Design of Incident Detection Algorithms Using Vehicle-to-Roadside Communication Sensors

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Incident detection methods for the automatic recognition of accidents and other freeway events requiring emergency responses have existed for over twenty years. Most of the developed and implemented algorithms rely on inductive loop data. Inductive loops are the most commonly used traffic sensor and collect data such as volume and occupancy at a point. However, the implemented algorithms using inductive loop data work with mixed success. Recently, there has been renewed interest in incident detection algorithms partly because of new sensors for obtaining traffic information. One of these new sensors is vehicle-to-roadside communications (VRC), which consists of electronic "tags" on the vehicles and readers along the roadway. These obtain counts, headways, travel times, lane switches, and other information about vehicles between subsequent readers. This paper explores the use of VRC data for incident detection. After a discussion of the use of VRC as a surveillance tool for incident detection, a few example pattern-based algorithms are described. Preliminary results of these algorithms suggest that VRC is a viable sensor to use for incident detection. The final section discusses further directions for this type of research.

A recent study suggests that incident-related congestion accounts for 64 percent of the total delay due to congestion and that this incident-related congestion could increase to 72 percent of total congestion by the year 2005 (*1*). Additionally, wasted fuel and lost productivity caused by congestion delays have great societal costs [one article suggests congestion delays cost $34 billion a year (*2*)]. The congestion-impact numbers are staggering and show that incident management that reduces these delays could provide a significant contribution toward the goals of increasing the capacity of existing roadways, enhancing air quality, reducing driver frustration, and increasing safety. Incident detection, the first step of incident management, is determining that an accident, stall, or something else that requires a response has occurred.

Automatic incident detection algorithms for freeways have existed and have been implemented since the early 1970s. Few algorithms have been developed for arterials because that is a much more complicated problem. For some researchers, new sensors and new data have led recently to renewed interest in incident detection. The goal of this paper is to show that the data obtained with vehicle-to-roadside communication devices (VRC), also called automatic vehicle identification (AVI) equipment, may lead to better-performing incident detection algorithms. Other work has been conducted recently in this area (*3–5*), but the approach and algorithms presented in this paper are unique.

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VRC has received considerable attention as the enabling technology for electronic toll collection and related applications such as congestion pricing. However, the data that can be obtained from VRC are also valuable for traffic monitoring and as inputs to traffic control algorithms. This multifunctionality helps to set VRC apart from other traffic sensors. An integrated congestion pricing, incident detection, and route guidance system is described further in Bernstein et al. (*6*). With such integrated systems, operating agencies are getting "double-duty" from their technology investment. Additionally, system operators may find it easier to get the public to accept a controversial component, for example, congestion pricing, when the public believes that the system is providing additional benefits such as incident detection and route guidance.

This research is concerned with detecting the beginning of accidents and stalls and other incidents that cause traffic disruptions on freeways and require the emergency response of an ambulance, police, and/or tow truck. The basic premise of this research is that it may be possible to replace the inductive loop data (or loop-emulated data) currently used for incident detection with data obtained from a VRC system.

There are two ways that this can be done. In the first the data obtained from the VRC system would be used with existing algorithms. However, this may not be effective for two reasons: existing inductive loop-based algorithms do not work very well [see, e.g., the review articles by Stephanedes et al. (*7*) and Chen and Chang (*8*)], and VRC data represent only a percentage of the vehicles and vehicle types on the freeway and, hence, to use these data in existing algorithms may require processing or manipulation to be representative of all traffic. The second way to use VRC for incident detection is to develop new algorithms that take advantage of the different attributes of VRC data. In this paper we ex-plore some of the properties of VRC data and take some initial steps toward the development of VRC-based incident detection algorithms.

The VRC-based algorithms we develop and describe in this paper incorporate several approaches to incident detection. The algorithms consider temporal and spatial patterns in the data. The algorithms detect in all traffic flow levels and require little persistence checking. It is expected that these algorithms can either stand alone or be combined with other sensor data and other incident detection methods for an incident detection system.

Vehicle-to-roadside communication is described here as a surveillance tool for incident detection along with a few possible incident detection algorithms that use VRC data, preliminary results for these algorithms, and future directions for this type of research.

VRC-BASED SURVEILLANCE FOR INCIDENT DETECTION

In our opinion there are three broad categories of data that can be used for incident detection. Point data are collected at a single, specific location and include occupancy, instantaneous speed, and flow. Area data are collected over a segment of roadway and include density. Finally, point-to-point data are collected between pairs of specific locations and include travel time.

Different types of sensors can (and should) be used to collect different types of data. The most common sensor in use today, inductive loops (and loop emulators), collect point data only. The potential advantage of a VRC-based surveillance system is that it can be used to collect both point data and point-to-point data. Very briefly, VRC consists of a transponder or "tag" on the vehicle and a reader along or over the road and the communications link between the two. In all VRC systems, the VRC readers obtain at least the individual vehicle identification number from each transponder-equipped vehicle that passes. With the identification numbers, the system knows, for example, what time car Number 123 passed Reader A and what time it passed Reader B and can calculate that car's travel time between the readers. Additionally, a VRC system can obtain lane-specific and station-specific headways (time between transponder-equipped, "tagged" vehicles), the volume of tagged vehicles on a section at any point in time, the number of tagged vehicles passing in each lane at a reader station, and the number of tagged vehicles that switch lanes between stations. More information is obtained with read-write capabilities as described below.

Even the more easily obtained data items—vehicle-specific travel times, lane- and station-specific headways, section volumes, and lane switches—are all parameters that can only best be obtained with a sensor that obtains data between two or more points such as VRC. This point-to-point data should better represent traffic compared with data collected at a certain point. Of course, VRC is not the only technology that can be used to collect point-to-point data. In fact, as discussed in the review paper by Bernstein and Kanaan (*9*), any automatic vehicle identification (AVI) technology can be used for this purpose. Hence, before moving to a discussion of the algorithms themselves, some of the issues regarding the development of algorithms with VRC are briefly discussed here. These issues include the number of sensors used, read-only versus read-write capabilities, and penetration rates (percentage of vehicles accurately detected) of the sensors.

Numbers of Sensors

Some people may presume that the only VRC sensors available will be those used for another purpose (such as electronic toll collection). However, it is possible to install "extra" readers. In fact, using VRC systems for incident detection likely will involve readers in additional locations to those required for electronic toll collection, which raises at least three institutional issues. First, although it is most likely that the cost of installation of extra readers and software for incident detection will be less than the benefits provided by having an incident detection system, extra readers are an extra expense, making it impossible to use the "toll collection and incident detection for the price of one" argument. Second, users need to understand that the extra readers will not deduct yet another toll but are there to aid in incident detection and thus reduce congestion. Third, on proposed systems where conventional toll payers (those using manual toll booths) must exit the roadway to pay a toll, the extra readers may be additionally confusing and a safety hazard.

Read-Only Versus Read-Write Capabilities

Read-write means the reader obtains information and also writes information on the "tag." In addition to the vehicle identification being passed, the transponder can pass information written to the tag such as initial reader passed (origin information), time passed last reader (making for easy travel time calculations), even processed data such as average volumes or headways passed from one reader to the next. A more sophisticated system may also pass the vehicle type, driver-input origin, and destination information, even the traveling speed from the vehicle's speedometer to the reader and, subsequently, an incident detection system. With a read-write system, VRC, unlike other surveillance technologies, allow for the passing of required information from one point to the next and traffic control such as incident detection to be performed locally.

Incident detection can be performed with a read-only system, but there would be advantages to using a read-write system. Most obviously and at the simplest level, the time passed the last reader and processed data may aid the calculations required at the downstream readers and may speed up the effort required for incident detection. The algorithms presented in this paper work with read-only technology but could be enhanced with read-write technology.

Penetration Rates

Although VRC-based systems have the advantage of being read-write-capable, they do have one important disadvantage. VRC data is incomplete in that not all vehicles and types of vehicles are represented with the data. This is because generally only a certain percentage of vehicles are equipped with transponders. Additionally, VRC may be used by a specific group of vehicles such as heavy trucks. For example, there are already two multi-state heavy truck implementations of VRC. All of this information is valuable, but it should be explored whether the partial information is sufficient to represent all traffic for incident detection algorithms. It is our guess that even a "small" (30%) portion of vehicles if they were autos or regular commuters would be sufficient data. However, if only a small percentage of vehicles are tagged, then the data obtained have greater variance and smaller reliability. For example, headway information would be subject to randomly distributed fluctuations, especially in light traffic, if a small number of vehicles are transponder-equipped. This variability may lead to using different algorithms for different percentages of tagged vehicles. Additional consideration should be given if only trucks or buses were tagged. This surely would add a bias to the data because trucks and other heavy vehicles do not travel as quickly or maneuver as smoothly as typical traffic. Yet, this bias may also work in favor of an algorithm. For example, an incident detection algorithm based on lane changes may be more powerful if it detects that a truck or several trucks have moved from the typically used right lane.

EXAMPLE PATTERN-BASED ALGORITHMS

There are several different approaches that may be used for incident detection algorithms. Recent research has investigated the use of processed video (*10*), catastrophe theory (*11*), and artificial intelligence (*12*) as methodologies for incident detection algorithms. More typical designs are either statistical (generally after a time series until an anomaly occurs) (*13,14*) or pattern-based where the data are typically compared with numerical thresholds to determine that a stoppage has occurred (*15,16*). Most of the implemented algorithms follow a pattern-based approach, probably for several reasons. First, the logic is simple and easily understood by traffic operators who must trust the results of the algorithms. Second, they use less computer time and hardware than other methods. Although it is considered by many current researchers that other methods will perform better and that computer requirements and other technology advances are less constraining now than fifteen or more years ago when different methods were first proposed, this research focuses on pattern-based approaches to show that VRC-based pattern algorithms work just as well as currently implemented algorithms using other sensors.

Previous research (*17*) and a previous paper (*18*) describe various VRC data "incident indicators" and four possible pattern-based algorithms. The following paragraphs describe the best-performing of these algorithms, named the Headway Algorithm, and two additional algorithms that we have named the Lane Switches Algorithm and Lane-Monitoring Algorithm. The algorithms are designed to be used with vehicle to roadside communication sensors (less than 100% of vehicles tagged, accurate identification of all tagged vehicles) but can also be used with other types of automatic vehicle identification sensors (e.g., processed video license plate readers). The motivation and logic behind these algorithms is given along with a flow chart of each algorithm. All three of these algorithms represent new logical approaches to incident detection. These ideas have not yet been described or implemented for any sensor.

Headways Algorithm

VRC data can be used in two major ways in an incident detection algorithm. First, it can be used to observe temporal differences. In general, increased travel times from one period to the next or any large difference in travel times from one period to the next strongly indicates unstable conditions and, possibly, incidents. Second, spatial comparisons can be made by either comparing headways (time between subsequent tagged vehicles) at two different readers or the volumes (number of tagged vehicles) on two different sections. Longer headways at downstream readers compared with upstream readers or smaller volumes on downstream sections compared with upstream sections may indicate an incident.

Both temporal and spatial comparisons of travel times and headways are used in the Headways Algorithm. The algorithm consists of three sequential tests; if the three tests are satisfied during a particular time interval, then an incident is declared. The first test looks for a significant difference in travel time from one time interval to the next. It is thought that slower travel times may be indicative of an incident. The second test, another temporal test, considers the differences in headways at the downstream reader for the current time interval and the previous time interval. An incident is likely to cause longer and longer headways as vehicles are queued and then have to maneuver around the incident. The third test makes the spatial comparison of whether headways are different at different reader locations. Again, headways may be longer in the vicinity of the incident and then decrease downstream of the incident. These different tests can be described mathematically as follows.

The following text describes the Headways Algorithm, which is illustrated in Figure 1. In the Figures, *int* denotes the length of the selected time interval. Let $Nv(t_{cur})$ denote the number of vehicles that passed the downstream reader location r_{down} during the current time interval, t_{cur}. Then the first test compares the average travel time during the current interval, t_{cur}, with the average travel time during the previous interval, t_{rev}. The average travel time, $ATT(t_{cur}, r_{down})$, between the upstream reader, r_{up}, and the downstream reader, r_{down}, during the current interval is given by

$$ATT(t_{cur}, r_{down}) = \frac{1}{Nv(t_{cur})} \sum_{j=1}^{Nv(t_{cur})} TT_j \qquad (1)$$

where TT_j is the travel time between readers r_{up} (upstream) and r_{down} (downstream) of the *j*th vehicle to pass reader r_{down} during the current interval, t_{cur}. If $|ATT(t_{cur}, r_{down}) - ATT(t_{prev}, r_{down})|$ is greater than a prespecified, possibly flow-dependent threshold, *HD_TH1*, then the next test is conducted.

The second test compares the headways (time between vehicles) at the downstream reader for two different time periods (current time interval and previous time interval) against a second threshold,

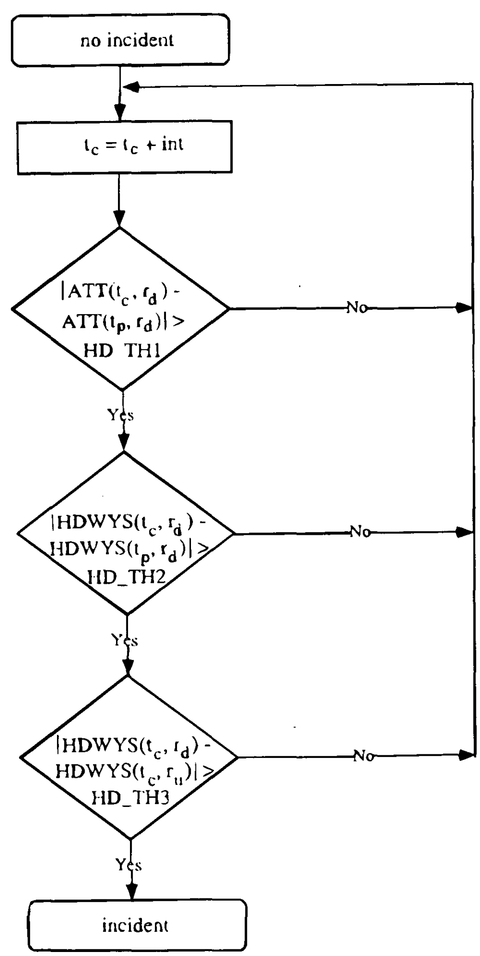

FIGURE 1 Headways algorithm.

HD_TH2. Our parameter for *average headways*, $HDWYS(t_{cur}, r_{down})$, is defined as follows:

$$HDWYS(t_{cur}, r_{down}) = \frac{1}{Nv(t_{cur})} \sum_{j=2}^{Nv(t_{cur})} t_j - t_{j-1} \quad (2)$$

where t_j is the actual time of the jth vehicle to pass reader r_{down} during the t_{cur} interval.

The final test before an incident is declared compares the headways at the downstream reader and the upstream reader during the current time interval against a third threshold, *HD_TH3*. We define r_{up} as the upstream reader. If $|HDWYS(t_{cur}, r_{down}) - HDWYS(t_{cur}, r_{up})|$ is greater than *HD_TH3*, then an incident is declared.

Lane Switches Algorithm

In addition to travel time and headway comparisons, there are other ways that VRC data may indicate that an incident has occurred. For example, VRC is able to provide vehicle-specific data such as lane change information. A large number of lane switches noted from one reader to the next likely indicates unstable traffic conditions.

Our Lane Switches Algorithm is depicted in Figure 2. Basically, the system determines the number of vehicles that have switched lanes between readers, $SWITCH(t_{cur}, r_{down})$, using the lane-specific, vehicle-specific data obtained at the reader r_{down} during the current time period, t_{cur}. This number is normalized by the number of tagged vehicles that pass during the time interval $Nv(t_{cur})$ to get $NM\_SW(t_{cur}, r_{down})$, the *normalized number of switches*:

$$NM\_SW(t_{cur}, r_{down}) = \frac{1}{Nv(t_{cur})} SWITCH\,(t_{cur}, r_{down}) \quad (3)$$

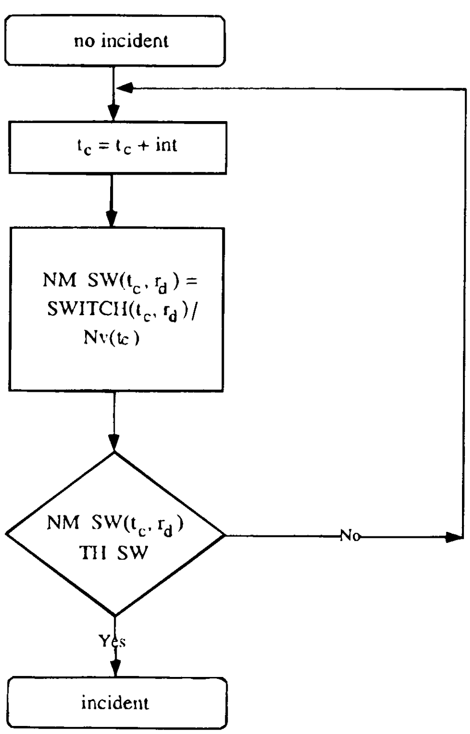

FIGURE 2 Lane switches algorithm.

If the result exceeds a certain threshold corresponding to the percentage of vehicles that have switched lanes (*TH_SW*), an incident is declared. The tested algorithm counted a lane switch from the right lane to the left lane (through the middle lane) as one switch. Perhaps counting such a maneuver as two lane switches would provide even more information about traffic conditions.

Lane-Monitoring Algorithm

The idea behind the Lane-Monitoring Algorithm is to track over two or more time intervals the vehicles that pass in each lane at a reader location. If fewer vehicles pass in a certain lane than expected, then the other lanes are checked to see if more vehicles than usual have passed. Rerouted vehicles may be indicative of an incident. Each interval, each lane in turn is compared against the low threshold. If the low threshold is met, then the other lanes are checked against a high threshold.

Figure 3 shows our Lane-Monitoring algorithm. To smooth out the data (and prevent false alarms), this algorithm uses the average number of vehicles that pass the reader in each lane over a prespecified number of intervals, say, two or three intervals. For example,

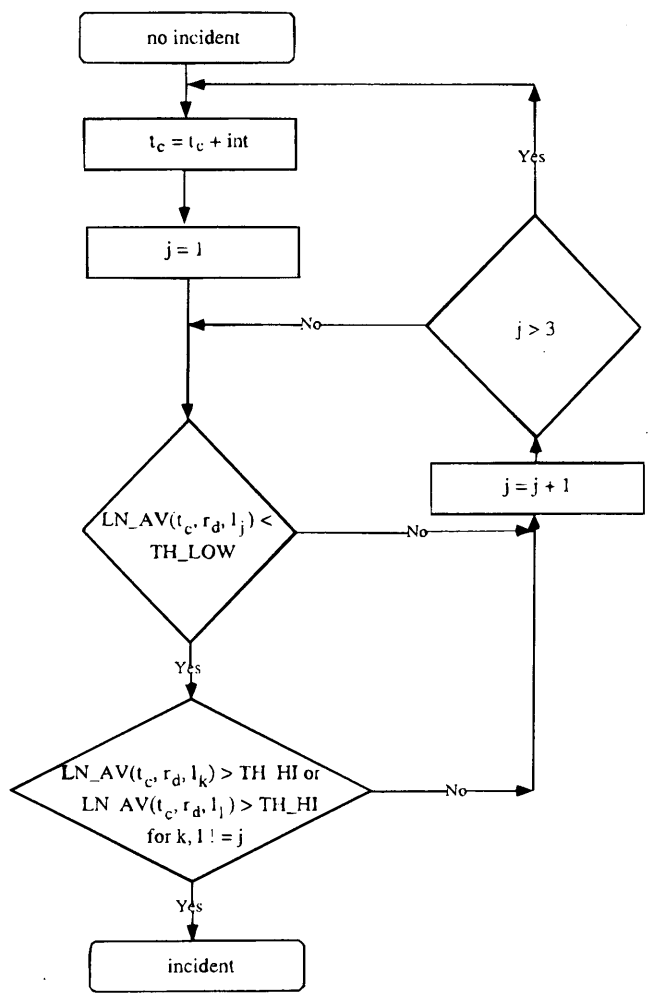

FIGURE 3 Lane monitoring algorithm.

the *lane average* for two time intervals for vehicles in the right lane (lane 1) is given by

$$LN\_AVG(t_{\text{cur}}, r_{\text{down}}, l_1) = \frac{Nv(l_1, t_{\text{prev}}) + Nv(l_1, t_{\text{cur}})}{2} \quad (4)$$

where t_{cur} is the final (current) time interval, r_{down} is the reader location, l_1 indicates the right lane, and $Nv(l_1, t_{\text{cur}})$ is the number of vehicles passing reader r_{down} in lane 1 (the right lane) during the current interval. The average number of vehicles in each lane is compared with a low threshold (*TH_LOW*). If the average number of vehicles is less than this threshold then the average number of vehicles at that reader passing during those time periods in the other lanes is compared with a high threshold (*TH_HIGH*). If any of the other lane volumes exceed the high threshold, then an incident is declared. For example, if few cars are in lane 3 but a higher than usual number of vehicles are in lanes 1 and 2, then probably an incident occurred in lane 3.

TESTING THE ALGORITHMS USING SIMULATION

Ideally, one would like to use field data to test and evaluate incident detection algorithms. In this case, this was not possible. One of the objectives of this research was to evaluate incident detection algorithms that use VRC data against an algorithm that uses inductive loop data. For this the VRC and loop data must be obtained from the same vehicles during the same time periods at the same points. Although field inductive loop and VRC data exist separately, both sensor types are not available at the same locations.

Instead of field data, the algorithms were tested on data generated by a microscopic traffic simulator described previously (*19*, *20*). The simulator has been tested with the San Diego data set used previously to illustrate the performance of INTRAS, another microsimulator, and was found to perform slightly better than INTRAS in replicating the data collected from the field (*19*). The tested incident detection algorithms were run on simulated inductive loop and VRC data. Although simulated data are not perfect, there are several advantages to using this simulator. First, the consistent (VRC and loop data at the same locations) data can be obtained. Second, it is easy to test different incident scenarios under different flow conditions. Third, it is possible to change detector spacings and configurations and roadway geometries to determine how the algorithms perform most optimally.

The network used to obtain these preliminary results is a 19.31 km (12.0 mi) long three-lane highway. The first half of the freeway is used for warm-up, and then the detectors are placed at typical 1.21 km (0.75 mi) intervals. Detectors are located in each lane at the 9.66, 10.86, 12.07, 13.28 km (6.0, 6.75, 7.5, and 8.25 mi) points. The first half [9.66 km (6.0 mi)] of the network is used for warm-up because vehicles are loaded gradually onto the network and reach the desired flows for the second half of the simulation.

Several different incident scenarios were designed to test algorithm performance with different incident types, different incident locations with respect to the sensors, and different traffic flow levels. The forty different incident data sets cover short-duration incidents (e.g., a single-vehicle stall on the mainline for 5 minutes), more serious accidents (three cars blocking traffic for 20 minutes), and incidents in between. To test the performance of the algorithms in relation to incidents' locations with respect to the sensor (reader or loop) locations, incidents were staged 0.40 km (0.25 mi) before the sensors, 0.81 km (0.50 mi) before the sensors, and at the sensors. To test the algorithms against false alarms, nonincident data sets included normal flowing traffic and sets where two vehicles traveled in adjacent lanes at speeds slower than the rest of the traffic flow. The tested flows include 1,000 vehicles per lane per hr, 1,200 vehicles per lane per hr, and 1,400 vehicles per lane per hr. These less-than-heavy traffic flows were dictated by hardware constraints, but it is assumed that if the algorithms perform adequately in medium flows they will perform as well or better with heavier flows.

A 40-min simulation is used that includes a 15-min warm-up time, incident occurrence, and clearance. The warm-up time and warm-up distance are necessary for traffic to follow normal behavior at the desired flow level by the time the sensor locations are reached. Thus, 25 effective minutes of simulation are obtained from each data set. The same input file is used for each flow level. Vehicles enter one end of the freeway according to specified rates and exit if they reach the other end of the freeway during the 40 simulated minutes.

All of the algorithms were tested with the same data. It was assumed that 50 percent of the vehicles were equipped with VRC transponders. This percentage was chosen because current toll collection systems have participation rates of 30 to 80 percent. Thirty-second time intervals were used. Data were averaged across all lanes at a sensor or considered separately according to the algorithm used.

PRELIMINARY RESULTS

Although we are not yet ready to draw any final conclusions about the performance of these algorithms, there are some important insights that can be drawn from these simulation results. The intent of these results is to show that even the simple VRC-based algorithms perform at least as well as implemented algorithms using other sensors. Additionally, compared with other simple VRC-based algorithms developed, implemented, and tested during the course of this research, these specific algorithms and their corresponding logics seem to give the most promising results.

Quantitative Results

The typical incident detection performance measures—detection rate, false alarm rate, and mean time to detect—were used here. These measures are defined as follows. First, the detection rate:

$$DETECTION\ RATE = \frac{\#inc_{\text{det}}}{\#inc_{\text{true}}} \quad (5)$$

where $\#inc_{\text{det}}$ is the number of detected incidents and $\#inc_{\text{true}}$ is the number of actual (simulated) incidents. There are two ways to define false alarm rates. First:

$$FALSE\ ALARM\ RATE\ (\text{def } 1) = \frac{\#inc_{\text{false}}}{hours\ of\ simulated\ time} \quad (6)$$

This provides a false alarm rate per hr. False alarms are counted when the algorithm detects that an incident has occurred and yet no incident has occurred at that time. Alarm triggers related to an initial false alarm are counted only once. This is similar to the case of detecting true incidents that cause many triggers—an incident can only be detected once. For this calculation the warm-up times were deleted from the hours of simulated time. For the second definition false alarm rates can be expressed as a percentage of false alarms over the number of times the algorithm is repeated:

$$FALSE\ ALARM\ RATE\ (def\,2) = \frac{\#inc_{\text{false}}}{\#algorithm\ repetitions} \quad (7)$$

The algorithm is used after an appropriate warm-up time. Finally, the average time to detect is calculated by

$$AVERAGE\ TIME\ TO\ DETECT = \frac{\sum time_{\text{det}}}{\#inc_{\text{det}}} \quad (8)$$

where $time_{\text{det}}$ is the time until the algorithms first declare a true incident from the time an incident is simulated to begin. Incidents that are not detected within 6 min are considered undetected (affecting the detection rate), and subsequent detections are considered false alarms. Thus, this statistic includes only those true incidents detected in less than 6 min.

Table 1 shows quantitative results of the VRC-based algorithms described here compared with our implementation of California Algorithm #7, a typically implemented pattern-based inductive loop-based algorithm. All three algorithms seem to be successful compared with the California Algorithm. It is important to consider that a different simulator, different flows, different detector spacings, and/or different percentages of vehicles used likely would lead to different numbers—what is important is the relative performances of the values.

These results have been obtained for all four algorithms (Headways Algorithm, Lane Switches Algorithm, Lane-Monitoring Algorithm, and California Algorithm) with the thresholds that jointly maximize the detection rate and minimize the false alarm rate and detection time. One expects a linear relationship or high positive correlation between detection rate and false alarm rate and between detection rate and time-to-detect. Previous research shows graphs with such relationships (7). However, this does not necessarily seem to be the case with the VRC-based algorithms. Different combinations of thresholds often led to one performance measure remaining fairly constant while the others fluctuated.

Several results may be ascertained. The table shows that although the false alarm rates for the Headways Algorithm and the California Algorithm are similar, the Headways Algorithm clearly performs better in terms of detection rate and average time to detect. If average time to detect is not of great concern (the difference between 2 and 3 min may not be large when an incident impacts traffic for 40 min or more), then the Lane Switches Algorithm clearly performs well. Finally, the Lane-Monitoring Algorithm works quickly with a high detection rate but a relatively high false alarm rate.

TABLE 1 Most Promising Evaluation Results

Algorithm Name	Detection Rate (#incidents detected/true incidents)	False Alarm Rate (def 1) (false alarms/ hour)	False Alarm Rate (def 2) (false alarms/ algorithm repetitions)	Average Time To Detect (minutes)
Headways Algorithm	0.75	1.30	0.0195	2.00
Lane Switches Algorithm	0.94	0.65	0.0098	2.94
Lane Monitoring Algorithm	0.92	2.20	0.0330	1.73
California Algorithm #7	0.53	1.05	0.0158	2.19

Qualitative Results

Although the numerical results seem promising, it is also valuable to describe the performance of the algorithms with respect to incident types, traffic flows, and incident location with respect to the detectors. It is helpful to note that slight modifications may improve results.

Headways Algorithm

The detection rate (~75%) was constant for the different flows tested. This algorithm is successful in detecting a short-duration, single-vehicle stall type incident. The algorithm seems to be insensitive to incident location with respect to the detectors. As expected, detection times are reduced as flow increases. False alarms seem to be uncorrelated to flow levels or incident types. This algorithm may work better if the spatial comparison is made between the reader and the reader downstream from it rather than upstream—at the downstream reader traffic would be flowing more normally.

Lane Switches Algorithm

This simple algorithm performs remarkably well. Although the time-to-detect is slow, the time-to-detect is lower for lower flow levels, which is the inverse of the performance of typical algorithms. As expected, detecting stalls requires the longest detection time. Also as expected, the closer the downstream detector to the incident location, in general, the quicker the detection. A simple modification such as counting switches across two lanes as two switches rather than one switch may improve the results significantly.

Lane-Monitoring Algorithm

Despite the high false alarm rate, this algorithm shows promise. In general, the detection rate, false alarm rate, and time-to-detect values are not correlated with the type of incident, traffic flow level, or location of the incident with respect to the readers. This robustness is very attractive in an incident detection algorithm. The algorithm is then appropriate for many different situations. This algorithm may have potential as a back-up or secondary algorithm in an incident detection system.

CONCLUSIONS

All three of these algorithms perform reasonably. They show that VRC has great potential as a stand-alone sensor for incident detection. The algorithms perform better or as well as expected and decisively better than the typically used California Algorithm. The algorithms' robustness to various situations make them additionally appropriate. Future research as described in the next section may enhance the performance of these and other VRC-based algorithms.

FUTURE RESEARCH

The following paragraphs introduce several ideas to spark future research. These include extensions to the current research, combining VRC data with data from other traffic sources, considering other algorithm methodologies, and performing a cost-benefit analysis of algorithms that use VRC compared with algorithms that use other sensors.

There are several obvious extensions to this research. These include testing the described algorithms with field data. A complete field test would provide the best indication of the algorithms' performance. Another extension proposed by this research but that has not been explored fully is to use thresholds that are functions of the flow. Although calibrating such equations would not be easy, threshold-flow functional relationships would reduce dramatically the overall calibration effort required. The threshold function may also have the percentage of vehicles tagged and/or types of vehicles tagged as parameter(s). Also, additional work may be performed in calibrating algorithm parameters considering detector spacings, configurations, and roadway design with both simulated and field data. There is assumed to be a relationship between sensor spacing and mean time to detect [closer spacing, lower time to detect (*21*)], thus spacing as close as financial and human factors constraints allow should be best. But it is possible that spacing too close together causes an intolerable false alarm level. Similarly, it is important to investigate how different percentages of tagged vehicles and different types of tagged vehicles will change the algorithms' parameters and performance. For example, in general, higher percentages of vehicles would result in better results. Additionally, some systems may have only heavy vehicles tagged, which would introduce a bias into the data and should be considered and weighted as such.

One of the more exciting future research topics is combining VRC data with data from other detector types. It is likely that VRC systems will be installed on systems already outfitted with inductive loops. The spatial, microscopic data from VRC can be combined with inductive loop data, or other point data sources such as infrared and ultrasonic detectors, representing all vehicles (VRC-tagged and nontagged) to obtain better parameters for use in incident detection algorithms. It is likely that even better parameters would result if VRC data were combined with video or radar images that produce density and other spatial information.

Currently, implemented incident detection algorithms are all pattern-based. However, there are several other proposed methodologies for incident detection. These include statistical methods including times series and filtering, the application of catastrophe theory or artificial neural networks, and the use of a traffic flow model. Some of the proposed VRC algorithms are statistically based. VRC data may require less computational power to obtain the space mean speed and density needed in traffic flow models. Model-based incident detection algorithms are expected to work better than other incident detection algorithms because the traffic flow model more accurately represents traffic and thus can determine better whether the traffic flow is non-normal, hence, that an incident has occurred. VRC can be used with any of these methodologies.

It would be beneficial to do a cost-benefit analysis comparing algorithms that use VRC with algorithms that use other sensors and other incident detection methods. Implemented inductive loop-based algorithms, proposed inductive loop algorithms, the VRC algorithms described here, other VRC algorithms, processed video algorithms, CCTV scanning by traffic management center operators, and cellular phone calls from drivers should all be compared. Such an analysis would include benefits described by the performance measures of detection rate, false alarm rate, time-to-detect, public awareness and acceptance, and ease of operation of the algorithm or system by the traffic management center. The costs should include the costs of the sensors, software development, maintenance, and the personnel required to run the system.

This paper has provided an initial contribution to the use of vehicle to roadside communication sensors for incident detection. After discussing the use of vehicle to roadside communication sensors as the surveillance sensor for incident detection, the paper has concentrated on three pattern-based algorithms for detection that show great promise. The above paragraphs suggest some of the many directions to follow to continue the research.

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