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Evaluation of Texas Incident Detection Algorithm after Years of Implementation

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***Abstract*—This paper summarizes a performance evaluation of the automatic incident detection algorithm deployed by many traffic management centers across the State of Texas, USA after a few years of implementation in the field. This analysis is the first step towards improving performance of incident detection which will eventually help optimizing freeway incident management practices at these TMCs. To conduct this analysis, the researchers used archived ITS data, particularly freeway incident alarms and incident scenarios data, as well as a geodatabase of ITS features. Matching alarm and scenario data enabled the determination of two performance measures: incident detection rates and false alarm rates. While many researchers evaluated the performance of their proposed incident detection algorithms, only a few assessed the actual performance of these algorithms after long period of implementation. Although the analysis described in this paper uses data from one jurisdiction (San Antonio, Texas), the methodology is sufficiently generic to enable implementation at other traffic management centers.**

***Index Terms*—automatic incident detection algorithm, Texas incident detection algorithm, performance evaluation, detection rate, false alarm rate, TransGuide**

I. Introduction

Congestion caused by freeway incidents is a major contributor to urban traffic congestion. Therefore, incidents related functions at transportation management centers (TMCs) constitute most of their daily operations, including detection, verification, response, and clearance of incidents to activating efficient traffic management plans to alleviate incident-related congestion.

The body of knowledge in this area is expanding and includes topics such as evaluation of incident management program benefits, development of procedures to estimate incident delay, forecasting of incident duration, prediction of incidents frequency, and automatic detection of freeway incidents.

The main purpose of this paper is to evaluate in greater detail incident detection performance at a sample TMC in Texas (San Antonio’s TransGuide) after several years of deployment. This analysis is the first step towards improving the performance of incident detection which will eventually help optimizing freeway incident management practices at the TMC.

The paper starts with a short literature review of some of the automatic incident detection (AID) algorithms, followed by a summary of the data-mining process to extract incident data from archived ITS data sources. An overall assessment of effectiveness of the automatic incident detection process at the selected sample TMC is also discussed, followed by a summary and conclusion.

II. Automatic Incident Detection Algorithms

TMCs use a variety of techniques to detect roadway incidents. Examples include detector-based alarms, 911-based alarms, closed caption television (CCTV) camera scanning, police radio scanning, courtesy patrols, motorist assistant dispatch, and commercial traffic services. TMCs are increasingly relying on drivers calling on their cell phones to report incidents, which has led some TMC officials to begin questioning the feasibility to continue making considerable investments on road-based detectors and associated hardware and software infrastructure. Nevertheless, in jurisdictions where road detectors are already in place, detector-based incident detection remains an important incident management tool.

Detector-based incident detection algorithms typically follow one of the following approaches:

A. Comparative Approach

Algorithms that follow this approach compare measured traffic conditions against predetermined thresholds and trigger an alarm if the field measures cross the thresholds. Examples of this type of algorithm are the California algorithm series, which use absolute and relative differences in occupancy values [1] and the Texas algorithm, which uses moving average occupancy values. The Texas AID algorithm falls within this category, except that it uses speed data from speed-trap detectors and percent occupancy data from non-speed-trap loop detectors. Comparative algorithms are simpler than other algorithms. Many implementations rely on static thresholds, making them relatively inefficient for handling fluctuating traffic demands [2]. Some implementations enable managers to vary thresholds using pre-specified criteria, e.g., by time of day, but populating threshold lookup tables frequently remains an incomplete task.

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B. Statistical Approach

Algorithms that follow this approach use statistical procedures to detect significant deviations in traffic patterns over time as compared to predictable patterns. Examples of this type of model include the standard normal deviate model [3], which uses the mean and standard deviation of occupancy values, time-series models [4], which use autoregressive integrated moving average (ARIMA) predictions of occupancy values, and the Minnesota algorithm [5], which uses a low-pass filter to remove high-frequency components in observed data. Statistical models require data to follow pre-specified statistical theory models, thus limiting their wide applicability.

C. Traffic Modeling Approach

Algorithms that follow this approach use complex traffic-flow theoretical models to predict deviations from normal conditions using current traffic measurements as well as historical trends. An example of this type of algorithm is the McMaster algorithm, which relies on the volume-occupancy relationship to determine when conditions change at individual detection stations [6].

D. Artificial Intelligence Approach

Algorithms that follow this approach use artificial intelligence techniques such as neural networks [7], fuzzy logic [8], and Wavelet [9]. Although these techniques do not pre-assume theoretical traffic models, they nonetheless require extensive calibration. They are also among the most recent examples of algorithm development work and for the most part remain untested under real-world operating conditions.

III. Incident Data Mining

To conduct their analysis, the researchers prepared two datasets for the analysis collected from San Antonio's TMC (TransGuide) in Texas, USA. The first dataset contained freeway incident data. The bulk of incident data was obtained from a database (called scenario database) that documents dynamic message sign (DMS) and lane control sign (LCS) messages displayed by operators of the TMC in response to events on the roads. The scenario database includes a header table, which keeps a log of all scenarios loaded and contains information the researchers considered useful for characterizing incidents, and an execution table, which keeps a log of all DMS and LCS messages displayed in the field.

For the analysis, the researchers used data from 792 days (about 27 months) during which the database included about 60,800 scenario records distributed among nine scenario categories (i.e. incident types): congestion, construction, weather, train crossing, major accident, minor accident, stalled vehicle, debris, and unknown type. Of interest to this research were four scenario types that pertained to nonrecurring, unplanned incidents: major accident, minor accident, stalled vehicle, and debris. Although compiling incident data for these four scenario types would seem straightforward, it was necessary to apply several quality control measures to the original data. The resulting incident (scenario) dataset which the researchers used in their analysis contained over 19,500 records.

The second dataset contained alarms (or events) triggered by the TransGuide's incident detection algorithm, which creates an event record in response to any noticeable abnormality in traffic resulting from an event on the road. Detector-based alarms rely on speed for speed-trap detectors (installed on main lanes and some ramps) and percent occupancy for non-speed-trap detectors (mostly installed on entrance and exit ramps). For speed-trap detectors, if a moving 2-minute average speed (continuously aggregated from 20-second speed data) drops below 25 mph, the system automatically triggers a minor (yellow) alarm. If the moving 2-minute average speed drops below 20 mph, the alarm becomes a major (red) alarm. For non-speed-trap detectors, the default minor and major alarm thresholds are 25 percent occupancy and 35 percent occupancy, respectively. It may be worth noting that these thresholds are default values and while the system allows users to set up different thresholds by time of day, day of week, or day of the year, TransGuide officials rarely modify the default settings, partly because of the lack of a formalized procedure to access and analyze archived ITS data trends that could suggest that modifying default values could result in a more effective incident detection and alarm handling process. In total, for the analysis period, the alarm dataset contained records for 202,690 alarms.

IV. Incident Detection Algorithm Assessment

A. Performance Measures Used

Three commonly used measures to conceptualize and/or assess the performance of incident detection algorithms are:

- Detection Rate (DR): It is the ratio of the number of detected incidents to the total number of recorded incidents.
- False Alarm Rate (FAR): It is the ratio of incorrect decisions (false positives) to the total number of algorithm decisions made.
- Detection Time (DT): It is the time interval between the moment the incident occurred and the time the incident was detected.

Typically, detection rate is directly proportional to the detection time. Likewise, the false alarm rate is inversely proportional to the detection time. Generally, by increasing the time it takes for the algorithm to detect incidents (which would result, e.g., from using a more sophisticated algorithm), it is possible to increase the detection rate while, at the same time, reducing false alarm rates. Unfortunately, a longer detection time would also result in a longer incident response time, which is normally undesirable. Likewise, a too short detection time (which would result, e.g., from using a relatively simple algorithm), while desirable, would also result in low detection rates and high false alarm rates. Consequently, it becomes necessary to calibrate the incident detection algorithm to achieve an acceptable balance between detection rates, false alarm rates, and detection times.

B. Matching Alarms to Incidents

In an ideal situation, the number of records in the two datasets would be the same, with a record in the incident dataset having a corresponding matching record in the alarm dataset. In practice, because of false alarms, potentially erroneous scenario records, and other factors, there is not a perfect match between incident records and alarm records. In general, as Figure 1 shows, there are three possible matching outcomes:

- Incident Detected: This occurs if an incident actually happened (a scenario was deployed) and the alarm incident handler triggered an alarm.
- False Negative: This occurs if an incident actually happened (a scenario was deployed) and the alarm incident handler did not trigger an alarm.
- False Positive: This occurs if an incident did not happen (a scenario was not deployed) but the alarm incident handler triggered an alarm.

			LCU Subsystem Triggered Alarm?	
			Yes	No
Scenario Deployed?	Yes	Incident Occurred	Incident Detected	False Negative
	No	No Incident Occurred	False Positive	

Figure 1. Possible Incident versus Alarm Dataset Matching Outcomes.

To find the number of detected incidents, the researchers attempted to match incidents reported in the incident (scenario) database to alarms recorded in the alarm (event) database. Because of the lack of a common link between these two datasets (more specifically, an incident ID), the researchers had to develop a "fuzzy" spatio-temporal query methodology whereby an incident would be considered detected if the system triggered an alarm within a pre-specified spatio-temporal window associated with an incident record (Figure 2). The reason behind this fuzzy range concept was to account for situations such as an alarm being triggered before or after operators deployed a scenario (which almost always happens because the two datasets are not synchronous), an alarm being triggered on a sector other than where the incident actually happened, and scenarios being reported on the wrong sector. Figure 3 illustrates the query building process, which used a geodatabase structure described in [10].

A preliminary analysis suggested using a spatio-temporal window composed of three highway sectors (including the sector of interest as well as the adjacent upstream and downstream sectors) and a 10-minute range before and after the scenario execution time. To test this hypothesis, the researchers conducted a sensitivity analysis (Figure 4). As Figure 4a shows, the number of matched incidents and alarms increased with the number of sectors considered.

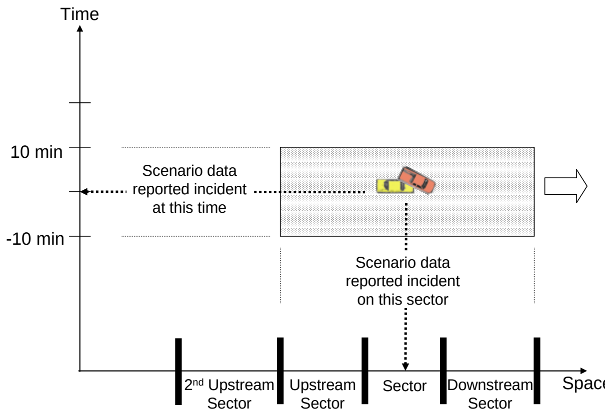


Figure 2. Spatio-Temporal Query Concept.

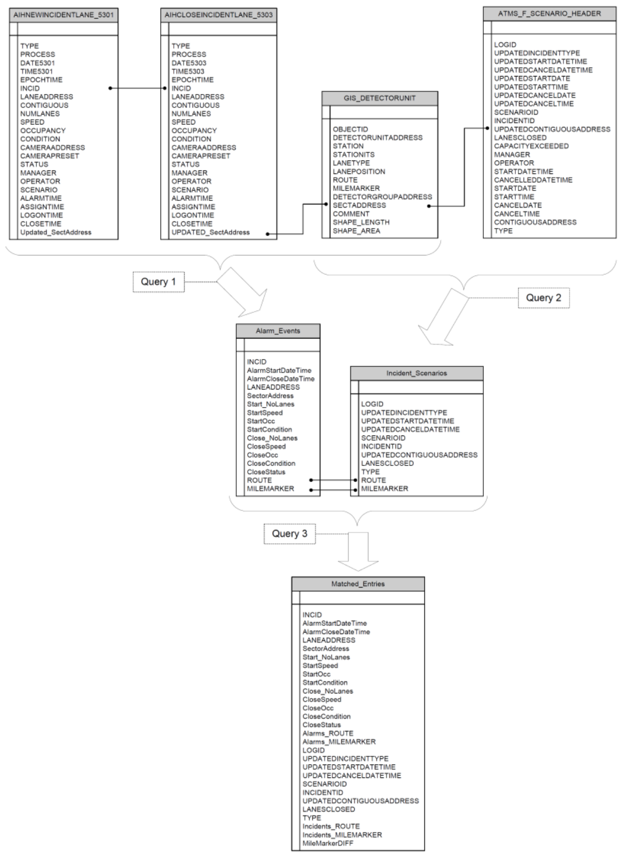
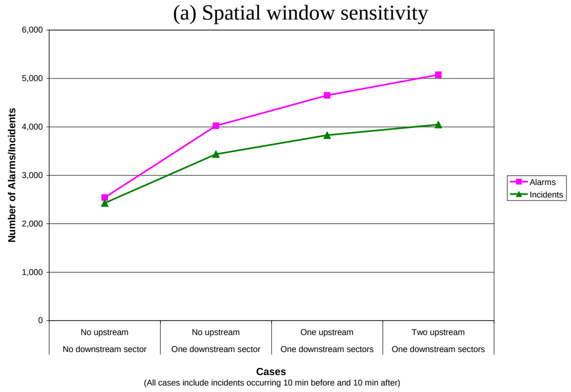


Figure 3. Query Building Process to Match Incidents to Alarms.

However, the rate of increase in the number of matches flattened after including more than three sectors in the query (the sector of interest as well as the adjacent upstream and downstream sectors), clearly suggesting that the chances of sector mismatch decreased considerably outside the three sector window. Figure 4b shows that the number of matched incidents and alarms increased as the time window size increased. In this case, the number of matches did not flatten, suggesting the possibility of an increasing number of alarm records incorrectly matching incident records and that using time window size was not necessarily a strong query parameter. Nonetheless, since it was necessary to use a time window factor for the query building process anyway, the researchers decided to maintain the 10-minute range before and after the scenario execution time.

(a) Spatial window sensitivity



(b) Temporal window sensitivity

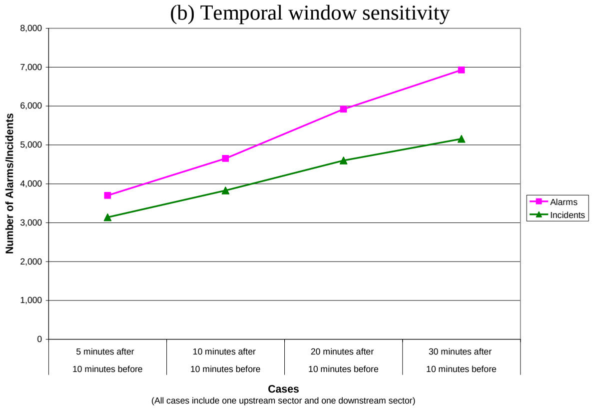


Figure 4. Sensitivity Results for Incident-Alarm Matching Query.

V. Results & Analysis

Figure 5 summarizes the results of the matching operation. Out of 19,553 incidents during the 792-day analysis period, 3,828 incident records had a matching alarm record. Likewise, 4,651 alarm records had a matching incident record. Therefore,

$$\text{Detection Rate (DR)} = \frac{\text{No. of detected incidents}}{\text{No. of recorded incidents}} = \frac{3{,}828}{19{,}553}100\% = 19.58\%$$

$$\text{False Alarm Rate (FAR)} = \frac{\text{No. of false positives}}{\text{No. of algorithm decisions}}$$
$$= \frac{198{,}039}{4{,}320 \times 1{,}463 \times 792}100\% = 0.0039\%$$

This calculation assumed for simplicity that the algorithm made 4,320 decisions per detector per day (once every 20 seconds) and that all 1,463 detectors in the geodatabase were operational all the time during the 792-day analysis period.

It was not possible to calculate the third performance measure (detection time) because the archived incident data did not provide a measure for when incidents actually happened in relation to the time the system detected the incidents.

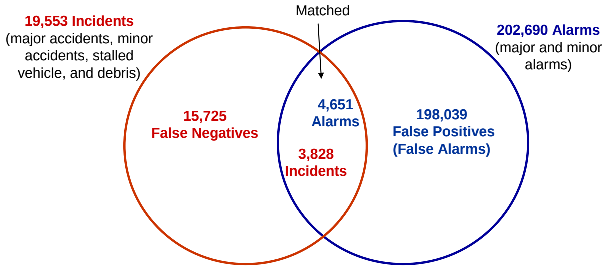


Figure 5. Summary of Matching Results.

An analysis of these numbers yields the following results:

- The incident detection rate was 19.6 percent. However, this detection rate included major and minor accidents, stalled vehicles, and debris. After excluding debris incidents from the analysis, the incident detection rate would grow to 20.0 percent (3,695 detected incidents relative to 18,427 recorded incidents). Likewise, excluding debris and stalled vehicle incidents from the analysis would result in an incident detection rate of 24.8 percent (2,755 detected incidents relative to 11,083 recorded incidents). Excluding debris, stalled vehicles, and minor accidents would result in an incident detection rate of 27.2 percent (1,789 detected incidents relative to 6,571 recorded incidents). In general, these percentages indicate that the incident detection algorithm is responsible for the detection of 20 to 27 percent of incidents detected at TransGuide. The literature reports detection rates that are typically much higher—between 60 and 100 percent [11] and [12], but it also includes references to detection rates in the 30 to 50 percent range [13]. Readers should be aware that many high detection rate reports in the literature use very small sample sizes and/or pre-set thresholds calibrated under the assumption of "normal flow" conditions; actual performance on the ground tends to be lower [14].
- A false alarm rate of 0.0039 percent is relatively low compared to rates typically found in the literature—between 0.0018 and 1.9 percent [12]. However, it may be worth noting that a very low false alarm rate, although desirable, is not a good performance measure by itself because it may be masking operator unacceptability issues that would stem from the use of strategies resulting in higher false alarm rates [14].

VI. Conclusion

This paper presented an evaluation of the performance of an incident detection algorithm after a few years of implementation. Towards this, the researchers prepared two datasets. The first dataset contained data from the scenario (incident) database, under the assumption that this database provided an accurate depiction of the history of incidents along the freeway network covered by the TMC. The second dataset contained alarms triggered by the incident detection algorithm in response to events on the road. The lack of a common link between the two datasets led to the use of a "fuzzy" spatio-temporal query methodology that considered an incident to be detected if the incident detection algorithm triggered an alarm within a pre-specified spatio-temporal window associated with an incident record.

Matching alarm and incident data enabled the determination of performance measures such as incident detection rates and false alarm rates. The incident detection rate, which included major and minor accidents, stalled vehicles, and debris, was 20 percent. After excluding debris, stalled vehicles, and minor accidents, the incident detection rate increased to 27 percent. The literature reports detection rates that are typically much higher (60 to 100 percent), but readers should be aware that many high detection rates in the literature are based on very small sample sizes and/or pre-set thresholds calibrated under the assumption of "normal flow" conditions. Actual performance on the ground tends to be lower. For example, there are references to detection rates in the 30 to 50 percent range. The false alarm rate was 0.0039 percent, which was low compared to rates typically found in the literature (0.002 to 1.9 percent). It may be worth noting that a very low false alarm rate, although desirable, is not a good performance indicator by itself because it may be masking operator unacceptability issues that would stem from the use of strategies resulting in higher false alarm rates.

Further research is recommended to assess the feasibility of modifying current incident detection alarm thresholds at the TMC to increasing detection rate while minimizing the impact on false alarm rate.

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