Weigh-In-Motion Station Monitoring and Calibration using Inductive Loop Signature Technology

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Word Count: 3,345 + 14 Figures and 1 Tables = 7,095 words

Submitted for Presentation
94th Annual Meeting of the Transportation Research Board
January 11-15, 2015, Washington, D.C.
ABSTRACT
Despite heavy vehicles representing a small portion of vehicles on the roads, they have significant influences on pavement, safety, environment, energy consumption, and the performance of traffic system. Weigh-In-Motion (WIM) is the major technology employed to collect truck data on the freeways over three decades. However, WIM stations usually are not calibrated in a timely fashion and the calibration is mainly performed using five-axle single-trailer trucks once every half a year to three years. A potential solution is to adopt a comprehensives remote calibration monitoring system. Therefore, this study proposed an inductive loop signature-WIM based approach, which utilized both inductive loop signatures and WIM data to track heavy vehicles at WIM stations and generated "Matched Vehicle Pairs (MVPs)" for WIM station monitoring and calibration. The algorithm was established based on a previously developed truck tracking algorithm, RTREID-2MT, and integrated with a Bayesian reidentification model to filter out the MVPs that were most likely incorrectly matched by the system. The MVPs were then utilized for WIM station monitoring and temporary approximate calibration applications. Case study showed that the upstream station reported low weights, while the downstream station reported high axle spacings. The average offsets of the drive tandem axle spacing, Gross Vehicle Weight (GVW), and steer axle weight between the stations were thus derived from MVPs on a per lane basis and successfully applied to calibrate the problematic stations.
INTRODUCTION
Despite heavy vehicles representing a small portion of vehicles on the roads, they have significant influences on pavement, safety, environment, energy consumption, and the performance of traffic system. Weigh-In-Motion (WIM) is the major technology employed to collect truck data on the freeways over three decades. A WIM system requires sophisticated data collection sensors and costly equipment for set-up and calibration. Both of which will function properly only under a controlled environment. A main challenge/limitation that has been identified while deploying WIM technologies is that WIM stations suffer from data accuracy issues due to the vehicle dynamics affected by the pavement conditions over time of day and season of year (1). Thus, WIM stations need to be calibrated in order to provide accurate data and the calibration needs to be repeated regularly. Although the ASTM E1318-09 is a widely used calibration procedure, different states are found to follow different procedures and have different calibration requirements (2). It is also found that the calibration of WIM stations is not performed in a timely fashion. Depending on the states, a WIM station is usually calibrated using five-axle single-trailer trucks (3) once every half a year to three years (4). In addition, onsite visit, road testing, and parameter fine-tuning at a WIM site are very expensive. Therefore, how to effectively utilize the valuable WIM data, monitor WIM stations' performance and identify out of calibration stations are especially important to government agencies.

A potential solution is to adopt a remote calibration monitoring system. A remote calibration monitoring system can assist in performing data quality checks and approximate calibration tuning. The objectives of the calibration monitoring procedures (5) include:

- Maintain system calibration throughout the life of the system.
- Verify the desired effects of calibration factor adjustments on WIM weight, axle spacing, and vehicle length outputs.
- Identify weigh sensors that are intermittently and/or subtly malfunctioning.
- Adjust calibration factors for a weigh sensor exhibiting calibration drift pending onsite recalibration using test trucks.
- Temporarily assign calibration factors for a weigh sensor replacement pending onsite recalibration using test trucks.
- Schedule onsite calibrations/validation for sites with most need when funding and/or resources for running test trucks is limited.

In addition to monitor the gross vehicle weight distribution and average drive tandem axle spacing, other useful statistics may include average steer axle weight, steer axle's average right and left wheel weights, and standard deviation for the steer axle's average right and left wheel weights (5).

A preliminary study from Cetin and Monsere (6) indicated that sensor calibration problems and some sensor failures would be consistent across all observations, causing a shift in the density plot rather than outliers. They also found that the means and standard deviations of the weight and spacing plots were most likely indicators of the difference in sensor calibration parameters. For example, large standard deviations in the axle-weight error are most likely attributed to the pavement profile at the WIM stations, different sensor types, poor calibration, or a failing sensor. In addition, the cause of increased standard deviations in the axle spacing could be failing axle-sensor detectors. It was because when a sensor failed, it would sometimes miss light-weight axles, causing axle-spacing data and classification data to be erroneous.

With a comprehensives remote calibration monitoring system, data analysts can promptly identify out of calibration WIM stations and the possible causes. Temporary approximate calibration tuning can then be performed offsite so that reasonable performance can be maintained at the problematic WIM stations before an onsite re-calibration can be a performed. Therefore, we propose an Inductive Loop Signature-WIM based monitoring system for existing WIM stations in this research. The system utilizes both Inductive Loop Signatures and WIM data to track heavy vehicles at WIM stations (7) to generate "Matched Vehicle Pairs (MVPs)." The MVPs are then utilized for WIM station monitoring and calibration.
This paper is organized into five main sections including this introductory section. The second section discusses truck tracking based on WIM and inductive loop signature technologies. The third section presents the proposed approach for WIM station monitoring and calibration. The fourth section presents the results and findings. The last section concludes this study and outlines future works.

**TRUCK TRACKING BASED ON WIM AND INDUCTIVE LOOP SIGNATURE TECHNOLOGIES**

Over the last decade, researchers have attempted to track trucks using WIM data. Cetin et al. investigated different methods for solving the truck reidentification problem and explored some of the factors that affected the accuracy of the results (6, 8, and 9). In their studies, archived data from WIM stations in Oregon were used for developing, calibrating, and testing the Bayesian reidentification algorithms. A comprehensive analysis was aimed to investigate the key factors affecting the accuracy of the results.

The analyses were performed by employing the Bayesian reidentification algorithm to match commercial vehicles that crossed upstream and downstream pairs of WIM sites that were separated by long distances ranging from 70 to 214 miles. Data from 14 different pairs of WIM sites were used to evaluate how the matching accuracy was affected by various factors such as the distance between two sites, travel time variability, truck volumes, and sensor accuracy or consistency of measurements. It was found that sensor accuracy and volumes had the greatest impacts on matching accuracy whereas the distance alone did not have a significant impact. Although these studies show good matching rates using WIM data, the Bayesian reidentification algorithms require sample data for training and calibration.

Researchers have also focused on developing vehicle tracking systems using other technologies (e.g., Inductive Loop Detection (ILD), Bluetooth, Global Positioning System (GPS), cell phone, image processing, Automatic Vehicle Identification (AVI) tags, etc.). Recently, Jeng and Chu developed a truck tracking algorithm, RTREID-2MT, which combines the use of both WIM data and the inductive loop signature data (7). The inductive loop signature data are the analog waveform outputs from advanced detector cards, which measure and output the inductance change (i.e., the analog waveform) in an inductive loop sensor. This analog waveform outputs generated by each traversing vehicle are referred to as the inductive loop signatures or inductive vehicle signatures.

The RTREID-2MT was developed and tested with three basic scenarios (7):

1) Scenario 1: Reidentification using vehicle signature data.
2) Scenario 2: Reidentification using vehicle signature and WIM vehicle class and axle spacings data.
3) Scenario 3: Reidentification using vehicle signature and WIM vehicle class, axle spacings, and weight data.

The performance was demonstrated between two WIM stations 19 miles apart from SR-57 SB Orange Station to I-5 SB Irvine Station, as shown in **FIGURE 1**. It was found that the proposed approach was able to work with different types of data and generate promising tracking performance with both vehicle signature and WIM data applied. The best results were obtained from Scenario 3 with about 61.5% Correct Match Rate (CMR) and 5.5% Error Rate (ER).

The output from the RTREID-2MT can be utilized to monitor the performance of WIM stations, identify off-calibrated WIM stations, and perform temporary approximate calibration. Possible out of calibration WIM stations can be identified by evaluating the axle spacing and axle weight information of the MVPs. However, the CMR should reach a desirable level so that satisfactory system reliability can be achieved. Therefore, the RTREID-2MT was modified to integrate with the Bayesian reidentification model (8) to further improve the CMR, as discussed in the following section.
THE PROPOSED TRUCK TRACKING ALGORITHM FOR WIM STATION MONITORING AND CALIBRATION

Based on the current results from the RTREID-2MT, the CMRs are about 61%. To further improve the CMRs, the Bayesian reidentification algorithm (8) developed by Cetin et al. was integrated into the RTREID-2MT to filter out the MVPs that were most likely incorrectly matched by the system, as shown in FIGURE 2.
The idea is to further narrow down the MVPs using the probability generated by the Bayesian reidentification model. By doing so, only vehicles with probability over a preferred threshold (e.g., 0.9~0.95) will be selected to help increase the CMR to be at least over 85%~90% for FHWA Class 9 vehicles (as defined in TABLE 1). Then, the MVPs will be used for WIM station monitoring and calibration applications.

**FIGURE 2** Framework of RTREID-2MT integrated with Bayesian reidentification model.

The objective was to investigate the threshold of the probability level. The selected results are shown in **FIGURE 3**, and **FIGURE 4**. It can be seen that better performances are obtained when vehicles from FHWA Class 6 and above are considered, and the CMRs range from 73% to 88% with the

**TABLE 1** FHWA Class Definition by FHWA Vehicle Types (3)

<table>
<thead>
<tr>
<th>FHWA Class</th>
<th>FHWA Vehicle Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>FHWA Class 1</td>
<td>Motorcycles</td>
</tr>
<tr>
<td>FHWA Class 2</td>
<td>Passenger Cars</td>
</tr>
<tr>
<td>FHWA Class 3</td>
<td>Other Two-Axle, Four-Tire Single Unit Vehicles</td>
</tr>
<tr>
<td>FHWA Class 4</td>
<td>Buses</td>
</tr>
<tr>
<td>FHWA Class 5</td>
<td>Two-Axle, Six-Tire, Single-Unit Trucks</td>
</tr>
<tr>
<td>FHWA Class 6</td>
<td>Three-Axle Single-Unit Trucks</td>
</tr>
<tr>
<td>FHWA Class 7</td>
<td>Four or More Axle Single-Unit Trucks</td>
</tr>
<tr>
<td>FHWA Class 8</td>
<td>Four or Fewer Axle Single-Trailer Trucks</td>
</tr>
<tr>
<td>FHWA Class 9</td>
<td>Five-Axle Single-Trailer Trucks</td>
</tr>
<tr>
<td>FHWA Class 10</td>
<td>Six or More Axle Single-Trailer Trucks</td>
</tr>
<tr>
<td>FHWA Class 11</td>
<td>Five or fewer Axle Multi- Trailer Trucks</td>
</tr>
<tr>
<td>FHWA Class 12</td>
<td>Six-Axle Multi-Trailer Trucks</td>
</tr>
<tr>
<td>FHWA Class 13</td>
<td>Seven or More Axle Multi- Trailer Trucks</td>
</tr>
</tbody>
</table>
probability level > 0.9. The CMRs of FHWA Class 9 vehicles are about the same for Scenarios 2 and 3, but larger number of correct match vehicles are observed for probability level = 0.9.

FIGURE 3  System performance by probability and scenarios.

In addition, when the probability level is < 0.9, the number of mismatch vehicles of FHWA Class 9 increases gradually, as shown in FIGURE 4. Therefore, the threshold of probability level is set to 0.9, and the reidentification results from Scenario 2 are selected.

FIGURE 4  Probability level by number of correct match vehicle, number of mismatch vehicles, and CMR for FHWA Class 9: Scenario 2.
WIM STATION MONITORING AND CALIBRATION
The WIM data used for evaluation include vehicle length, axle spacing 2-3, gross vehicle weight (GVW), axle weight 1, axle weight 2, axle weight 3, axle weight 4, and axle weight 5. **FIGURE 5** compares the selected variables at SR-57 SB Orange Station (upstream) and I-5 SB Irvine Station (downstream) based on Matched Vehicle Pairs (MVPs).

**FIGURE 5** Comparisons of WIM data at SR-57 SB Orange Station and I-5 SB Irvine Station.

It can be observed that either the WIM sensors at the downstream station grossly overestimate the length and weight, or the WIM sensors at the upstream station grossly underestimate the length and weight.

**FHWA Class 9 GVW Distribution and Axle Spacings**
A FHWA Class 9 GVW distribution graph and drive tandem axle spacing histograms of the MVPs were prepared to examine and identify the problematic station, as shown in **FIGURE 6** and **FIGURE 7**. The information presented in **FIGURE 6** and **FIGURE 7** are obtained from the same vehicles (FHWA Class 9 MVPs) but at different locations (i.e., SR-57 SB Orange Station and I-5 SB Irvine Station). Therefore, reasonable and similar distributions between the two WIM stations should be found in **FIGURE 6** and **FIGURE 7** if the two stations are under normal conditions.

It is known that the empty truck distribution will typically peak at "30~35" kips and the loaded truck distribution will typically peak at "70~80" kips (10). However, **FIGURE 6** shows that the WIM sensors at SR-57 SB Orange Station (plotted as red dot line) reported lower weights for both the empty and loaded truck distribution peaks. The empty truck distribution peaks at "27.5~30" kips and the loaded truck distribution peaks at "65~67.5" kips, which are both lower than their corresponding typical values.
FIGURE 6  FHWA Class 9 GVW distribution by station and count for the MVPs.

For the axle spacings, the average drive tandem axle spacing (i.e., axle spacing 2-3) for FHWA Class 9 vehicles is about 4.3 feet \((5\text{ and }10)\). However, as shown in FIGURE 7, the WIM sensors at I-5 SB Irvine Station (plotted as blue bar) reported high drive tandem axle spacings. The majority of FHWA Class 9 vehicles at this station have the drive tandem axle spacing at 4.5 ft and 4.4 ft, which is above the average value.

FIGURE 7  Drive tandem axle spacing histograms by station and count for the MVPs.

Temporary Approximate Calibration of Drive Tandem Axle Spacings
The drive tandem axle spacings were found too high at the I-5 SB Irvine station. Since the drive tandem axle spacing histograms observed from the SR-57 SB Orange Station seems normal, the average offsets for each lane can be calculated and applied to the I-5 SB Irvine Station. The lane-based average offsets can be directly derived from the MVPs. FIGURE 8 shows that the calibrated drive tandem axle spacing at the I-5 SB Irvine Station has the peak at 4.3 ft after applying the average offsets for each lane to the MVPs.
The lane based average offsets for the drive tandem axle spacing can be applied to the whole dataset collected at the I-5 SB Irvine Station. **FIGURE 9** shows the FHWA Class 9 drive tandem axle spacing histograms using WIM data collected on 03/21/13. It can be seen that lane 4 (plotted as red bar) is the most problematic one, which has the peak at 4.5 ft. **FIGURE 10** shows the drive tandem axle spacing histograms before and after the calibration at the I-5 SB Irvine Station for the 03/21/13 WIM data. The SR-57 SB Orange Station is also included for comparison.
Temporary Approximate Calibration of Steer Axle Weight and Gross Vehicle Weight

For weight calibration, it was known from FIGURE 6 that the SR-57 SB Orange station reported weights that were too low. This information was further investigated on a per-lane basis using the 03/21/13 WIM data. As shown in FIGURE 11 and FIGURE 12, it was found that lane 4 reported lower weights while lane 5 actually reported higher weights at the SR-57 SB Orange station.
Again, the lane-based average offsets can be directly derived from the MVPs. Therefore, the average offsets (i.e., $ADJ^i_{\text{grw&axw1}}$) of the GVW and the steer axle weight for each lane were calculated and applied using the following equations:

$$ADJ^i_{\text{grw&axw1}} = \frac{\text{avgoffsetGVW}^i + \text{avgoffsetAXW1}^i}{2}$$  \hspace{1cm} (1)$$

$$\text{avgoffsetGVW}^i = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} Veh_{ij} \times \text{avgGVW}^j_i}{\sum_{i=1}^{m} \sum_{j=1}^{n} Veh_{ij}}$$  \hspace{1cm} (2)$$

$$\text{avgoffsetAXW1}^i = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} Veh_{ij} \times \text{avgAXW1}^j_i}{\sum_{i=1}^{m} \sum_{j=1}^{n} Veh_{ij}}$$  \hspace{1cm} (3)$$

where,

$\text{avgoffsetGVW}^i$: average offset of GVW for lane $i$ at station $c$ that needs adjustment

$\text{avgGVW}^j_i$: average GVW for lane $j$ at station $t$ that does not need adjustment

$\text{avgGVW}^c_i$: average GVW for lane $i$ at station $c$ that needs adjustment

$\text{avgoffsetAXW1}^i$: average offset of axle weight 1 for lane $i$ at station $c$

$\text{avgAXW1}^j_i$: average of axle weight 1 for lane $j$ at station $t$

$\text{avgAXW1}^c_i$: average of axle weight 1 for lane $i$ at station $c$

$Veh_{ij}$: number of vehicles traveling from lane $i$ at station $c$ to lane $j$ and station $t$

$m$: number of lanes at station $c$

$n$: number of lanes at station $t$

**FIGURE 13** shows the calibrated GVWs of the MVPs at the SR-57 SB Orange Station generally match the trend of the GVWs at the I-5 SB Irvine Station.
CONCLUSIONS AND FUTURE RESEARCHES
In this study, an inductive loop signature-WIM based approach for WIM station monitoring and calibration was proposed. A previously developed truck tracking algorithm, RTREID-2MT was modified to integrate a Bayesian reidentification model to filter out the matched vehicle pairs (MVPs) that were most likely incorrectly matched by the system. Only the matched FHWA Class 9 vehicle pairs with probability over 0.9, which would increase the CMR to 89%, were selected for WIM station monitoring.
and temporary approximate calibration applications. It was found from the MVPs that the upstream station reported weights that were too low, while the downstream station reported the axle spacings that were too high. The average offsets of the drive tandem axle spacing, GVW, and steer axle weight between the stations were thus derived from the MVPs on a per lane basis and applied to approximately calibrate the problematic stations.

The proposed approach has potential to fundamentally change the way WIM stations are operated and monitored in practices. Because existing WIM stations require sophisticated data collection sensors, periodic and proper calibration is critical to their performance. The integration of inductive loop signature technology offers a low-cost solution to keep track of truck movement, provide truck movement data for WIM calibration, monitor performance of WIM stations, identify out-of-calibration stations, and perform temporary calibration. Therefore, the proposed approach will not only reduce the cost of WIM calibration, but also provide the ability to monitor system performance continuously. Future researches will focus on developing a comprehensively remote WIM performance evaluation and calibration monitoring system. In addition, to implement the proposed approach in the real world, a pioneer research is undergoing to verify the performance of the proposed approach with data collected from well calibrated WIM stations. Once the performance of the proposed approach is validated, the federal and state agencies can discuss and approve the use of the proposed approach.

ACKNOWLEDGEMENT

The research was supported by Federal Highway Administration's SBIR program. The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented. This paper does not constitute a standard, specification, or regulation. The authors thank to the FHWA Contracting Officer Technical Representative, Mr. Steven Jessberger, for his guidance on our research. We also would like to thank Prof. Andrew Nichols of West Virginia University for his inputs on WIM data quality control and Mr. Stan Norikane of California Department of Transportation (Caltrans) for his supports on the use of Caltrans WIM facilities in the research.

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