Enhancing The Data Quality of Infrared-based Automatic Pedestrian Sensors Using a Nonparametric Statistical Method

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ABSTRACT

With the advent of Intelligent Transportation Systems in the last several decades, sensors are being extensively used to detect and count vehicle movements. On the other hand, the use of similar sensing technologies to detect pedestrian movements is relatively new. Pedestrian counts are essential for decision-making for pedestrian facility planning, signal timing, and pedestrian safety modeling. Conventional methods such as manual counting and videotaping can hardly satisfy the requirements of long-term pedestrian data collection programs. Fortunately, advances in sensing technologies have increased the ability of automating pedestrian data collection using infrared sensors. However, data quality of the infrared sensors is still a problem because several field studies showed that this type of sensors do not always perform perfectly. Field tests conducted by this study and by other research teams show that infrared sensors usually count significantly less than the actual number of pedestrians. Thus there are needs to enhance the data quality of infrared sensors. This paper proposes a nonparametric statistical method to calibrate raw sensor data to achieve this goal. Instead of using regression-based approaches that are traditionally preferred by traffic engineers, a bivariate bootstrap sampling procedure is used to obtain correction factors for new counts. Two case studies are used to test the validation of the proposed calibration procedure. Test results show that the proposed procedure can improve the sensor data quality in terms of reducing the discrepancy between sensor counts and ground truth data. The transferability of the calibration procedure is also verified through the case studies.
INTRODUCTION

With the advent of Intelligent Transportation Systems (ITS), sensors are being extensively used to detect and count vehicle movements for the last several decades. On the other hand, the use of similar sensor to detect pedestrian movements is relatively new. In the past, transportation planners have relied on conventional methods such as manual counting and video reviewing (1, 2) to obtain pedestrian data. Pedestrian data availability and quality were limited by the timeliness of data collection, the labor cost, the need for a series of manual data processing steps, and associated human errors. Pedestrian traffic data are essential to support decision-making in many pedestrian traffic studies. Efficient and high-quality data collection is still the subject of much concern by practitioners.

With the advent of sensor technologies, the ability to automate pedestrian data collection has increased dramatically. Pedestrian counting products based on image, microwave and infrared technologies are now commercially available (3). Among them, infrared counters are one of the frequently used counting devices. It is now easy to find examples of their application in shopping malls, stores, libraries and visitor centers. However, the application of these infrared counters outdoors such as on sidewalk and trail is less widespread, partly because of the complexity of adapting the technology to work correctly outdoors where many factors will affect the results (4). Most infrared counters require pedestrians to pass the sensing area in single file for maximum accuracy (5). It is particularly inaccurate when counting group arrivals and pedestrians simultaneously walking side by side (6). Other factors such as falling leaves and moving objects may also adversely affect the accuracy of counts. Nevertheless, with sufficient samples, it is possible to establish a procedure that can improve the quality in the long run.

The first objective of this study is to evaluate the performance of the infrared sensor using field tests. The second objective is, to propose a calibration procedure to enhance the data quality of original sensor output. Multiple field tests are conducted to show the errors associated with raw sensor counts. A non-parametric statistical method is then proposed to reduce the discrepancy between sensor data and ground truth counts.

This paper is organized as follows. A review of the studies that evaluated and calibrated infrared pedestrian sensors is presented in the next section. Field tests conducted as part of this study are described in Section 3. The proposed methodology for calibrating sensor outputs is presented in Section 4. Case studies using the proposed method are described in Section 5. Finally, major findings and their implications on pedestrian data collection are summarized.

LITERATURE REVIEW

Although it is not as common as indoor applications, infrared sensors have been used in a limited number of urban transportation projects. For instance, the city government of Cheyenne, Wyoming, installed an infrared counter to record path counts to justify the usage of the greenway system in 1990s (5). Passive infrared counters were installed along a shared-use path system to provide data for a comprehensive bicycle and pedestrian plan in Ohio (7). An active infrared counter was placed above the Norwottuck trail in Amherst, Massachusetts to measure pedestrians and bicycles use in 2001 (8). Most recently, infrared counters were deployed to measure bicycle and pedestrian activity in San Diego County (9). Experience from these applications suggested that neither passive nor active counters performed perfectly.

In order to understand more about the counting performance, automatic pedestrian counters were tested in the field (10, 11). All infrared counters were found to contain inaccuracies depending on factors such as location, usage patterns and the surroundings. Trail
counts in Indiana using infrared counters suggested that the sensor systematically undercounted
trail users by 15 percent (12). The study in San Diego County found a 15 percent to 21 percent
non-detection rate for active infrared counters and 12 percent to 48 percent no-detection rate for
passive infrared counters (9). Greene-Roesel et al. (13) tested a dual-sensor passive infrared
pedestrian counter and reported that the sensor consistently undercounted pedestrians by 9
percent to 19 percent. This is well above the results of 2 percent to 5 percent undercounting rate
obtained from tests on sidewalks in Montpelier, Vermont (14, 15). Latest tests in New Jersey
found that the infrared undercounting error can be over 20 percent in high volume sites (16).
These field tests indicated that the vendor recommended performances under ideal conditions,
i.e. ±5.0 percent, were not always guaranteed. The studies mentioned above provided examples
that a specific counter cannot perform perfectly when used for certain set-ups. However, none of
them was set out to enhance the accuracy of collected data using statistical techniques.

Little effort has been made to improve the data quality of infrared sensor counts. One of
the pilot studies calibrated infrared counts in shopping malls (17). Simple regression models
were developed in relational model of $Y = f(X)$, where $X$ represents the raw sensor count, and $Y$
is the calibrated count. Similarly, Lindsey and Nguyen (18) also used a linear regression model to
adjust the infrared counts collected in Indiana trail system. However, follow-up studies (19, 20)
showed that either the adjustment factor (coefficient) or the structure of the regression model was
not consistent among locations even the same type of counter was deployed. The errors reported
above also suggest there is not a common adjustment factor. Moreover, it is difficult and
impractical to collect large enough samples of counter outputs and the corresponding ground-
truth counts to build reliable regression models for each site. Therefore, the transferability of
these calibration models is problematic. Therefore, in this study, we propose a more practical
calibration approach to enhance quality of infrared sensor data.

FIELD TESTS of an INFRARED SENSOR
There are three types of infrared sensors: active, passive, and target reflective. Active counter
uses body mass to break an invisible beam crossing a path. Passive infrared counter detect heat
emitted from pedestrians passing through the sensing area. Target reflective counter counts
pedestrians by detecting breaks of invisible beam between transmitter and reflector mounted at
opposite sides. Some studies have specifically compared the performance of these sensors (i.e. 8,
10, 11, 16). In this study, a dual sensor pyroelectric infrared counter, namely EcoCounter is
selected as a typical representative of passive sensor. FIGURE 1 shows the structure of the
sensor. Its two lenses detect the infrared radiation emitted by the human body crossing the
sensing area. The counter uses a four-threshold algorithm to avoid false counts generated by
vegetation movement, rain, or the sun. Its double-direction vertical technology allows dual-
direction count in any temperature (21). Its metal box keeps it working properly in all weather
conditions. Internal battery life is up to 10 years, and the data logger can store data in 15-minute
intervals for up to one year. Therefore, EcoCounter is suitable for long-term deployment for
pedestrian counting.
The sensor was deployed at three sites in New Jersey. Selection of the test sites was based on criteria such as pedestrian volume, mounting facility, location accessibility and the suggestions from the New Jersey Department of Transportation (NJDOT). FIGURE 2 shows the selected sites and TABLE 1 summarizes the information about the field tests. EcoCounter supposed to be most reliable when positioned facing a wall (or a fixed surface). Site 1 and Site 2 were carefully checked before the data collection to ensure that no potential source of error existed because of missing fixed surface. Even though they do not have the wall, the sensor was found to function correctly and only the pedestrians crossing the detection area can be counted. To investigate the accuracy of the infrared sensor, the sensor counts have to be compared with ground-truth data. In this study, ground-truth data were collected by carefully reviewing the video records simultaneously collected during the field tests. It should be noted that the camcorder was always hidden in a vehicle so that the normal pedestrian behaviors were not affected by the presence of the camcorder. Moreover, the videos were reviewed frame-by-frame to make sure no missing count occurred. Reviewing 1-hour video needs approximately 5 hours, which is the most time-consuming feature of manual counting. Both baseline data and sensor outputs were initially integrated into 15-minute time intervals.

### TABLE 1 Summary of Field Tests

<table>
<thead>
<tr>
<th>Site</th>
<th>City</th>
<th>Facility Type</th>
<th>Test Date</th>
<th>Test Period</th>
<th>Volume (ped)</th>
<th>Flow (ped/hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Piscataway</td>
<td>Trail</td>
<td>04/10/2009</td>
<td>10:30am-10:30pm</td>
<td>3103</td>
<td>259</td>
</tr>
<tr>
<td>2</td>
<td>Piscataway</td>
<td>Trail</td>
<td>10/19/2009</td>
<td>09:00am-10:00pm</td>
<td>8570</td>
<td>659</td>
</tr>
<tr>
<td>3</td>
<td>Piscataway</td>
<td>Trail</td>
<td>10/26/2009</td>
<td>09:00am-11:00pm</td>
<td>8294</td>
<td>592</td>
</tr>
<tr>
<td>4</td>
<td>New Brunswick</td>
<td>Sidewalk</td>
<td>10/12/2009</td>
<td>09:00am-06:00pm</td>
<td>2011</td>
<td>223</td>
</tr>
</tbody>
</table>

The accuracy of the infrared sensor is evaluated by comparing the sensor outputs and the ground-truth counts. The overall errors computed in TABLE 2 show that the sensor is
systematically undercounting by 14.3 percent to 24.8 percent. The results confirm the undercounting fact reported in the literature \((13, 22)\). The errors vary in a large range among test sites. Therefore, it is incorrect to adjust the raw outputs by simply using a common correction factor. Wilcoxon paired signed-rank test is applied to further test the difference between the sensor output and corresponding ground truth data. This nonparametric statistical test gives the direction of the difference between sensor counts and the ground truth integrated in 15-minute time intervals. The null hypothesis and the alternative hypothesis are proposed:

- \(H_0\): There is no difference (Difference=Sensor Count-Ground Truth=0) between sensor count and the ground-truth count.
- \(H_1\): Sensor count is less than the true count (Difference < 0).

P-values of each test is reported in TABLE 2. The results suggest that the null hypothesis is rejected and there is a statistically significant difference between the sensor outputs and the ground truth given the significance level of \(\alpha=0.05\). Specifically, the sensor undercounted in a statistically significant manner compared to the true counts.

### TABLE 2 Infrared Sensor Counting Errors at Test Sites

<table>
<thead>
<tr>
<th>Site</th>
<th>Date</th>
<th>Number of Period (15-minute)</th>
<th>Ground Truth</th>
<th>Sensor Count</th>
<th>Overall Error (%)</th>
<th>Wilcoxon Paired Signed-Rank Test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>04/10</td>
<td>48</td>
<td>3103</td>
<td>2468</td>
<td>-20.5</td>
<td>(6.753 \times 10^{-10})</td>
</tr>
<tr>
<td>2</td>
<td>10/19</td>
<td>52</td>
<td>8570</td>
<td>6674</td>
<td>-22.1</td>
<td>(4.441 \times 10^{-16})</td>
</tr>
<tr>
<td>2</td>
<td>10/26</td>
<td>56</td>
<td>8294</td>
<td>6236</td>
<td>-24.8</td>
<td>(1.11 \times 10^{-16})</td>
</tr>
<tr>
<td>3</td>
<td>10/12</td>
<td>36</td>
<td>2011</td>
<td>1723</td>
<td>-14.3</td>
<td>(5.297 \times 10^{-9})</td>
</tr>
</tbody>
</table>

### CALIBRATION METHODOLOGY

Generally, infrared counters require a single pedestrian passing to achieve maximum accuracy. They will systematically undercount when pedestrians walk side by side or in groups \((6)\). FIGURE 3 illustrates an example when the counter will undercount. In this example, the counter counted only one pedestrian in all three patterns. If the information about how many times each of these patterns occurred in a time period is known, then the actual counts can be obtained. However, when aggregated sensor data (i.e., 15-minute interval) is used, it is impossible to get such information because the sensor itself does not recognize and record the passing patterns of pedestrians. Moreover, passing patterns change over time and locations because pedestrians randomly arrive in single, paired or large groups. The randomness of the arrival pattern also prevents the possibility of having a unique correction factor for all locations. For instance, if all arrivals are in a pattern of \((b)\) in FIGURE 3, then a unique correction factor of 0.5 can be used since one person will be missed in each arrival of pattern 2. In reality, however, the arrival patterns can be in the form of 1, 2, 3 pedestrians, and/or combinations of them.

![Counter](image1.png)

![Counter](image2.png)

![Counter](image3.png)

**FIGURE 3** Example of possible passing patterns given counter output is one.
Instead of using a unique correction factor for all sensor outputs, this study attempts to develop a calibration approach based on small interval data and applies it to all future counts to enhance the quality of larger interval data. To achieve this goal, a bivariate bootstrap sampling procedure is proposed to estimate the hourly pedestrian counts using the 15-minute interval raw counts of an infrared pedestrian counter. Use of the bootstrap sampling procedure makes it possible to build a large synthetic dataset from the limited number of training datasets (23). This allows us to maximize the utilization of the valuable training data (sensor counts and ground truth) manually collected using videotapes (this type of ground truth data collection reviews video records and requires at least 5 hours of manual processing for 1 hour of field data).

The calibration procedure is summarized as follows:

**Step 1**: Let \((X_i, Y_i)\) be a pair of counter output and corresponding actual (ground truth) pedestrian volume at the \(i^{th}\) 15-minute interval, \(i=1, 2, \ldots, N\).

**Step 2**: Randomly sample 4 pairs of \((X_1, Y_1), (X_2, Y_2), (X_3, Y_3)\) and \((X_4, Y_4)\) from \((X_i, Y_i)\) with replacement. Define \((C_b, M_b)\) as the \(b^{th}\) pair of synthetic hourly counter output and actual volume, and calculate the hourly counting error rate \(\varepsilon_b\) as follows:

\[
\begin{align*}
C_b &= \frac{4}{j=1} X_j \
M_b &= \frac{4}{j=1} Y_j \
\varepsilon_b &= \frac{C_b - M_b}{M_b} \times 100\%
\end{align*}
\]

**Step 3**: Repeat procedure in step 2 \(B\) times (\(B\) is a large number, i.e., 5000), and list \((C_b, M_b, \varepsilon_b)\) in a lookup table, where \(b=1, 2, \ldots, B\). The table includes synthetic results of hourly sensor counts, true counts and corresponding errors.

**Step 4**: Given a new hourly counter observation \(Q\), define an interval \(S = [Q-\delta, Q+\delta]\), where \(\delta\) is a small value (i.e., 5~10) used to create a range that includes \(Q\). Selecting vectors \((C_k, M_k, \varepsilon_k)\) from the lookup table where \(C_k \in S\) and denote them as subset \((C_k', M_k', \varepsilon_k')\), where \(k=1, 2, \ldots, K\) (\(K\) is total number of vectors in the subset). The aim of this step is to find reference counter outputs which are close or equal to the new count \(Q\).

**Step 5**: The correction factor for \(Q\) is thus determined as \(\hat{\varepsilon} = E(\varepsilon_k')\), where \(E(\varepsilon_k')\) is the expectation of \(\varepsilon_k'\) in the subset obtained in step 4. Here we define \(\hat{\varepsilon} = \frac{1}{K} \sum_{k=1}^{K} \varepsilon_k'\). The calibrated counter output is then computed as:

\[
\hat{Q} = \frac{Q}{1 + \hat{\varepsilon}}
\]

**Step 6**: If necessary, construct percentile confidence interval for \(\hat{Q}\): order \(\varepsilon_k'\) from smallest to largest. Identify \(\varepsilon_{L} = [\frac{K}{2} \times 100\% \times K]^{th}\) and \(\varepsilon_{U} = [(1 - \frac{K}{2}) \times 100\% \times K]^{th}\) values of the ordered \(\varepsilon_k'\). These values represent the lower and upper limits for the \((1 - \alpha)\times 100\%\) confidence interval of correction factor for \(Q\). Then use them to calculate the lower and upper limits for \(\hat{Q}\):

\[
\begin{align*}
\hat{Q}_L &= \frac{Q}{1 + \varepsilon_{U}} \
\hat{Q}_U &= \frac{Q}{1 + \varepsilon_{L}}
\end{align*}
\]

The above procedure is summarized in FIGURE 4. It demonstrates the process to calibrate the hourly sensor data based on the created lookup table using 15-minute interval data.
If there are training data with a smaller interval (i.e., 5-minute), the same calibration idea can be employed to calibrate 15-minute, 30-minute, and hourly data according to the requirements of data aggregation.

CASE STUDIES

To validate the proposed calibration method, data collected from the field tests in Section 3 are used to conduct calibration case studies. Specifically, the training dataset consists of 15-minute interval sensor output and actual counts collected at site 2 on October 19 and 26, 2009. Following the calibration step 1 to 3, a lookup table with $B = 5000$ samples is created by sampling from the training dataset. Samples are a combination of synthetic records of sensor counts, true counts. The error $\epsilon_b$ of each synthetic record is then computed using equation (3) in step 2.

When extracting a subset from the lookup table in Step 4, the parameter $\delta$ is set to $\delta = 5$. This means when a new hourly sensor count $Q$ is observed, sensor counts within $Q \pm \delta$ from lookup table will be extracted. The average error of these extracted sensor counts will be used as the correction factor for new sensor count $Q$.

Two test datasets are used for validation: (a) dataset collected on April 10 at site 1; (b) dataset collected on October 12 at site 3. The test datasets were collected at locations different than the one where training data were collected. Thus, the transferability of the calibration procedure can also be tested.

The calibration results for the two test datasets are shown in FIGURE 5. From the figure we can see that the infrared counter obviously undercounted pedestrians at both sites. For the dataset collected at site 1, the original overall error rate of the infrared counter was -20.5 percent. By using the proposed calibration method, the estimated overall undercounting errors are only -1.5 percent. The overall undercounting error rate was -14.3 percent at the sidewalk at site 3. The overall calibrated count is only 4.1 percent more than the actual counts. These results show that the calibration procedure successfully reduced the overall counting errors to the range of ±5 percent at the two test sites. We have also showed that in spite of the fact that the training data...
Automatic pedestrian counting methods based on sensor technologies provide alternatives to manual data collection for long-term pedestrian data collection. These data collection methods that take advantage of new sensor technologies as parts of ITS are important for future pedestrian traffic studies. Among the commercially available sensors, infrared counters are one of the most frequently used ones because this type of sensor is relatively inexpensive and easy to deploy. Though infrared sensors are frequently used, their data quality is still a problem. Field tests conducted in this study demonstrated that the difference between the infrared sensor counts and the ground truth data can be more than 20 percent in many cases. Moreover, errors rates change from location to location. These relatively large error rates may raise concerns when using the sensor data to support decision-making by practitioners.

To improve the quality of the automated counting results, correction of the raw counter outputs is needed. Previous regression-based calibration approaches discussed in the literature requires the collection of relatively large ground truth data to build a robust regression model to identify a reliable correction factor. But traditional off-line manual data collection techniques that are virtually free of counting errors are not efficient for collecting such large scale training data for model development. More interestingly, there might be no unique correction factor for all the sites. The correction factor may vary by time and location. A correction factor identified for one location might not be easily transferred to other locations without collecting new ground truth data at these locations too. This can be both an expensive and time consuming way of obtaining these important correction factors without which sensor data might not be very useful due to high error rates. Therefore, this study proposes a nonparametric statistical method to adjust the raw counts using limited ground truth data. Using the bootstrap sampling procedure, a lookup table including a large synthetic dataset is created based on the limited ground truth data. TABLE 3 shows an example of preparing the lookup table. This lookup table serves as a reference table for new observations. For instance, if a new sensor count is 90, the suggested
correction factor is 15.4 percent. If the new sensor count is 150, then the factor is 11.3 percent. Whenever there are new infrared sensor counts, they can be calibrated by using the reference suggested correction factors in the lookup table. The details of the procedure are depicted step by step. To test the validation of the procedure, two calibration studies are conducted using independent datasets collected at two sites. The validation tests show that the proposed calibration methodology can successfully reduce the overall errors of the raw sensor data.

**TABLE 3 Example of Preparing Lookup Table**

<table>
<thead>
<tr>
<th>Historical Sensor Counts</th>
<th>Historical Ground Truth Counts</th>
<th>Historical Errors</th>
<th>Suggested Correction Factor for New Sensor Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>90</td>
<td>108</td>
<td>16.7%</td>
<td>15.4% (Average of the historical errors)</td>
</tr>
<tr>
<td>90</td>
<td>106</td>
<td>15.1%</td>
<td></td>
</tr>
<tr>
<td>90</td>
<td>105</td>
<td>14.3%</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>150</td>
<td>171</td>
<td>12.3%</td>
<td></td>
</tr>
<tr>
<td>150</td>
<td>170</td>
<td>11.8%</td>
<td>11.3% (Average of the historical errors)</td>
</tr>
<tr>
<td>150</td>
<td>168</td>
<td>10.7%</td>
<td></td>
</tr>
<tr>
<td>150</td>
<td>167</td>
<td>10.2%</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Without establishing a specific correction factor for each site, it is safe to assume that the results are transferable for similar locations even though the lookup table is built using data from a different site. The method in this study was tested using trail and sidewalk data. It should also be tested at other pedestrian facilities such as intersection crosswalks, where pedestrian traffic characteristics are different from trails and sidewalks. In order to have more general and practical implementation approach, sensor manufactures can build lookup tables that represent typical traffic conditions that can be used without collecting new calibration data to save time and cost. If the studied locations are somehow very unique (i.e. extremely high volume), it is better for the users to build reference tables for these sites using the proposed calibration procedure.

Additional data are currently being collected to further study the calibration procedure described in this paper for enhancing data quality of infrared sensors. Further research is also needed to investigate and validate the performance of the procedure through other types of sensors.

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