Automated Vehicle Classifier for Traffic Management and Control

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I. INTRODUCTION

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

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the severity of traffic accidents is highly correlated with vehicle types. To summarize, an area-wide assessment of the component of vehicle classes in traffic is essential for more reliable and accurate traffic analysis and modeling. This paper focuses on automatic vehicle classification algorithm development based on the advanced loop detector data and expands · the study scope by testing proposed algorithm transferability.

This paper consists of 5 sections including this introduction. Illustration on study site and description on newly developed loop detector cards as well as detector data processing module are presented in section 2. Reviews on previous studies on vehicle classification are also mentioned in this section. Section 3 focuses on the algorithm development for automated vehicle classification. Result analysis based on three different classification schemes are followed in section 4. The final section is dedicated to the contribution and future direction of the proposed paper.

II. BACKGROUND

1. UCI Testbed

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

TheTestbed has the capability to perform real-time, computer-assisted traffic management and communication. The real-time information system collects both arterial and freeway data from the Testbed area of Orange County, California. The Testbed communications network links the Transportation Management Centers (TMCs) of the City of Irivine, City of Anaheim, California Department of Transportation (Caltrans) District 12, and University of California at Irvine (UCI) Institute of Transportation Studies. Figure 1a summarizes the major functions and current communication system of Testbed with real world TMC and field.

In addition to the existing multi-jurisdictional and multi-agency operated surveillance and communications infrastructure, the Testbed features a 0.7 mile freeway section on northbound I-405, between Laguna Canyon and Sand Canyon, and a major signalized intersection in Irvine that are both fully instrumented with the latest detector technologies for advanced traffic control and surveillance. We refer to this site as the Traffic Detector and Surveillance Sub-Testbed (TDS^2). The overall purpose of the TDS^2 is to provide a real-world laboratory for the development and evaluation of emerging traffic detection and surveillance technologies. As illustrated in Figure 1b, double inductive loops are

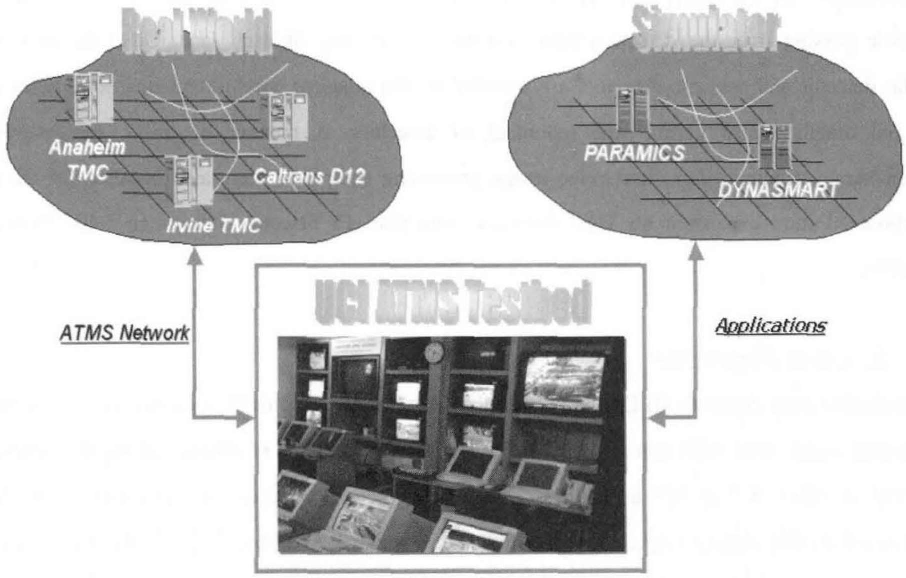

Figure 1a. UCI Testbed

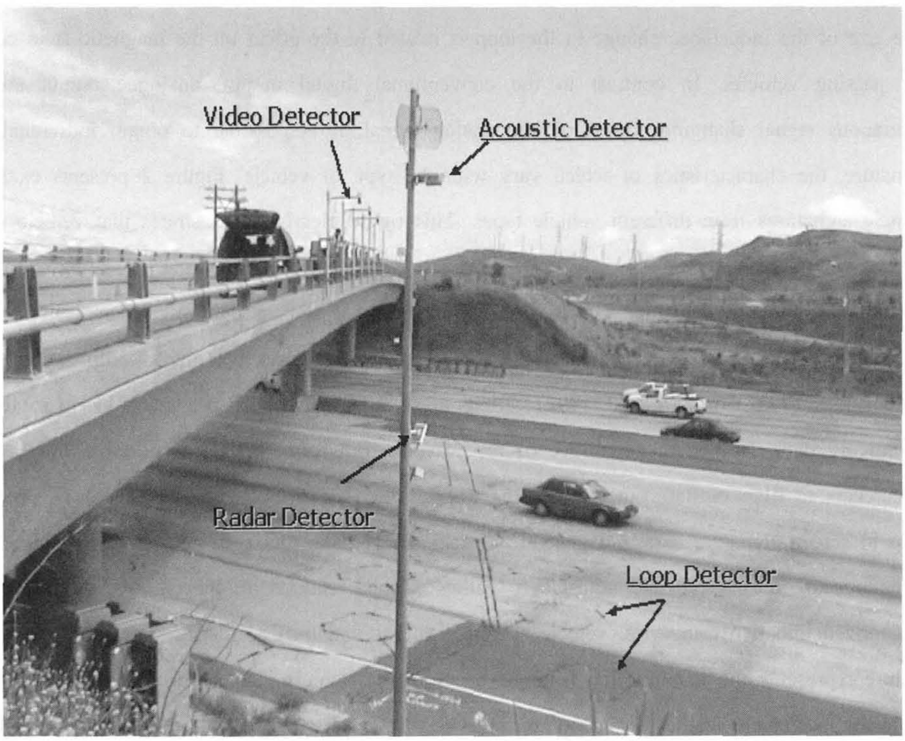

Figure 1b. Traffic Detector and Surveillance Sub-Testbed (TDS2)

Figure 1. UCI Testbed and Study Site

implemented for all lanes, and special cameras, that capture the horizontal images of each single vehicle passing over the detection zone, are installed on top of each lane. Other detectors such as radar detector and acoustic detectors are installed on the adjacent wireless antenna pole. Poles adjacent to the mainline also permit side mounting of detectors. A number of traffic cabinets to house computers, communications, and video image processing equipment were also installed for the research purposes. Future expansion on TDS^2 includes more than 15 detector stations on I-405 freeway road section.

2. Loop Signature

Inductive loop detectors (ILDs) have been the most widely used traffic detector system in the world. 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". The size of the inductance change in the loop is related to the effect on the magnetic field caused by the passing vehicles. In contrast to the conventional digital output, analogue output shows the continuous signal changing. By using the analog signal, it is possible to obtain individual vehicle signature, the characteristics of which vary with the type of vehicle. Figure 2 presents examples of vehicle signatures from different vehicle types. This figure clearly demonstrates that vehicle signature is function of vehicle type.

Field-collected raw signature data is filtered and pre-processed through wavelet analysis. Ever since wavelet transform, a technique of analyzing various types of signals, was introducedin the early 1990s (Daubechies 1992; Coifman et al. 1992) various applications have been presented due to robustness of de-noising data. De-nosing capability of the wavelet transformallows transportation engineers and researchers to filter outliers out of real-time traffic data. Therefore, the wavelet analysis process will help to screen signature data and generate cleaner signal data. Once the pre-processing is completed, signatures are normalized and adjusted to gather various features. In this study, feature vectors are categorized into two categories: vehicle specific features and traffic specific features. Vehicle specific feature represents the features that isunique according to vehicle itself, therefore, invariant over time or location. Vehicle length is a good example as this category. Traffic specific feature indicates the feature that could describe either traffic condition or road geometry. Speed and lane information falls into this category. By processing raw signatures, useful vehicle specific features such as vehicle

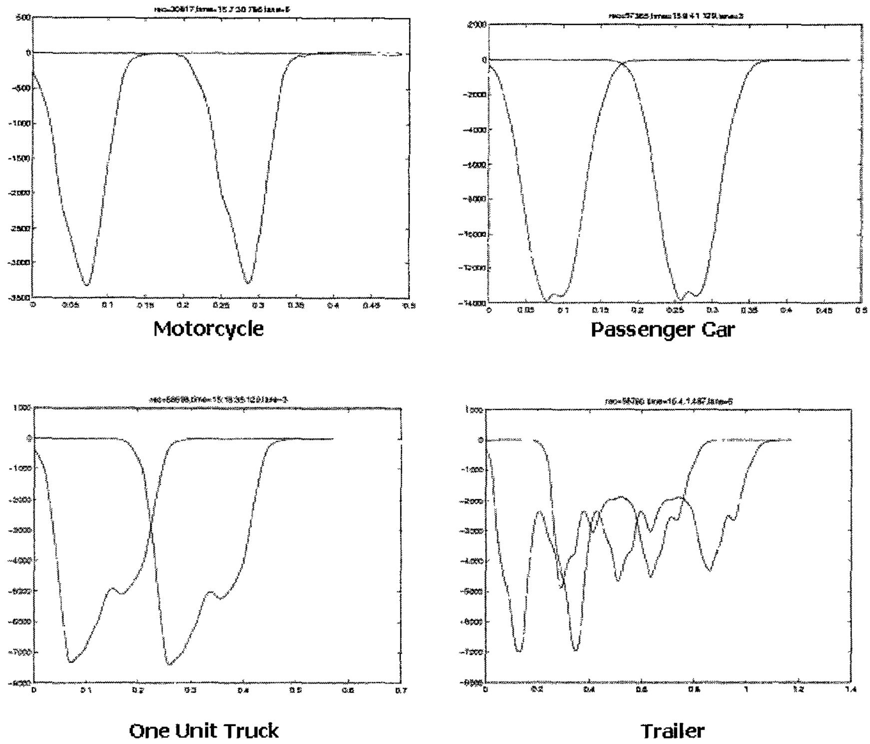

Figure 2. Sample Vehicle Signatures

length, which is the dominant element in vehicle classification algorithm, can be obtained. Based on the extensive signature analysis, following features were chosen to represent the vehicle specific features and Table 1 shows each feature description. The notations used in Table 1a are illustrated in

Table 1. Signature Features

Feature	Feature Description
Maximum Magnitude	Maximum absolute magnitude value (a)
Shannon Entropy	Entropy calculated from wavelet analysis
Log Entropy	Entropy calculated from wavelet analysis
Shape Parameter (SP)	Degree of Symmetry ((b)/(b+c))
Electronic Vehicle Length	(d)
Degree of Symmetry (DOS)	Degree of Symmetry for upper signature part (e): median Sum of the distance from median (g), to each point that is above "0.5" y value
Number of High Magnitude (NHM)	Sample number above "0.5" y value after x, y normalization

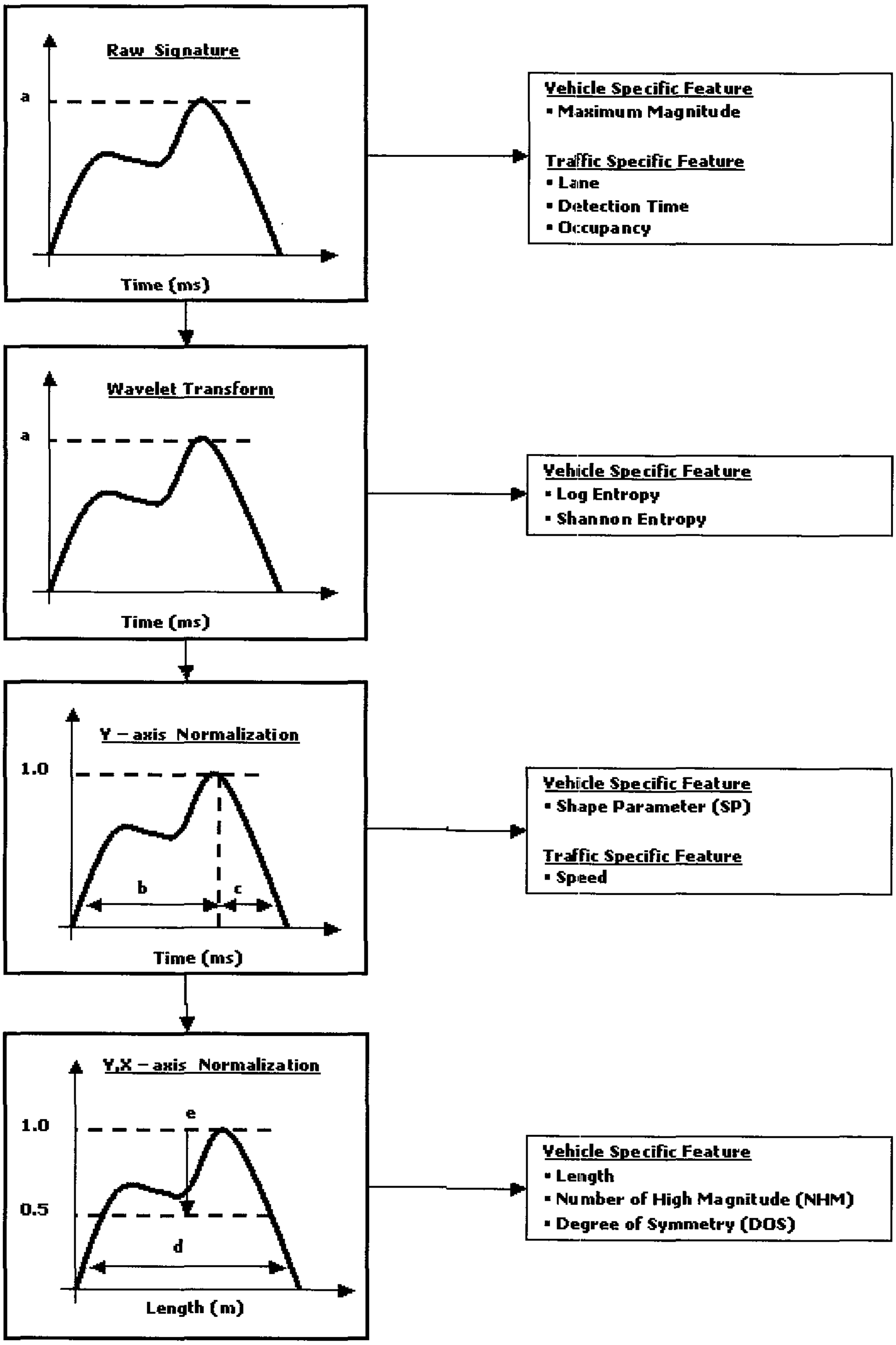

Figure 3. Signature Feature Extraction

Figure 3. Illustrations on inductive loop signature data processing and feature vectors extraction are presented in Figure 3.

3. Preceding Studies

In recent years, several researches have been conducted using different sensors for development of vehicle classification methodologies. Preceding studies are summarized in Table 2 along with applied sensor in corresponding study.

Table 2. Preceding Studies on Vehicle Classification

Author	Sensor	Method	Vehicle Type	Comments
Davies (1986)	Inductive loop	Neural Network	5 types	Earlier study in vehicle classification Mainly relies on vehicle length
Lu et al. (1989)	Infrared detector	k nearest-neighbor	4 types	
Pursula et al. (1994)	Inductive loop	Neural Network, Self-Organizing Map	7 types	80% classification rate
Matti et al. (1994)	Inductive loop	Neural Network, Self-Organizing Map	7 types	About 81% overall classification rate
Yuan et al. (1994)	Video	Image Processing, k nearest-neighbor	6 types	Two-level classification algorithm 95% classificatoin rate
Wei et al. (1996)	Video	Image Processing, Neural Network	3 types	Algorithm performance was satisfactory but only 3 vehicle types
Nooralahiyan et al. (1997)	Acoustic Sensor	Neural Network	4 types	Sensitive to environmental condition
Sun et al. (2000)	Inductive loop	Heuristic algorithm	7 types	81%~91% overall classification rate
Harlow et al. (2001)	Range sensor	Rule-based classifier	3 types	92% classification rate
Wang et al. (2001)	Inductive loop	Pattern discrimination	4 types	
Gupte et al. (2002)	Video	Image processing	2 types (cars and noncars)	Around 65% correct classification rate
Sun et al. (2003)	InductiveLoop	Neural Network, Self-Organizing Map	7 types	82%~87% overall classification rate
Avery et al. (2004)	Video	Image Processing	2 types (truck and rest)	Mainly focuses on detecting trucks

Most of the listed studies focus more on detecting long vehicles, such as trailer and trucks. In this study, not only the differentiation short vehicles from long vehicles but also detailed classifications in short vehicles are discussed. Comparison between Federal Highway Administration (FHWA) vehicle classification methods is also one of the focal points of this study.

III. SYSTEM DEVELOPMENT

Three different vehicle classification schemes are introduced. Two categories are based on FHWA classification. FHWA classification scheme is separated into categories depending on whether the

Table 3. Vehicle Class Category

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

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

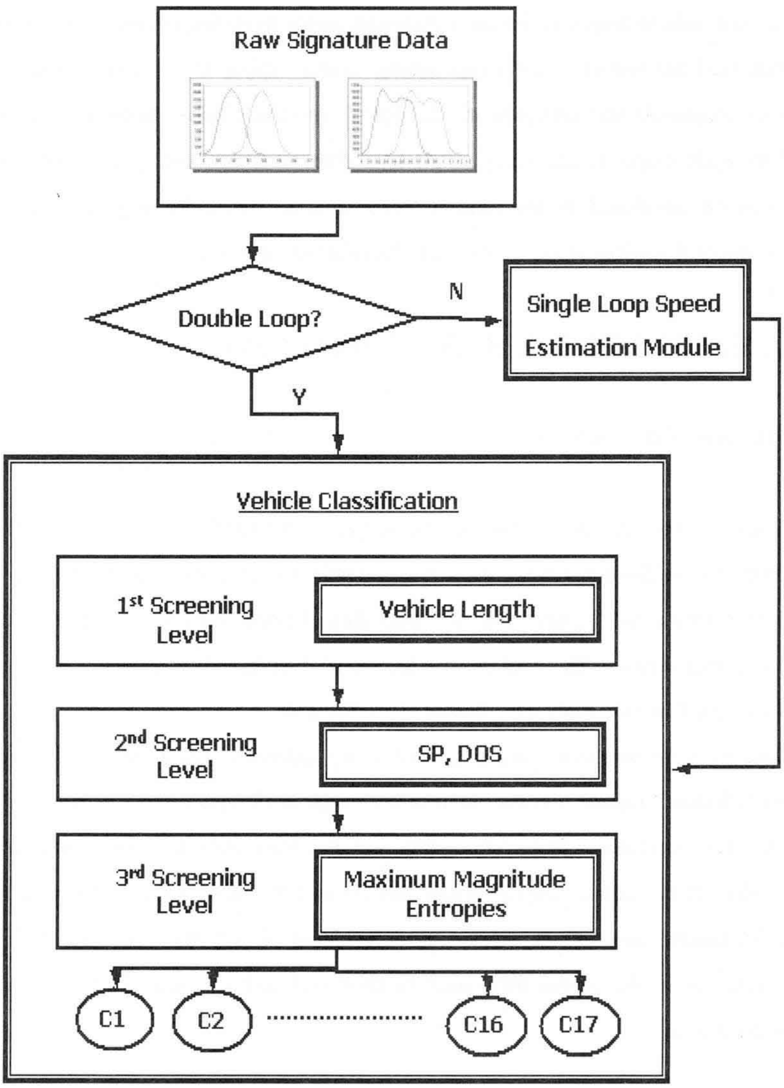

Figure 4. Vehicle Classification Flow Chart

procedure is required at this stage.

Heuristic decision tree method, comparable to sequential screening approach, is deployed for vehicle classification model development. The advantage of suggested model is its simplicity, which is one of the most important elements for fast algorithm computation process. This feature will also contribute on possible future real-time algorithm implementation. This is very significant from both practice and research aspects. Sequential splitting approach is based on threshold values selected from corresponding feature vector distribution of each vehicle class. This sequential approach helps to reduce the dimension of possible vehicle classes and therefore minimize the misclassification rate. It was shown that vehicle length is the most dominant factor in distinguishing vehicle classes. DOS and SP are then used for further classification among similar vehicle length groups. Other variables such as maximum magnitude and entropies are all applied for detailed classifications. This paper also have expanded its study scope by simulating single loop detector layout and by applying single loop speed estimation model, developed by the same author (Oh et al 2002), for proposed vehicle classification algorithm. Figure 4 depicts above mentioned classification process.

IV. EXPERIMENTAL RESULT ANALYSIS

1. Dataset Description

In this study, two datasets, calibration and testing, were used and manually verified for vehicle classification. The calibration dataset consists of vehicle signature data collected from 14:00 to 14:30 PM at Sand Canyon and Laguna Canyon. Data from Laguna canyon at morning peak period was applied for testing dataset. This will satisfy for model transferability testing at different time of the day. Datasets used in this study are illustrated in Table 4.

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

Table 4. Dataset Description

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

2. Model Result Analysis

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

Calibration Results

Table 5 summarizes calibrationdataset classification results under different classification categories using different loop configurations. Double loop configuration classification yield better results compared to single loop configuration case. The results are very promising in that proposed algorithm not only separates small vehicles from long vehicles such as truck or multi trailer but also generates comprehensive differentiation within small vehicles, such as SUV and passenger cars.

Detailed result analysis was also conducted according to the three proposed classification schemes. It was obvious that the misclassification rate is high among passenger cars, SUVs, pickup trucks andvans. For trucks and trailers, the misclassification occurs when the signatures are similar but only differs in axle number. For instance, in case of category 8 and 9 the axle count differs by one but because of signature similarities, the misclassified category vehicle 8 are all assigned as category 9. Same pattern is observed for category 5 and 6. Recently developed traffic detector, blade detector, can be used to overcome these limitations by addressing vehicle axle number counting. However, these detectors were not available to be fully implemented at the time of this study and integration with these blade detectors for enhanced and robust vehicle classification system is an area of future study. It is also remarking point that classification results based on single loop are also encouraging.

Table 5. Vehicle Classification Summary (Calibration Dataset)

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

Especially, in FHWA I and II categories classification outcomes are very encouraging with over 90% correct classification rate. It should also be noted that for some vehicle classes, such as multi trailer, even under single loop configuration, classification results show almost perfect classification rate because of unique vehicle signatures.

Model Transferability

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

Table 6. Vehicle Classification Summary (Test Dataset)

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

5. DISCUSSIONS AND FINDINGS

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

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