A Wireless Accelerometer-Based Automatic Vehicle Classification Prototype System

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Abstract

Automatic Vehicle Classification (AVC) systems provide data about vehicle classes that are used for many purposes. This paper describes a prototype axle count and spacing AVC system using wireless accelerometers and magnetometers. The accelerometers detect vehicle axles and the magnetometers report vehicle arrivals and departures and estimate speed. The prototype system is installed on I-80 at Pinole, CA and tested under various traffic conditions. Video images and reports from a nearby commercial Weigh-In-Motion (WIM) station provide ground truth to evaluate the performance of the system, including classification, axle spacing and vehicle counts. The results show the prototype AVC system is reliable in classifying vehicles even under congested traffic with 99% accuracy.

Keywords: automatic vehicle classification, axle count, axle spacing, accelerometer, magnetometer, wireless sensor

Word Count: 4101 words + 13 x 250 figures/table = 7351 words
1. Introduction

Vehicle classification data are collected for many purposes. For example, each state annually reports vehicle counts by class for the Highway Performance Monitoring System (HPMS). Automatic Vehicle Classification (AVC) is also the basis for Intelligent Transportation System (ITS) applications such as automated toll collection.

Current AVC technologies have some deficiencies. Commercial systems using piezoelectric devices are expensive to install and maintain (1). Non-intrusive technologies such as video imaging, acoustic and infrared sensing are sensitive to weather and lighting conditions (2, 3, 4). Loop-based technologies do not perform well under congestion (5). Methods based on vehicle length can only distinguish cars and trucks, and are thus unsuited for applications that need more detailed classification, such as axle count and spacing (6, 7, 8).

This study describes a wireless sensor-based prototype AVC system that estimates the number of axles and axle spacing under both free flow and congested traffic. The system is based on the Sensys wireless Vehicle Detection System (VDS), which offers a reliable, accurate, and cost-effective sensing platform with the flexibility to address a wide range of traffic management applications (9, 10). Each sensor can be installed in 10 minutes. The system is easy to maintain and can operate 24 × 7 under various weather and geometric environments (11, 12).

The paper is organized as follows. A description of the prototype AVC system is given in Section 2. A field study at Pinole, CA with ground truth validation is described in Section 3. Conclusions and further research are discussed in Section 4.

2. Automatic Vehicle Classification System

2.1. System Architecture

The prototype AVC system includes two subsystems: the axle detection system uses accelerometer sensors to detect vehicle axles; and the speed measurement system uses magnetometers to estimate vehicle speed. As depicted in Figure 1, accelerometers detect pavement vibration when a vehicle travels over their detection zones. The sensors locate the axle peaks in the vibration data and send the peak location time to the Access Point (AP) installed by the roadside. Magnetometers perceive changes in the magnetic field caused by a vehicle and transmit the vehicle’s magnetic signatures to the AP. The signatures are processed by the High Accuracy Speed (HAS) application running on the AP to calculate the speed and the peak clustering window to group axle peaks from the same vehicle. Another application, called APAxle, combines HAS data and accelerometer peak data to output the number of axles and axle spacing between each
axle pair on a per vehicle basis. Using a predefined vehicle classification scheme, the class of the vehicle can then be determined and logged. The most common classification scheme, the FHWA 13-categories Scheme F, is used in this study (13). The magnetometer sensors, accelerometer sensors, and AP are all time synchronized to within 2 microseconds. Consequently, even if sensors report their measurements asynchronously, the AP can align magnetometer readings with corresponding accelerometer readings.

![AVC System Architecture Diagram](image)

**Figure 1 AVC System Architecture**

### 2.2. Field Installation Prototype

The spatial configuration of the prototype AVC system is shown in Figure 2. The blue circles represent accelerometer sensors and the green triangles represent magnetometer sensors within one lane. Each sensor contains a transducer (accelerometer or magnetometer), a microprocessor, a radio and a battery.

Typically, the accelerometer response dies down quickly when the tire of a vehicle is slightly offset from the accelerometer. To counter this effect and reduce the sensitivity requirement of the accelerometer, an array of accelerometer sensors (labeled S1, S2 ... S6) spaced closely together is necessary to guarantee that a tire rolls directly on top of at least one sensor. The installed accelerometer sensors need to cover at least half of the lane to detect the leftmost/rightmost tires. The lateral spacing between two adjacent sensors should be narrower than the smallest effective width of the tire of a target vehicle, usually 6-8 inches.
Three magnetometer sensors (labeled *Lead*, *Middle* and *Trail*) are needed for high speed accuracy. They are usually placed close to the lane center. The vertical spacing is 4-6 feet so that individual vehicles will overlap all three sensors at one moment in time. This is important for distinguishing axle peaks from consecutive vehicles.

One Access Point (shown as the grey rectangle) is installed by the roadside. The sensors continuously transmit detection data via low power radio to the AP. Depending on the needs of the traffic application, AP forwards the data to local traffic controllers, remote traffic management centers via wired or wireless connections, or both.

### 2.3. Axle Detection

When a vehicle’s wheel moves across an accelerometer, the force causes the pavement to vibrate. The accelerometer measures these vibrations. The measurements are recorded and analyzed. Figure 3 shows the acceleration signal of a 2-axle vehicle that moves over an accelerometer. The x-axis is time in seconds and the y-axis is acceleration in g’s (Note that when no vehicle is present the acceleration is 1 g). The two axles can be clearly identified from the raw signal shown in Figure 3(a) without any filtering. However, to accurately calculate axle spacing and reliably identify tandem axles (whose spacing is usually 3-5 feet), an appropriate signal filter is needed to remove the noise from surrounding environment and smooth the signal. Figure 3(b) shows the absolute value of the raw signal (relative to 1 g) after a Moving Average filter. The position of the circled peaks can be treated as the time when the axle tire is on top of the sensor. The time
between peaks is inversely proportional to vehicle speed. If we know the speed \( v \), the axle spacing \( d \) is

\[
d = v \cdot t
\]

where \( t \) is the time between the two peaks.

![Figure 3](image)

**Figure 3** Acceleration Signal of a 2-axle Vehicle

Figure 4 depicts how the vibration data is processed in an accelerometer sensor. The pavement vibrations are captured by the accelerometer in hex values that are first decoded into acceleration (g’s) by a decoding function, and then the absolute value of the acceleration is smoothed by a signal filter (Moving Average / Butterworth). Acceleration values that exceed a preset threshold are selected and considered as peaks. Next, peak filters are applied at both sensor level and AP level. At the sensor level, the first-round peak filter removes redundant peaks due to the noise of the highway environment; and at the AP level, the second-round peak filter removes redundant peaks generated across the accelerometer sensor array.

![Figure 4](image)

**Figure 4** Axle Detection Flowchart

Figure 5 illustrates the peak filter procedures for a 5-axle truck. The red stars represent peaks from multiple sensors, and those with blue circles are the selected axle peaks after peak filters. As seen in the figure, the truck is detected by six sensors labeled \( S1 \), \( S2 \) ... \( S6 \).
The first axle is detected by $S_4$ and $S_5$ only, each outputs two peaks after the signal filter. The first-round peak filter is applied at the sensor level and the sensor sends only the highest amplitude peak to AP for the second-round peak filter. In this case, the one from $S_4$ (green circle) is removed due to its lower amplitude, and the one from $S_5$ is selected to represent the location of Axle 1. Similarly, the other four axles are all detected by multiple sensors and their locations are represented only with the highest amplitude peaks (blue circles). The vehicle is then classified as a 5-axle vehicle, and the spacing between the axles can be estimated from the peak time stamps and the speed following Equation 1.

![Figure 5: Peak Filter of a 5-axle Heavy Truck Sample](image)

**2.4. Speed Measurement and Clustering**

The magnetometer perceives a change in the magnetic field when a vehicle drives over it. The magnetic signatures of different vehicles are different, depending on the ferrous materials in the vehicle, as well as its size and orientation. The sensor also reports the time when a vehicle arrives at (an up-event) and leaves (a down-event) the detection zone. The data is delivered to HAS to calculate speed and peak clustering window. A state machine determines whether the events originate from the same vehicle, especially under congested traffic conditions.

HAS calculates vehicle speed in real time. Two types of speeds are reported which differ in accuracy. Type 1 speed is based solely on up-events. The magnetometer sensors, positioned along the direction of travel, report the timestamp when they first detect the
front of the vehicle. The speed is calculated by dividing the spacing between the sensors by the time difference between up-event detections. This type of speed is subject to sensor inaccuracies in sampling the vehicle’s detection zone. Type 2 speed is calculated based on the magnetic signatures captured by the sensors. It is highly accurate (within ±1 mph speed error tolerance, 14). Cross correlations of the signatures are used to determine the best time offset which is used to correct the edge based Type 1 speeds. This measurement is important because it directly affects the accuracy of the axle spacing estimates. However, if valid comparisons between the signatures cannot be made, Type 1 speed serves as the backup for the speed calculation.

HAS also outputs a peak clustering window to decide which axles belong to the same vehicle. Usually the left edge of the window is the up-event time of the Lead sensor, and the right edge is the down-event time of the Trail sensor (see Figure 2). However, due to measurement noise, the up/down events might be missed or delayed. In this case, corresponding events from other magnetometer sensors in the set can be used as replacement. The missing events could also cause two successive vehicles to be incorrectly grouped as one vehicle if they are close together. On the other hand, sensors could fail to detect vehicle sections (e.g. a vehicle with a trailer) that don’t have significant ferrous composition and report it as two vehicles. A best effort approach based on generalized vehicle specifications is applied to correct those errors. Axle spacing greater than the maximum specified wheel base can dictate the splitting of a sample into two vehicles. For example, a 4-axle vehicle would be considered two 2-axle vehicles if its middle axle spacing is greater than a reasonable value (e.g. 60 feet). By contrast, if a vehicle is detected as a 2-axle vehicle but its spacing is as small as tandem axle spacing, it could be considered as a trailer and grouped with its previous vehicle, if they are close enough.

3. Case Study

3.1. Study Site

The prototype AVC system has been running continuously since it was installed on the westbound I-80 at Pinole, CA on March 12, 2012 as shown in Figure 6. The top half of the figure is a bird’s-eye view of the study site. There are four lanes and the system is installed in Lane 2 from the curb. An AP, a pan-tilt-zoom (PTZ) camera and a hard drive are installed and can be remotely accessed via a cellular internet connection. The camera is installed to take images to validate the system. Its rate is three frames per second, which is sufficient to capture vehicles at highway speeds. The lower half of the figure displays two sample images taken by the webcam. The faint black dots within the white rectangle are the installed accelerometer and magnetometer sensors. The UTC time and local time are recorded at the top of each image. The images and sensor data are all stored on the hard drive.
The site is ideal for this study since there is a Caltrans commercial Weigh-In-Motion (WIM) system 460 feet downstream of the AVC system. The WIM system reports axle counts, spacing and weight of every truck. The reports can be used as an additional independent ground truth source to validate the AVC system.

The sensor installation layout at Pinole is depicted in Figure 7. The blue and yellow circles are accelerometer sensors, and the green triangles are magnetometer sensors. The accelerometer sensors are staggered 8 inches vertically to maintain the structural integrity of the road by not placing sensors too close to each other. To verify the best sensor installation spacing in a field highway environment, two sets of accelerometer sensors are installed. The left 9 sensors (yellow) are 8 inches apart, and the right 11 sensors (blue) are closer with 6 inches spacing. For the same purpose, three sets of magnetometer sensors are installed in the middle of the lane. The lateral distance between sets is 3 feet and the vertical distance within each set is 4 feet.

Figure 6  Study Site on West I-80 at Pinole, CA
3.2. Image Validation

Sensor Layout Selection

A 20-minute dataset was collected on March 15, 2012 from 10:25–10:45 am. Field images were recorded to evaluate the performance of the AVC system. Six scenarios with different accelerometer sensors and magnetometer sensor sets are compared:

- Scenario 1 – use all 20 accelerometer sensors and all three magnetometer sensor sets;
- Scenario 2 – use the left 9 8-inch-spacing accelerometer sensors and the left and center magnetometer sensor sets;
- Scenario 3 – use the right 11 6-inch-spacing accelerometer sensors and the right and center magnetometer sensor sets;
- Scenario 4 – use all 20 accelerometer sensors and the center magnetometer sensor set;
- Scenario 5 – use the left 9 8-inch-spacing accelerometer sensors and all three magnetometer sensor sets;
- Scenario 6 – use the right 11 6-inch-spacing accelerometer sensors and all three magnetometer sensor sets.

Figure 8 shows a 10-second record of the vehicle classification plot of Scenario 6. The x-axis is time in seconds and the y-axis is the peak acceleration from the right 11 accelerometer sensors. A pair of vertical lines illustrates peak clustering window for a classified vehicle. The first, dashed line shows the up-event time and the second, solid line shows the down-event time. The red stars are the peaks over the threshold and the blue circled ones are the selected peaks after peak filters.

The performances of the scenarios are compared in Table 1. During the 20 minutes, 345 vehicles passed the detection zone. Among them 299 were 2-axle vehicles (i.e. passenger cars, light / medium trucks, and pickups), 3 were 3-axle vehicles, and 43 were 5-axle heavy trucks. Vehicle speeds varied from 32 mph to 80 mph. As expected, Scenario 1 gets the best performance and successfully classified all 345 vehicles. Scenarios 3 and 6 are also very good and only failed in 4 and 1 vehicles, respectively. On the other hand, Scenarios 2 and 5 missed more than 20 vehicles, because the sensor spacing of the left set is wider than the effective tire width of some vehicles. Scenario 4 is considered the worst because it failed in 5 heavy trucks, which are usually more important in vehicle classification. As can be seen, heavy trucks are all correctly classified if all the three sets
of the magnetometers are used, and with fewer sets, more trucks fail classification. The reason is the up/down events are more likely delayed or missed when a heavy truck travels over the detection zone. In this case, multiple magnetometer sensor sets can recover the missed events and significantly improve the performance of the HAS system. It should be noted that vehicles during a lane-changing movement at the detection zone (not very common) are not included because only parts of the vehicle can be detected by the sensors. Based on the results in Table 1, Scenario 6 is recommended considering both performance and cost.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Accelero-meter Sensor</th>
<th>Magneto-meter Sensor</th>
<th>2-axle Car</th>
<th>3-axle Car</th>
<th>5-axle Heavy Truck</th>
<th>Successful Classified</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>All</td>
<td>All</td>
<td>299</td>
<td>3</td>
<td>43</td>
<td>345</td>
<td>100%</td>
</tr>
<tr>
<td>2</td>
<td>L (8”)</td>
<td>L &amp; C</td>
<td>272</td>
<td>3</td>
<td>42</td>
<td>317</td>
<td>91.9%</td>
</tr>
<tr>
<td>3</td>
<td>R (6”)</td>
<td>R &amp; C</td>
<td>296</td>
<td>3</td>
<td>42</td>
<td>341</td>
<td>98.8%</td>
</tr>
<tr>
<td>4</td>
<td>All</td>
<td>C</td>
<td>285</td>
<td>3</td>
<td>38</td>
<td>326</td>
<td>94.5%</td>
</tr>
<tr>
<td>5</td>
<td>L (8”)</td>
<td>All</td>
<td>277</td>
<td>3</td>
<td>43</td>
<td>323</td>
<td>93.6%</td>
</tr>
<tr>
<td>6</td>
<td>R (6”)</td>
<td>All</td>
<td>298</td>
<td>3</td>
<td>43</td>
<td>344</td>
<td>99.7%</td>
</tr>
<tr>
<td>Video</td>
<td>Image (ground truth)</td>
<td></td>
<td>299</td>
<td>3</td>
<td>43</td>
<td>345</td>
<td>–</td>
</tr>
</tbody>
</table>

Rush-Hour Validation

A 3.5-hour dataset from 5:20–8:50 am was collected on April 18, 2012 to further evaluate the performance of the prototype AVC system in congested traffic conditions, as well as for a longer time period. The 90-minute rush hour (from around 7:20 – 8:50 am) data is shown as in Figure 9, in which the colors of the vertical lines (peak clustering windows) indicate vehicle speed as explained by the color bar – blue lines represent lower speed (i.e. < 30 mph), green and yellow lines represent medium speed (i.e. 30 – 50 mph), and red lines represent higher speed (i.e. > 50 mph). The speed changes during the rush hour can be clearly seen. The lowest speed during the rush hour is 4.7 mph.

The total number of vehicles classified by the AVC system during the 90 minutes is 2253. However, it is very difficult to individually verify all the vehicles from the images. Considering the good performance from the previous image validation and the importance of classification of 3-plus-axle vehicles, we randomly validate 5% of the major vehicle class at the study site (i.e. 2-axle vehicles), and individually validate all the other 3-plus-axle vehicles. All randomly selected 102 2-axle vehicles (Class 2, 3, 4, & 5) are correctly classified.
The performance for the 226 3-plus-axle vehicles is shown in Table 2. 223 vehicles in different classes are successfully classified, including a 6-axle heavy truck which has 3 tandem rear axles. Only 3 vehicles are not correctly classified during the 90-minute rush hour: a semi-truck with a long-spacing trailer is classified as 2 vehicles; two bumper-to-bumper 2-axle vehicles are classified as one 4-axle vehicle at speed of 15.6 mph; and a 5-axle heavy truck is classified as a 4-axle vehicle because the peaks of two tandem axles are grouped into a single peak due to its low speed 4.7 mph. Thus the overall performance of the AVC system is very good under congested traffic conditions.

Figure 9  90-minute Rush-Hour Data on April 18, 2012

Table 2  Image Validation of 3-plus-axle Vehicles under Rush-Hour

<table>
<thead>
<tr>
<th># of Axles</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>3/6/8</td>
<td>3/8</td>
<td>5/9/11</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>AVC Output</td>
<td>15</td>
<td>7</td>
<td>203</td>
<td>1</td>
<td>226</td>
</tr>
<tr>
<td>Correct Classification</td>
<td>14</td>
<td>5</td>
<td>203</td>
<td>1</td>
<td>223</td>
</tr>
</tbody>
</table>
3.3. WIM Validation

Image validation is very accurate for vehicle count and classification. However, it is labor intensive and thus not suitable for a large dataset. But more importantly, video cannot be used to measure axle spacing. Therefore, reports from the nearby commercial WIM station are used as another ground truth to evaluate the performance of the prototype AVC system.

Axle Spacing

To evaluate the results of axle spacing, we first need to match vehicles detected by the two systems. Considering their sample size in the traffic stream and variation of the axle spacing of the vehicles, 5-axle Class 9/11 heavy trucks are selected from the 90-minute dataset. 179 heavy trucks are matched and the results are shown as in Figure 10. The blue stars are WIM data and the red circles are AVC data. The horizontal axes are the number of samples. The speed differences of all matched samples and their accumulated error are shown in Figures a3 and a4. The matched samples with axle spacing differences larger than half feet are shown in Figures b1–b4 (axle pairs 1/2, 2/3, 3/4 and 4/5 accordingly). The cumulative absolute axle spacing errors of all matched samples are shown in Figures c1–c4, and the cumulative percentage errors are shown in Figure d1–d4. The majority of the matched samples are Class 9 vehicles, which has two tandem axle pairs (2/3 and 4/5). As can be seen, the axle spacing calculated by the AVC system is very close to that from the commercial WIM station. The estimations of regular and tandem axle spacing are mostly within 1 foot and 0.5 feet, respectively. 95 percent of the errors are within 5%. It should be noted that the errors are the composite of estimation errors in both the WIM and AVC systems.

Vehicle Counts

The vehicle count report from WIM is used to validate the performance of the AVC system over a longer time period. Two full hours’ data (6-7 am and 7-8 am) are selected from the 3.5-hour dataset collected on April 18, 2012. The results are shown as in Table 3. Note that the classification scheme used by WIM is the Long-Term Pavement Performance (LTPP) (15), which uses not only axle spacing but axle weights to classify vehicles. Vehicles in four categories: Class 2–5, Class 9, Class 11 and all classes, are compared based on their definitions in both classification schemes. As shown, the vehicle counts for both hours matched very well. The small differences come from possible lane-changing vehicles, classification errors in both systems, time boundary effects, and definition differences between Scheme F and LTPP.
Table 3  Hourly Vehicle Counts Comparing between AVC & WIM

<table>
<thead>
<tr>
<th>April 18, 2012</th>
<th>Class 2 – 5 (2-axle)</th>
<th>Class 9 (5-axle)</th>
<th>Class 11 (5-axle)</th>
<th>All Classes (all-axles)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 am – 7 am</td>
<td>AVC</td>
<td>1676</td>
<td>85</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>WIM</td>
<td>1679</td>
<td>86</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>diff</td>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>7 am – 8 am</td>
<td>AVC</td>
<td>1519</td>
<td>124</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>WIM</td>
<td>1523</td>
<td>124</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>diff</td>
<td>4</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Figure 10  Comparison of Axle Spacing of 5-axle Heavy Trucks with WIM
4. Conclusion

This study describes a reliable AVC prototype system using wireless sensors. The accelerometers are used to convert pavement vibration into axle locations, and the magnetometers are used to detect magnetic field changes and estimate vehicle speed and peak clustering window. The sensor data are synchronized and processed in real-time on the Access Point. Based on the calculated vehicle axle count and spacing, each vehicle is classified according to a predefined classification scheme, such as Scheme F.

A prototype AVC system was installed and tested on I-80 at Pinole, CA. Six sensor layout scenarios are evaluated in terms of accelerometer sensor spacing and sets of magnetometer sensors needed. System performance was evaluated using video images and reports from a nearby WIM station under both free and congested traffic. The video validation shows that the system classifies vehicles with 99% accuracy for the recommended configuration; and the WIM validation shows the system can generate a comparable report in terms of classification, axle spacing and vehicle counts.

Future developments of this study include the improvement of power efficiency to increase battery life. More field evaluations of the prototype AVC system are needed in different traffic environments such as toll plazas and arterial corridors, where the traffic patterns are quite different.

Acknowledgement

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