SYSTEM OPERATIONS DATA INTEGRITY ASSESSMENT

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### Abstract

Traffic sensors are being deployed widely across the nation, and their data is increasingly being archived for use in multiple applications. However, before the data can be used, it is important to ask, “can we really trust the data?” This may be addressed through two basic and important value-added services of a traffic data archive. Firstly, data screening checks the feasibility (i.e. is the data reasonable?) and usability of the data already collected. In the second phase, the health of the detection system is continuously monitored to support proactive maintenance of the sensor infrastructure. This research effort focused on developing a methodology to tailor these functions for specific archives. The report presents the methodology, as well as examples of its application in the Regional Integrated Transportation Information System (RITIS) of the Washington, D.C. area.
ABSTRACT

Traffic sensors are being deployed widely across the nation, and their data is increasingly being archived for use in multiple applications. However, before the data can be used, it is important to ask, “can we really trust the data?” This may be addressed through two basic and important value-added services of a traffic data archive. Firstly, data screening checks the feasibility (i.e. is the data reasonable?) and usability of the data already collected. In the second phase, the health of the detection system is continuously monitored to support proactive maintenance of the sensor infrastructure. This research effort focused on developing a methodology to tailor these functions for specific archives. The report presents the methodology, as well as examples of its application in the Regional Integrated Transportation Information System (RITIS) of the Washington, D.C. area.
INTRODUCTION

Archived traffic data is required for many applications, and experts predict that the need (and use) of archived traffic data will only grow in the future (1). Because of this, over the past decade there has been considerable effort devoted to developing and implementing large-scale archives of traffic data originally collected by “real-time” intelligent transportation systems (ITS). The archived data user service (ADUS) in the National ITS Architecture identifies several important functions of these archives, including data quality and data characterization (2).

As noted in (3), a number of research studies have addressed the theoretical aspects of assessing traffic data quality. However, these studies are generally applied to a single data stream from a specific data archive. Practical aspects of tailoring data quality assessment techniques to different data streams have received little attention. Furthermore, existing techniques generally work after the fact, and do not seek to identify failing sensors in an on-line setting. Diagnosing the health status of a sensor system in a proactive manner is very important to ensure systems collect as much quality data as possible.

The purpose of this research project was to develop a general methodology to support traffic data screening, and detector health monitoring. The methodology is demonstrated through application to a range of traffic data streams feeding the Regional Integrated Transportation Information System (RITIS) of the Washington, D.C. area. The remainder of the report first describes the RITIS project, and then provides the research results.

RITIS OVERVIEW

The RITIS project’s goals are to improve transportation efficiency, safety, and security through the integration of existing transit and transportation management system data in Virginia, Maryland, and the District of Columbia. RITIS emphasizes data fusion and its support of regional transportation systems management, regional traveler information dissemination, and systems evaluation.

The Smart Travel Laboratory (STL) at the University of Virginia has been involved in early RITIS development in the following ways:

- Exploring the characteristics of the two primary incoming traffic data streams - the Maryland CHART (Coordinated Highways Action Response Team) data, and the Northern Virginia Smart Traffic Center (NVSTC) data.
- Reviewing literature for existing practices in data quality assessment, imputation and detector data diagnostics
- Designing, applying, and evaluating appropriate data quality screening tests for the incoming data streams
- Designing, applying, and evaluating appropriate imputation techniques
- Designing, applying, and evaluating appropriate detector diagnostic checks
Given that the purpose of RITIS is to integrate data from multiple traffic data sources, it was essential to develop a flexible methodology that could be easily applied to a range of data. The methodology was tested on the two data streams identified above, CHART and NVSTC. The important considerations that were addressed in this process are highlighted in this report for the benefit of practitioners.

It should be noted that this research effort specifically addresses “traditional” traffic variables – volume, occupancy and speed measurements from the sensors. However, most of the methodology is relevant for other data streams such as signal operations, vehicle classification, pavement conditions, and even link travel times and speeds estimated by new probe-monitoring systems.

**TRAFFIC DATA SCREENING**

Assessing the quality of archived data is critical to guide the appropriate application of the data. There are several different measures associated with data quality (4). The most common approach taken for quality assessment is traffic data screening for validity. In other words, the incoming data values are checked for their reasonableness (i.e., is it physically possible that the data represents a traffic state in the real world?). Only this aspect of the data quality is readily quantifiable in any given data stream, and only this measure is focused on in this project.

In the last several years, traffic data screening has matured considerably. Turner (4, 5) recommends several general guidelines that are very important for data archives, such as:

- Provide a data quality report with the data if quality is assessed
- Regardless of where quality control is performed, it is important to mark or “flag” data values that have failed quality control or have been modified by quality control processes.

However, when it comes to actually instituting the tests, their applicability to the current data stream has to be understood. First, we note that there is no one-size-fits-all solution. The purpose of this section therefore, is to explain the general methodology developed in this research, identify the steps requiring custom solutions, and demonstrate our application of the methodology. The methodology is summarized below:

1. Review the range of screening test categories.

2. Explore and understand the current data streams.
   a. Coordination with the field experts responsible for data collection. The knowledge possessed by these experts can be directly obtained by coordination, instead of exploring the data laboriously. However, this knowledge is important and necessary, but not sufficient.
   b. Data exploration. Some aspects of exploring and analyzing data can also be generalized. The exploration should ideally consider different types of days, such as
weekdays, weekends, holidays, incident days etc. Data for several months should ideally be analyzed to avoid specific issues that might affect a few detectors at a few times. The other important considerations involve the various detector attributes, such as:

i. Lane type (mainline general purpose, reversible HOV, HOV, shoulder lanes, ramps etc.)
ii. Detector type (double loops, single loops, other detector types – RTMS, video, acoustic etc.)
iii. Lane (which lane of traffic – 1, 2, 3 etc.)

Data exploration further involves the calculation of several statistics, including:

i. Maximum and minimum values of variables
ii. Distinct values of variables that occur, and the frequencies of their occurrence
iii. Traditional plots, such as the time series plots of the variables (volume occupancy, and speed), Volume-Speed plots, Occupancy-Volume plots

3. Evaluate the applicability of the available tests to the current data stream. Several theoretically sound tests may not be practically applicable. The real data reflect practical decisions in hardware, software etc. which may invalidate the assumptions on which the theory strictly rests. These findings follow directly from the data exploration above, and an understanding of the assumptions of the tests. Several such examples from our application are presented in the following subsections.

4. Select parameters for use in specific tests. Many of the screening tests require specific decisions towards customizing them to a given data stream. An example is the threshold number of sequential records that may exhibit vehicle/occupancy/speed (VOS) values of all zeroes and still be acceptable as reasonable. Coordination with the field experts for both data collection and usage may be important for finalizing such decisions.

5. Identify additional tests from data exploration. For example, we identified acceptable occupancy values in the range of 128-228, for the reversible HOV detectors in the NVSTC data stream. This situation and the corresponding modification in the test are explained in one of the following subsections.

6. Validation of the tests. A dataset different from the one used for exploration is necessary for validating the final set of tests selected for the given data archive.

Based on the RITIS application described earlier, the following subsections illustrate key steps in the methodology presented above.
Step 1: Screening Test Categories

Several specific screening tests are described in different studies (for example, see 6, 7). We recommend the initial consideration of as many tests as possible, and filter the inappropriate ones later. However, this vast set can be daunting for data archive developers. In this research, we have classified all these tests into these five distinct categories (in the order of increasing complexity):

1. Known errors recorded in the field,
2. Thresholds on single variable,
3. Relationship among the variables,
4. Relationship among records at the same sensor over time, and
5. Relationship among records reported by neighboring sensors over time.

The first category, known errors recorded in the field, is the least ambiguous and can be readily applied to any dataset. In case of NVSTC data, the value 255 is logged by the detector equipment when the system internally identifies a detection error. In case of the CHART data, a status field is recorded as ‘0’ in case of field errors.

The second set of tests, thresholds on single variable, is also quite straightforward. In this case, minimum and maximum values are identified where it would be unreasonable to obtain a measure that is lower or higher than the threshold. For example, a threshold of 100% would be reasonable for occupancy. However, there may be cases, as with the NVSTC data stream, where specific system design decisions call for logging of detector values that at first glance are illogical and not compliant with traditional thresholds.

Turner (5) notes that “many Traffic Management Centers (TMCs) are reported to be testing the data only for individual variable thresholds, and are criticized for providing only a “minimal examination of credibility.” To address this, the relationships between volume and occupancy, volume and speed, and the average vehicle length test (with all the 3 variables) are used in data screening. We evaluated several of these tests and found them to require customization for each data stream. These evaluation details are explained in later subsections.

Sequential data tests such as speed variance at 5-minute aggregation (5) and continuous runs of VOS=000 or some other constant value (6) fall under the fourth set, relationship among records at the same sensor over time. In these cases, some engineering judgment is required for selecting the maximum number of consecutive records allowed to have the same values. We note that the test for potentially comparing current data with the historic data requires knowledge of the typical traffic pattern. Determining these patterns is largely an art today, and has yet to become a rigorous science (8).

The last set of tests, relationship among records at neighboring sensors over time, requires detectors to be placed closely, and provide consistently good records (from the perspective of the other tests). The premise of this category of tests is that the traffic state should not change drastically from one sensor location to the next. Therefore, neighboring sensors should measure similar quantities.
Step 2: Explore and Understand the Data

The NVSTC data stream consists of both detector (lane level) data and station (all lanes aggregated) data from freeways in the region. For analyses, the system had a total of 939 detectors belonging to 500 stations, with all the required attributes for the screening tests. For visual exploration, several detectors were selected randomly, while still conforming to the recommendations set in the methodology section. Figure 3, presented later, is a typical example of the plots generated for visual exploration. To understand the current trends, data from the years 2005 and 2006 was analyzed fully to obtain statistics on all the detectors.

The CHART system has only station data, from many highways. A total of 29 stations had all the attributes required for all the tests. These and other stations were considered randomly for visual exploration, using plots. All the stations were analyzed for the other statistics described in the methodology. Again, all the data available from 2005 and 2006 were used for this purpose.

For both the NVSTC and the CHART data streams, several meetings, phone calls and email exchanges facilitated the coordination with the field experts.

Step 3: Evaluate the Applicability of Screening Tests

As explained in earlier, several theoretically sound tests were not applicable to the actual field data. In particular, four of them are analyzed in detail, and presented in this subsection. The first one is a single variable threshold test (belonging to the second category), and the other three tests are relationships among the variables (belonging to the third category). The four tests analyzed are:

1. Speed below 5 mph
2. Average Effective Vehicle Length
3. Volume-Speed Relationship
4. Volume-Occupancy Relationship

**Speed below 5 mph**

Lomax et al. (6) suggest that the loop detectors are incapable of accurately measuring low speed values, as in the range of 0-5 mph. We collected statistics on the number of NVSTC loop detector records that fall under this condition. In general, there were few records in this category for any given day. Visual inspection revealed that such records occurred usually during incident conditions. Given the volume and the occupancy, the low speeds during incidents seem quite justified. Figure 1 below presents a set of plots from one such incident. These are the same set of traditional plots recommended in the methodology for visual data exploration: volume time-series, occupancy time-series, speed time-series, volume-occupancy plot, and speed-volume plot. This figure corresponds to NVSTC detector 278 (speed trap on the 3rd mainline lane on I-66 EB, on 01-May-2006).
Based on the literature review, the following 2 situations were not expected to occur. However, after exploring the NVSTC data, we identified several instances of records with these situations:

1. Volume=0, with positive speeds, and
2. Speed=0, with positive volumes.

The field experts identified the first case as an artifact of the NVSTC data. Several controllers retain the last recorded positive speed in memory. Any subsequent records with volume=0 would
be associated with this speed value in the memory. Therefore, even though the detector record reflects volume=0, occupancy=0 and speed>0 (i.e. in short, VOS=00?), the actual condition it represents is that there was no vehicle passing over the detector (i.e. VOS should be 000). Therefore, if a record has VOS=00?, this speed is compared to the speed of the previous record. If the two speeds are equal, and if the previous record had passed the Volume-Speed relationship, then the subsequent record is also passed. In effect, we consider the VOS=00? record on par with VOS=000, when appropriate, and pass it. This situation is illustrated in Figure 2.

We do not recommend substituting the VOS=00? records with VOS=000 values, for two reasons. First, the actual field values may sometimes prove useful in later analyses for detection system health diagnostics. Second, the speed values also behave in other unanticipated ways than the known controller artifacts. For example, some speed fluctuations have also been observed at times, even though VO=00 for all those contiguous records.

![Speed > 0, Volume=0](image)

**FIGURE 2 Unanticipated volume-speed relationship**

The second case is typically accepted as reasonable for single loop detectors. After consultation with the field experts, we identified that this case may be reasonable for double loops also. If one of the loops is damaged, or the communication broken, then the other loop effectively behaves like a single loop detector. For this reason, these records are also passed by default. We note that it may be appropriate to set the speed values to NULL, instead of leaving them as zeros. Otherwise, there is a possibility of final users aggregating speed values for large periods of time, and wrongly interpreting the resultant low speeds as real values.
**Volume-Occupancy Relationship**

A number of tests are available in the literature to test records for reasonable combinations of volume and occupancy values \( (7, 9, 10) \). However, we identified several cases where the occupancy values are ‘0’ or are not within the theoretical expectations. However, the volumes exhibited a reasonable daily pattern, consistently over several days. An example of this situation is demonstrated in Figure 3 below.

![Figure 3: Detector data with reasonable volumes, but zero speeds and occupancies](image)

**FIGURE 3** Detector data with reasonable volumes, but zero speeds and occupancies

The data archive manager needs to decide between passing the reasonable volume values and failing the unreasonable occupancy values. It should be noted that no literature has been found that uses archived occupancy values for any practical purposes (other than estimating speeds using the volume and occupancy values). For this reason, we recommend passing all these cases.

**Average Effective Vehicle Length (AEVL)**

The AEVL is the only known test that evaluates all the variables in the multivariate traffic data record together \( (11) \). Although, theoretically sound, these tests fall prey to two particular situations:

1. When the occupancy values exhibit a wide range of values, often insensitive to the volumes,
2. When screening station data records (i.e. aggregated data over all lanes), even though all the lane detectors pass the test.

The proposed range of AEVL values is 2.7 meters \( (9 \text{ ft}) \) to 18 meters \( (60 \text{ ft}) \). Many records were observed with AEVL significantly below 2.5 or 2 meters. This situation occurs often during incidents. However, the combination of volume, occupancy and speed values seems reasonable upon visual inspection. It should be noted that a slight change in the occupancy value is capable
of significantly affecting the AEVL value. For the first reason mentioned above, the AEVL test has been changed to mark a record as “highly theoretically suspect” but not fail it. Figure 4 illustrates an example of this situation. The data comes from NVSTC detector 721, a speed trap on the 4th mainline lane on I-66 EB, on 13-Apr-2006.

![Volume Plot]

![Occupancy Plot]

![Speed Plot]

![AEVL Plot]

**FIGURE 4** Records failing AEVL test due to high variance in occupancy

Upon close inspection, the second reason is identified to be legitimate. The AEVL value is not a linear combination of the volume, occupancy and speed values. So, the station data records could fail, even though all its lane detectors pass the test. The average vehicle length across a lane detector is a conceptual value from several actual vehicles that pass the detectors. However, no such definition is readily apparent for AEVL calculation at the station level. Therefore, the station records are also not failed for AEVL tests.
Step 4: Select Parameters for the Tests

Parameters include the thresholds on individual variables, on other calculations. These have to be customized for each dataset. For example, one parameter is the maximum number of consequent records that are acceptable as reasonable when each one of them is VOS=000. For NVSTC data, experts stated that 2 hours could pass during night times when no vehicles go over the detector. However, after 2 such hours, the controllers would lock up until reset manually. Therefore, it was decided that a continuous run of up to 120 records with VOS=000 will be passed for any detector. However, any record beyond this limit is failed.

Step 5: Identify Additional Tests from Data Exploration

One of the new tests identified in this research is the adjustment and passing of some detector data records that exhibited occupancy above 100%. Several detectors in NVSTC consistently reported values of occupancy above 100. In theory, this situation is impossible and should indicate erroneous data. However, we found some useful information, upon close examination. We identified these to be associated with reversible high occupancy vehicle (RHOV) lanes for a particular direction of travel (the other direction yielded reasonable traffic records). As shown in Figure 5, the data passed the “original” tests in one direction, but failed in the other direction. After the adjustment explained below, many more records became usable. Figure 5 represents data from NVSTC mainline station 90 on I-95 RHOV, from 5 AM to 9:30 PM. The gap in the middle represents the time when the RHOV is closed for changing the travel direction.

![Traffic data on RHOV lanes](image-url)

**FIGURE 5 Traffic data on RHOV lanes**
A total of 7 bits is sufficient for recording any value between 0 and 127. Normally, the occupancy should lie between 0 and 100, and 7 bits would serve this purpose adequately. We suspect that the controller software encodes a value of ‘1’ for the first digit of an 8-bit record to indicate the opposite travel direction, than the “usual”. However, if the central TMS software does not decode the first digit in line with the field controller encoding, occupancy values between 128 and 255 result. In fact, the higher occupancy values were found to fall exactly in the 128-228 range. After subtracting a value of 128 from these occupancy values (above 100%), all the traffic variables aligned in tune with the theoretical expectations.

**Step 6: Validation of the Selected Screening Tests**

For all the screening tests accepted as applicable for our data streams, additional validation with other detectors and time periods were carried out. If the validation results are not in line with the expectations, additional modifications are necessary. For example, in this study, the linear Volume-Occupancy relationship for occupancy <20 was iterated a few times with further data exploration. Finally, sufficient justification was available to completely abandon this test – because reasonable volume values often co-existed with unreasonable occupancy values. In such cases, a volume-occupancy relationship did not meet the theoretical expectations.

**DETECTOR SYSTEM HEALTH DIAGNOSTICS**

The detector diagnostics identify potential “health” problems with the detection system, given specific patterns in the data. Knowledge on the health of the detection system could influence the agency plans and action, such as maintenance and asset management decisions. And these actions in turn affect the entire future dataset. The sensors provide the eyes and ears for monitoring and managing the transportation system. So, preventing them from deteriorating is of great importance. In effect, detector health diagnosis completes the loop for the agencies that operate and maintain these field devices.

A detailed comparison between data screening and diagnostics is presented first. Then, our methodology, results and an example are provided.

**Comparison of Data Screening and Diagnostics**

There is a significant difference between data quality screening and detection system health diagnostics. The data quality flags have to draw a strict decision boundary between reasonable data and suspect data. i.e. a single record is judged as either reasonable or unreasonable, for usage purposes. This decision involves the following tradeoff: (1) a number of reasonable records that may be failed wrongly, and (2) a number of unreasonable records that may be passed wrongly.

For example, an occurrence of Volume=0, Speed=0 and Occupancy=0 (in short, VOS=000) could occur legitimately over a detector at any time of the day. For this reason, an intermittent
VOS=000 may not be failed by a screening test, without further justification. However, such an occurrence during the peak hour is highly unlikely. Therefore, flagging such records in the diagnostics provides more information to the agency.

The decision boundary for each screening test is similar to Figure 6 below. However, it should be noted that most distributions of “unreasonable” data records are not as crisp and definable as in this figure. To pass even a marginally reasonable record, one selects the right decision boundary. To fail even a marginally unreasonable record, one selects the left boundary. Often, the decision boundary lies in between. In all these cases, identifying and grouping the records that seem unreasonable to any degree is beneficial for the maintenance crew.

As explained and demonstrated earlier, we had to abandon several tests recommended in the literature. In essence, if a record is possible, we pass it. And we fail all impossible records. i.e., we decided to allow even a marginally reasonable record. Therefore, a number of records lie in between the two extreme decision boundaries. The diagnostics “catches” all these records and prepares a summary for the user.

![Decision Boundary for Screening Tests](image)

**FIGURE 6 Decision boundary for screening tests**

**Methodology**

Several research studies on detector diagnostics can be found in the literature (for example, see 10, 12, 13). However, they focus mainly on known detection errors, and the ensuing patterns in the data. This approach is similar to Turner’s (5) suggestion that the data quality flags could also
help the maintenance personnel in identifying problem locations in need of maintenance. Such an approach is applicable for known-systemic errors in data collection. However, we acknowledge three important aspects:

i. Health problems can exist in any part of the detection system, and not just the detectors. For example, an inconsistent polling interval needs to be identified and rectified to ensure maximum usability of the data in future.

ii. Several potential errors might not be fully understood yet to proceed in a top-down manner. For example, it is not clear how intermittent VOS=000 records were registered. However, they are highly suspect in some cases. And

iii. As explained earlier, the purpose of data screening and diagnostics are very different.

Proposed Method

To account for the above-mentioned reasons, we identified a different approach to directly analyze unreasonable patterns in the data. Even when a direct relation to the potential errors was not known, the highly suspect data patterns were identified for further inspection by the field maintenance personnel. This was also possible only from the extensive data exploration in the 2

step of the data screening methodology explained earlier. Several of our results are presented in Table 1 below. A specific example is illustrated in detail following the table.

### TABLE 1 Detection Diagnostics Tests

<table>
<thead>
<tr>
<th>Nature of error</th>
<th>Detection methodology or symptoms</th>
</tr>
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<tbody>
<tr>
<td>Controller Clock Drifting</td>
<td>The time stamps of the data records are not at regular intervals. Other causes for this error include: (1) Irregular polling by the software at the central system, and (2) Communication lags. If the time stamps vary from the expected interval, the detector is flagged.</td>
</tr>
<tr>
<td>Intermittent VOS=000</td>
<td>A detector yielding reasonable data may give out a VOS=000 record for one time stamp, and then return back to giving out reasonable records. Data surrounding (in time for the same detector with) a VOS=000 data point is considered. If the median of these records is above a threshold, the detector is marked as having intermittent VOS=000 errors for that day. This test is performed only for the day from 6:00 AM to 10:00 PM.</td>
</tr>
<tr>
<td>High Occupancies</td>
<td>Some detectors exhibit a pattern of high occupancies for the corresponding volumes. This potential error is probably because of improper tuning of the detector. This error is also identified using a threshold.</td>
</tr>
</tbody>
</table>
Stepped speeds | Some detectors exhibit a pattern of stepped speeds. i.e. a few values of speeds seem to occur many more times than the other values of speeds, creating a suspicious pattern caught by visual examination. In a further exaggerated situation, only a few values of speeds may actually appear, instead of a vast range of possible values. If the number of data points for a detector, in one day, with any one speed value is above the threshold, the detector is flagged.

Potential power, communication, software or hardware failure | If all detectors at a cabinet are stuck at VOS=000 or VOS=NULL, they are all flagged as a potential power/communication/software/hardware error. (Similar test is also recommended by Turner et al (2000))

Stuck detectors | If a detector gives out records with the same volume, occupancy, AND speed value, sequentially, more than a threshold number of times, it is considered as “stuck.”

Unknown errors in the hardware or software | Occupancy >100; or Volume/Occupancy/Speed <0; or Volume>0, but Speed =0 and Occupancy=0

Reasons are unknown.

Figure 7 presents an example where the detector records for a day contain a suspiciously high number of same speed value. In this case, Speed=50 mph occurs 436 times. Further, frequency of occurrence of the speed values 75, 62 etc. are also conspicuously high.
CONCLUSION

This research developed a methodology for tailoring data quality screening tests for traffic data. It was successfully applied to two data streams, and illustrated through several examples. A new way of diagnosing detector health from the data patterns, instead of just from known errors was also developed. It is recommended that those responsible for traffic data archives consider the use of the new methodologies in order to protect their investment in archived traffic data.

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