT

Accurate traffic data acquisition is essential for effective traffic surveillance, which is the backbone of Advanced Transportation Management and Information Systems (ATMIS). Inductive loop detectors (ILDs) are still widely used for traffic data collection in US and many other countries. Three fundamental traffic parameters, speed, volume and occupancy, are obtainable via single or double (speed-trap) ILDs. Real-time knowledge of such traffic parameters is typically required for use in ATMIS from a single loop detector station, which is the most commonly used. However, vehicle speeds can not be obtained directly. Hence, the ability to estimate vehicle speeds accurately from single loop detectors is of considerable interest. In addition, operating agencies report that conventional loop detectors are unable to achieve volume count accuracies of more than 90-95%.

The main objective of this paper is to demonstrate the improved derivation of fundamental real-time traffic parameters such as speed, volume, occupancy, and vehicle class from single loop detectors and inductive signatures.

INTRODUCTION

Accurate traffic data acquisition is essential for effective traffic surveillance, which is the backbone of Advanced Transportation Management and Information Systems (ATMIS). Inductive loop detectors (ILDs) are still widely used for traffic data collection in US and many other countries. Three fundamental traffic parameters, speed, volume and occupancy, are obtainable via single or double (speed-trap) ILDs. Real-time knowledge of such traffic parameters is typically required for use in ATMIS from a single loop detector station, which is the most commonly used. However, vehicle speeds can not be obtained directly. Hence, the ability to estimate vehicle speeds accurately from single loop detectors is of considerable interest. In addition, operating agencies report that conventional loop detectors are unable to achieve volume count accuracies of more than 90-95%.

As pointed out by Gardner (1), the state of the art of traffic monitoring and surveillance systems can be divided into three areas : sensor technology, data recording and transfer, and data sampling and analysis. Recently, in the field of sensor technology, many devices have been proposed to obtain improved traffic data. These involve the development of radar detectors, video detectors, and automated vehicle identification (AVI) systems among them. However, many of these new sensors involve high initial costs with reliabilities that are yet to be proven. Moreover, integration with existing sensors, in most cases ILDs, would be more desirable rather than implementing new technologies and disregarding existing investments. From this perspective new ILD detector card technology which permits collection of vehicle inductive signatures is of great interest.

Accordingly, the main objective of this paper is to demonstrate the derivation of fundamental real-time traffic parameters, focusing particularly on improved vehicle speed estimation, from single loop detectors and inductive signatures. In this respect the paper extends the recent work of Sun and Ritchie (2). In addition to improved volume and occupancy estimation, the approach presented also real-time vehicle class information to be derived.

BACKGROUND

Vehicle Inductive Signatures

Detector cards used with conventional ILDs are usually bivalent in nature, where the detector card output is either "0" or "1" depending on vehicle presence. However, detector card technology has advanced to the degree where now the inductance change over the loop is obtainable due to the vehicle's passage. Especially, the detector's high scan rate enables to produce different level of inductance change. This inductance change produces a waveform or a so called "vehicle signature". Figure 1 and Figure 2 present examples of vehicle signatures for different vehicle types for the case of a single loop configuration. It is clear that high scan rate gives more accurate vehicle signature. But at the same time, the trade off between the scan rate and the manipulation of signature data was observed. In this study, detector scan rate was set 7millisecond. In each case vertical axis is proportional to the change in inductance and the horizontal axis is time. Vehicle signatures are function of vehicle speed and vehicle type, and exhibit different features. Therefore, many features can be derived by exploiting those vehicle signatures directly or indirectly. Table 1 lists some available features from a vehicle signature; these features are illustrated in Figure 3. In this study feature vectors are divided into two categories ; vehicle specific feature vectors and traffic specific feature vectors. The vehicle feature vectors refer to the ones that are mainly dependent on the vehicle type. Vehicle length is a good example for this category. These features are expected to be invariant, assuming that the same sensor is used with the same installation configuration and under the same driver's behavior. On the other hand, traffic specific features are highly correlated with the traffic conditions such as speed and occupancy. Slew rate, which is uncommon feature, represents the slope value at the point 0.5 of the normalized signature and is clearly described on Figure 3. In this study, the proposed real time traffic measurement system includes a signature processing routine that identifies, and extracts feature vectors from regular and problematic signatures. The problematic signatures will be explained in detail in the next section.

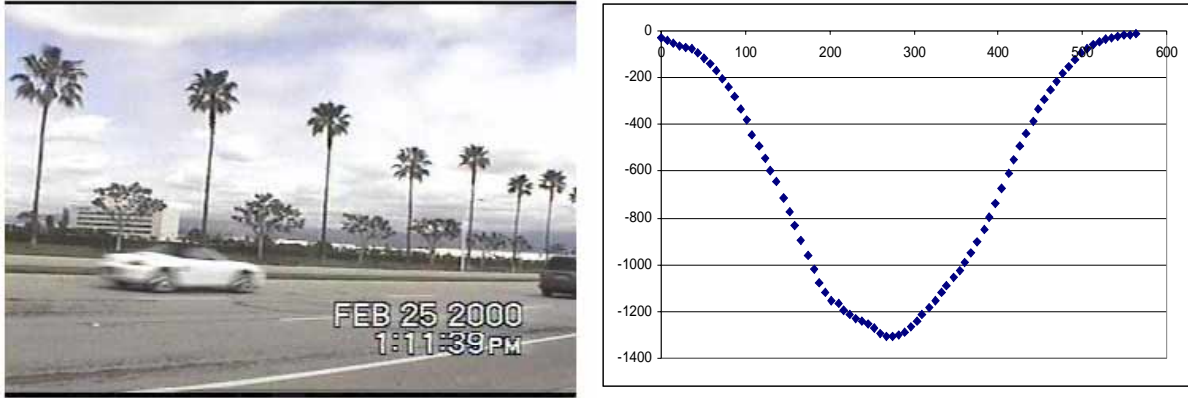


Figure 1 Passenger Car Signature

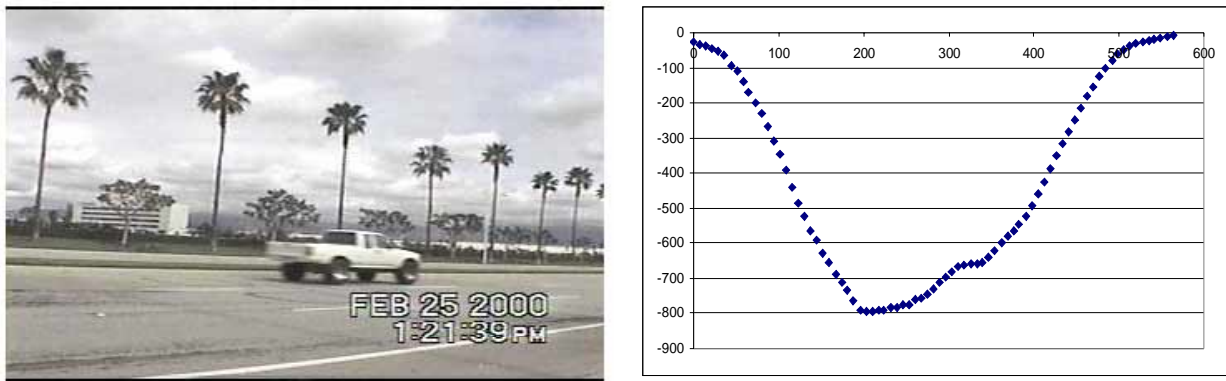


Figure 2 Pickup Truck Signature

Table 1 Signature Feature Vectors

Signature Features		Description
Vehicle Specific Features	Maximum Magnitude	A
	Magnetic Length	d + e
	Shape Parameter	d / (d+e), related to signature symmetry and skewness
	Signature Area	F
Traffic Specific Features	Slew Rate	c, slope at point "0.5"
	Duration	b, same as vehicle occupancy

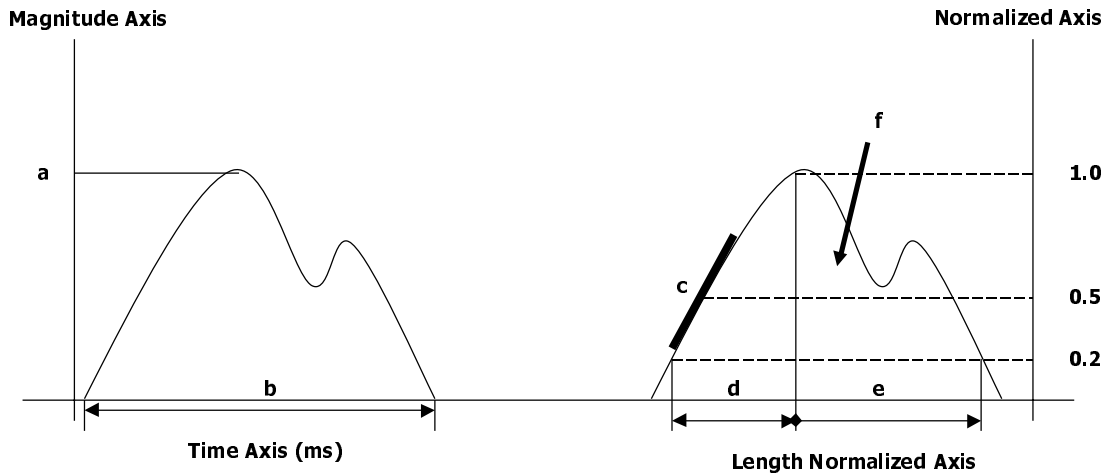


Figure 3 Signature Feature Vectors

Literature Review

Speed is one of the fundamental traffic variables and at the same time, it can be interpreted as an indicator of transportation system effectiveness. This is because travel time, which is an essential parameter of the transportation system, can be represented as the inverse of speed. It is well known that double ILLDs in a speed trap configuration can measure vehicle speeds. However, with the widespread use of single ILLDs, a number of researchers have investigated speed estimation from single loops.

By using either a constant or a function to convert loop occupancy into density, the most commonly applied method to obtain speed from a single ILLD is based on the relationship between fundamental traffic variables. This approach was first developed by Athol (3) and has been expanded by many researchers such as Mikhalkin et al (4), Courage et al (5), Hall et al (6), Dailey et al (7), Coifman (8), Wang et al (9) and Cherrett et al (10). Approaches that assume a constant vehicle effective length for estimating speed from single loop occupancies are known to produce poor estimates of speed when vehicles of different lengths sometimes are present in the traffic stream and when their proportions change over time. Other approaches to speed estimation from single loop include the use of cusp catastrophe theory (11), statistical methods(12) and video analysis (13).

Recently, Sun and Ritchie (2) proposed a new and straightforward speed estimation technique from single ILLD inductive signatures that was based on signal processing and linear regression with very promising initial results. The methodology presented in this paper extends the work of Sun and Ritchie (2) to develop an expanded and improved system for real-time traffic measurement from single ILLDs.

METHODOLOGY & EXPERIMENTAL RESULTS

Using advanced loop detector card technology (high speed scanning detector cards that generate vehicle inductive signature), the proposed system aims to gather accurate and real time traffic measurements such as volume, occupancy, speed, and vehicle classification. In this paper, estimating vehicle speed is the principal focus. Volume and occupancy are directly derived from processing raw vehicle signatures whereas speed is estimated based on the vehicle signature feature vectors. Vehicle length is obtained based on vehicle speed. By combining vehicle length with existing vehicle signature features, vehicle classification is achieved. Figure 4 describes the overall parameter derivation relationship. Field data from a major four - way intersection in the City of Irvine, California is used for system development and performance testing. Details on the dataset can be found in Table 5. The data were

obtained either from single loops or double loops for several different days (for the double loop data only one loop was used).

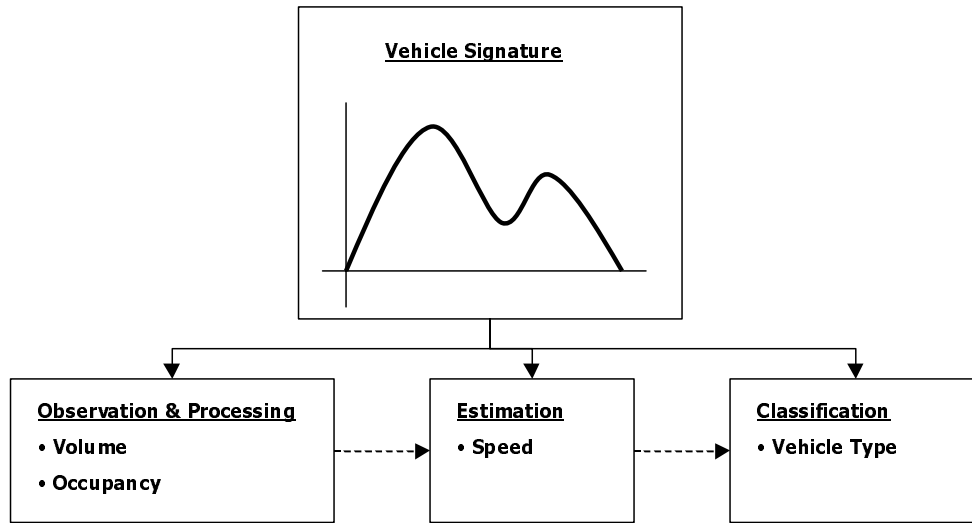


Figure 4 Traffic Measurements

Table 5 Data Description

	Double Loop Vehicles	Single Loop Vehicles
Passenger Car	550	-
Sport Utility Car	150	-
Pickup Truck	190	12
Mini Van	150	-
Van	70	13
One Unit Truck	41	50
Trailer / Vehicle with Boat	45	50
Mini Bus	16	3
Bus	10	-
Total Vehicles	1,222	128

Speed

The study by Sun and Ritchie (2) resulted in a simple linear regression equation between vehicle speed and signature slew rate based on vehicle signatures from single ILDs. For the data used, average speed errors only about 7 % were obtained from the regression equation. However, when the equation was applied without re-estimation to the data in this study, the results in Table 6 for the uncalibrated case were obtained when the regression parameters were re-estimated. The results for the calibrated case in Table 6 were obtained. Interestingly, the results for vehicles with magnetic length less than 6 m (mostly passenger cars, but including mini vans, pickup trucks and SUVs) were very good. However, the average speed estimation errors for longer vehicles were quite large. Analysis revealed that the data used by Sun and Ritchie comprised about 94% of vehicles with magnetic length less than 6m, explaining the good fit for shorter vehicles and larger errors for longer vehicles. This finding led to a search for an improved approach to estimating single loop vehicle speed. The approach reported in this paper relies on categorizing vehicles by type (prior to deriving their magnetic length) and estimating separate speed regression equations for each vehicle category.

Table 6 Average speed errors for different vehicle lengths from using the model of Sun and Ritchie (2)

Magnetic Vehicle Length (ML) Range	Average % error	
	Calibrated case	Uncalibrated case
$ML \leq 6$ m	4.19	7.94
$6 < ML \leq 9$ m	33.49	30.36
$9 < ML \leq 15$ m	33.28	28.36
$15 \text{ m} \leq ML$	16.56	18.38

Features for Speed Estimation

Figure 6 shows signatures for the same vehicle (a passenger car) but at different speeds. It is easy to observe signature differences arising from the vehicle's speed. Duration or occupancy has an inverse proportional relationship with speed while slew rate shows a proportional correspondence with speed. Therefore, two traffic specific features, duration and slew rate were chosen as input variables for new speed estimation models.

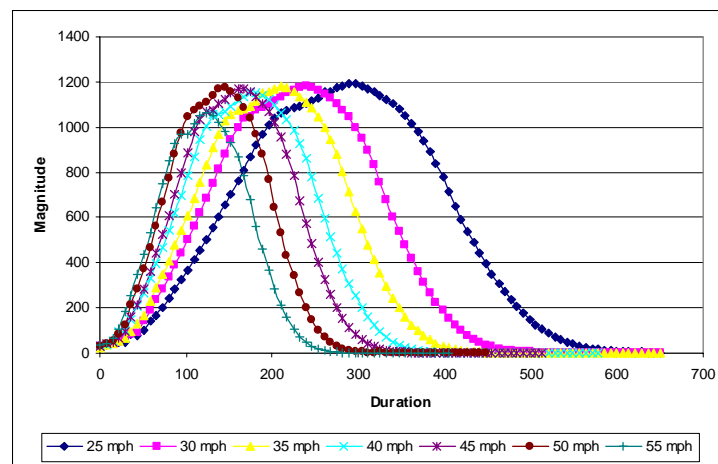


Figure 6 Vehicle signatures at different speed for the same vehicle

Figure 7 supports the basic concept of the vehicle grouping module, which is discussed in the next section. The two signatures show the same duration with similar but different speeds. Even though the truck signature has the same duration as other passenger car signature, the speeds are somewhat different, while the vehicle magnetic lengths are quite different. Therefore, the vehicle grouping module minimizes speed estimation errors originating from incorrect vehicle length assumptions.

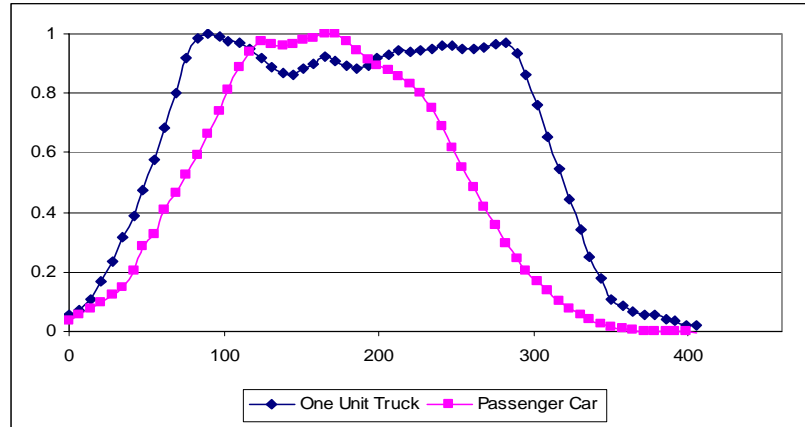


Figure 7 Same duration from different vehicle, and at different speed

Speed Estimation Model

Vehicle Grouping Module

According to Table 6, it is clear that the percentage error increases significantly after a vehicle length of 6 m. This suggests that different speed estimation models should be applied and, prior to this, it is necessary to allocate vehicles to different categories. Six large vehicle classes exist according to Federal Highway Administration (FHWA) vehicle categorizations: passenger cars, motor-cycles, buses, other 2-axle 4-tire vehicles, single-unit 2-axle 6-tire or more trucks, and combination trucks. In this case, other 2-axle 4-tire vehicles include vans, pickup trucks, and sport utility vehicles. Passenger cars and some of the 2-axle 4-tire vehicles show magnetic vehicle lengths less than 6 m. Therefore, based on the FHWA vehicle categorization and extensive data analysis on vehicle magnetic length, four predefined vehicle groups were used. It should be noted that vehicle magnetic lengths can only be derived after speeds are determined. Table 7 summarizes four suggested vehicle groups and the corresponding vehicle types as well as the FHWA vehicle category.

Table 7 Vehicle Grouping

Vehicle Group	Vehicle Type	FHWA Vehicle Category	Magnetic Length (ML)
Group 1	Passenger car, mini van, pickup truck, SUV	Passenger car, other 2-axle 4-tire vehicles	$ML \leq 6$
Group 2	Small bus, van, pickup truck	Other 2-axle 4-tire vehicles	$6 < ML \leq 9$
Group 3	Big bus, one unit truck	Bus, single unit 2-axle 6-tire or more trucks	$9 < ML \leq 15$
Group 4	Trailer, vehicle with boats	Combination trucks	$ML > 15$

For the purpose of real-time vehicle grouping, a Probabilistic Neural Network (PNN) was applied. The PNN is a neural network implementation of the well established multivariate Bayesian classifier using Parzen estimators to construct the probability density functions (PDFs) of the different classes (14). Application of the PNN is illustrated in Figure 8.

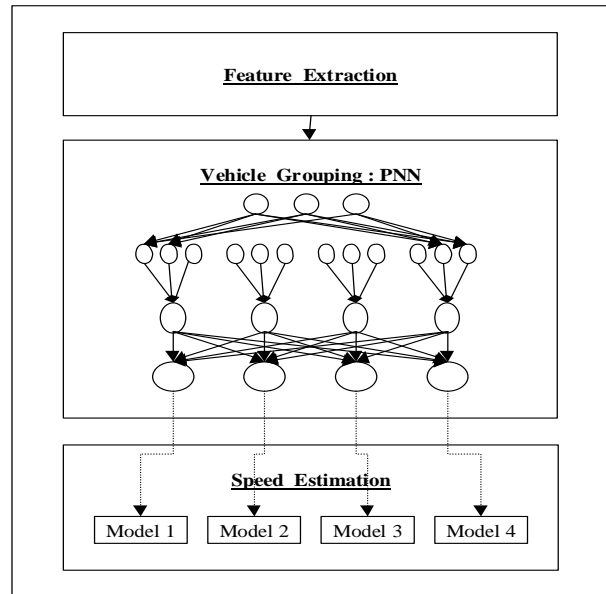


Figure 8 Overall Procedure

Result

The PNN was trained on a data set of 390 vehicles, and trained with a data set of 195 vehicles. The test results are presented in Table 9. Vehicle group 1 shows the highest matching rate (90%) as expected because it had the biggest training dataset. It is also interesting to note the high classification rate (89%) for vehicle group 4 despite its small training sample size of 50 vehicles. By examining the wrongly classified vehicles, it was found that their corresponding magnetic lengths were close to the threshold values of neighboring vehicle groups. For example, in the case of vehicle group 2, six vehicles were misclassified as belonging to vehicle group 3. Five out of those six vehicles show values over 9.2 m for the vehicle magnetic length. This is a reasonable result considering the basic criterion in partitioning vehicle groups.

Table 9 PNN Vehicle Grouping Result

	Testing Data Results					Correct Classification Rate(%)
	Group 1	Group 2	Group 3	Group 4	Total	
Group 1	45	5	0	0	50	90
Group 2	4	39	7	0	50	78
Group 3	0	6	43	1	50	86
Group 4	0	0	4	41	45	89
Total	49	44	54	42	195	85.8

Statistical Module

Figure 9 illustrates the correlation between duration and speed for different vehicle groups. It can be observed that the two variables show a log linear correlation. Therefore, rather than using duration directly, the speed estimation model uses log transformed duration. A linear relationship between speed and slew rate was established by Sun et al (2). Accordingly the following linear regression model was proposed for the speed estimation models for individual vehicles in each vehicle group.

$$S_{est_i} = a + b \cdot sr_i + c \cdot \ln(d_i)$$

where

s_{est_i} : estimated speed of individual vehicle i , (m/s)

sr_i : slew rate of individual vehicle i

d_i : duration of individual vehicle i , milliseconds

a, b, c : regression parameters

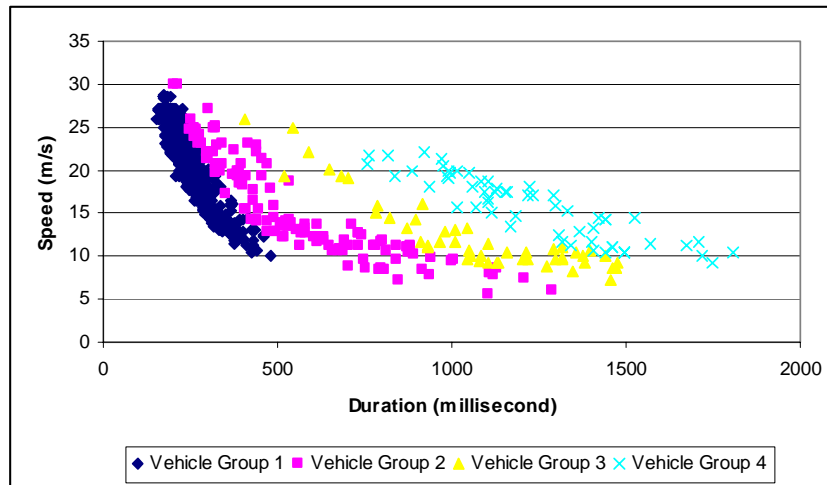


Figure 9 Speed and Duration

Table 11 summarizes the regression results for the proposed statistical speed estimation models for each vehicle group. It should be remembered that errors mentioned in this section solely relate to the regression models. The overall procedure evaluation including the PNN vehicle grouping module is presented in the next section. All the parameters were significant by examining the t-statistics for all models. It is interesting to observe that the t-statistic value decreases as vehicle magnetic length increases. The average error in estimated speeds ranged between 5 and 10 %.

Table 11 Statistical Module Summary

Vehicle Group	Calibration			Testing		
	Sample Number	Model	Model R ²	Sample Number	Average Error (m/s)	Average Speed Error
Group1	800	91.672 + 436.540*SR – 13.698*ln(DUR) (39.393) (13.287) (-36.450)	0.901	200	1.081	5.03
Group2	65	75.311 + 534.741*SR – 10.228*ln(DUR) (10.874) (4.759) (-10.228)	0.864	61	1.746	9.87
Group3	35	85.146 + 431.342*SR – 10.908*ln(DUR) (9.191) (3.526) (-8.724)	0.895	16	0.976	6.89
Group4	45	136.092 – 24.259*SR – 16.955*ln(DUR) (5.261) (-0.094) (-4.975)	0.784	45	1.245	7.14
		133.824 – 16.658*ln(DUR) (14.199) (-12.721)	0.784	45	1.236	7.11

Table 12 represents the overall results from combining the PNN and regression equation for speed estimation. The results offer a clear improvement over those of Sun and Ritchie (2) with average speed estimation errors of between about 4-15% depending on the vehicle group. The overall average error was less than 10%, which is a very encouraging result. Figure 10 presents a scatter diagram of the estimated and actual vehicle speeds. Clearly, most speeds are estimated quite well.

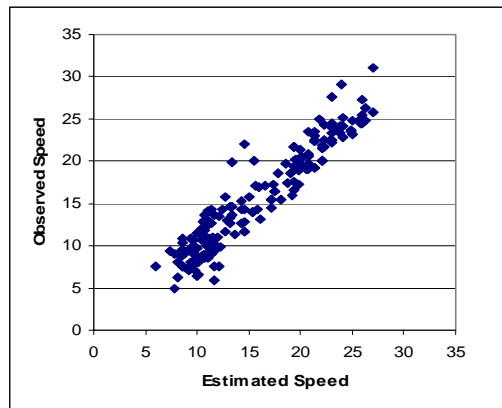


Figure 10 Observed Speed vs Estimated Speed

Table 12 Overall procedure results

	Sample Number	PNN	Statistical Analysis	
		Correct Classification Rate	Average Error (m/s)	Error (%)
Group 1	50	90	1.05	4.16
Group 2	50	78	1.97	15.17
Group 3	50	86	1.34	9.51
Group 4	45	89	1.70	9.78
		85.8	1.52	9.66

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. One good example is road maintenance, which is strongly related to the monitoring of heavy vehicles. Incorporating information about vehicle classification in the analysis of environmental impact is also highly desirable. Improvement of highway safety can also benefit from vehicle classification information, knowing that the severity of traffic accidents is highly correlated with vehicle types. To summarize, an area-wide assessment of the mix of vehicle classes in traffic is essential for more reliable and accurate traffic analysis and modeling. Therefore, since the seventies, a lot of research has been conducted in this field and the recent new detector technology has contributed to the enhancement of vehicle classification performance.

In this section, three different neural network (NN) architectures are presented for vehicle classification : backpropagation neural network (BNN), probabilistic neural network (PNN), and self-organizing map (SOM). While the PNN described in the previous section performed well in allocating vehicles to one of four groups or classes, the neural nets described in this section utilize seven different vehicle types for classification purposes. Including vehicle length, the most important parameter for vehicle classification, four vehicle specific feature vectors were used as input. Figure 12 shows the overall architecture of the BNN and SOM models. The same dataset for speed estimation was used for NN performance evaluation. The vehicle classification results are presented in Table 13.

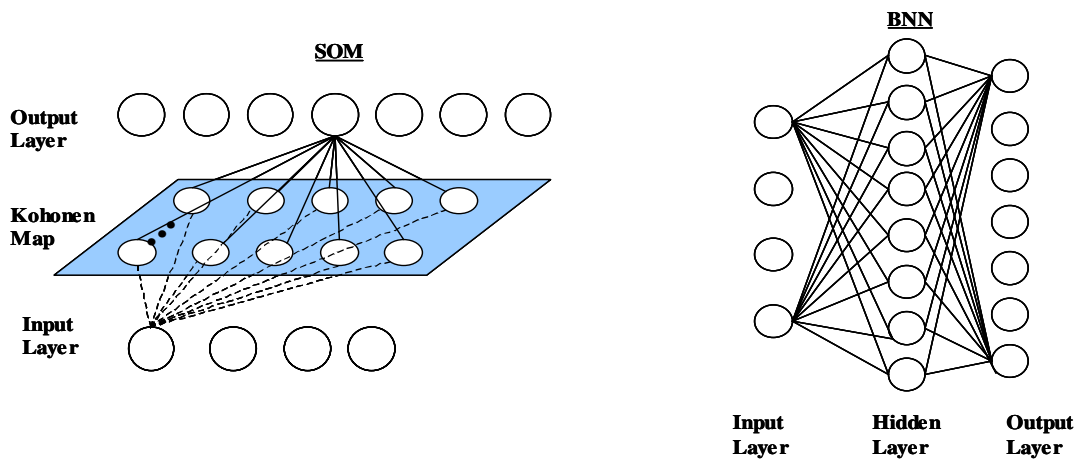


Figure 12 Neural Network Architecture

Table 13 Vehicle Classification Results

Vehicle Type	Training Dataset	Testing Dataset	Correct Classification (Test Dataset, %)		
			BNN	PNN	SOM
Passenger Car, minivan	100	70	88.6	92.9	90.0
Sport Utility Car	80	70	74.3	70.0	71.4
Van, minibus	62	40	75.0	65.0	72.5
Pickup Truck	100	70	75.7	71.4	64.3
One Unit Truck	50	41	85.4	80.5	80.5
Trailer / Vehicle with Boat	50	45	100.0	100.0	100.0
Bus	6	4	100.0	100.0	100.0
Total	448	340	82.6	80.3	78.8

Volume / Occupancy

In most cases, ILD output is acceptable and reasonable under light traffic conditions unless the ILD is defective. However, with bivalent detector cards tailgating vehicles may be counted as one vehicle, and vehicles with trailers as two vehicles. This results in an incorrect volume count. Figure 13 and Figure 14 show the signatures obtained for tailgating vehicles and a vehicle towing a boat, respectively. These signatures were obtained using high speed scanning detector cards. We have developed software to preprocess all signatures and to identify “irregular” signatures such as these. As a result, the accuracy of volume counts and occupancies can be significantly increased.

In Table 14, the counting result and accuracy are presented for a sample dataset. For this analysis, signature data from an arterial in the City of Irvine, CA was used. Motor cycles were not included in the volume count but can always be detected by changing the sensitivity parameters of the detector card. The true count is based on the manual count observed from the video ground truth while system count represents the value obtained after processing the vehicle signatures through the proposed system. In this case, the proposed system was able to address three abnormal vehicle signatures and achieve a volume count accuracy of 99.3%.

Table 14 Volume Count Results

True Count	Detector Count	System Count	System Accuracy
601	594	597	99.3 %

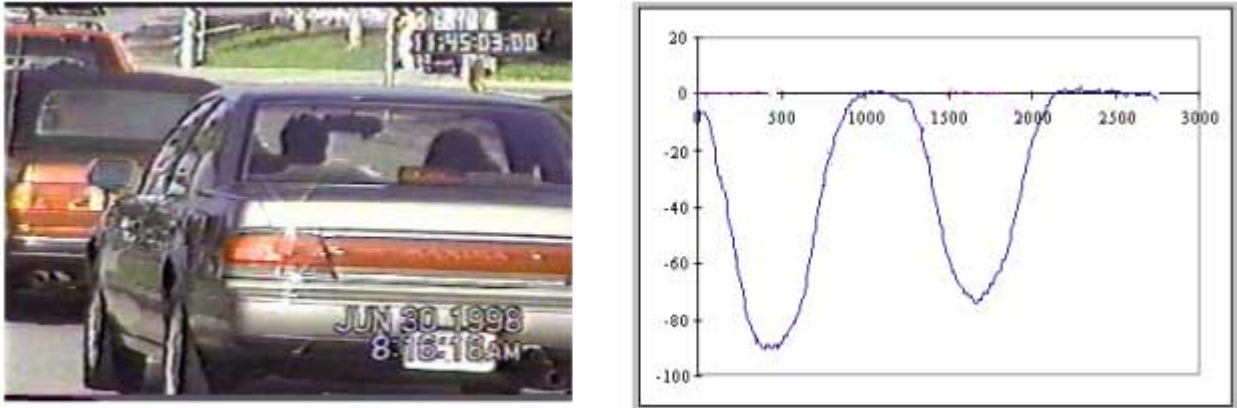


Figure 13 Tailgating Vehicles Signature

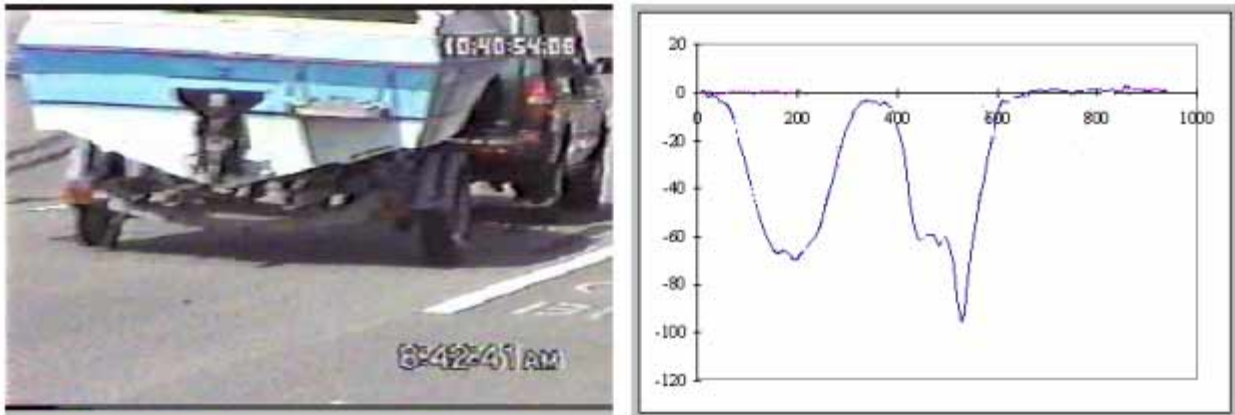


Figure 14 Vehicle with Boat Signature

CONCLUSION

This paper has presented a new for obtaining real-time traffic measurements by using vehicle signatures that are available by integrating existing ILDs with advanced loop detector cards. This approach suggests many advantages. First, by using the current loop infrastructure, it is cost-effective. In addition, unlike other sensors that require a unique vehicle uidentity, like AVI, this system is non-intrusive and anonymous. Also, advanced sensor technology enables researchers to gather more accurate and reliable traffic data that contributes to more efficient traffic surveillance and control.

In particular, this paper has demonstrated a new method of individual vehicle speed estimation from single loop detectors. The proposed model estimates individual vehicle speeds in two stages; using vehicle grouping, and speed estimation by group. The strength of this study lies in the first stage where the PNN vehicle grouping is accomplished based on the vehicle signature features. Vehicle length influences on speed estimation are considered in this stage as well.

In addition to estimating the individual vehicle speed distribution, the proposed model enables the derivation of useful speed statistics for a specific analysis period. Speed variance, which is a good indicator of traffic flow stability, is also available according to the presented estimation method. Moreover, vehicle classification information yields the composition of vehicle types on the road. This information is an essential requirement for a more accurate analysis of road maintenance and air pollution.

ACKNOWLEDGEMENT

This work was performed as part of the California PATH Program of the University of California, in cooperation with the State of California Business, Transportation and Housing Agency, Department of Transportation; and the United States Department of Transportation, Federal Highway Administration. The contents of this report reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the State of California. This report does not constitute a standard, specification, or regulation. The authors gratefully acknowledge the assistance of Richard Nelson, City of Irvine, and Joe Palen, California Department of Transportation, in conducting this research.

REFERENCES

1. Gardner, M.P. Highway Traffic Monitoring. Transportation Research Board. *Transportation in the New Millennium*, 2000, pp 5.
2. Sun, C., and Ritchie, S. G. Individual Vehicle Speed Estimation Using Single Loop Inductive Waveforms. *Journal of Transportation Engineering*, 1999, pp 531- 538
3. Athol, P. Interdependence of Certain Operational Characteristics Within a Moving Traffic Stream. *Highway Research Record 72*, HRB, National Research Council, Washington D.C.,1965, pp 58 – 87
4. Mikhalkin, B., Payne, H.J., and Isaksen, L. Estimation of Speed from Presence Detectors. *Highway Research Record 388*, HRB, National Research Council, Washington D.C.,1972, pp 73 – 83
5. Courage, K. G., Bauer, C. S., and Ross, D. W. Operating Parameters for Main – Line Sensors in Freeway Surveillance Systems. *Highway Research Record 602*, HRB, National Research Council, Washington D.C.,1976, pp 19 – 28
6. Hall, F. L., and Persaud, B. N., Evaluation of Speed Estimates Made with Single – Detector Data from Freeway Traffic Management Systems. *Transportation Research Record 1232*, 1989, pp 9 – 16
7. Dailey, D. J., Haselkorn, M. P., and Nihan, N. L. *Improved Estimates of Travel from Real Time Inductance Loop Sensors*. Washington State Department of Transportation, Washington State Transportation Center, University of Washington. 1993
8. Coifman, B. A New Methodology for Smoothing Freeway Loop Detector Data : Introducing to Digital Filtering. *Transportation Research Record 1554*,1996, pp 142 – 152.
9. Wang, Y., and Nihan, N. L. Freeway traffic Speed Estimation with Single Loop Outputs. *Transportation research Record 1727*,2000, pp 120 – 126
10. Cherrett, T., Bell, H., and McDonald, M. Traffic Measurement Parameters from Single Inductive Loop Detectors. *Transportation Research Record 1719*, 2000, pp 112 – 120
11. Pushkar, A., Hall, F. L., and Acha-Daza, J. A. Estimation of Speeds from Single Loop Freeway Flow and Occupancy Data Using Cusp Catastrophe Theory Model. *Transportation Research Record 1457*,1994, pp 149 – 157
12. Dailey, D. J. A statistical Algorithm for Estimating Speed from Single Loop Volume and Occupancy Measurements. *Transportation Research B Vol 33*,1999, pp 313 – 322
13. Dailey, D. J., and Li, L. Algorithm for Estimating Mean Traffic Speed with Uncalibrated Cameras. *Transportation Research Record 1719*, 2000, pp 27 – 32
14. Specht, D.F. Probabilistic Neural Networks and General Regression Neural Networks. In: Chen, C.H. (Ed.), *Fuzzy Logic and Neural Network Handbook*, 1996