Enhancing a Vehicle Re-Identification Methodology based on WIM Data to Minimize the Need for Ground Truth Data

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Presentation Overview

- Background
  - Overall research objective
  - In-pavement WIM systems
  - Previous related research
  - Re-Identification methodology
  - Methodology shortcomings

- Methodology Enhancements

- Case Study
  - Comparison of results
  - Application of re-identification for WIM calibration

- Summary
Background

Overall Research Objective

- Identify individual commercial vehicles at multiple locations along a route by matching its axle attributes (number, spacing, weight) measured by weigh-in-motion (WIM) or automated vehicle classification (AVC) stations

Applications
- Travel time estimation
- Origin-destination flows
- Sensor accuracy assessment
Background

In-Pavement Weigh-in-Motion Systems

- In-pavement sensors and roadside equipment
  - Inductive loops (speed and vehicle length)
  - Piezometer (axle spacing and weight)
  - Bending plate (weight)
  - Load cell (weight)

- Pertinent Output
  - Speed
  - Axle-to-Axle Spacing
  - Axle Weight
  - Vehicle Classification (based on scheme and axle attributes)
Background

Research on Re-Identification of Vehicles

- Automatic Vehicle Identification (AVI)
  - Transponder
  - Automatic License Plate Recognition
  - Bluetooth
  - Wi-fi
- Indirectly through Sensor Outputs
  - Vehicle Length from Inductive Loops
  - Inductive Loop Signature
  - Video Imagery
  - Weigh-in-Motion
Background

Re-Identification Research by Authors

- Based WIM/AVC Data
  - 2006 NATMEC - “Utilizing Weigh-in-Motion Data for Vehicle Re-Identification.”
  - 2007 TRB - “Commercial Vehicle Re-identification Using WIM and AVC Data.”
  - 2009 TRB - “Improving the Accuracy of Vehicle Re-identification Algorithms by Solving the Assignment Problem.”
  - 2010 TRB - “Bayesian Models for Re-identification of Trucks over Long Distances Based on Axle Measurement Data.”
  - 2014 TRB - “Re-identification of Trucks Based on Axle Spacing Measurements to Facilitate Analysis of Weigh-in-Motion Accuracy.”
2012 SBIR Project 12.2-FH4-007

Title: Tracking Heavy Vehicles based on WIM and Vehicle Signature Technologies

Awardee: CLR Analytics Inc.

Status: Phase 1 complete, awaiting Phase 2

Methodology: Combine re-identification algorithm based on axle attributes (from WIM or AVC) with re-identification algorithm based on inductive loop signatures to be able to match individual vehicles at WIM and/or AVC stations
Background

Re-Identification Methodology

- **Step 1. Bayesian Model Training and Calibration**
  - Determine Probability Distribution Functions (PDFs) based on “known” matches between a pair of WIM stations
  - PDFs developed for Axle Spacing and Vehicle Length
  - Accounts for difference in speed calibration

![Graph showing the distribution of vehicle length differences between upstream and downstream stations. The average is +0.4% with a standard deviation of 1.7%.]
Step 2. Search for Vehicle Crossing Upstream WIM at Downstream WIM (re-identification)

- Define Search Space (SS) based on a travel time window between the two WIM stations
- Calculate the probability (Bayes theorem) of a match between the upstream vehicle and each vehicle in the downstream SS
- Assign as a match, the vehicle from downstream SS that yielded the largest probability
- Minimum probability thresholds can be defined per application
  - Higher probability threshold – fewer matches but higher reliability
  - Lower probability threshold – more matches but less reliability
Background

Re-Identification Methodology

- Bayesian Model for Matching
  - For a vehicle pair \( i-j \) (upstream-downstream), the probability of a match (\( \delta_{ij} = 1 \)) is:

    \[
    P(\delta_{ij} = 1|\chi_{ij}) \sim \frac{f(x_{ij}|\delta_{ij} = 1)g(t_{ij})}{f(x_{ij}|\delta_{ij} = 1)g(t_{ij}) + \alpha}
    \]

  - \( g(t_{ij}) \): PDF for travel time between stations
  - \( f(x_{ij}|\delta_{ij} = 1) \): PDF for axle attributes (axle spacing and vehicle length) if \( i \) and \( j \) are the same truck
Background

Methodology Shortcomings

- Model training accounts for calibration variations between stations, and is therefore needed for each pair of stations being used for re-identification.

- Models are trained using the WIM measurements of known vehicle matches (ground truth).
  - **Manual Video Analysis** – Roadside cameras at 2 WIM systems 1 mile apart in Indiana. Manually match same vehicle in videos.
  - **Automatic Transponder** – Oregon commercial vehicle transponder program and readers at 14 WIM systems statewide. Transponder ID captured in WIM record.
  - **Manual Data Analysis** – Manual analysis of likely “matches” based on expected travel time between 2 WIM stations and WIM axle measurements to identify high correlations. Applied to WV data.
Step A. Select all vehicles at upstream WIM that have only one possible match in downstream WIM “search space”
- Search space defined based on reasonable travel time range
- Must be same vehicle class and number of axles

Step B. Compare total vehicle length of each “match” to determine highly correlated vehicle types
- Unique vehicle types are most commonly identified

Step C. Compare axle spacing measurements of each “match” in highly correlated vehicle types and eliminate matches that differ by more than 10%
Background

Training Dataset w/ Manual Data Analysis

- Technique applied to 2 WIM stations in West Virginia

- **Step A.** 862 vehicles at upstream WIM with single match at downstream WIM

- **Step B.** Vehicle types with highest correlation
  - Class 10 with 7+ axles (n = 9)
  - Class 12 or 13 (n = 27)
  - Class 15 with 6+ axles (n = 16)

- **Step C.** 3 suspected outliers removed based on axle spacing analysis
Background

Methodology Shortcomings

- "Single Window" search space
  - Applies to Step 1 (Training w/ Manual Data Analysis) and Step 2 (Re-identification)
  - Search for best upstream vehicle match @ downstream WIM
  - Two or more upstream vehicles may get matched to the same downstream vehicle
  - All vehicles are matched including those with a low probability
Methodology Enhancements

- Update the methodology to utilize “Dual Window” search space
- Additionally search for best match at upstream WIM for each downstream vehicle (still in same direction of travel)
- Step 1A of the Manual Data Analysis Technique for Training
  - Identify vehicle pairs as possible matches by selecting all vehicles from upstream WIM with only one vehicle in downstream search space AND verify that this upstream vehicle is the only vehicle in the upstream search space
- Step 2 Re-identification
  - Same as above, but make sure the vehicle pair is the “highest probability” match from upstream→downstream AND downstream→upstream
Analysis Case Study
West Virginia WIM Stations

Data Overview
- 5 days of data in 7/2011
- Site 5 = 10,247 veh
- Site 6 = 6,178 veh

<table>
<thead>
<tr>
<th>Site 5 to Site 6</th>
<th>Distance</th>
<th>Travel time window</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Lower bound</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Upper bound</td>
</tr>
<tr>
<td>86 miles</td>
<td>60 min</td>
<td>100 min</td>
</tr>
</tbody>
</table>

Site 5 to Site 6 Distance: 86 miles
Travel time window: 60 min to 100 min

Map showing the location of Site 5 and Site 6 with a distance of 86 miles and a travel time window of 60 min to 100 min.
Step 1A. Training Comparison

Single vs. Dual Window Results

- Identify pairs with only 1 possible match in search space based on vehicle class and number of axles only

![Bar graph showing the comparison between Single Window and Dual Window results for different vehicle classes with all Class 9 eliminated from training.]
Step 1B/1C. Training Comparison

Single vs. Dual Window Results

- Eliminate pairs where vehicle length and axle spacing are > ±10%
Step 1B/1C. Training Comparison
Single vs. Dual Window Results

- Eliminate pairs where vehicle length and axle spacing are > ±10%
Step 1. Training Comparison
*Single vs. Dual Window Results*

- **Probability Distribution Function Comparisons**
  - (Upstream-Downstream)/Downstream
  - Standard Deviations decrease from Single to Dual

<table>
<thead>
<tr>
<th></th>
<th>Single Window (5→6)</th>
<th>Dual Window</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Vehicle Pairs w/in ±10%</td>
<td>161</td>
<td>82</td>
</tr>
<tr>
<td>Vehicle Length PDF</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-1.1%</td>
<td>-0.5%</td>
</tr>
<tr>
<td>Std Dev</td>
<td>3.1%</td>
<td>2.6%</td>
</tr>
<tr>
<td>Axle 1-2 Spacing PDF</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>+1.2%</td>
<td>+1.3%</td>
</tr>
<tr>
<td>Std Dev</td>
<td>3.2%</td>
<td>2.0%</td>
</tr>
</tbody>
</table>
Step 2. Re-Identification

Single vs. Dual Window Results

- Bayesian probabilities of a match

**Single Window**
- \( n = 4,917 \)

**Dual Window**
- \( n = 3,325 \)

**Single Window Only**
- \( n = 1,592 \)
Application of Re-Identification Results

- Utilized matched vehicles using Dual Window
- For WIM calibration assessment, matches with high probabilities (>98%) were used for this analysis
- Can be used to assess differential calibration between Site 5 and Site 6 in southbound direction
  - Vehicle length used to compare (inductive) loop spacing calibration (distance between leading edge)
  - Axle spacing used to compare axle sensor calibration (distance between sensors)
  - Axle weight used to compare axle weight calibration
Application of Re-Identification Results

Vehicle Classification of Matches

Used for Calibration Assessment

Majority of matched vehicles are Class 9
Application of Re-Identification Results

Comparison of Vehicle Lengths (Class 9-12)

\[ y = 0.9981x \]
\[ R^2 = 0.9892 \]

Very close calibration
Application of Re-Identification Results

Comparison of Axle Spacing (Class 9-12)

Axle 1-2: $y = 0.9838x$, $R^2 = 0.9988$
Axle 2-3: $y = 0.9859x$, $R^2 = 0.9988$
Axle 3-4: $y = 0.9866x$, $R^2 = 0.9998$
Axle 4-5: $y = 0.9863x$, $R^2 = 0.9999$

Very close calibration
Application of Re-Identification Results

Comparison of Axle Weights (Class 9-12)

Intercept = 0

Axle 2 consistently heavier than Axle 3

Axle 2 heavier upstream compared to Axle 3

Upstream ~10% heavier

Not much “spread” in Axle 1
Summary

- Model Training with manual data analysis increases the applicability of the re-identification methodology.
- Dual window search space helps eliminate unlikely matches in both the training and re-identification steps.
- Attributes of re-identified vehicles can be used to compare the relative calibration of two WIM sites.
  - Perhaps field calibration can be performed at a few reference sites and calibration checked at other sites through re-identification.
  - Axle weight comparisons could be utilized to improve portable WIM if two sensors/systems placed side-by-side (rather than averaging the two weights).
Vehicle length and axle spacing calibrations were very close.

Based on axle weight comparisons, there appear to be some possible outliers or mis-matched vehicles.

Axle 1 weights do not vary enough to reliably estimate the differential weight calibration.

Axle weight calibration varied across different axles, but upstream WIM appeared to weigh ~10% heavier than downstream WIM based on Axles 3-5.

Axle 2 weights tended to be heavier than Axle 3 weights.

Axle 4 and 5 didn’t have same relationship.