Assessment of the Current Status of Incident Detection Algorithms: Results of a Nationwide Survey

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ABSTRACT

Use of automatic incident detection algorithms (AIDA) in advanced freeway management systems has been sporadic and scarce. The current study investigates the causes of such limited implementation. A survey was carried out among the system managers, operators and end users, as well as the decision makers who set the operational policies and the priorities for future system enhancements. The survey responses point to a general consensus that the unacceptably high rates of false alarms generated by available incident detection algorithms is the major deterrent. This study not only provides an understanding of the causes of the limited implementation of incident detection algorithms, but also allows a direct comparison between the conventional incident detection technologies and automatic incident detection technology on the basis of their performance.

Despite the lackluster performance of AIDA to date, 90% of the survey respondents feel that the current methods of incident detection are insufficient either at present (70%) or will be so in the future (20%). This finding alone motivates a need to redouble research efforts aimed at developing robust and accurate automatic detection methods. In this regard, the paper presents promising directions to overcome the past AIDA deficiencies.
INTRODUCTION

Automatic Incident Detection Algorithms (AIDA) have been part of freeway management system software from the beginnings of ITS deployment. However, the operational performance of AIDA has been on the whole very poor to the extent that in many cases the automatic incident alarms have been disabled or are simply ignored (1). Fortunately, the negative impact of the poor performance of incident detection algorithms has been mitigated by both the increased market penetration of mobile phone users able and willing to phone in incident information and by the evolving expertise of transportation management center operators who combine past experience and their intuition about the emerging conditions to help them focus on likely scenes and quickly recognize incident indicators.

However, the size and scope of the urban transportation networks under direct monitoring by transportation management centers are growing faster than are staffing levels and center resources. This trend is motivating renewed interest in the quest for reliable and accurate AIDA functionality.

BACKGROUND

The last four decades have seen significant developments in the area of automatic incident detection. Starting with the Standard Normal Deviate (SND) algorithm developed by the Texas Transportation Institute in the early 1970s (2), several algorithms have been proposed, each investigating a new approach for incident detection. The California algorithms (3, 4) compare the occupancies at two adjacent stations against some preset thresholds. Ahmed and Cook's algorithm proposes a Time Series approach (5). Dudek et al. (6) formulated an algorithm for incident detection under low volume conditions. Filtering and smoothing based approaches were also investigated (7, 8). Willsky et al. (9) developed a dynamic model based algorithm. A correlation analysis based algorithm has been developed by Takaba et al. (10). The McMaster algorithm (11) is based on an application of the Catastrophe theory. A mathematical model based algorithm was presented by Lin and Daganzo (12). Apart from these conventional algorithms there has been substantial development in the artificial intelligence based algorithms. Fuzzy logic (13), Artificial Neural Networks (14), Fuzzy set theory (15), Wavelet Transform (16) and Genetic algorithm over Neural Networks (17) have recently been used to develop a group of algorithms that are usually referred to as the advanced algorithms.

From time to time comparative analyses of these algorithms were done in order to find out the relative advantages of one over the others. (18, 19, 20) Abdulhai and Ritchie (21) discussed the problems arising during implementing an incident detection algorithm and proposed a set of characteristics for an operationally successful incident detection algorithm. But still the developments in incident detection algorithms seemed to be mostly at a scholastic level. In spite of the rapid development of numerous algorithms the response of the industry seemed to be hesitant. A nationwide survey was envisioned in order to understand the lukewarm response by the industry.

OBJECTIVE

The objective of the survey was to evaluate the current status of existing implementation of algorithm based incident detection technology. The study compared the performance of this technology with other concurrent technologies like floating vehicle based and mobile phone based technologies. The study investigated the causes for limited implementation of Incident Detection Algorithms.

SURVEY DESIGN

The survey was designed specifically to elicit responses from professionals, mostly state and federal employees, who are concerned about incident detection. The people who would be in a position to take a decision, or substantially influence a decision regarding the integration of algorithm based incident detection technology into the local advanced transportation management system were identified and chosen as the target population of the survey.

The survey was conducted over the internet. The internet survey methodology was chosen over other methods because it was deemed to produce the quickest responses, while it eliminated any interviewer bias. It also facilitated easy follow-up, such as sending reminders or clarifying responses if
necessary. The requests were sent out by email to the target population. Candidate respondents were invited to visit the survey website and fill in a questionnaire. Each invitee was provided a unique id and the IP address of their machine was logged when the completed questionnaire was submitted. These steps facilitated the elimination of any duplicate responses. Also, the target population was provided with the option of asking for a paper copy of the questionnaire by fax or regular mail if they preferred to fill out a hard copy version. This helped mitigate biases related to internet usage that might otherwise have been introduced in the survey.

As is common in most email based internet surveys, the expected participation rate was quite low. To induce a higher rate of response one of the constraints imposed on the survey was its length. The survey questions were therefore limited to only sixteen questions, the bare minimum necessary to establish the key information.

The survey was also designed to be as objective as possible. Most of the questions were multiple choice or numeric open end type. While an opportunity to give subjective answers was provided at all stages, the questions were designed to be clear and direct and yield simple objective answers with little or no room for ambiguity. This facilitated statistical analysis of the responses without introducing any interpretative bias from the surveyor. The questionnaire was pre-tested using a small respondent group. Adjustments were made to the questionnaire based on the responses and feedback from this pilot-study.

The questions were separated into two groups. The first group consisted of questions regarding the operational statistics of the conventional incident detection technologies being used and the framework of data collection technology being used. While the basic infrastructure related information was available from sources such as the ITS deployment tracking website, these questions were targeted to obtain more specific information. The second group consisted of algorithm based automatic incident detection related questions. While each of these question sets provided information that had significant informative value they, together, formed the superset that allowed for a case-by-case comparison and analysis.

**SURVEY RESPONSE**

The survey was sent out to key personnel in Transportation Management Centers all over the United States and the Ontario Ministry of Transportation at Ontario, Canada. Out of the several Transportation Management Centers, 39 were specifically chosen as targets for the survey based on their area of coverage and the load on the network that they serve. Out of these 39, 32 Centers responded, resulting in an 82% effective response. The survey results are based on responses from these 32 Centers from 20 States within the United States and Canada. Fifty-two percent of the survey respondents constituted of people who were in a position to make the decisions regarding incident detection policies in their respective Transportation Management Centers. Another forty percent were in a position to influence such decisions.

**SURVEY RESULTS**

**Incident Detection Technologies**

Review of the research and practice literature clearly reveals that previously developed automatic incident detection algorithms were designed and evaluated from a fully automated, stand-alone perspective. When the respondents were asked about their view on algorithm-based incident detection technology, an overwhelming majority (81 percent) agreed that if reliable and accurate automatic incident detection algorithms are developed, the algorithms will not completely replace other state-of-the-practice methods (such as mobile phone calls, operator visual detection, etc.) but rather will serve as a complement to these other detection methods in an overall incident detection system.

Visual detection of incidents by operators, detection by floating vehicles and detection by mobile phone operators were found to be the most widely used incident detection technologies. Whereas, visual detection of incidents by operators monitoring Closed-Circuit Television (CCTV) cameras was the most popular one, it was followed closely by detection by floating vehicles and detection by mobile-phone operators. (Figure 2) The other incident detection technologies that are used include Aerial detection (using helicopters or planes), detection by co-ordination with other agencies like emergency centers or the police, detection using call boxes, etc.
The average time taken to detect an incident varies with the detection technology and also from center to center (Figure 3). It depends on several factors like the size of the network being served, number of units/operators deployed, efficiency of the operators, design of the center/consoles, etc. But the most predominant factor is usually the detection technology. The overall average time taken to detect an incident, averaged across all the TMC was found to be 8.5 minutes. Out of the several technologies, detection by mobile-phone operators has the lowest average time to detect, 4.5 minutes.

It was found during the pilot study that detection by mobile-phone users was one of the popular technologies. However, a drawback with this detection method is the number of duplicate calls made for the same incident. To assess the extent to which this drawback is tolerated in favor of the perceived advantages, information pertaining to the number of duplicate mobile phone calls was obtained. The average number of duplicate mobile phone calls received per incident on an average day of regular traffic flows was reported to be nine, a relatively high level of call redundancy. Although duplicate calls can aid in incident confirmation, they put additional pressure on operator time and resources. However this downside appears to be quite acceptable judging by the widespread use of this detection technology. While a small proportion (10%) of the respondents deemed that the current methods are sufficient for their organizations in the present as well as in the near future, 20% of the respondents agreed that the even if the current methods are sufficient at present they would fall short in the imminent future. Majority of the respondents (70%) considered the current methods of incident detection to be insufficient to meet the current demands. This strongly suggests that the need for alternative methods of detection has not been mitigated and the need for an automated detection technology like incident detection algorithms is more pertinent than ever.

**Presence of Advanced Traffic Management System**

Out of the 32 TMC surveyed only 5 do not have an Advanced Traffic Management System (ATMS) whereas the rest have an ATMS with real time operations data collection capabilities. While these five present infrastructure-related hurdles in implementation of incident detection algorithms, the others can integrate a well designed incident detection algorithm into their system with minimal cost and effort.

Most of the ATMS systems collect data at 20 second or 30 second intervals while a few collect data at 1 minute or 5 minute intervals. (Figure 4) With a detector spacing of about \( \frac{1}{3} \) to a \( \frac{1}{2} \) mile, if the observations are at 20 or 30 seconds interval, the surveillance offered by the system is quite sufficient for using an incident detection system. Larger time intervals between observations or widely spaced observation stations would negatively impact the accuracy of the algorithms as well as the time to detect an incident. But with 20 or 30 second intervals, which are observed to be more prevalent, a well designed incident detection algorithm can provide accurate and fast detection. ( With a detector spacing of \( \frac{1}{3} \) mile or \( \frac{1}{2} \) mile and assuming a free flow speed of 60 mph., the cameras, theoretically, capture the state of the traffic in a piecewise continuous fashion. This setup is compatible/ideal for incident detection using a model of detection where the values of traffic parameters observed at a detection point and that expected based on states at previous points in time or adjacent points in space. )

**Vehicle Detection Technologies**

While RADAR and video detection technologies for traffic monitoring are being implemented in several transportation management systems, magnetic induction loop technology is still predominant (Figure 5). Generally the data that can be obtained directly from this technology consists of three parameters: vehicle count, average vehicle speed, and lane occupancy.

Average vehicle speed is usually computed by taking the arithmetic mean of the individual vehicle speed observations. It should be noted that this computation gives the time-mean-speed. But, traffic flow theory relationships are formulated in terms of space-mean-speed. Therefore, applications that are based on traffic flow theory and use speed values as input would require space-mean-speed values. The space-mean-speed can be easily computed from the same individual vehicle speed measurements by computing the harmonic mean instead of the arithmetic mean. This computation is the equivalent of inverting the speeds to obtain vehicle pace in terms of time per distance, computing the arithmetic mean of the vehicle paces, and then inverting the average pace to return to speed in terms of distance per time. If correctly calculated space-mean-speeds are to be aggregated across lanes and or across multiple time intervals, they must be
converted back to average vehicle pace before volume-weighted averaging. As an aside, this rigorous approach to computing speed averages should be included in future system software editions.

Lane occupancy can be used as a surrogate for traffic density. Lane occupancy can be measured by presence detectors as the percentage of time a detector is occupied by vehicles in a given time interval. Among other factors, occupancy is dependent on the length of the detector because of the nature of its measurement – a longer detector will require more time to cross and hence would indicate a higher occupancy. To estimate the density from the occupancy, the length of detector is important and should be obtained from the detector configuration instead of assuming any default value. This difference usually prevents defining definite thresholds such as those for detecting congestion using occupancy.

An application built on top of real-time operations data, such as an application for algorithm-based incident detection, should ideally be developed to work with these three parameters – vehicle count, average vehicle speed and lane occupancy – at a satisfactory level. Otherwise, implementation of the application will require an upgrade of the traffic monitoring technologies in many of the current systems. Such a requirement could significantly delay or preclude implementation of the real-time application.

It could be argued that the need for automatic incident detection algorithms is for larger, more heavily congested systems, and that such systems are more likely to have one of the advanced video or radar detection systems. However, it should be noted that some of the larger systems have different technologies at various locations within the systems. Table 1 shows several examples of organizations that are using different vehicle detection technologies within the same system. Therefore, feasibility at the system-wide level require that real-time applications be designed for the highest-common-factor of the data available from these different technologies, which usually boils down to the above mentioned three traffic parameters, vehicle count, average vehicle speed, and lane occupancy.

Incident Detection Algorithms

It was observed that about 53% of the centers have an automatic incident detection algorithm integrated into their system (Figure 6). However, the percentage of the centers which had the detection algorithm fully functional was only 12.5%. There are a few things worth noting here. Firstly, more than a 50% level of integration shows that there is sufficient interest in algorithm based detection. This in turn points towards the need of such methods to address the problem of incident detection. A large percentage of centers did not integrate the algorithm into their system. This shows a reservation on the part of the centers, or a guarded approach. This observation is ratified by the low percentage of full functionality of the method. Also, the low percentage of full functionality purports that the experience of algorithm integration was not fully satisfactory to the centers that did it.

Reasons for Limited Integration of Incident Detection Algorithms

When asked for the reasons for the limited integration of incident detection algorithms in the system, the users cited three principal reasons – occurrence of false alarms, difficulty of algorithm calibration and low detection rates.

False Alarms

The primary and most commonly cited reason was an unacceptable rate of false alarms (Figure 7). The number of false alarms generated by the AIDA systems currently in use is high for operator comfort, and the distraction caused by the false alarms overweighs the benefits of faster detection.

The survey requested input on the tolerance level for false alarms for two time intervals – hourly and daily. It was found that on an average, a maximum of three false alarms per hour are considered acceptable. On a daily basis, the average response was ten, i.e., more than ten false alarms per day would cause too much distraction and render the automatic system unacceptable.

Algorithm Calibration

The problem of initially calibrating the algorithm came up second on the list of reasons for dissatisfaction generated by this technology. Unless the algorithm is properly calibrated it cannot be expected to function
with an acceptable level of efficiency and accuracy. The calibration process in most of the algorithms is complicated and time-consuming and also requires an understanding of the details of the algorithm to a degree which is not realistically attainable for the local staff.

The pattern matching, statistical and mathematical modeling based algorithms that are currently available rely mostly on heuristic and inductive modeling based approaches for calibration. Such procedures of calibration require data pertinent to a diverse set of incidents that represent all possible scenarios. The accuracy of the available information determines the efficiency of the calibration. Although incidents in traffic streams are abundant, information pertaining to these incidents is often insufficient and scarce. In practice therefore, in some cases – for example in the artificial neural network based algorithms – it is necessary to use simulation generated artificial incident data for calibration. Not only does this limit the accuracy of the calibration, the simulation process involves substantial time and effort. Development of new simulation networks for the specific site of implementation is arduous. Some algorithms are capable of improving with time after implementation, with availability of more data. But that requires manual feedback, which in turn delegates additional tasks for the local staffs.

There are two ways of addressing this problem. One way would be to find out ways to automate the calibration process as far as possible in the existing algorithms. If the algorithm implementation can be designed to adjust itself automatically to the existing and changing conditions of the environments and sites then it can be deployed with some initial configuration and minimal calibration. With the passage of time the accuracy of the algorithm would improve. There have been some efforts in this direction (21).

However there is an alternative approach. If instead of the usual inductive modeling approach, a deductive modeling approach based on traffic flow theory is adopted, the algorithm would not suffer from the usual data constraints. The calibration would mostly involve operations data (flow, speed and occupancy). This data is definitely more accessible than incident information data. Some Traffic Management Centers already archive this data and most of them can archive them if necessary at minimal costs. No elaborate simulations would be necessary for incident data generation.

Detection Rate
Low detection rate i.e. the percentage of incidents that was actually detected by the incident detection algorithm usually was considered a tertiary reason by the survey respondents. Since a center usually employs several technologies which work in tandem to detect incidents, the chances of not detecting an incident that is seriously affecting traffic, is quite low. Therefore a high detection rate is quite desirable, but that is not considered a critically decisive factor in rejecting the use of an algorithm.

CONCLUSIONS
The survey shows that a sizeable number of the transportation management centers have the infrastructure to collect operations data over the traffic network at short (less than a minute) and regular intervals of time. These systems are ideal for using algorithms for automatic detection of incidents. It is quite apparent, therefore, that the infrastructure is ready to implement these algorithms. Also, the survey indicates that the need for alternative detection procedures is present and increasing with the increase in the size of the coverage areas of the ATMS. These indicate a need for further research in this field.

However, based on general consensus among the survey respondents, it must be acknowledged that this new research thrust should recognize that automatic incident detection algorithms will not provide stand-alone incident detection, as was originally envisioned, but rather will be one component of an overall incident detection system that includes mobile phone call in, operator visual detection, freeway service patrol discovery, etc.

Also, since the predominant cause for dissatisfaction of the users is the rate of false alarms, incident detection algorithms must be designed to operate with a low false alarms rate. The efforts should be directed towards achieving stringent ceiling rates on the order of three false alarms per hour and ten false alarms per day. Though detection ratios and time to detect incidents are still important parameters for estimating the efficiency of algorithms, a substantial effort should be devoted towards addressing the problem of false alarms which is ranked as the primary deterrent for deployment of automatic incident algorithms.
detection algorithms. The desired outcome of the AIDA research and development effort will be readily implementable algorithms that provide the maximum reduction in overall detection times without violating acceptable false alarm thresholds. Automatic incident detection built on traffic flow theory-based deductive modeling is a promising, yet essentially unexploited approach that should be fully explored in this new AIDA research thrust.
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