Algorithm for Detector-Error Screening on Basis of Temporal and Spatial Information

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Although average effective vehicle length (AEVL) has been recognized as one of the most popular methods for detecting data errors, how to set proper thresholds so as to prevent false alarms and missed detections remains a challenging ongoing issue. This study proposed a sequential screening algorithm that employed multiple comparisons with the best statistics to compare concurrently the estimated AEVLs between lanes and stations for assessment of the data quality of a target detector. With both the temporal and spatial information, the proposed method can reliably generate a confidence interval and determine whether the target detector is malfunctioning or in need of calibration. The proposed algorithm was tested with 2 weeks of detector data from Ocean City, Maryland. The analysis results demonstrate the effectiveness of the proposed sequential screening algorithm and its potential for field applications.

Different types of traffic detectors, such as loop, radar, and video detectors, have been widely deployed at freeways and major urban arterials to support advanced traffic management systems and advanced traveler information systems (*1*). However, most existing studies have shown that, because of the lack of maintenance and calibration, data errors inevitably exist in most surveillance systems, and this lack prevents effective applications of most control strategies (*2–4*). Hence, a well-designed screening algorithm to identify detector quality is essential for any advanced traffic management systems deployment.

Since the 1970s, a large number of studies have been devoted to detection of sensor errors. Most existing screening algorithms can be divided into two categories: (*a*) microscopic algorithms to identify the errors in the hardware through analysis of abnormal signal patterns and (*b*) macroscopic algorithms based on aggregated traffic flow relationships (such as flow, occupancy, and speed).

At the microscopic level, Chen and May (*3*) and Coifman (*5*) have conducted studies to test average actuation time of detectors. Recently, Lee and Coifman proposed some algorithms to assess the sensitivity of detectors (*6*) and to identify their pulse breakup errors (*7*) as well as splashover errors (*8*). Cheevarunothai et al. developed a system to collect data on detector events and then corrected dual loop sensitivity errors on the basis of the event data (*9*). Corey et al. further used a Gaussian mixture model to fit the distribution of detector actuation times and then implemented the Gaussian mixture model to correct the errors (*10*).

At the macroscopic level, several threshold methods related to single traffic variables have been proposed to rule out the most obvious errors. In 1976, Payne et al. introduced several single-variable thresholds for 5-min volume, occupancy, and speed data to identify malfunctioned sensors when they developed incident detection algorithms (*11*). Payne and Thompson later proposed 13 checking rules on 30-s and 5-min volume, occupancy, and speed data by using the I-880 database (*2*). Along with the development of traffic flow theory, some researchers used mathematical relationships between traffic flow variables to perform diagnosis of detector quality. For example, Jacobson et al. (*12*) and Cleghorn et al. (*13*) applied the threshold method to multiple traffic variables. They proposed to use the volume–occupancy ratio threshold for different occupancy regions for which the data will be regarded as invalid if the computed value is beyond the predefined threshold for that region. In addition, time series detector data could also be incorporated into the screening algorithm as temporal supplemental information. Additional spatial relationships from direct upstream and downstream detectors on neighboring lanes could also be used to uncover hidden errors (*14–16*). Chen et al. developed a daily-statistics algorithm that uses whole-day time series data to define four statistics and their corresponding thresholds (*15*). If any statistic is above its threshold, the loop is set as malfunctioning for that day. Nihan considered the vehicles stored between two detector stations and concluded that, if the number of stored vehicles keeps increasing or decreasing over a 24-h period, either of these two neighboring detectors may have yielded unreliable volume data (*14*).

After 2000, most researchers have devoted their efforts to error screening for dual loop detectors. Following the same classification of algorithms as for single loop detectors, Turochy and Smith's algorithm could be classified in the category of multiple-variable threshold (*4*), and the methods by Al-Deek and Chandra (*17*), Achillides and Bullock (*18*), and Vanajakshi and Rilett (*19*) would belong to the temporal–spatial information class. Most of those studies adopted average effective vehicle length (AEVL) to check the erroneous data. Since its introduction, AEVL has shown its effectiveness in uncovering some hidden errors that could pass the regular single- or multiple-threshold tests or both. Vanajakshi and Rilett considered the consistency of cumulative volume data between nearby stations and proposed an optimization method to correct the imbalance value (*19*).

In most existing studies, when the estimated AEVLs exceed the defined threshold, the corresponding detected data may be classified

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as inaccurate. However, one critical issue to be addressed is selection of the threshold for AEVL. Failing to select a proper threshold may cause the algorithm to yield significant false alarms or a number of missed detections. Unfortunately, guidelines to define such thresholds for AEVL to indicate the boundaries of erroneous data are not available in the literature. Furthermore, differences in vehicle compositions and their lane use distributions can cause difficulty in selecting proper thresholds.

With the same logic of AEVL, this study presents a sequential algorithm that employs both temporal and spatial information within and between detector stations to evaluate the quality of detector data. With the embedded test multiple comparison with the best (MCB), one can concurrently compare the AEVLs estimated from all travel lanes and between stations and establish a robust confidence interval for performance. The evaluation process will enable responsible agencies to effectively identify detectors as malfunctioning or in need of maintenance and calibration.

METHODOLOGY

By application of the concept of AEVL, the proposed algorithm for assessing detector quality consists of the following three stages:

Stage 1. Preliminary check of data abnormalities with traffic flow characteristics,
Stage 2. Statistical test and comparison of the computed AEVLs between neighboring lanes and stations, and
Stage 3. Spatial comparison of the estimated AEVLs with further upstream and downstream stations.

A graphical description of the stages of the detection process is shown in Figure 1.

Stage 1. Preliminary Data Check

At the first stage, the proposed algorithm will activate the following checks by using basic traffic flow characteristics:

- Flow threshold check. The detected flow rate shall lie within the following range:

$$0 \le q_d \le q_{\max} \tag{1}$$

where q_d is the detected flow rate per lane by the data aggregation interval and $q_{\max}$ is the maximal flow rate under the given geometric conditions. Equation 1 is used to identify loop detector errors caused by pulse breakup in heavy traffic. In practice, $q_{\max}$ per minute is set to be 51 vehicles per lane, corresponding to the hourly flow of 3,060 vehicles per hour per lane. This threshold shall vary with roadway and traffic conditions.

- Occupancy threshold check. The detected occupancy shall also lie within the following range:

$$0 \le o_d \le o_{\max} \tag{2}$$

where o_d is the obtained occupancy rate (as a percentage) per lane of the target detector and $o_{\max}$ is the maximum occupancy rate (e.g., 95% in practice). This check can help find a detector's errors from being stuck in the on position.

- Speed threshold check. The detected speed shall be below the maximum speed threshold, as shown in Equation 3:

$$0 \le v_d \le v_{\max} \tag{3}$$

where v_d is the measured speed per lane and $v_{\max}$ is the maximum physical speed on the target roadway segment (e.g., 100 mph for the study site). This stage can catch some obvious speed measurement errors.

A further check with the speed–density–flow rate relationships can also be conducted to assess detector quality. For example, the detected flow rate cannot be positive when the detected speed equals zero.

Stage 2. Statistical Comparison

Figure 2 illustrates the procedure for the statistical comparison, for which the AEVL computed from the target detector (the midbottom, crosshatched one) is first compared with other sensors (the midupper two) in the same station (Figure 2*a*) and then with its direct upstream and downstream detectors (Figure 2*b*).

Same-Station Comparison

The AEVL for detector quality test is defined as follows:

$$\mathrm{AEVL} = \frac{10 \cdot o_d \cdot v_d}{60 \cdot q_d} \tag{4}$$

The core logic of the proposed algorithm is that no statistical difference in the estimated AEVLs shall exist between adjacent lanes or between neighboring stations. Such a comparison shall be based on both the temporal information (i.e., 1-day data) and spatial data (i.e., adjacent lanes and stations).

Given the temporal and spatial information, Figure 3 shows the sequential steps for comparing the estimated AEVLs within each detector station. By selecting the data that pass the preliminary check, the whole data set will be further divided into a set of groups by different times of day (e.g., 30 min per interval for each group in the case study). Then, the mean and variance of the estimated AEVL for each lane of each group can be computed as follows:

$$\overline{\mathrm{AEVL}}_{\mathrm{group}(k,m)} = \frac{1}{n_{k,m}} \sum_{i=1}^{n_{k,m}} \left(\mathrm{AEVL}_{\mathrm{group}(k,m)}(i) \right) \tag{5}$$

$$S^2\left(n_{k,m}\right) = \frac{\sum_{i=1}^{n_{k,m}} \left[\mathrm{AEVL}_{\mathrm{group}(k,m)}(i) - \overline{\mathrm{AEVL}}_{\mathrm{group}(k,m)} \right]^2}{n_{k,m} - 1} \tag{6}$$

for

$$k = 1:48, k \in Z$$

$$m = 1: \text{number of lanes}, m \in Z$$

where

S^2 = mean estimate of variance,
k = time interval,
m = lane number, and
$n_{k,m}$ = sample size from lane m in group k.

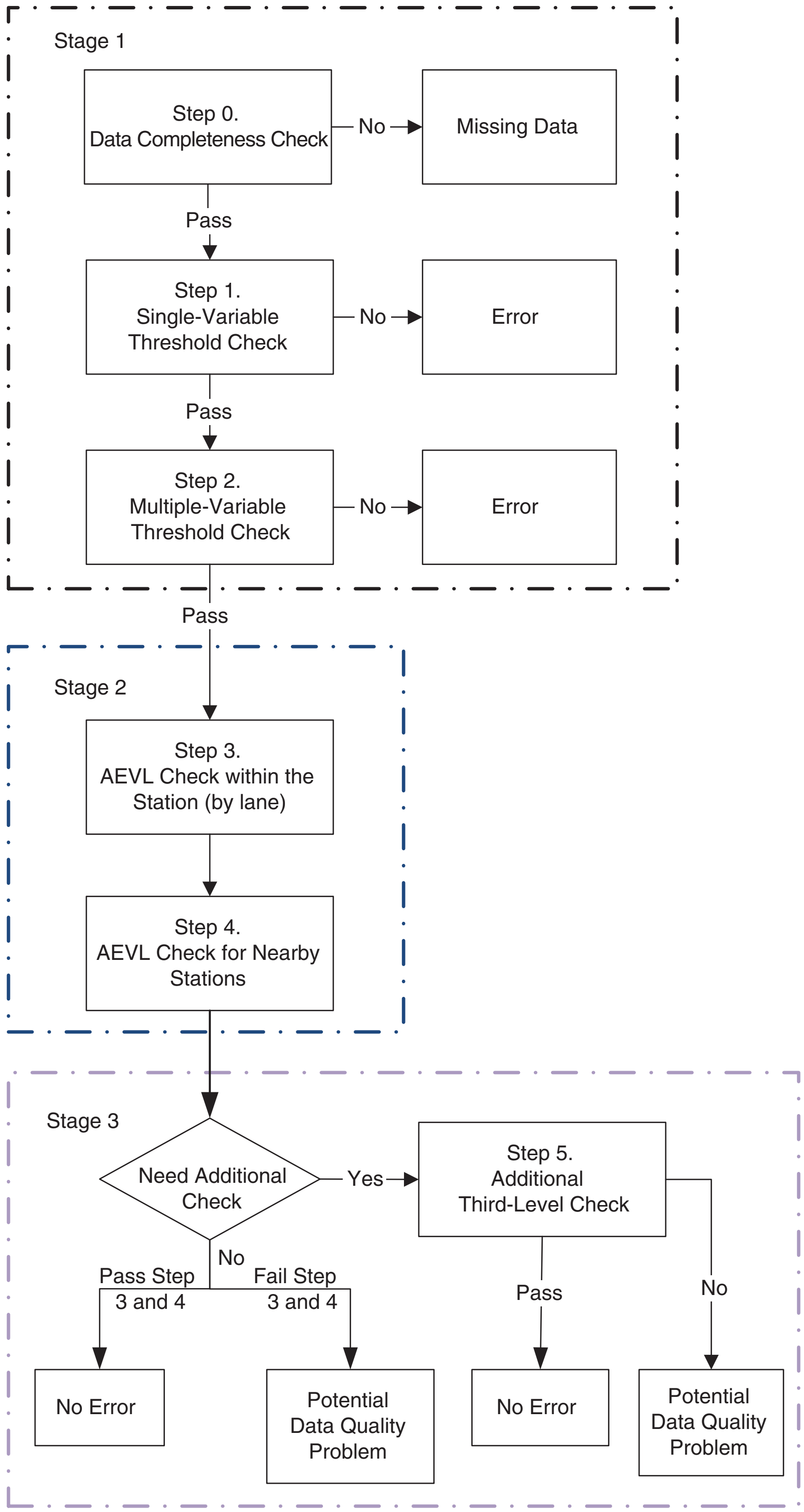

FIGURE 1 Flowchart of screening algorithm.

As Figure 3 shows, Step 4 is to compare the AEVL estimated from different lanes within the same station. Because a pairwise comparison between lanes may be quite cumbersome if the roadway segment contains multiple travel lanes (e.g., C_4^2 combinations for four lanes), this study proposes a new method, the MCB method, which can concurrently compare the target lane with multiple adjacent lanes and form a confidence interval for statistical assessment (*20*). An obtained confidence interval containing 0 indicates that no significant difference in AEVL exists between the target and the other lanes and vice versa.

The advantage of MCB over the traditional pairwise comparison is that it can significantly reduce the number of comparisons from

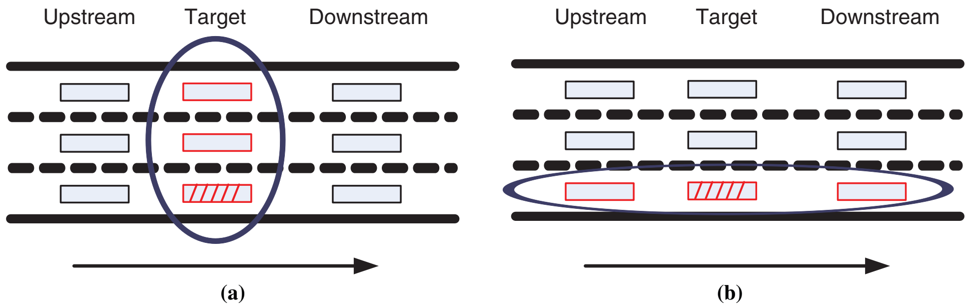

FIGURE 2 Procedure of statistical comparison for detectors: (*a*) with sensors in same station and (*b*) with direct upstream and downstream detectors.

$\binom{k}{2}$ to k, where k is the number of lanes. The confidence interval for concurrent comparison with MCB can be calculated with Equation 7:

$$\left[\min\left\{0,\begin{pmatrix}\overline{\mathrm{AEVL}}_i-\max\left(\overline{\mathrm{AEVL}}_{l(l\neq i)}\right)\\ -\sqrt{2}\times T^{\alpha}_{k-1,k(n_i-1),0.5}\times\sqrt{\dfrac{S^2(n_i)}{n_i}}\end{pmatrix}\right\},\ \max\left\{0,\begin{pmatrix}\overline{\mathrm{AEVL}}_i-\max\left(\overline{\mathrm{AEVL}}_{l(l\neq i)}\right)\\ +\sqrt{2}\times T^{\alpha}_{k-1,k(n_i-1),0.5}\times\sqrt{\dfrac{S^2(n_i)}{n_i}}\end{pmatrix}\right\}\right] \quad (7)$$

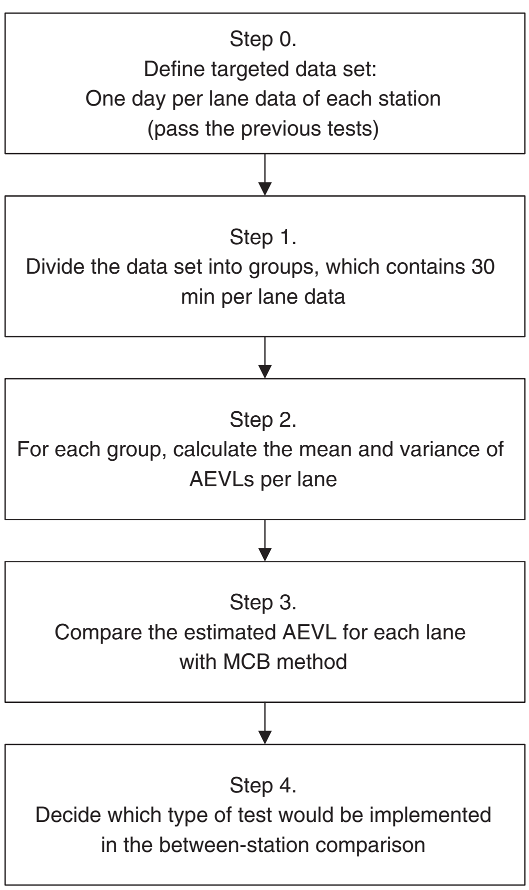

FIGURE 3 Comparison of AEVL within same station (by lane).

where

- i = target lane,
- l = other lanes in same station,
- n_i = sample size of lane i, and
- α = significance level.

The value of parameter T varies with the number of lanes, sample size, and the level of significance, which is available from statistics tables in Hochberg and Tamhane (*21*).

By taking one detector station with three lanes, for example, seven types of potential comparison results with the proposed MCB are summarized in Figure 4.

Figure 4*a* shows the performance of a perfectly functioning detector, reflecting no significant difference between the three estimated AEVLs from different lanes because their confidence intervals include zero. Thus, no data error can be concluded from this case. However, one possible exception is that all detectors in the three lanes are concurrently malfunctioning. Figure 4, *b* through *g,* show six types of potential errors that are based on the MCB results; for these errors, one detector may produce a higher or lower AEVL compared with that of the others. However, as they depend on driving patterns and vehicle distributions, the AEVL test results shown in Figure 4 may not be the result of detector malfunction but due to the concentration of heavy vehicles on some particular lanes. For example, most trucks may use the rightmost lane on a freeway segment, and the imbalanced distribution of heavy vehicles can result in a difference in AEVLs between lanes. Hence, further statistical tests among nearby stations are necessary to confirm the evaluation results.

Between-Station Comparison

For further verification of the preliminary conclusions from the in-station comparisons, one should also conduct a spatial AEVL comparison between the target detector and its upstream and downstream detectors. With respect to the two types of results generated from the in-station comparisons (Figure 4), the screening decision trees incorporated with the between-station comparisons are shown in Figures 5 and 6.

If no statistical difference is found from the within-station comparison, one could tentatively reach two types of conclusions: (*a*) all detectors in the target station can provide reliable data and (*b*) all detectors in the target station are malfunctioning so that errors cannot be found by the comparison. Hence, by using the data from each lane's upstream and downstream detectors, a further between-station comparison can help identify potential data errors. As Figure 5 shows, all detectors within the target stations will be identified as having potential errors if their AEVLs are significantly larger or smaller than the AEVLs of their upstream and downstream detectors.

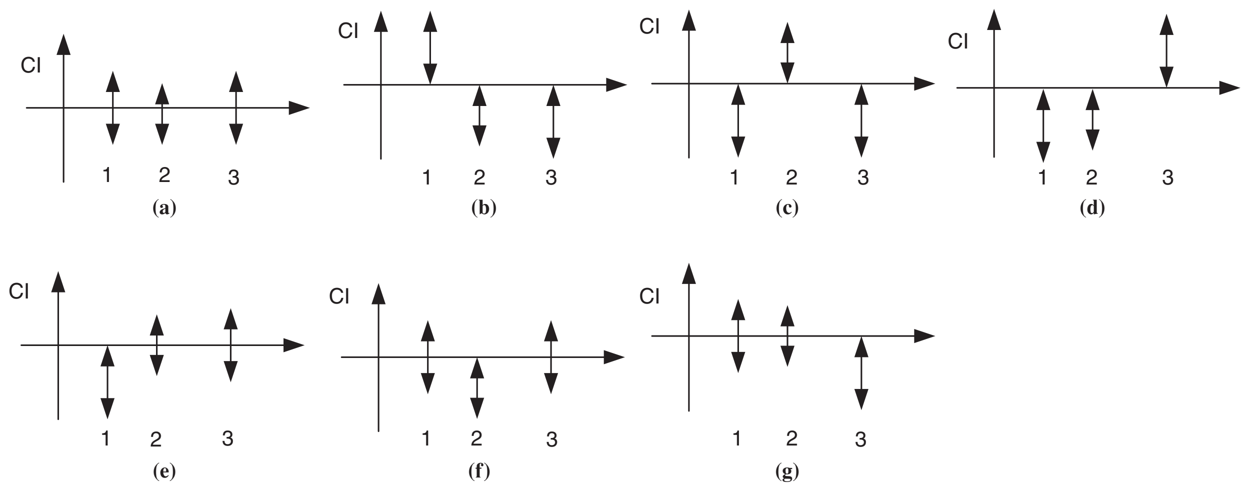

FIGURE 4 MCB results within same station, by lane (CI = confidence interval).

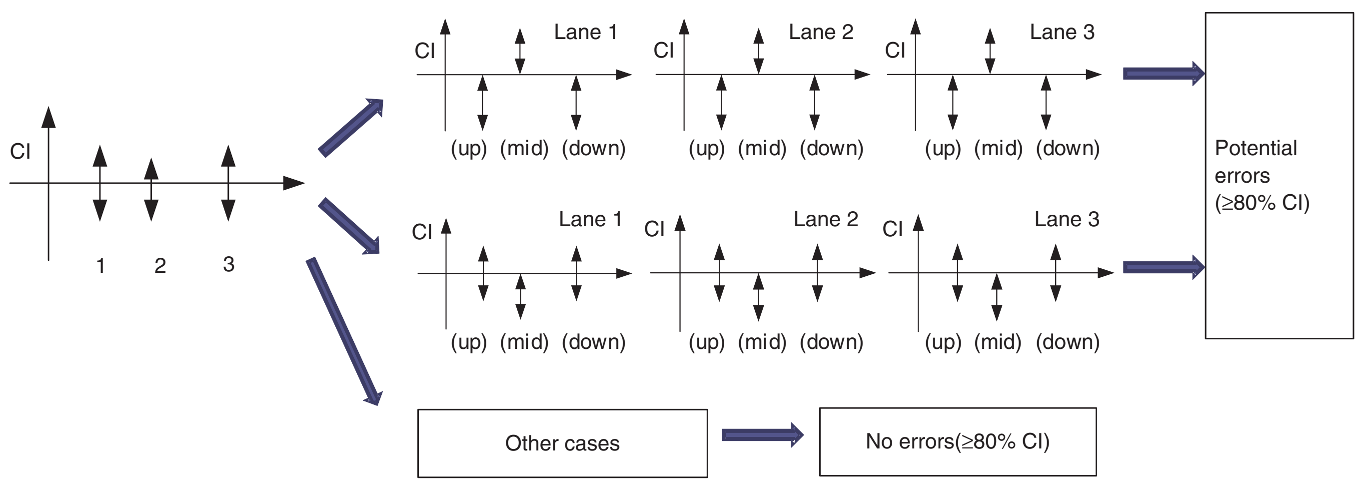

FIGURE 5 Decision tree of between-station comparisons when no difference is found in within-station comparisons.

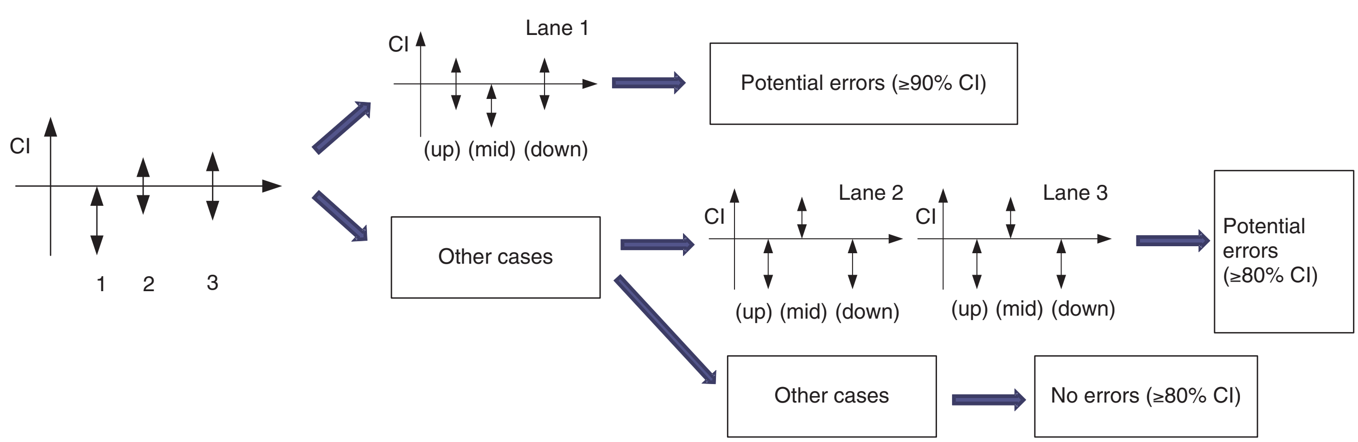

FIGURE 6 Decision tree of between-station comparisons when difference is found in within-station comparisons.

If the results of the within-station test indicate that the AEVL from one lane is larger (or smaller) than the others (Figure 6), two possible scenarios may exist: (*a*) the detector in the target lane (e.g., Lane 1 in Figure 6) cannot function properly or (*b*) the target detector is in good condition, but all other detectors in the same station (e.g., Lanes 2 and 3 in Figure 6) have malfunctioned. The first possible condition could be proved if the results from the between-station comparison shows that the AEVL from the target lane is also larger (or smaller) than the AEVLs from its upstream and downstream detectors. The second possible condition will be confirmed if the AEVLs from all other lanes are found smaller (or larger) than the AEVLs estimated from their corresponding upstream and downstream lanes.

Stage 3. Third-Level Check

In the case that the nearest neighboring sensors are known to suffer severe quality problems, one can further adopt the upstream and downstream stations to perform the spatial comparisons as shown in Figure 7, where the stations are numbered 1 to 5 from left to right, with No. 3 being the target station.

For example, in Figure 7*a,* because Station 4 has quality issues, one can use its upstream (No. 2) or further downstream (No. 5) station to perform the test; the same holds true for the cases in Figure 7*b,* for which Station 1 or 4 (as Station 2 has problems) and, in Figure 1, for which Stations 1 and 5 (as Stations 2 and 4 have problems) can be used. This additional level of check is applicable only to the location where geometric and traffic conditions between neighboring stations have no significant difference.

CASE STUDY

This section illustrates an application of the proposed algorithm to the surveillance system in Ocean City, Maryland, and discusses its effectiveness in evaluating detector quality.

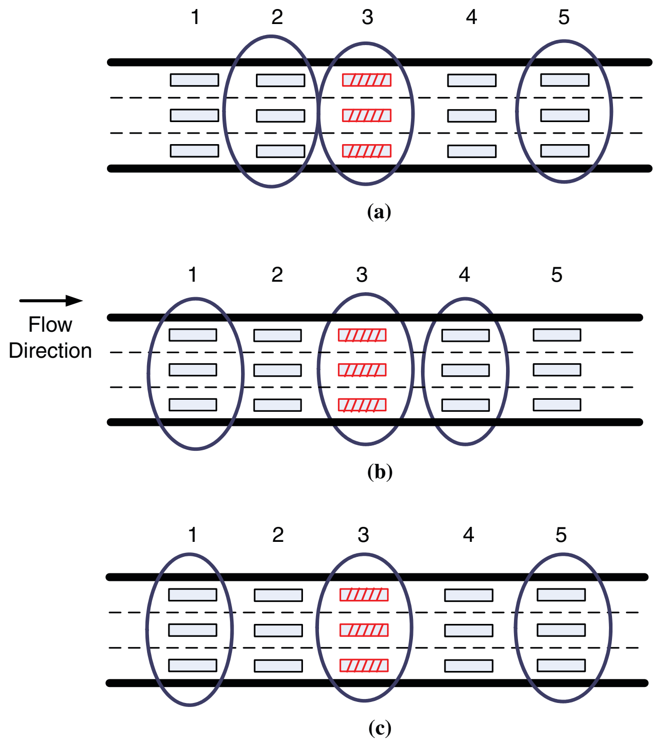

FIGURE 7 Comparison with further upstream and downstream stations.

Data Site

As Figure 8 shows, the Traffic Safety and Operations Laboratory at the University of Maryland, College Park, in collaboration with Maryland State Highway Administration, deployed a traffic monitoring system for the Ocean City region and provided real-time travel time information updated every minute for US-50 and

FIGURE 8 Locations of sensors around Ocean City.

TABLE 1 Distribution of Detector Status for Stage 1 Evaluation

	Total		US-50		MD-90	
Detector Status	Number of Records	Percentage	Number of Records	Percentage	Number of Records	Percentage
No error	425,040	91.67	298,146	92.43	126,891	89.92
Error	375	0.08	117	0.04	258	0.18
Missing data	38,265	8.25	24,294	7.53	13,971	9.90

TABLE 2 Distribution Detector Status for Stage 2 Evaluation

	Total		US-50		MD-90	
Detector Status	Number of Records	Percentage	Number of Records	Percentage	Number of Records	Percentage
No error	404,153	87.16	288,333	89.39	115,820	82.07
Error	375	0.08	117	0.04	258	0.18
Missing data	38,265	8.25	24,294	7.53	13,971	9.90
Potential data quality problem	20,887	4.50	9,816	3.04	11,071	7.85

MD-90 (*22*). The surveillance system contains 43 sensors for the entire region; among these, 35 are Wavetronix SmartSensor HDs that use dual radars to capture speed information, and eight are SmartSensor 105s that function as a single loop does. Sixteen sensors (five 105s, 11 HD) and eight sensors (all HD) are along US-50 and MD-90, respectively. Because most of US-50 has two lanes in each direction, one can use a simple paired *t*-test for the between-lane AEVL comparison. However, MD-90 has only one lane in each direction, so only the between-station comparison with the proposed MCB is necessary. This study uses 1-min data over 2 weeks for the HD sensors along US-50 and MD-90 to conduct the test. These 2 weeks were August 6 to 12, 2012, to represent the peak season and February 18 to 24, 2013, to represent the off-peak season. The locations of these sensors are shown in Figure 8.

Malfunction Distribution with Stage 1 Evaluation

After the Stage 1 evaluation is performed, the detector status can be classified into three types: no error, error, and missing data. "No error" means that the detector passes all tests in Stage 1 sequentially. The "error" type suggests that the detector fails the proposed single- and multiple-threshold tests and indicates that the detector needs either maintenance or calibration. The term "missing data" refers to no data reported for that time period.

Distribution of detector status for the Stage 1 test for Ocean City is shown in Table 1.

From Table 1, one can see that the overall condition of the detectors is acceptable because more than 91% of the data points are correct. Missing data seem to be the most obvious problem, which is caused mainly by wireless misconnection and low battery to support the solar-panel power. If one further splits the data set into US-50 and MD-90, one see that the sensors in US-50 obviously have better data quality than those in MD-90 with respect to every performance measure.

Malfunction Distribution with Stage 2 Evaluation

After the Stage 2 test, several data originally classified into the no-error group can be further classified as a potential data quality problem, which indicates that the target detector may not produce reliable data even though its produced speed, occupancy, and flow rate are within the feasible range. As Table 2 shows, around 5% of the detector records may have potential quality problems, reflecting the need to conduct rigorous calibration.

After evaluation of the overall performance, the evaluation focus centers on the quality of each sensor to identify the one with the highest error rate. With the following procedures, the problematic sensors can be viewed as being in need of further maintenance and calibration.

The evaluation results associated with each sensor's quality are shown in Figure 9, in which Detectors 115 to 127 belong to US-50 and the rest to MD-90. The results in Figure 9 reveal the following findings:

1. Detectors 115, 120, 139, 138, 136, and 131 have severe communication problems, evidenced by their high percentage of missing data. For example, Detector 120 has about 40% missing data.
2. Because a large portion of Detector 120's data are missing, the rate of identified potential errors at its neighboring detectors (i.e., Detectors 118 and 122) are extremely low. The between-station

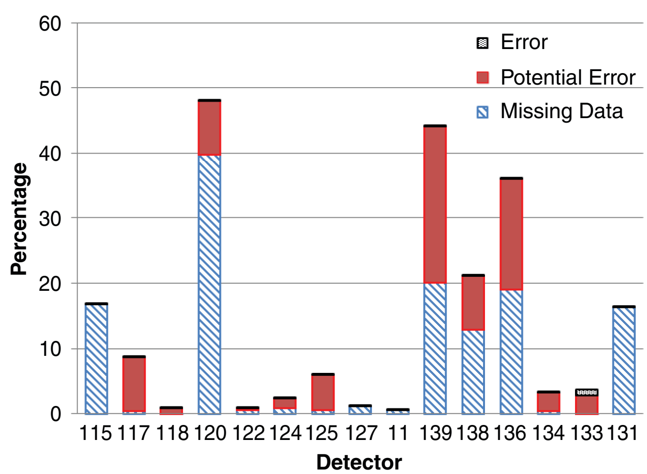

FIGURE 9 Error rates for each sensor after Stage 2 evaluation.

TABLE 3 Stage 3 Check: Status of Detectors 118 and 122

	Detector 118[a] (%)		Detector 122[b] (%)	
Detector Status	Before	After	Before	After
No error	99.06	99.50	99.16	98.73
Error	0.05	0.05	0.01	0.01
Missing data	0.01	0.01	0.61	0.61
Potential data quality problem	0.87	0.43	0.22	0.65

[a]Compared with Detectors 117 and 122.
[b]Compared with Detectors 118 and 124.

comparison requires the information from upstream and downstream detectors. Hence, the large missing data at Detector 120 can cause the comparisons with its neighboring detectors to be meaningless.

3. Three neighboring detectors, 139, 138, and 136 along MD-90 show the likelihood of having malfunctioned and need further investigation to verify their actual conditions.

4. Because detectors at the boundaries do not have neighboring stations at one side, the test for between-station comparisons cannot be conducted.

Necessity of Including Stage 3 Evaluation

The second and third findings of the preceding section both suggest the need for conducting a Stage 3 check. As Detectors 118 and 122 exhibit a potential error rate that is quite low, one should conduct the Stage 3 test to verify the status of their quality. Here, Detector 118 is compared with Detectors 117 and 122 and Detector 122 with Detectors 118 and 124. The results before and after the Stage 3 check are shown in Table 3.

The results of the Stage 3 test clearly indicate that both Detector 118 and 122 indeed produce reliable data.

The third finding is Detectors 139, 138, and 136 have severe problems. Then, comparing them does not make sense. Instead, one should consider using the farther normal sensors to join the between-station tests to avoid potential false alarms. Detectors 139, 138, and 136 are all compared with Detectors 11 and 134 in the between-station test. The comparison results with and without the additional check are shown in Table 4.

After the potential data quality row from Table 4 is examined, one can see that before the Stage 3 check, the results from the Stage 2 test yield some false alarms for Detectors 139 and 138, and several potential data quality problems were not identified for Detector 136. Hence, the Stage 3 check could help reduce the percentage of both Types I and II errors. The same pattern can be found for each sensor

TABLE 4 Status of Detectors 139, 138, and 136 Before and After Stage 3 Check

	Detector 139[a] (%)		Detector 138[a] (%)		Detector 136[a] (%)	
Detector Status	Before	After	Before	After	Before	After
No error	55.84	72.42	78.72	84.65	63.80	56.64
Potential data quality problem	24.08	7.5	8.28	2.35	16.95	24.12

[a]Compared with Detectors 11 and 134.

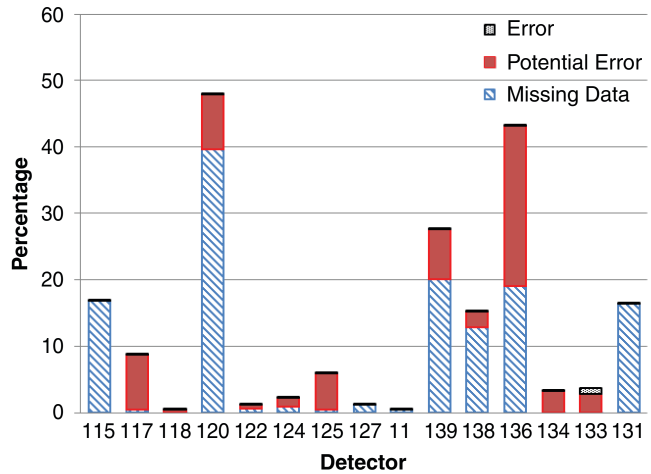

FIGURE 10 Error rates for each sensor after Stage 3 evaluation.

along MD-90, except for Detector 136, which showed a much lower AEVL value. And the revised status distribution for all detectors is updated in Figure 10.

CONCLUSIONS

This study has presented a sequential screening algorithm for reliable classification of detector data into three categories: missing data, errors, and potential errors, which means that a detector needs to be maintained or calibrated. The proposed algorithm, with its embedded MCB tests, is capable of distinguishing malfunctioning detectors from detectors in need of calibration or maintenance. Hence, proper use of the proposed algorithm can help responsible highway agencies to best maintain their detector systems with minimum resource needs. An application of the proposed method into Ocean City has proved its potential for use in real-world applications.

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