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Abstract

Trucks have a significant impact on infrastructure, traffic congestion, energy consumption, pollution and quality of life. To better understand truck characteristics, comprehensive high resolution truck data is needed. Higher quality truck data can enable more accurate estimates of GHGs and emissions, allow for better management of infrastructure, provide insight to truck travel behavior, and enhance freight forecasting. Currently, truck traffic data is collected through limited means and with limited detail. Agencies can obtain or estimate truck travel statistics from surveys, inductive loop detectors (ILD) and weigh-in-motion (WIM) stations, or from manual counts, each of which have various limitations. Of these sources, WIM and ILD seem to be the most promising tools for capturing detailed truck information. Axle spacing and weight from existing WIM devices and unique inductive signatures indicative of body type from ILDs equipped with high sampling rate detector cards are complementary data sources that can be integrated to provide a synergistic resource that otherwise does not exist in practice, a resource that is able to overcome the drawbacks of the traditional truck data collection methods by providing data that is detailed, link specific, temporally continuous, up-to-date, and representative of the full truck population. This integrated data resource lends itself very readily toward detailed truck body classification which is presented as a case study. This body classification model is able to predict 35 different trailer body types for FHWA class 9 semi-tractors, achieving an 80 percent correct classification rate. In addition to the body classification model, the large data set resulting from the case study is itself a valuable and novel resource for truck studies.

Keywords: weigh-in-motion (WIM), inductive loop detector, inductive signature, truck monitoring, truck body type, vehicle classification

Introduction

At the national level, trucks account for approximately 10 percent of the annual vehicle distance traveled *(1)*. Although this represents a small portion of the total travel, the impacts of trucks on the economy and freight transportation, air quality, traffic performance, pavement and infrastructure, and safety are much more substantial than that of passenger vehicles. The economic impacts of trucks in regard to freight transport are considerable. The Bureau of Transportation Statistics reported that "trucking as a single mode (including for-hire and private use) was the most frequently used mode, hauling an estimated 70 percent of the total value, 60 percent of the weight, and 34 percent of the overall ton-miles" *(1)*. In terms of environmental impacts, according to the California Air Resources Board (CARB) Mobile Source Emissions Inventory, heavy-duty diesel trucks are the "single largest source of nitrogen oxide emissions in California" as well as the "largest source of diesel particulate matter", both pollutants that have significant health impacts in addition to their contribution to environmental degradation *(2)*. Further, due to their large size and mass, medium and large commercial vehicles often travel slower, possess lower acceleration rates and require much longer braking distances, leading to moving bottlenecks which have adverse impacts on traffic performance *(3)*. This concern has led to investigations into traffic performance impacts such as increased congestion as well as potential operational solutions like truck only lanes *(4)*. Studies of commercial vehicle safety impacts have confirmed that accidents involving large commercial vehicular traffic are often severe with higher fatality rates, due to their larger profile and mass compared with passenger vehicles *(5)*.

The availability of detailed truck data pales in comparison to the large impact trucks have on our environment, health, and infrastructure. Agencies can obtain or estimate truck information from truck Global Positioning Systems (GPS) data, paper-based surveys, vehicle detection stations (VDS) and weigh-in-motion (WIM) stations, or from manual counts. Truck GPS data is capable of providing origin destination (OD) tracking and performance statistics *(6)* but it does not provide truck characteristics such as body types or industry served and represents only subpopulations. Additionally, there are significant privacy concerns that limit the availability of GPS data, and large commercially available datasets can be costly. Paper based surveys, such as the Vehicle Inventory and Use Survey (VIUS), conducted by the US Census Bureau *(7)*, require expensive and time consuming data collection tasks like interviews, intercept surveys, and mail-based surveys, and are only able to provide data from one point in time from a sub-sample of the truck population and cannot be related to specific routes or links. A further drawback of VIUS is that it was conducted only every five years, leaving a major data gap for years in between, and was discontinued in 2002. Loop detector data from VDS, such as that provided by the Caltrans Performance Measurement System (PeMS) in California cannot measure truck volumes directly and must rely on estimation algorithms to estimate broad truck classes, and can only be used at aggregate levels *(8)*. Furthermore, while VDS are prevalent in metropolitan areas, they are limited outside of them, and may not be ideal for capturing long haul truck traffic. WIM sites, on the other hand, are able to provide truck counts by axle-based classes along with gross vehicle weights, but lack further detail about the cargo type or distance traveled by trucks. Finally, manual counting entails recording truck traffic for short sampling periods, and then extrapolating the sample counts to get an estimate for a whole year, i.e. Annual Average Daily Truck Traffic (AADTT). AADTTs typically possess significant errors, as they depend on short sampling periods which do not effectively capture the seasonal and diurnal trends of truck travel patterns, even with the use of adjustment factors, due to the heterogeneous disposition of truck travel patterns *(8)*. Not surprisingly, the last method is discouraged by the USDOT *(9)*.

In this paper, we present a novel approach of integrating WIM and inductive signature data for building more advanced models for monitoring truck travel. WIM and inductive signature data are exceptionally complementary. WIM data provides information on a truck's axle configuration and weights; however, the axle-based information cannot be directly associated with a truck's function or body configuration. On the other hand, inductive signatures have been demonstrated an ability to distinguish trucks by body configuration, although inductive signatures obtained from conventional loop sensors are not suited for obtaining detailed axle configuration information *(10)*. Furthermore, the location of axles from WIM data can be used to partition signatures into body components in multi-unit trucks, allowing each component, such as the drive unit and the trailer unit to be analyzed separately. The detailed truck data provided by this integrated data resource can then be applied to obtain classification and truck behavior through vehicle re-identification analyses. As demonstrated through the case study presented in this paper, integration of WIM and inductive signature data can be used to develop detailed body type classification models. Knowledge of body type permits many kinds of useful analyses, such as calculating fees and cost allocations to highway users by class or associated industry, spatial and temporal analysis of safety risks, energy efficiency and environmental impact of truck fleets through VMT estimation, determining fuel demands, and linking between sampled/survey data and population data.

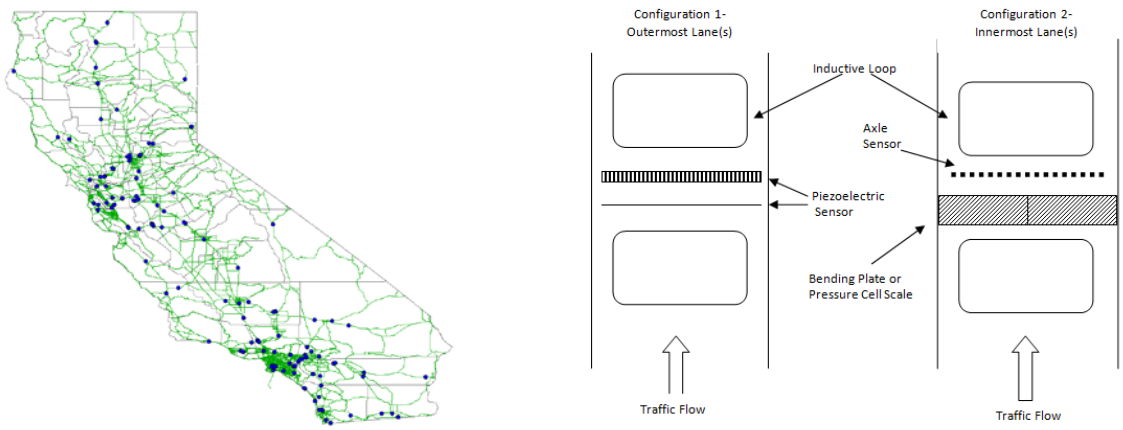
This paper outlines the procedure used to integrate WIM and inductive loop signature data at the hardware and data handling levels. A case study of truck body type classification using data collected in California is presented as a demonstration of the potential of the proposed integrated data source.

Background

Conventionally, WIM technology is used to obtain axle-configuration-based classification of trucks, such as the scheme used by the Federal Highway Administration (FHWA), while inductive loop sensors are used to provide volume measures. However, the instrumentation of existing inductive loop sensors with signature capability provides significant potential improvements in truck data. In this paper, we integrate WIM data with inductive loop signature technology to provide a high resolution truck data source. To the best of our knowledge there have not been any prior studies which integrate WIM data with inductive loop signatures, thus the integration method described in this paper is quite novel.

WIM Detectors

WIM detectors are implemented in many states for the purpose of reducing delay at static scales by pre-screening, and for collecting site specific continuous truck traffic information. WIM data can be used for pavement studies, highway monitoring and capacity studies, accident rate calculations, and general truck transport practices *(11)*. There are a limited number of vendors of WIM devices that operate in each state and for California all 106 WIM data stations are controlled by a single vendor, International Road Dynamics (IRD) *(11)*. In California, WIM sites are located throughout the state but concentrated in urban regions (see Figure 1a). A typical WIM station includes bending plates or pressure sensors surrounded by square inductive loop detectors in the outermost lanes and piezoelectric sensors surrounded by inductive loops in the innermost lanes (see Figure 1b). WIM stations collect vehicle arrival time and date, axle weights and gross weight, axle spacing, and speed *(12)*. Vehicle classification is determined from these measures according to the truck specific classes of FHWA Scheme F which includes 13 axle-based classes (14 classes for the State of California). Based on the axle spacing and weights the truck class is assigned by a predetermined table.



(a) WIM sensor locations in California (b) WIM sensor configuration *(12)*

Figure 1 WIM Sensor Characteristics

Inductive Loop Detectors

Conventional loop detectors measure bivalent signals from inductive loops embedded in the pavement and are capable of measuring aggregated volumes and occupancies. Unlike many other detector systems such as imaging or acoustic sensors, loop detectors are inherently accurate, achieving volume count accuracies typically between 98 and 99 percent even in conventional bivalent system applications, providing a good technology platform to develop the proposed system. Finally, because magnetic inductance is invariant to changes in temperature, lighting, visibility and humidity, ILDs are robust. Advanced inductive loop detectors measure the inductance change in an inductive loop sensor at rates of up to 1200 samples per second *(13)*, producing analog waveform outputs, referred to as inductive signatures, for each traversing vehicle. A significant advantage of advanced inductive loop detectors is their compatibility with existing conventional bivalent ILDs. This allows existing conventional ILDs to be swapped with advanced ILDs without suffering any loss in system functionality.

Integrating Data Sources

Given the complementary nature of the WIM and inductive signature data, along with the physical embedded configuration of inductive loops within the WIM station, the two are ideally suited for integration to provide a synergistic data resource. The data integration procedure is presented in the following section in two parts: hardware integration and data handling. Hardware integration involves replacing the existing bivalent inductive loop module of the WIM controller with advanced inductive loop signature detector cards. Data handling includes the pre-processing of inductive signatures and WIM records into a database structure that is then accessed through a customized user interface. A third dimension of the integrated data source that is necessary for model development, but not needed for actual implementation, is the addition of still image capture hardware triggered by the loop detectors. This is to obtain detailed side picture profiles of trucks which are incorporated into the database and user interface for later identification of truck characteristics such as body type.

Hardware Integration

Two main types of WIM controllers are currently deployed in California: the earlier DOS-based IRD 1060 series controllers and the current Linux based IRD iSinc family of controllers, which include the iSinc WCU-II and iSinc WCU-3 Lite. We have found the main distinction between the controllers for the purpose of this study is in their built-in ability to log inductive signature data. The loop sensor module (LSM) of the 1060 WIM controllers is designed only to obtain conventional bivalent inductive loop data. On the other hand, the LSM of the iSINC controllers have the ability to obtain inductive signature data. The caveat for the iSINC controller however, is that inductive signature data is currently designed only for diagnostic and troubleshooting purposes. Hence, the inductive signature data can only be manually logged when the system is in diagnostic mode, and is not currently available as an operational feature within the system. Furthermore, 1060 series controllers are currently deployed at about 80 percent of current WIM sites within the California. Hence, despite their age, a hardware integration solution with the 1060 series controllers would be applicable to a much larger number of candidate sites currently available for deployment consideration.

A prototype LSM adapter was designed to adapt advanced inductive loop signature detector cards to replace the 1060 WIM LSM. Inductive loop signature data was logged into a field processing unit via the USB port located on the front panel of each signature detector card. Schematic layouts showing a comparison of the hardware setup for a standalone 1060 WIM controller and the proposed integration with an advanced signature detector card are shown in Figure 2. With this set-up both inductive loop signatures and WIM weight and axle spacing data can be collected at the WIM site. Lastly, in addition to inductive loop signature and WIM data, still image data was collected for each passing vehicle by connecting a digital SLR camera with a remote trigger to the loop detector card such that each loop activation triggered the camera and a series of still images were captured for each passing vehicle at a rate of three frames per second while the vehicle was over the loop. In the next section, the data processing to join the data types and photos is described.

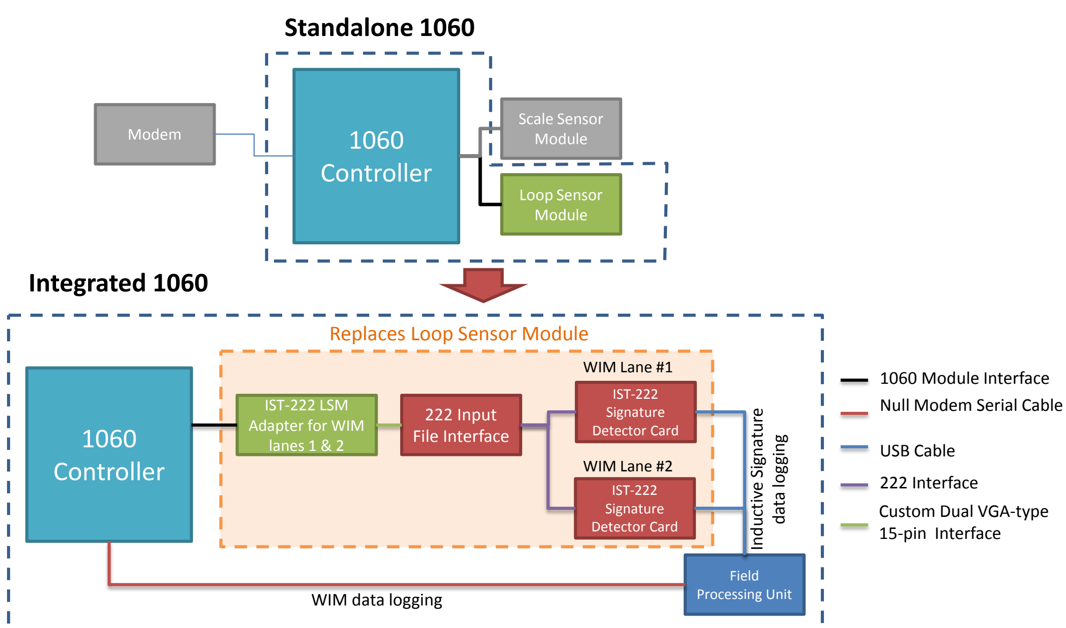


Figure 2 Comparison of Hardware Setup for Standalone 1060 WIM Controller (top) and 1060 WIM Controller Integrated with Advanced Inductive Loop Signature Detector Cards for Inductive Signature Data Logging

Data Handling

All inductive loop signature, WIM record, and photo data was stored in a relational database powered by PostgreSQL. Currently, the 1060 WIM controller output is captured as a text file which is processed and stored as individual vehicle records according to a unique vehicle identification number. Future work will investigate the ability to replace the text file readout with binary data output from the serial port of the WIM 1060 controller so that it can be directly inserted into the database without pre-processing. The inductive signature data is also pre-processed prior to insertion into the database where each signature is stored according to a unique identification number.

A specially developed software user interface was developed in Visual Basic to efficiently integrate the WIM data and signature data while also examining photos of each vehicle record for classification or other desired purposes. The user interface was designed to communicate with the database and allow the user to scroll through photos and select the vehicle class parameters while also linking inductive loop signature records and WIM data records to the appropriate vehicle record. Figure 3 shows the user interface for truck classification purposes. The rightmost image is the inductive loop signature and the table below the signature is the list of vehicle signature records within the user-designated time window. The center FHWA image based on the FHWA class predicted by the WIM controller and the table below is the list of WIM vehicle records with the user-designated time window for the WIM data. The largest table in the upper right is the list of vehicle records derived from the set of photos taken by the still camera and grouped into vehicle records such that there may be one to five photos for each vehicle record which the user can scroll through. The photo corresponding to the vehicle record, WIM record, and inductive signature is show at the left. Lastly, since this interface was developed to classify vehicles by body type, below the photo there is a selection region where the user designates the axle and body configuration of the vehicle.

Classification is only one of the applications of this integrated data source and the method in which the data is collected, pre-processed, and managed by the database can be applied for other uses for which alternate user interfaces could be developed. For example, for vehicle re-identification, using the same pre-processing techniques and database structure, the user interface could display signature and WIM information from two sites which the user could then toggle through to find matched vehicle pairs. Also, pairing of the WIM and signature data can be undertaken by a simple program that can map the signature to its WIM record based on time, headways, and duration, for example. In the next section, we present an application of the integrated data source for truck body classification.

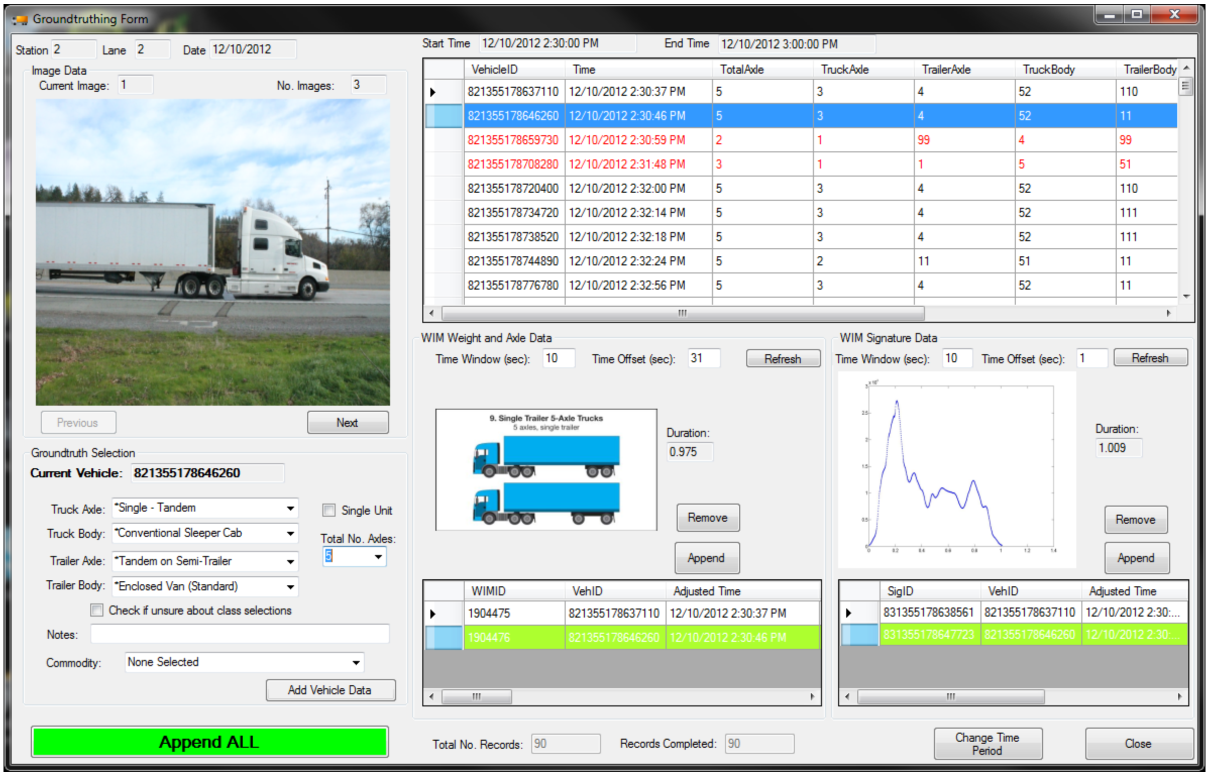


Figure 3 Integrated Data System User Interface Example for Vehicle Classification

Case Study: Body Classification

The integration of WIM and inductive loop signatures lends itself readily to detailed truck body classification which is presented as case study of the integrated data source described in this paper. In addition to the body classification model, the large data set resulting from the case study is itself a valuable and novel resource for truck studies.

Background

Body classification data of commercial trucks can contribute significantly towards improved emissions estimates, infrastructure and pavement management, and freight forecasting. Currently, the main truck data available for emissions and freight models is limited to axle based classification from WIM, count estimates from inductive loops, fleet size and commercial use from vehicle registration records, trip patterns, commodity type, vehicle type, and trip lengths from state and national shipper/carrier surveys, and vehicle miles traveled from AADTT counts. The data from these sources is commonly mapped to the FHWA 13 class axle-based scheme, or simplified schemes based on weight classes which divide trucks into medium, heavy, or light duty types. None of the sources are capable of providing body type information, which can be a key indicator of the industry served by the truck as well as the travel patterns of the truck. And while survey data is capable of providing origin-destination information and truck or body type, surveys are limited by costs and cannot yet provide individual link or route level data.

As an illustrative example of the lack of detail in axle-based classification, consider the most common truck axle configuration, the five axle tractor trailer corresponding to FHWA class 9. Within class 9, there exists a diverse distribution of trailer body types as shown in Figure 4, with the most common being enclosed and refrigerated vans, platforms, and tanks. It is important to know the specific trailer type because each trailer body type may have dissimilar travel patterns, unique emission rates, and distinct effects on congestion and safety. For example, in relation to travel patterns, box containers travel between ports and intermodal facilities whereas enclosed vans might be commercial delivery vehicles traveling between regional distribution centers and businesses. The breakdown of class 9 into the wide variety shown in Figure 4 clearly illustrates the significant amount of unknown information that exists in existing truck monitoring data.

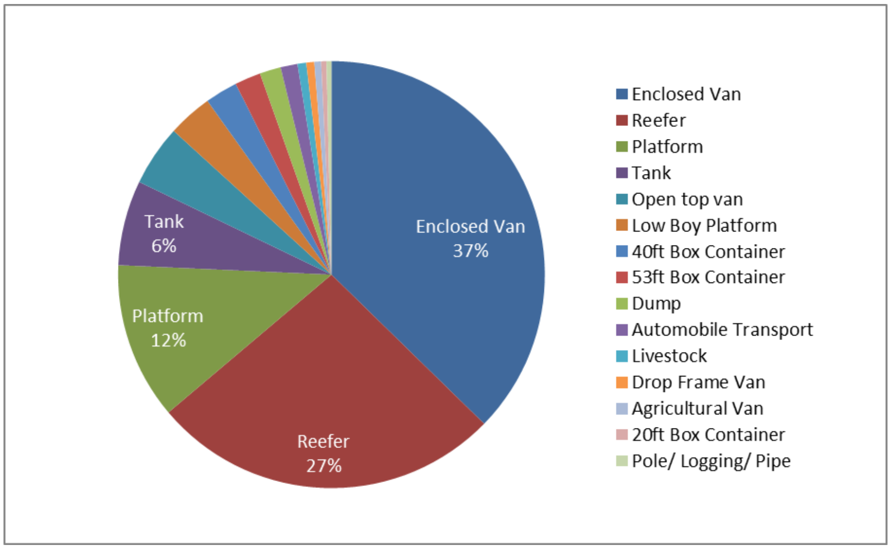


Figure 4 Trailer Body Type breakdown of FHWA Class 9 tractor-trailers

In comparison to the previous classification methods which use inductive loop detectors *(13-19)*, none have been capable of distinguishing trucks into detailed body types shown in Figure 4. Even the most detailed model by Tok and Ritchie *(10)* which focused on commercial vehicles contains only 10 trailer unit types, and this level of detail required an advanced prototype loop detector to be installed in the pavement.

As for body classification based on WIM data, there has only been one study by the FHWA *(20)*, in which data from WIM devices and truck characteristics from the 1992 Truck Inventory and Use Survey (TIUS) were merged in an attempt to relate truck body type, weight, and cargo carried. The study examined the potential of determining 11 distinctly defined body types from characteristics found in TIUS- the total number of axles, the number of lift axles, total vehicle length, average gross vehicle weight (GVW), the number of axles on trailers pulled by truck tractors, and the number of axles on trailers pulled by straight trucks *(20)*. The authors noted that “significant overlaps” were found in the body types that are possible for a given set of variables and that using all five variables would provide the most accurate inference on body type. The level of detail in body types achieved in this study is an improvement over existing available data sources, but still lacks detail in the body type classification that are needed for freight modeling.

Classification Scheme Development

A key component in the development of the body classification model was the creation of a classification scheme that captured the diversity of truck bodies found in the data. The truck body type classification scheme originally based on the 28 VIUS defined body classes was further refined to 35 trailer body types as revealed by the collected data and shown in Table 1. Definitions of each body type including a photo and inductive signature example can be found online[1].

Table 1 Classification Scheme for Trailer Units

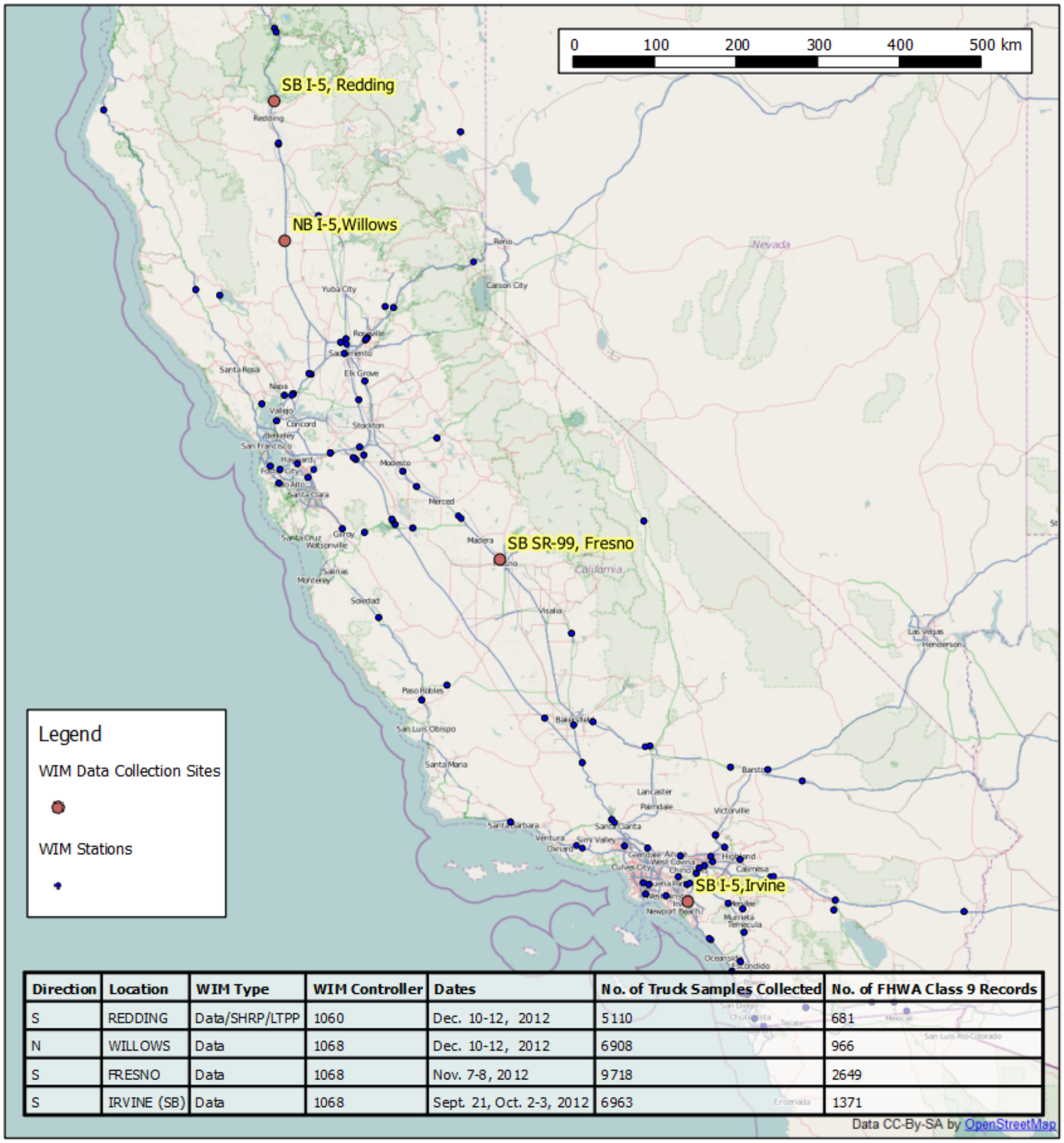
Body Category	Body Type
Vans	Enclosed
	Reefer
	Drop Frame
	Curtain-side
	Open Top
	Agricultural
	Open Agricultural Van
Platforms	Basic
	Low Boy
	Platform with devices
Tanks	Hot Product Tank
	Deep Drop Tank
	Food Grade Tank
	Petroleum Tank
	Chemical Tank
	Crude Oil Tank
	Air Compression Tank
	Propane Tank
	Pneumatic
Specialty	Hopper
	Beverage
	Pole/logging/pipe (with and without platform)
	Automobile Transport
	Livestock
Dump	End Dump
	Bottom Dump
	Bulk Waste Transport
Containers	Container Chassis
	40ft Box Container
	20ft Box Container
	20ft Box Container on 40ft Chassis
	53ft Box Container
Small Trailers	Recreational Vehicle or ‘5th Wheel’
	Towed Passenger Vehicle
	Small trailer or dolly

Study Locations and Data

Four sites were selected for data collection ranging geographically from urban centers in Southern California to more rural areas in Northern California. Sites were selected to enhance the variety body types collected. The location, site name, data type, date of collection, and number of collected truck

[1] Trailer Unit Body Type Dictionary: http://goo.gl/nACH7

samples as well as the total number of FHWA Class 9 records are shown and summarized in Figure 5. Figure 6 shows a typical data collection hardware setup at the southbound SR-99 Fresno WIM station.



Direction	Location	WIM Type	WIM Controller	Dates	No. of Truck Samples Collected	No. of FHWA Class 9 Records
S	REDDING	Data/SHRP/LTPP	1060	Dec. 10-12, 2012	5110	681
N	WILLOWS	Data	1068	Dec. 10-12, 2012	6908	966
S	FRESNO	Data	1068	Nov. 7-8, 2012	9718	2649
S	IRVINE (SB)	Data	1068	Sept. 21, Oct. 2-3, 2012	6963	1371

Figure 5 WIM Data collection sites

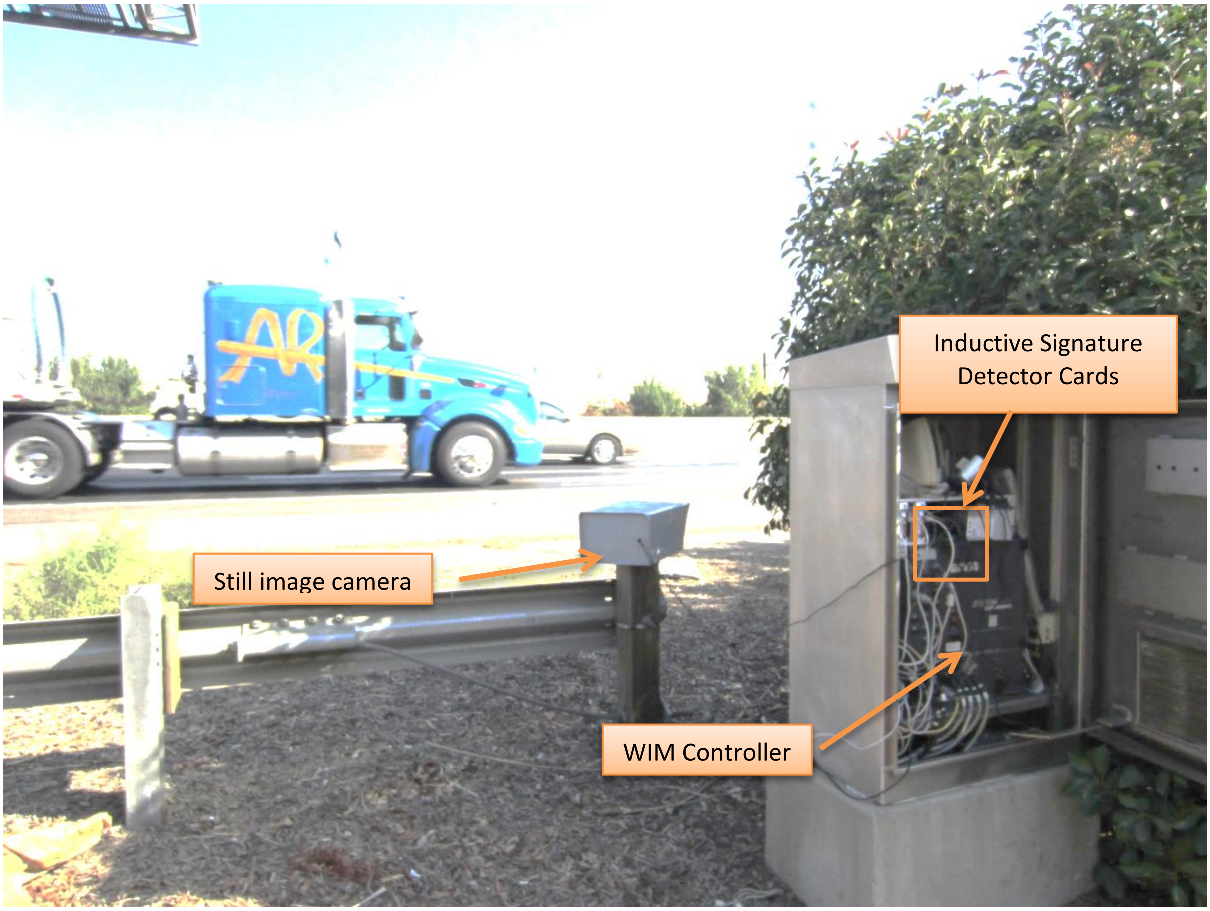


Figure 6 Data collection setup at SB SR-99 Fresno WIM station

Preliminary Body Classification Model

The body classification model developed in this case study focuses on the trailer portion of FHWA Class 9 semi-truck configurations since these represent the most commonly observed truck types and have a very diverse set of trailer body types. A total of 5,667 FHWA class 9 truck records were fully processed, i.e. still captured image, vehicle body configuration, inductive loop signature, and WIM-based vehicle length, axle spacing and weight records were assigned to each vehicle record. The completed records were used for model development and testing. The classification methodology was divided into two parts: feature extraction and model development.

Feature Extraction

At the most primitive level, if inductive loop signature data is used to distinguish body type, then weight data can be included to differentiate weight classes (i.e. medium-heavy, heavy, heavy-heavy, etc. as used by the California Air Resources Board) by body type. A more enhanced method, and that adopted here, was to use the WIM axle spacing and vehicle length data to parse the inductive loop signature of each vehicle such that features are only extracted for the portion of the signature pertaining to the body unit being distinguished. For example, given a signature from a semi-tractor-trailer combination, the WIM axle spacing was used to break the signature into the tractor portion and the trailer portion which would then be feed separately into classification models. Figure 7 shows an example of how the WIM axle spacing data was used to parse the tractor and trailer portions of an inductive loop signature resulting in change in magnitude between each pair of equally spaced interpolated magnitudes.

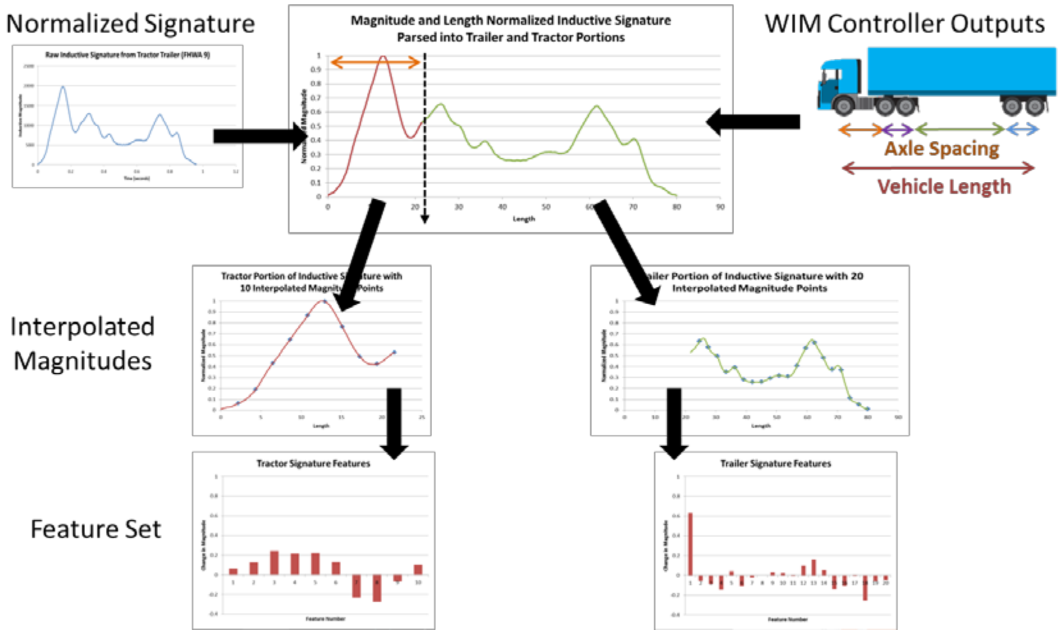


Figure 7 Data Fusion Approach for Combined WIM and Inductive Loop Signature Model

<u>Model Development</u>

The body classification model using the parsed features defined above was implemented as Feed Forward Neural Network with a single hidden layer comprised on 15 neurons. A neural network approach was chosen based on the previous success of this method with classifying inductive signatures *(10, 20)* and the ease of implementation through Matlab. The simplicity and effectiveness of the model implementation makes it ideal as a baseline reference. Each dataset was proportionally split by vehicle body class into training (60% of the total samples), validation (20%), and testing (20%) sets.

Preliminary Body Classification Model Results

The Correct Classification Rate (CCR) by vehicle class, as well as the average CCR for the model is used as the performance criteria for evaluating the classification model. CCR is defined as the number of correctly matched vehicles divided by the total number of vehicles. The overall CCR for the Class 9 trailer body classification model was 75%. Figure 8 shows the confusion matrix for the collapsed set of 18 body classes with an overall CCR of 80%. Classes were collapsed based on body type group and misclassification distribution. For FHWA Class 9 trailer body classes, individual class CCRs ranged between 29 and 100%, for classes with more than five samples in the test dataset. Tank semi-trailers had a low CCR (70%) and were commonly misclassified as basic platform semi-trailers. 53ft Box Containers also had a low CCR (36%) and were commonly misclassified as enclosed van semi-trailers. On the other hand, several classes showed high CCRs including basic and low boy platform semi-trailers, enclosed van semi-trailers, open top van semi-trailers, 40ft box containers, automobile transport semi-trailers, livestock semi-trailers, and non-semi-trailers listed in the confusion matrix as ‘Single Trailers’.

Target Classes	Single Trailers	Basic Platform	Low Boy Platform	Enclosed Vans	Reefer	Open Top Van	Drop Frame Van	Agricultural Van	40ft Container	20 ft Container	53 ft Container	Logging	Auto Transport	Dump	Livestock	Pneumatic Tank	Tank	Other	**Count**	**CCR**
	Predicted Classes																			
Single Trailers	2	2				1											1		6	33%
Basic Platform		232	7	7	4	4	1		6		2						4		267	87%
Low Boy Platform	1	2	60							1				1	1		1	1	68	88%
Enclosed Vans	1	9	1	370	51	6		2	1		1			2			1	1	446	83%
Reefer Van		6		43	246	1			1		2		1						300	82%
Open Top Van		3		2	2	64	1		2	1			1				1		77	83%
Drop Frame Van				1	1		13						1						16	81%
Agricultural Van		1				1		10									1		13	77%
40ft Container		3		1		1			39					1					45	87%
20 ft Container		1		1	1				1	2				1					7	29%
53 ft Container		2		25	1						16								44	36%
Logging		1										9							10	90%
Auto Transport		2	1		1								18		1				23	78%
Dump	1		1	2		2		4	1					11			6		28	39%
Livestock															18				18	100%
Pneumatic Tank																0			0	-
Tank		19			2	5			2	1			1	6			86		122	70%
Other		1																4	5	80%
																			1495	**80%**

Figure 8 Cross-classification Matrix for FHWA Class 9 Trailer Body Classification Model Collapsed Classes for Inductive Loop Signature and WIM

Conclusion

The integrated data source presented in this paper is a result of combining two highly complementary technologies, WIM and inductive signatures, to create a synergistic resource that is highly detailed, link specific, temporally continuous, up-to-date, and representative of the full truck population. The integrated data is a valuable and novel resource that fills a significant gap in truck data sources and has broader implications for emissions estimation and operations and monitoring in terms of safety, pavement management, and enforcement. While this case study focuses on body type classification, the integrated data source can also be leveraged to track truck OD patterns and travel times through truck re-identification techniques.

In this paper, we described the hardware interface between inductive signature equipment and WIM controllers which yielded a working configuration by which inductive signatures could be collected from a WIM controller. In addition, we described the data handling and storage procedures that allow the data to be easily joined to still images collected from a digital SLR camera triggered by vehicle presence over the inductive loop sensor. Also, a specialized software user interface was established to link photo, inductive loop signatures, and WIM data.

As a demonstration of the potential of the integrated data source, a truck body classification model was developed from the dataset collected at four WIM sites in California. The truck body classification scheme, initially based on VIUS, grew to include 35 trailer body types reflecting various body configurations found in the collected data. Results were promising with a CCR of 80% for multi-unit truck trailers consisting 18 trailer body classes.

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