Integration of Weigh-in-Motion and Inductive Signature Technology for Advanced Truck Monitoring

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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.

1 **Introduction**

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

20 The availability of detailed truck data pales in comparison to the large impact trucks have on our
21 environment, health, and infrastructure.   Agencies can obtain or estimate truck information from truck
22 Global Positioning Systems (GPS) data, paper-based surveys, vehicle detection stations (VDS) and weigh-
23 in-motion (WIM) stations, or from manual counts. Truck GPS data is capable of providing origin
24 destination (OD) tracking and performance statistics *(6)* but it does not provide truck characteristics
25 such as body types or industry served and represents only subpopulations. Additionally, there are
26 significant privacy concerns that limit the availability of GPS data, and large commercially available
27 datasets can be costly. Paper based surveys, such as the Vehicle Inventory and Use Survey (VIUS),
28 conducted by the US Census Bureau *(7)*, require expensive and time consuming data collection tasks like
29 interviews, intercept surveys, and mail-based surveys, and are only able to provide data from one point
30 in time from a sub-sample of the truck population and cannot be related to specific routes or links. A
31 further drawback of VIUS is that it was conducted only every five years, leaving a major data gap for
32 years in between, and was discontinued in 2002.   Loop detector data from VDS, such as that provided
33 by the Caltrans Performance Measurement System (PeMS) in California cannot measure truck volumes
34 directly and must rely on estimation algorithms to estimate broad truck classes, and can only be used at
35 aggregate levels *(8)*. Furthermore, while VDS are prevalent in metropolitan areas, they are limited
36 outside of them, and may not be ideal for capturing long haul truck traffic. WIM sites, on the other hand,
37 are able to provide truck counts by axle-based classes along with gross vehicle weights, but lack further
38 detail about the cargo type or distance traveled by trucks. Finally, manual counting entails recording
39 truck traffic for short sampling periods, and then extrapolating the sample counts to get an estimate for
40 a whole year, i.e. Annual Average Daily Truck Traffic (AADTT). AADTTs typically possess significant errors,
41 as they depend on short sampling periods which do not effectively capture the seasonal and diurnal
42 trends of truck travel patterns, even with the use of adjustment factors, due to the heterogeneous
43 disposition of truck travel patterns *(8)*.   Not surprisingly, the last method is discouraged by the USDOT
44 *(9)*.

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

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

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

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

1
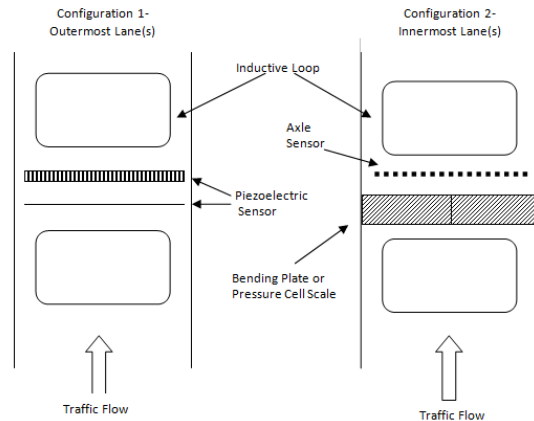
2   (a) WIM sensor locations in California   (b) WIM sensor configuration *(12)*

3   **Figure 1 WIM Sensor Characteristics**

4

5

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

18   # Integrating Data Sources

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

30

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

15 A prototype LSM adapter was designed to adapt advanced inductive loop signature detector cards to
16 replace the 1060 WIM LSM. Inductive loop signature data was logged into a field processing unit via the
17 USB port located on the front panel of each signature detector card. Schematic layouts showing a
18 comparison of the hardware setup for a standalone 1060 WIM controller and the proposed integration
19 with an advanced signature detector card are shown in Figure 2. With this set-up both inductive loop
20 signatures and WIM weight and axle spacing data can be collected at the WIM site.   Lastly, in addition
21 to inductive loop signature and WIM data, still image data was collected for each passing vehicle by
22 connecting a digital SLR camera with a remote trigger to the loop detector card such that each loop
23 activation triggered the camera and a series of still images were captured for each passing vehicle at a
24 rate of three frames per second while the vehicle was over the loop. In the next section, the data
25 processing to join the data types and photos is described.
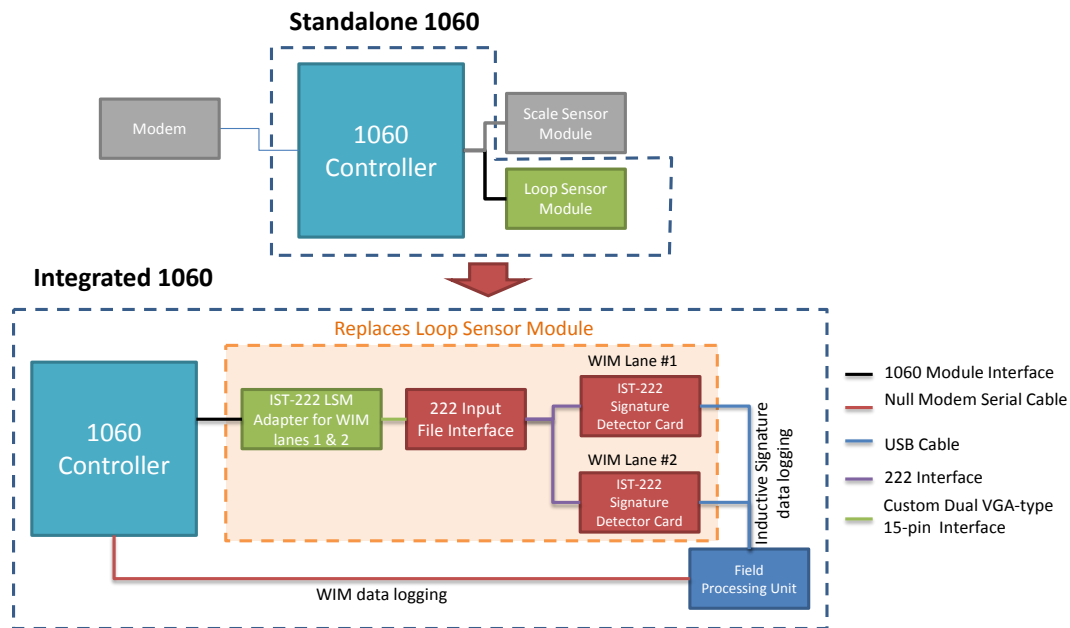
26

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

1
2 ***Data Handling***
3 All inductive loop signature, WIM record, and photo data was stored in a relational database powered
4 by PostgreSQL. Currently, the 1060 WIM controller output is captured as a text file which is processed
5 and stored as individual vehicle records according to a unique vehicle identification number.   Future
6 work will investigate the ability to replace the text file readout with binary data output from the serial
7 port of the WIM 1060 controller so that it can be directly inserted into the database without pre-
8 processing.   The inductive signature data is also pre-processed prior to insertion into the database
9 where each signature is stored according to a unique identification number.
10
11 A specially developed software user interface was developed in Visual Basic to efficiently integrate the
12 WIM data and signature data while also examining photos of each vehicle record for classification or
13 other desired purposes. The user interface was designed to communicate with the database and allow
14 the user to scroll through photos and select the vehicle class parameters while also linking inductive
15 loop signature records and WIM data records to the appropriate vehicle record. Figure 3 shows the user
16 interface for truck classification purposes.   The rightmost image is the inductive loop signature and the
17 table below the signature is the list of vehicle signature records within the user-designated time window.
18 The center FHWA image based on the FHWA class predicted by the WIM controller and the table below
19 is the list of WIM vehicle records with the user-designated time window for the WIM data.   The largest
20 table in the upper right is the list of vehicle records derived from the set of photos taken by the still
21 camera and grouped into vehicle records such that there may be one to five photos for each vehicle
22 record which the user can scroll through. The photo corresponding to the vehicle record, WIM record,
23 and inductive signature is show at the left. Lastly, since this interface was developed to classify vehicles
24 by body type, below the photo there is a selection region where the user designates the axle and body
25 configuration of the vehicle.

26 Classification is only one of the applications of this integrated data source and the method in which the
27 data is collected, pre-processed, and managed by the database can be applied for other uses for which
28 alternate user interfaces could be developed.   For example, for vehicle re-identification, using the same
29 pre-processing techniques and database structure, the user interface could display signature and WIM
30 information from two sites which the user could then toggle through to find matched vehicle pairs. Also,
31 pairing of the WIM and signature data can be undertaken by a simple program that can map the
32 signature to its WIM record based on time, headways, and duration, for example.   In the next section,
33 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

6

1 because each trailer body type may have dissimilar travel patterns, unique emission rates, and distinct
2 effects on congestion and safety. For example, in relation to travel patterns, box containers travel
3 between ports and intermodal facilities whereas enclosed vans might be commercial delivery vehicles
4 traveling between regional distribution centers and businesses. The breakdown of class 9 into the wide
5 variety shown in Figure 4 clearly illustrates the significant amount of unknown information that exists in
6 existing truck monitoring data.
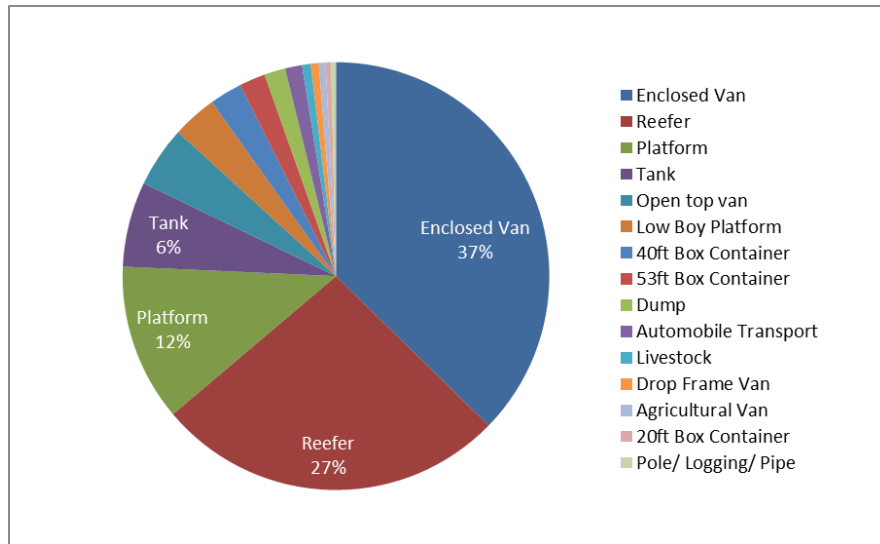
7

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

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

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

26 ***Classification Scheme Development***
27 A key component in the development of the body classification model was the creation of a
28 classification scheme that captured the diversity of truck bodies found in the data.   The truck body type
29 classification scheme originally based on the 28 VIUS defined body classes was further refined to 35

1   trailer body types as revealed by the collected data and shown in Table 1. Definitions of each body type

2   including a photo and inductive signature example can be found online[1].

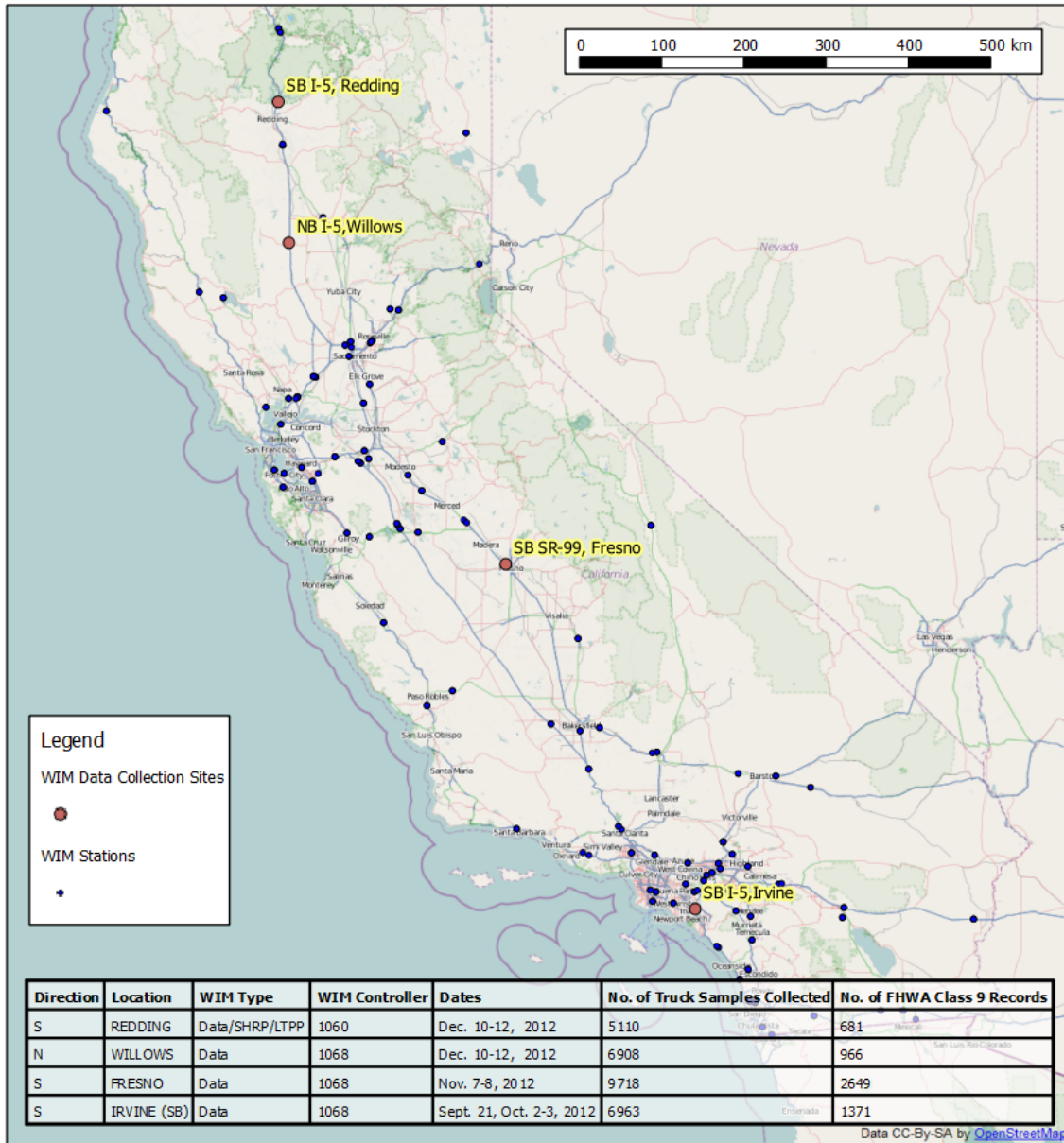3   **Table 1 Classification Scheme for Trailer Units**

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

4

5   ***Study Locations and Data***

6   Four sites were selected for data collection ranging geographically from urban centers in Southern

7   California to more rural areas in Northern California. Sites were selected to enhance the variety body

8   types collected. The location, site name, data type, date of collection, and number of collected truck
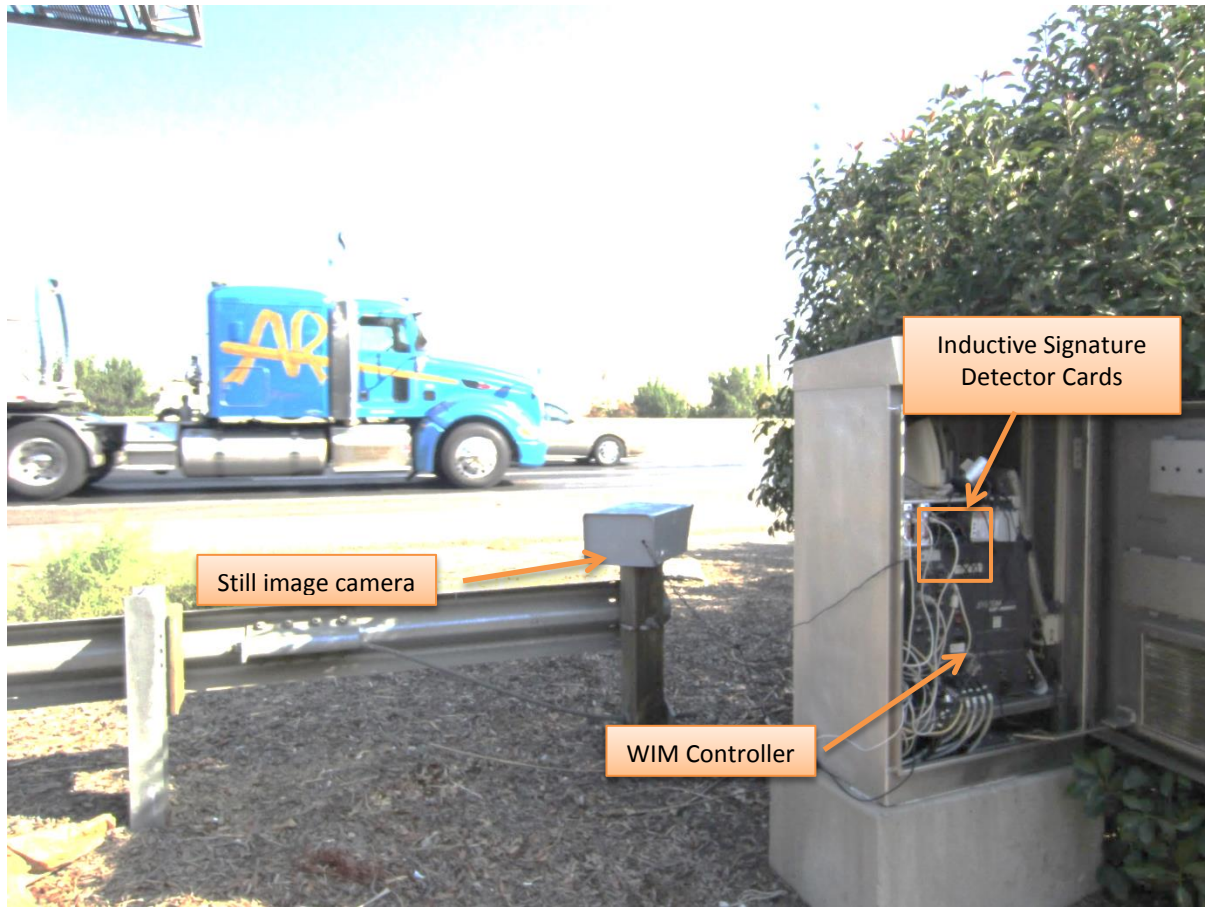
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[1] Trailer Unit Body Type Dictionary: http://goo.gl/nACH7

1   samples as well as the total number of FHWA Class 9 records are shown and summarized in Figure 5.

2   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

3

4   **Figure 5 WIM Data collection sites**

5

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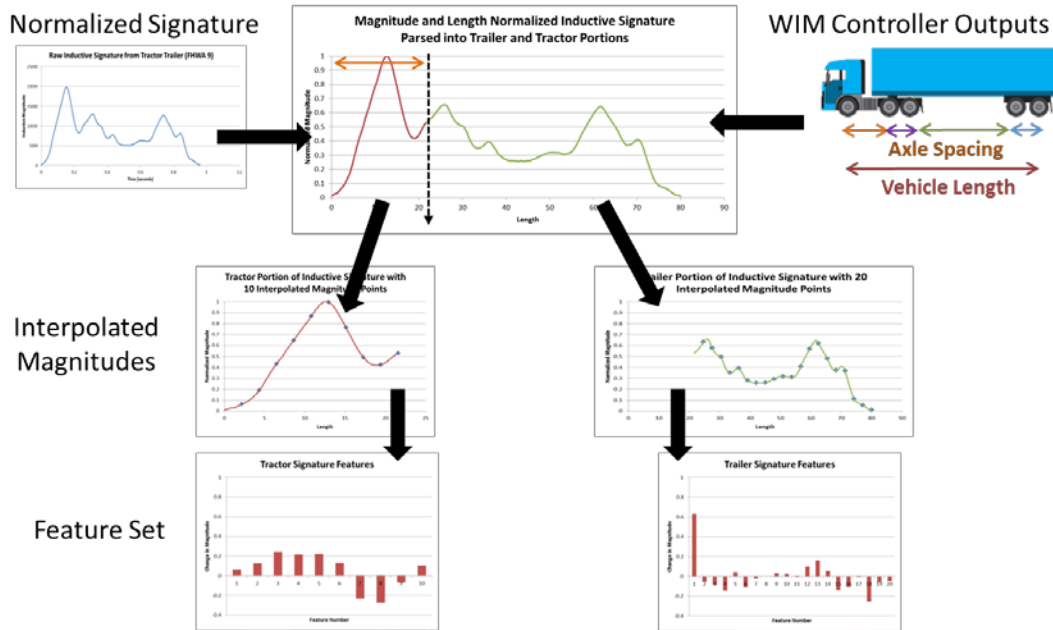
Figure 7 Data Fusion Approach for Combined WIM and Inductive Loop Signature Model

Model Development

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
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.

12

Acknowledgments

References

(1) Bureau of Transportation Statistics, Freight in America, January 2006,
http://www.bts.gov/publications/freight_in_america/, accessed online June 2012.

(2) California Air Resources Board, Mobile Source Emissions Inventory, Appendix G, Emissions Analysis
Methodology and Results: Medium-Heavy Duty Trucks, Heavy-Heavy Duty Diesel Trucks, and
Regulated Bus Categories, http://www.arb.ca.gov/regact/2010/truckbus10/truckbusappg.pdf,
accessed June 2012.

(3) Newell, G.F., A moving bottleneck, Transportation Research Part B: Methodological, Vol. 32, Issue 8,
November 1998, pp. 531-537.

(4) Douglas, J.G., Strategies for Managing Increasing Truck Traffic: A Synthesis of Highway Practice,
NCHRP Synthesis 314, 2003.

(5) Park, L. and Pierce, D., Large Truck Safety Trends, American Transportation Research Institute, May
2013.

(6) McCormack, E. and Hallenbeck, M., ITS Devices Used to Collect Truck Data for Performance
Benchmarks, Transportation Research Record: Journal of the Transportation Research Board, No.
1957, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 43-50.

(7) Vehicle Inventory and Use Survey (Discontinued), U.S. Census Bureau, 2002 Economic Census.

(8) Kwon, J., Varaiya, P., and Skabardonis, A., Estimation of Truck Traffic Volume from Single Loop
Detectors with Lane-to-Lane Speed Correlation, Transportation Research Record, 1856, 2003, pp.
106-117.

(9) Traffic Monitoring Guide, US Department of Transportation, Federal Highway Administration Office
of Highway Policy Information, 2001.

(10)Tok, A. and Ritchie, S.G., Vector Classification of Commercial Vehicles using a High Fidelity Inductive
Loop Detection System, In proceedings of the 89h Annual Meeting of the Transportation Research
Board, Washington D.C, 2010.

1   (11)Caltrans Truck Services, Data Weigh-in-Motion Webpage,
2   http://www.dot.ca.gov/hq/traffops/trucks/datawim/, accessed online June 2013.

3   (12)Lu, Q., Harvey, J., Le, J., Quinley, R., Redo, D., and Avis, J., Truck Traffic Analysis using Weigh-In-
4   Motion (WIM) Data in California, Pavement Research Center, Institute of Transportation Studies,
5   University of California, Berkeley, CA, 2002.

6   (13)Zhang, G., Wang, Y., and Wei, H., Artificial Neural Network Method for length-Based Vehicle
7   Classification Using Single Loop Outputs, Transportation Research Record: Journal of the
8   Transportation Research Board, No. 1945, 2006, pp 100-108.

9   (14)Coifman, B., and Kim, S., Speed Estimation and Length Based Vehicle Classification from Freeway
10   Single Loop Detectors, Transportation Research: Part C, Vol. 17, No. 4, 2009, pp. 349-364.

11 (15)Sun C. and Ritchie, S.G., Inductive Classifying Artificial Network for Vehicle Type Categorization,
12   Computer-Aided Civil and Infrastructure Engineering, Vol. 18, 2003, pp. 161-172.

13 (16)Cheung, S.Y., Coleri, S., Dundar, B., Ganesh, S., Tan, CW., and Varaiya, P., Traffic Measurement and
14   Vehicle Classification with Single Magnetic Sensor, Transportation Research Record: Journal of the
15   Transportation Research Board, No. 1917, 2005, pp. 173-181.

16 (17)Ki, Y.K., Baik, D.K., 2006. Vehicle-Classification Algorithm for Single-Loop Detectors Using Neural
17   Networks, IEEE Transactions on Vehicular Technology 55(6).

18 (18)Jeng, S.T. and Ritchie, S.G., Real-time vehicle classification using inductive loop signature data,
19   Transportation Research Record No. 2086, 2008, pp 8-22.

20 (19)Liu, H., Tok, Y.C.A., and Ritchie, S.G., Development of a Real-Time On-Road Emissions Estimation and
21   Monitoring System, IEEE ITSC 2011 Conference Paper, October 5-7, 2011, Washington, D.C.

22 (20)Federal Highway Administration, Truck Characteristics Analysis, Washington, D.C. July 1999

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