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A Method for Accuracy Assessment of Aggregated Freeway Traffic Data

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Abstract

Accurate traffic data is crucial for advanced traveller information and traffic management applications. However, it is widely acknowledged that limitations in the monitoring and communication technologies lead to significant inaccuracies in the estimates of traffic parameters such as traffic volume and travel speed. Currently deployed traffic data quality control methods do little more than identifying implausible outliers. This paper presents an efficient method based on the concept of spatial consistency for assessing the accuracies of aggregated segment-wise traffic volumes in a freeway network. A novelty of the proposed approach is that unlike most other comparable solutions, it does not depend on the availability of good quality historical traffic data or well-calibrated reference stations. The method has been validated using simulated data generated by a microscopic traffic simulator. It has been found that the accuracy estimates produced by the proposed method strongly correlate with the actual accuracies of the input traffic data that has been corrupted with two types of synthetic errors.

1. Introduction

Collection of traffic data through on-road sensors has traditionally been intended to serve the needs of offline analytical applications such as transportation planning and congestion monitoring. In recent years, traffic data is also consumed by emerging real-time operational applications such as advanced traveller information systems and adaptive traffic control systems. Real-time applications that make use of traffic data are significantly dependent on the quality of the input data. Depending upon the application, some or all of several traffic data quality metrics such as accuracy, completeness, validity, timeliness, coverage and accessibility are considered [1]. Of these, accuracy (the degree of agreement between the reported values and the true values) is arguably the most important metric for real-time applications. It has been estimated that traffic data errors should not exceed 20% for traveller information applications and 10% for traffic management applications [2].

Several surveys commissioned by the U.S. Federal Highway Administration have raised concerns about the quality of archived traffic data [3]. The difficulty in maintaining extensive electronic field equipment

for traffic monitoring and communication has been cited as an important factor influencing traffic data quality. Widely-used traffic monitoring technologies such as inductive loop detectors and video imaging based sensors are known to have several vulnerabilities. The performance of inductive loop detectors is often degraded due to the poor condition of the loop wires caused by wear and tear from heavy vehicles, improper installation, road opening and resurfacing. The accuracy of video imaging based traffic sensors are affected by a number of factors such as changes in illumination, shadows, reflections, unusual weather and camera jitter [4]. Sensor faults often cause the estimates of traffic parameters such as volume (flow) and mean speed to be highly inaccurate.

Most of the methods currently used for traffic data quality control are limited to identifying implausible values mainly through range checks on a simple pass/fail basis [3]. Methods based on range checks involve establishing a minimum, maximum or range of expected values for a single traffic parameter or a combination of traffic parameters and examining if the measured value falls within this range. For instance, a volume value greater than 3000 vehicles per hour per lane or a mean speed value exceeding 160 km/h is typically flagged as invalid. Some validity criteria check for impossible or improbable occurrences such as positive volume with zero speed and a number of consecutive identical volume values. While methods based on range checks are adequate for identifying obvious outliers, they are potentially incapable of detecting relatively small biases. Another approach, which uses spatial and temporal consistency as a validity criteria, examines data values by comparing to historical data at the same location, or to other current data values at nearby locations. Traffic data quality control based on the concept of spatial consistency remains a field of active research.

This paper presents and evaluates a method based on the concept of spatial consistency for assessing the accuracy of aggregated freeway traffic data and identifying erroneous values. A clear delimitation of the scope of the presented work may be in order here. Firstly, it is confined to freeway networks, which are characterized by an unhindered flow of traffic free of at-grade crossings and traffic signals. Secondly, the proposed method targets macroscopic traffic volume data aggregated and averaged over several minutes at the road-segment level, rather than at the sensor level. One of the motivations for this choice is that the traffic data disseminated in the authors' country of interest, Singapore, is aggregated at 5-minute intervals for each road segment. Each road segment typically has one or more sensors that measure the traffic along it. In practice, a wide range of sensor technologies are used for collecting traffic data on freeways and heterogeneous data from different sensors are fused together to obtain the traffic data for each road segment.

The rest of the paper is organised as follows: Section 2 presents a survey of the literature in the area of spatial consistency based traffic data validation. Section 3 formally describes the relationship between the flows of upstream and downstream road segments. The proposed accuracy assessment method is

explained in Section 4. The process of evaluating the effectiveness of the method using a traffic simulator and the results are presented in Section 5. Finally, Section 6 concludes the paper with some directions for future research.

2. Related Work on Spatial Consistency Based Traffic Data Validation

The methods that seek to detect or rectify the inaccuracies in traffic data based on the concept of spatial consistency rely on some consistent relationship between the traffic data measured at nearby locations. Some solutions [5] [6] favour a data-driven approach and define the relationship between the traffic parameters of neighboring stations based on historical data. However, the availability of good-quality historical data is not always guaranteed and spatial relationships modeled on the basis of erroneous historical data could produce deleterious results. Also, they are not suitable for situations where significant deviations from historical patterns occur due to traffic incidents or changes in the network.

Another class of methods are based on the vehicle conservation principle, which requires the volumes of vehicles entering and exiting a section of road to be consistent with number of vehicles remaining on it. It can also be stated simply as 'vehicles cannot be created or lost along the road' [7]. The vehicle conservation principle is formally expressed using the conservation equation, which is derived and described in Section 3.

Nihan [8] proposed that the cumulative storage along a section of a freeway can be used for detecting sensor errors. The cumulative storage, which corresponds to the difference between the total number of vehicles counted by the upstream and downstream sensors, should not exceed the maximum number of vehicles that can be accommodated along the section at jam density. A steady increase or decrease in the cumulative storage is symptomatic of a constant sensor bias. Vanajakshi and Rilett [9] relied on the above concept to check if a group of sensors obey the conservation principle. If a violation is detected, they apply a constrained nonlinear optimization approach to adjust the data so that the volumes conform to the conservation principle with the least change from the original data. Kikuchi [10] proposed a method based on fuzzy linear programming that similarly seeks to adjust the observed values until the conservation principle is satisfied. A major weakness of the methods described above is that they can only detect that a set of neighboring sensors are violating the conservation principle, but cannot determine which of the sensors is faulty. Instead they adjust the volumes of all sensors, including the accurate ones.

Wall and Dailey [11] proposed an error detection algorithm which first identifies a pair of well-calibrated reference stations, whose historical data shows a strong conformity to the conservation principle. Subsequently, faulty sensors adjacent to the reference stations are identified by comparing with the

latter. A correction factor is applied to the flows of the faulty sensors based on the number of vehicles overcounted or undercounted. After applying the correction factor to a faulty sensor, it is used as a reference for sensors adjacent to it. However, in some scenarios, such serial comparisons and adjustments could lead to an accumulation of errors. Also, the algorithm, which relies on long-term historical data, targets archived traffic data and it is doubtful if it can be extended to real-time operation.

A method to detect faulty sensors solely on the basis of currently observed data without relying on historical data was proposed by de Oña et al. [12]. This method, which uses linear optimization, has been applied to a small urban network with 7 intersections and 86 sensors. Theoretical values that satisfy the conservation principle are used as the 'true' flow data, which is randomly deformed with a tolerance of $\pm 3\%$. Subsequently, a relatively large error is introduced to one of the sensors and the method is tasked to detect it. It was found that the a good success rate ($>90\%$) is achieved only when the error is high ($>75\%$) and the success rate reduces drastically for smaller errors ($<25\%$).

Lin et al. [13] proposed a fuzzy-logic based classifier for assessing the reliability of traffic data by combining network consistency (conformity to the conservation principle) with fundamental consistency (physical plausibility) and historical consistency (agreement with past observations). In this method, a reliability index is calculated for each sensor based on the above criteria. While the reliability indices have been calculated for a freeway section with 3 sensors using archived data, the correctness of the reliability assessment has not been demonstrated either using ground truth data or through simulation.

The methods based on the vehicle conservation principle are best suited for freeways where it is generally not possible for vehicles to enter or leave the road except through the entry/exit slip roads. Also, they have the most potential for identifying values that are inaccurate yet plausible. It has been reported that 95% of the invalid data detected by quality checks based on flow inconsistencies between upstream and downstream stations were not detected by basic range checks [14].

3. Vehicle Conservation Equation and the Consistency of Flows

It is intuitive to view the traffic on a freeway as a fluid flowing through a pipeline. Based on this analogy, Lighthill and Whitham [15] and Richards [16] proposed a macroscopic traffic model known as the LWR model that relies on the concept of conservation of vehicles. The latter is expressed by the conservation equation that relates the flow and density of traffic along a road with space and time. The conservation equation can be derived as follows [17].

Figure 1: Illustration for deriving the conservation equation

Let a unidirectional section of a freeway with two counting stations S_1 and S_2 separated by a distance Δx as shown in Figure 1 be considered. Let N_i be the number of vehicles passing station S_i during time interval Δt . The flow q_i at station S_i is given by:

$$q_i = \frac{N_i}{\Delta t} \quad (1)$$

Let $\Delta q = (q_2 - q_1)$. Let it be assumed that $N_1 > N_2$. This would result in an increase in the number of vehicles ΔV along the section Δx , which can be expressed as the difference in the number of vehicles entering and exiting the section:

$$\Delta V = N_1 - N_2 = (q_1 - q_2)\Delta t = -\Delta q \Delta t \quad (2)$$

If k_1 and k_2 are the traffic densities along the section Δx at the start and end of the time interval Δt and the change in density $\Delta k = (k_2 - k_1)$, then the increase in the number of vehicles along the section can also be expressed as:

$$\Delta V = (k_2 - k_1)\Delta x = \Delta k \Delta x \quad (3)$$

Since vehicles are conserved within the section Δx , Equations 2 and 3 lead to:

$$\frac{\Delta q}{\Delta x} + \frac{\Delta k}{\Delta t} = 0 \quad (4)$$

If the increments are considered to be infinitesimal, the following first-order partial differential equation is obtained.

$$\frac{\partial q}{\partial x} + \frac{\partial k}{\partial t} = 0 \quad (5)$$

Equation 5 expresses the vehicle conservation principle and is known as the conservation equation. It implies that an increase (decrease) in flow q over space x is accompanied by a corresponding decrease (increase) in density k over time t .

Lighthill and Whitham [15] proposed a solution for the conservation equation using the fundamental relationship $q = ku$, where u is the space mean speed. It was shown that slight changes in flow between upstream and downstream points are propagated back through the stream of vehicles along shock waves, whose speed u_w relative to the road is:

$$u_w = \frac{q_d - q_u}{k_d - k_u} \quad (6)$$

where the subscripts u and d refer to the upstream and downstream points respectively.

It needs to be noted that shock waves are propagated only when the upstream and downstream locations are in different traffic states. A mere difference in upstream and downstream densities does not generate a shock wave as long as free flow of traffic is maintained. Only when one or both of the densities exceed the critical density and free flow of traffic is impeded, shock waves ensue. When the downstream density is higher than upstream, the congested condition is propagated upstream through shockwaves generally accompanied by the formation of a queue. When the downstream density is lower than upstream, it results in the diffusion of congestion.

From Equation 6 and the following discussion, it can be inferred that a significant difference between upstream and downstream flow rates is unlikely to persist for a long time as the discontinuity is propagated by a shock wave at a speed proportional to the difference in the flow rates. This observation is very relevant to the work presented in this paper, which is based on the idea that reasonably-spaced upstream and downstream locations will experience almost similar flow rates over a sufficiently long period of time. It is suggested in [17] that the LWR model based on the conservation equation is better suited to model traffic when speed, flow and density are averaged over long time spans (i.e., in the order of 5 minutes) rather than short ones (i.e., in the order of 30 seconds).

4. Proposed Method for Accuracy Assessment of Traffic Data

The presented work is directed towards the problem of rating the accuracy of road-segment-wise traffic volumes aggregated over time intervals in the order of 5 minutes. A key requirement is that the method should not rely on inferences drawn from long-term historical data or the presence of well-calibrated reference stations. It should also have low computational complexity and be capable of high-speed processing of a voluminous amount of data. The proposed approach, which is based on the expected consistency in the volumes of upstream and downstream road segments, can be broadly summarized as follows:

- The accuracy of each road segment's aggregated volume is rated by each of its neighbour segments using the latter's volume as a reference.

- The rating from each neighbour segment is weighted by its own estimated accuracy score and accumulated to determine an accuracy score for the road segment being assessed.

The above approach requires the road network to be preprocessed in order to identify the neighbours of each road segment. Here, the term ‘neighbour’ is used to denote a segment or a combination of segments, whose combined traffic volume aggregated over a time interval is expected to be consistent with the volume of the segment under consideration. Figure 2 shows the schematic of a set of connected road segments along with a list of neighbours for each segment. The set of neighbours for a given segment X is denoted by G_X , which includes the immediate and second-degree connected segments in the upstream and downstream directions. Multiple segments that originate from the same source or end at the same sink are referred to as complements of each other. For instance, segments D and E in Figure 2 are considered as complements and their combined volume is expected to be in broad agreement with the upstream segments B and C . In this case, segments D and E are collectively considered as a multi-segment neighbour of segments B and C . A second-degree connected segment that occurs before or after a multi-segment neighbour is not considered as a neighbour. For instance, segment F is not considered a neighbour of segment C , as their volumes are not expected to agree. When the volume of a segment is compared with that of its neighbours, its complements, if any, should also be included in the comparisons in the appropriate manner. For instance, a comparison of traffic volumes of segments D and C should take into consideration the traffic branching out through segment E . However, it is obviously not necessary to do so when the volumes of segments D and F are compared.

Figure 2: A schematic of a set of road segments with neighbour information

It is important to note that in the proposed approach, it is assumed that the traffic volume reported for each road segment is independently measured. In other words, multiple road segments should not have identical volumes measured by a single common sensor. However, the practice of extrapolating the measurement made by a single sensor to a number of consecutive road segments has been observed in real traffic data. In such a scenario, comparing adjacent segments that always report the same volume may wrongly lead to inferring excellent spatial consistency between them. Therefore, a preprocessing

step is performed to identify consecutive road segments that always have the same volume and concatenate them into a single macro segment. In the steps described below, a macro segment is treated just like any other road segment.

The method requires an efficient way of quantifying the disagreement in volumes between a road segment and a given neighbour. For this purpose, a simple measure of disagreement is calculated as given in Equation 7. The measure of disagreement D_{jkt} between a road segment j and its neighbour k at time interval t is given by

$$D_{jkt} = \frac{|V_{jt} - V_{kt}|}{\max(V_{jt}, V_{kt})} \quad (7)$$

where V_{jt} and V_{kt} are the volumes at time t for road segment j and its neighbour k respectively. The value of D_{jkt} in Equation 7 ranges from 0 to 1.

It is quite rare for the aggregated volumes of two neighboring segments to be exactly same. Small differences between them are to be expected most of the time. Hence, the method needs to be immune to relatively small differences in volume between spatially close segments. Also, it is possible for genuine differences in the traffic volumes of neighboring segments caused by traffic incidents to prevail for short durations. However, as explained in Section 3, these flow imbalances resolve within a short span of time (typically one or two 5-minute intervals) as the effect of the traffic incident propagates through the road network. Hence any volume comparisons between neighboring segments should account for the possibility of genuine short-term differences in the reported volume. Taking the above factors into consideration, a measure of agreement or ‘match score’ M_{jkt} for road segment j and its neighbour k at time t is calculated as:

$$M_{jkt} = \begin{cases} 1, & D_{jkt} < 0.1 \\ 1 - \min(D_{jkt}, D_{jkt-1}, \dots, D_{jkt-h}), & \text{otherwise} \end{cases} \quad (8)$$

where D_{jkt} is the measure of disagreement as defined by Equation 7 and h is the number of recent time intervals considered. (The value of h is set as 2 in the current implementation.) As it can be seen, a D_{jkt} value less than 0.1 has no impact on the match score. This means that volume differences of up to 10% between neighboring segments are tolerated and not treated as a disagreement.

While assessing the accuracy of the volume of a road segment, a match score is calculated between itself and each of its neighbours. The match scores from all the neighbours are weighted by their own estimated accuracies to estimate the accuracy of the road segment under consideration. The accuracy A_{jt} of a road segment j at time t is estimated as given in Equation 9.

$$A_{jt} = \frac{\sum_{k \in G_j} A_{kt} M_{jkt}}{\sum_{k \in G_j} A_{kt}} \quad (9)$$

where G_j is the set of neighbours of segment j and M_{jkt} is the match score defined in Equation 8. At the start of the computation process, the accuracy of all the segments are initialized to 1. The accuracy values are subsequently updated in an iterative manner until convergence is observed. It has been determined that 2 iterations are adequate for the accuracy scores to converge.

Segment	Ground truth volume	Measured volume			Actual accuracy (%)	Estimated accuracy (%)
		V_{t-2}	V_{t-1}	V_t		
A	410	521	499	521	74.72	43.88
B	407	395	412	416	99.84	82.73
C	396	220	219	223	55.72	53.35
D	293	298	291	297	99.20	90.16
E	102	104	99	102	99.67	82.66
F	305	312	303	314	98.47	100.00

Table 1: A hypothetical numerical example for the proposed method with reference to Figure 2

A simple numerical example to demonstrate the above method is given in Table 1 with reference to the road network schematic in Figure 2. For all the road segments shown in Figure 2, hypothetical values that conform, within a small tolerance band, to the vehicle conservation principle are considered as the ground truth volumes (Table 1, column 2). Hypothetical volume measurements for three consecutive intervals are provided in columns 3 to 5. It can be seen that while most of the segments have largely accurate measurements, segments A and C overcount and undercount respectively by significant margins. The actual percentage accuracies (100% minus the absolute percentage error) of the measurements with reference to the given ground truth values is provided in column 6. Based on the neighbour list given in Figure 2, applying the proposed method to the volume measurements produces the accuracy estimates provided in the last column in percentage terms. It is evident that the estimated accuracies of the two erroneous segments, A and C, are significantly lower than those of the other segments. While the estimated accuracies deviate considerably from the actual accuracies for some segments, they are nevertheless adequate for detecting the segments with erroneous measurements. However, it needs to be said that some scenarios encountered in traffic data quality control could be more nuanced and complicated than the above simplified hypothetical example.

5. Simulation-based Evaluation and Results

The performance of the proposed method for traffic data accuracy assessment has been validated using a microscopic traffic simulator. The MITSIM traffic simulator [18] is used to simulate the traffic on the Singapore freeway network and its output is considered as the ground truth. The test network consists of 2125 freeway road segments with an average segment length of 138 m. In addition, there are 897 slip road segments that serve as entry/exit roads connecting other parts of the road network to the freeways. The time-dependent travel demand on this network is supplied to the simulator in terms of origin-destination (O-D) trip tables. A random number of departing vehicles, within carefully chosen limits, are assigned for each O-D pair. A scaling factor is used to vary the demand with time in accordance with the known traffic patterns. Simulation is carried out for a two-hour period from 8 AM to 10 AM, such that the peak traffic occurs around 9 AM.

Figure 3: The evaluation setup

The setup used for evaluating the proposed traffic data accuracy assessment method is shown in Figure 3. Upon successful completion of the simulation for the specified time period, MITSIM outputs the segment-wise volumes for each 5-minute period within the simulation window. This data, which is considered as the ground truth, is injected with known errors in order to obtain the corrupted, inaccurate data to which the proposed method is applied. Errors are introduced according to one of the following two synthetic error models.

Error Model 1: In this error model, the traffic volume of each road segment is associated with a fixed error percentage. The error percentages of all the road segments are randomly assigned such that they are normally distributed with zero mean and a standard deviation of 10%. This implies that based on the 3-sigma rule, nearly all the errors would range from -30% to +30%.

Error Model 2: This is intended to be a more realistic error model that permits significantly high errors to occur, as is the case with real traffic data. In this error model, 15% of the road segments are randomly assigned with a fixed, potentially high error ranging from -100% to +100%. All the other road segments are subjected to a random error within a tolerance of $\pm 5\%$.

The proposed accuracy assessment method is applied to the corrupted traffic volume data. At any given time interval, the accuracy of each road segment's current traffic volume is rated as described in Section 4 and an accuracy score is assigned to each segment. The estimated accuracy score, expressed as a percentage, for each segment is compared with the corresponding known accuracy, which is defined as 100% minus the injected absolute error percentage.

Results indicate that a strong correlation exists between the estimated and actual accuracies of the freeway road segments as shown in Figures 4 and 5. Considering all the time intervals within the simulation period, correlation coefficients of 0.67 and 0.89 have been obtained for traffic data corrupted with Error Model 1 and Error Model 2 respectively. It is worth noting that the method achieves greater success when applied to data corrupted with Error Model 2, which is more representative of real-world traffic data.

Figure 4: Correlation between estimated and actual accuracies for Error Model 1

Figure 5: Correlation between estimated and actual accuracies for Error Model 2

There are a couple of anomalies apparent in the correlation plots in Figures 4 and 5 that are worth explaining. Firstly, for Error Model 1 (normally-distributed errors with a standard deviation of 10%), none of the estimated accuracy percentages fall between 97.8% and 100%. Intuitively, such a high estimated score in the above range would suggest that the given segment's volume closely agrees with that of all its neighbours. However, since the proposed method tolerates differences in volume of up to 10%, each of the neighbours yields a perfect match score of 1 (see Equation 8), resulting in an estimated accuracy of 100%. This behaviour is not as prominent for Error Model 2, where a much wider error range is used. A second anomaly can be seen in Figure 5, where a considerable number of data points have estimated accuracies between 50% and 75% while their corresponding actual accuracies are below 50%. Upon examination of the data, it has been found that these data points are mostly associated with segments whose volumes are overcounted by a high margin. This is the result of the max operator present in the denominator of Equation 7, which causes the disagreement between an accurate volume and a grossly overcounted volume to be considerably underestimated. Error Model 2, which permits errors of up to 100%, is more likely to give rise to such situations. It needs to be noted that this behaviour is unlikely to adversely affect the effectiveness of the method for traffic data quality control as estimated accuracies in the 50%-75% range would still be rejected as unacceptable for most ITS applications.

The potential of using the estimated accuracy scores to detect values that fall beyond a specified error margin has been evaluated. As errors greater than 20% in traffic data are generally considered

unacceptable for real-time applications [2], values beyond this limit are defined as erroneous data that should be detected and removed. In the case of normally distributed errors (Error Model 1), it has been found that the estimated accuracy scores can be used to detect segments with absolute percentage error greater than 20% with an equal error rate (EER) of 12.51% as shown in Figure 6. However, a better EER of 3.35% has been achieved with Error Model 2 for detecting errors beyond the 20% margin as shown in Figure 7. The results imply that the proposed approach is more effective in a scenario where most of the traffic sensors are functioning acceptably and only a small proportion of sensors are reporting significantly inaccurate values.

Figure 6: Equal error rate for detecting errors greater than 20% for Error Model 1

Figure 7: Equal error rate for detecting errors greater than 20% for Error Model 2

It has been found that the proposed method is capable of performing the traffic data accuracy assessment within a trivial computation time. For the given test network with a total of 3022 road segments, the execution time is approximately 20 ms on a PC with a 2.9 GHz processor. Given that the interval between traffic data updates is typically in the order of minutes, a sub-second computational time for accuracy assessment and error detection can be considered as completely acceptable. The following subsections analyze the sensitivity of the proposed method to variations in the operating conditions and present the results.

5.1 Performance Under Different Traffic States

The travel demand supplied to the traffic simulator is designed to replicate the behavior observed during the morning hours when the traffic changes from a free-flow state to a congested state before subsequently returning to the former. The median speed among all the freeway segments is used as an indicator of the level of overall congestion in the network. At the start of the simulation, the network remains in a near-free-flow condition with the median speed remaining above 85 km/h (close to the speed limit of 90 km/h). This is considered as the normal traffic state. For about 20 minutes during the middle of the simulation, the peak traffic occurs with the median speed dropping slightly below 70 km/h. Subsequently, the congestion eases up gradually and the median speed increases to 87 km/h at the end of the simulation. The performance of the proposed method is examined under the following four scenarios: normal traffic, peak traffic, normal to peak, and peak to normal.

Traffic state	Error Model 1		Error Model 2	
	Correlation coefficient	EER(%)	Correlation coefficient	EER(%)
Normal	0.643	13.58	0.878	4.57
Normal to peak	0.679	12.21	0.891	3.08
Peak	0.681	12.24	0.891	3.07
Peak to normal	0.674	12.36	0.889	3.41

Table 2: Performance of the method under different traffic states

The results presented in Table 2 show that the performance of the accuracy assessment method remains virtually similar for the peak and normal-to-peak scenarios. However, there is a considerable decrease in the EER for normal traffic and a marginal decrease for the peak-to-normal scenario. Upon investigation, it has been found that in the simulations, the normal traffic state was associated with low traffic volumes in most parts of the road network. During low-flow conditions, even small genuine differences between the volumes of upstream and downstream segments could sometimes lead to a high measure of

disagreement as given in Equation 7. The results appear to suggest that the proposed method performs better when there is a higher utilization of the freeway network.

5.2 Sensitivity to the Aggregation Period

An evaluation has been performed to assess the sensitivity of the accuracy assessment method to the time period over which the traffic volume is aggregated. The results given in Table 3, suggest that a longer aggregation period results in improved performance. This is in agreement with the idea that better conformity to the conservation equation can be obtained when traffic data is aggregated over longer time spans [17]. The results show that while increasing the aggregation period produces only a modest improvement in performance for Error Model 1, the improvement is more pronounced for Error Model 2, which permits a wider range of errors to occur. Although longer aggregation periods facilitate better error detection, a 5-minute aggregation period may still be preferable due to the responsiveness requirements of the applications that consume traffic data.

Aggregation period (minutes)	Error Model 1		Error Model 2	
	Correlation coefficient	EER(%)	Correlation coefficient	EER(%)
5	0.672	12.51	0.888	3.35
10	0.680	12.20	0.891	3.11
15	0.683	12.16	0.892	2.82

Table 3: Sensitivity to the aggregation period

5.3 Sensitivity to Missing Data

In all the experiments presented above, traffic volumes for all the segments in the network were provided by the traffic simulator. However, in real traffic data it is common for a considerable number of segments to not have data for a given time interval due to communication breakdown or other problems. As the proposed method estimates the accuracy of each road segment's reported volume based on its agreement with the volumes of its neighbours, the method's performance could conceivably reduce in the presence of missing data. An experiment has been conducted by removing the volume data for a varying number of randomly chosen road segments. The results are provided in Table 4. As expected, there is a gradual deterioration in the method's performance when the proportion of segments with missing data is increased.

Proportion of missing data (%)	Error Model 1		Error Model 2	
	Correlation coefficient	EER(%)	Correlation coefficient	EER(%)
0	0.672	12.51	0.888	3.35
10	0.626	14.06	0.877	4.23
20	0.595	14.76	0.859	4.58
30	0.550	17.86	0.792	4.93

Table 4: Sensitivity to the proportion of missing data

6. Conclusions

Several emerging applications that seek to guide travellers and manage traffic are dependent on the availability of accurate real-time traffic data. However, conventional traffic monitoring technologies have several vulnerabilities that make it quite common for on-road sensors to generate significantly inaccurate measurements. While existing traffic data quality control methods are capable of filtering out implausible outliers, they are inadequate for detecting inaccurate values that are within the plausible range. Methods based on the concept of spatial consistency attempt to overcome this limitation by comparing the measurements from neighboring locations. Most of these methods either rely on good quality historical data to establish the relationship between spatially close sensors or require well-calibrated reference sensors, which are not always feasible.

When traffic data is aggregated over several minutes, a measure of consistency can be expected between the volumes of reasonably-spaced upstream and downstream road segments on the basis of the vehicle conservation principle. Based on the above idea, this paper presented a computationally simple, yet effective, approach where the accuracy of each road segment's traffic volume is estimated by comparisons with its connected neighbour segments without relying on long-term historical data or other a priori information. Through simulation-based evaluation it has been found that the accuracy ratings generated by the proposed method exhibit a strong correlation with the actual accuracies of the input values. The results also attest to the method's potential to detect values that fall beyond a specified error margin. The performance of the method under different traffic states and its sensitivity to changes in the operating conditions have also been examined.

The practical issues related to applying the proposed method for quality control of real-world traffic data will be investigated as part of future research. In particular, the authors intend to examine its resilience to flow disruptions caused by traffic incidents using accurate ground truth data obtained from the field. The feasibility of extending this work to non-freeway roads with signalized intersections also needs to be studied.

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