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16. Abstract

The detection of freeway incidents is an essential element of an area's traffic management system. Incidents need to be detected and handled as promptly as possible to minimize delay to the public. Various algorithms and detection technologies are examined to determine which combinations offer optimal detection performance.

The objectives of this research are to compile, compare, rank, and recommend incident detection strategies in use today. Incident management and its components are described in this report to provide background. Extensive literature reviews, site visits, and interviews have been conducted and continue to be pursued as new incident detection schemes emerge. The most prevalent and practical incident detection algorithms are coded into software for testing and performance comparison. Large amounts of traffic data have been acquired for input into detection algorithms. An integrated incident detection data and algorithm fusion model is proposed as well. This model can be used both as a management tool and as a method to combine data sources and algorithms in ways that take advantage of their respective strengths in differing circumstances. The status of tasks that are required to complete this work is also described.

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EVALUATION OF INCIDENT DETECTION METHODOLOGIES

by

Hani S. Mahmassani, Carl Haas, Sam Zhou, and Josh Peterman

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EXECUTIVE SUMMARY

The objectives of this research are to compile, compare, rank, and recommend incident detection strategies in use today. Incident management and its components are described in this report to provide background. Extensive literature reviews, site visits, and interviews have been conducted and continue to be pursued as new incident detection schemes emerge. The most prevalent and practical incident detection algorithms are coded into software for testing and performance comparison. Large amounts of traffic data have been acquired for input into the detection algorithms. An integrated incident detection data and algorithm fusion model is proposed as well. This model can be used both as a management tool and as a method to combine data sources and algorithms in ways that take advantage of their respective strengths in differing circumstances. The status of tasks that are required to complete this work is also described.

CHAPTER 1. INTRODUCTION

Intelligent transportation systems (ITS) promise more efficient transportation networks. These systems use advanced information processing and communication technologies to manage traffic systems (signal setting, ramp metering, incident detection, verification, and clearance) and to control the flow of vehicles in order to achieve greater network efficiency. Central to an ITS are Advanced Traffic Management Systems (ATMS), which use advanced technology to assist the operator in managing traffic networks. An ATMS aims to assist control center operators by providing tools for (1) managing data coming into the control center; (2) generating information (from the incoming data) that depicts from various diverse resources the operational status of a roadway network; (3) detecting and resolving incidents; and (4) controlling the traffic network. The focus of this project is on the third of these four tasks.

Incident-related congestion on freeways costs the United States billions of dollars a year in lost productivity, property damage, and personal injuries. The Federal Highway Administration (FHWA) predicts that, by the year 2005, incidents will cause 70 percent of all urban freeway congestion, with such congestion costing road users some $35 billion (Gordon 1996). Incident detection, verification, and clearance are among the important capabilities offered by an ATMS to control traffic and improve operations in congested networks. This report describes work undertaken to assess and compare automatic incident detection (AID) techniques meant to improve the capabilities of an ATMS.

CHAPTER 2. INCIDENT MANAGEMENT COMPONENTS

The objectives of incident management are to inform travelers of incident characteristics and to restore roadways to full capacity after an incident occurs (Gordon 1996). Given the importance of incident management to traffic flow and traveler safety, departments of transportation have sought to develop methods of incident management that, by and large, occur in two stages: (1) Incident managers first detect and verify the incident, and (2) incident managers respond in an appropriate manner to that incident.

2.1 DETECTION

Roadway incidents cause traffic delays, the extent of which is a function of two incident characteristics: first, the extent to which the facility's capacity has been reduced, and, second, the incident's total duration (Gordon 1996). Duration can be further divided into detection, response, and clearance times. Of these three, detection duration is what incident detection techniques strive to minimize. Constant human observance of a traffic facility, of course, will lead to the smallest detection time (provided the incident occurs on that observed facility). The traffic management centers (TMCs) in Houston (TranStar) and in San Antonio (TransGuide) are designed with this kind of observation in mind. Large TV monitors provide operators with live video images of most of the region's freeways. However, to observe increasingly large and complex traffic networks simultaneously, TMCs require some degree of automated, electronic monitoring. It is within this context that incident detection techniques are investigated in this report. Incident detection techniques use sensors to automatically and continuously monitor traffic characteristics and detection algorithms to identify incident patterns. The following sections describe various sensor technologies and incident detection algorithms.

2.1.1. Sensors

Many incident detection algorithms are "blind" in that they function in the absence of a visual picture of the traffic. Whereas humans may observe an accident or stalled vehicle, detection algorithms rely on a continuous stream of such traffic data as volume, speed, and occupancy. The consistency, reliability, and cost of obtaining these traffic variables differ according to the type of sensor used. Typical sensing techniques, including the more recently developed monitoring methods that offer promise but have achieved limited implementation, are described next.

2.1.1.1. Conventional Sensor Technologies

Various detection technologies are available for monitoring traffic conditions. The most commonly used detection systems include inductive loop, video image processor, microwave, infrared, and radar-based products. Currently, incident detection is predominantly performed using inductive loop detectors buried in the roadway pavement. These loop detectors have certain disadvantages: For example, installation and maintenance of these devices is difficult and expensive. Also, as previously mentioned, loop detection is "blind" in the sense that it cannot provide a human operator with some form of visual validation and assessment of the nature of the detected incidents. To offset the drawbacks of loop detectors, video cameras and closed-circuit TV (CCTV) systems have been programmed to serve as detection mechanisms. Both inductive loop detectors and video image processors (VIPs) have achieved more than a 95 percent detection rate on vehicle counts and have a margin of error of less than 5 mph on speed measurements (Ahmed 1986). Such performance meets the requirements of most traffic management systems. Table 2-1 summarizes the qualitative advantages and disadvantages of these technologies.

Table 2-1. Performance Comparison among Existing Incident Detection Technologies

Type	Advantages	Disadvantages
Inductive loop detector	• Low per-unit cost • Large experience base • Relatively good performance	• Installation and maintenance require traffic disruption • Easily damaged by heavy vehicles, road repairs, etc.
Microwave (Radar)	• Installation and repair do not require traffic disruption • Direct measurement of speed • Multilane operation • Compact size	• May have vehicle masking in multilane application • Resolution impacted by Federal Communications Commission (FCC)–approved transmit frequency • Relatively low precision
Laser	• Can provide presence, speed, and length data • May be used in an along-the-road or an across-the-road orientation with a twin detector unit	• Affected by poor visibility and heavy precipitation • High cost

Type	Advantages	Disadvantages
Infrared	• Day/night operation • Installation and repair do not require traffic disruption • Better than visible wavelength sensors in fog • Compact size	• Sensors have unstable detection zone • May require cooled IR detector for high sensitivity • Susceptible to atmospheric obscurants and weather • One per lane required
Ultrasonic	• Can measure volume, speed, occupancy, presence, and queue length	• Subject to attenuation and distortion from a number of environmental factors (changes in ambient temperature, air turbulence, and humidity) • Difficult to detect snow-covered vehicles
Magneto-meter	• Suitable for installation in bridge decks or other hard concrete surfaces where loop detectors cannot be installed	• Limited application • Medium cost
Video image processing	• Provides live image of traffic (more information) • Multiple lanes observed • No traffic interruption for installation and repair • Vehicle tracking	• Live video image requires expensive data communication equipment • Different algorithms usually required for day and night use • Possible errors in traffic data transition period • Susceptible to atmospheric obscurants and adverse weather

2.1.1.2. Video Image Processing

The use of video image processing for traffic surveillance was initiated in the mid-1970s in the United States and abroad, most notably in Japan, France, Australia, England, and Belgium (Michalopoulos 1991). The earliest incident detection system in North America, a fourteen-camera CCTV surveillance system, was set up on the Gulf Freeway in Houston in 1967 (Goolsby 1969). In 1971 a similar system was installed on the San Francisco-Oakland Bay Bridge in California (MacCalden 1984). In addition, Minnesota's Department of Transportation has been employing video detection mechanisms since 1984 (Michalopoulos et al. 1990). Typically, video cameras are employed on roadways for surveillance purposes. They provide to operators a real-time view of traffic, using cameras that can pan, tilt, and zoom (PTZ) as needed to monitor traffic conditions. It should be noted that video detection does not typically occur using this equipment. VIPs do not require color, but do require camera stability. Thus, the cameras used for video detection are typically monochrome cameras without PTZ control. The cameras do provide a live image of traffic, and operators use software to draw virtual detectors on the roadway. The video camera can detect traffic in multiple lanes within the camera's field of view. Detection boxes are not physically placed in the pavement, but rather are manually placed on the TV monitors. Every time a car's image crosses these lines, the device generates a detection signal (presence or passage). This signal is similar to that produced by loop detectors. The accuracy of video detectors still falls short of that achieved by loop detectors. This apparent disadvantage diminishes, however, when one considers that a single camera can substitute for loop detectors on multiple lanes of a facility (Michalopoulos et al. 1990, 1991). Still, video detection devices have neither the data collection performance nor the robustness (e.g., the ability to withstand adverse weather) of loop detectors (MacCarley et al. 1992).

Video image processing systems are now being considered as key components of advanced traffic management systems (ATMS). MacCarley et al. (1992), for example, evaluated the effectiveness of eight commercially available video image processing systems for the California Department of Transportation. Test procedures were intended to duplicate conditions typically encountered on California's freeway systems. MacCarley's study targeted the ability of the systems to count vehicles and determine individual vehicle speeds as the primary metrics of performance. All systems used standard monochrome video cameras. Most systems performed well under optimal conditions but degraded significantly under adverse conditions, which varied from system to system. For all systems, error rates less than 20 percent for vehicle counts and speed measurements over a mix of low, moderate, and high traffic densities were observed, usually with optimal camera placement and under clear, daylight, nonshadow conditions. Under optimal conditions, no system was clearly superior to the others.

The AUTOSCOPE system has also been extensively tested (Michalopoulos et al. 1990, 1991, 1993, 1998) in the laboratory since 1990 using video recordings made during all weather conditions (e.g., rain, snow, dusk, dawn, night, lightning, moving clouds, and shadows). In order to demonstrate further hardiness and reliability, the system was installed at two freeway locations and at an intersection where it was continuously tested and compared with loops on a 24-hour basis. AUTOSCOPE has worked reliably and continuously in the field for long time spans with at least a 95 percent accuracy (no system breakdowns have been reported in over 2 years).

Video detection is receiving much attention for incident detection applications because of its ability to detect over a wide area and to extract a range of traffic parameters, such as density, queuing length, and speed profiles. Additionally, because lane closures are typically not needed during their installation, video detection techniques can increase driver and traffic personnel safety and can minimize traffic disruptions. Transportation personnel in a few mid-sized and large urban areas in Texas have installed video image detection systems for either short-term tests or for permanent installations. These urban areas include Austin, Fort Worth, Houston, Laredo, San Antonio, and Waco. TranStar in Houston, for example, installed and evaluated video image detection systems (AUTOSCOPE VIPs) on freeway sections having two to seven lanes. TranStar has not released results, so no published reports are currently available.

Klein et al. (1996) conducted a comprehensive field test on the accuracy of the emerging traffic detection technologies in 1993 and 1994. The test included the following technologies: ultrasonic, microwave radar, infrared laser radar, nonimaging passive infrared, imaging infrared, video image processing using visible spectrum imagery, passive acoustic array, high sampling rate inductive loop, conventional inductive loop, microloop, and magnetometer. Some results are shown in Table 2-1.

2.1.1.3. Microwave Sensors

When compared with inductive loops, the microwave-based monitors, when fired sideways, missed about 3 percent of the vehicles counted by inductive loops. When the monitors fired in the direction of traffic, the error margin was less than 1 percent (Klein et al. 1994). These error margins are within the typical tolerance range. In general, microwave-based traffic monitors were rated highly by the study. Besides the advantages listed, some of the microwave radar detectors have vehicle classification capability; they are also cost-effective.

In 1994 the New York City Department of Transportation (NYCDOT) tested a microwave-based detector as an alternative to existing inductive loops to collect traffic data (Saito and Patel 1994). The research showed a 1 percent to 6 percent vehicle count difference between those two technologies. Similar results were obtained by tests completed by the New Jersey Turnpike, by the Texas Department of Transportation (TxDOT 1993), and by researchers examining the Lincoln Tunnel (JHK 1994). These test results showed that microwave-based detectors can collect required traffic data as accurately as inductive loop detectors and that they can be installed and maintained without causing traffic congestion. Moreover, they can be easily mounted on existing poles and allow for all-weather and day/night operations. They also permit direct measurement of vehicle speed when programmed to do so.

As mentioned above, inductive loops, still the most popular detection technology used in the U.S., represent the primary detection tool now used by many states, including Texas. The desirable approach, as implied previously, should integrate video cameras with loop detectors. An algorithm detects an unusual traffic pattern and determines whether it is a suspected incident based on volume and speed collected by loop detectors. Then, the suspected incident triggers the video surveillance system, which will automatically turn on the nearest camera. The system aims the camera at the suspected incident's location or uses the video image algorithm to confirm the alarm and show the incident scene automatically. The system is being designed to be highly automated so that minimal staffing will be required to achieve substantial improvements in roadway operations.

2.1.1.4. Potential of Cellular (Wireless) Phones

The widespread adoption of cellular (i.e., wireless) phone use among the motoring public suggests considerable potential for incident reporting through cellular phones. While they do not themselves record traffic characteristics, cellular phones allow calling motorists to alert traffic management personnel to information that can be used to make incident management decisions. The primary advantages of cellular phones are their low cost (to the agency, compared with the cost of a network-wide sensing system) and their abundance. Nonetheless, caller incident information tends to be somewhat inconsistent. A recent report

(Skabardonis 1997) found that only approximately 75 percent of incident locations reported by cellular callers were correct, and only half of the cellular callers reported incident severity correctly. In addition, cellular phones achieved a lackluster 37.9 percent detection rate (DR) (see Section 2.3 for definitions) and an 8 percent false alarm rate (FAR). Accordingly, it should be said that an incident management scheme should not rely solely on incoming cellular calls; rather, such calls can function as an effective tool in building a robust incident management system.

Nevertheless, reported experience at several traffic control centers nationwide suggests that wireless phone callers provide an important source of incident detection information, sometimes resulting in detection that is much faster than that provided by existing methods. The major drawback of this method is the relatively high number of false alarms. On June 12, 1996, the FCC began requiring the identification of a wireless caller's phone number and physical location when that caller dialed emergency services (e.g., 911). This requirement has greatly enhanced the ability of traffic control authorities to harness the potential of wireless phone users, who are akin to a fleet of volunteer patrol cars operating 24 hours a day, 7 days a week.

To quantify the potential of wireless phone calls in incident detection, a probabilistic analysis was conducted as part of this study, with the results of that analysis summarized below. (A paper based on that work was presented at the 78th annual meeting of the Transportation Research Board [TRB] in January 1999 [Tavanah et al. 1999]).

Locating Wireless Phones: Several technological developments are underway to satisfy the FCC E911 mandate. Most of these developments require no modification to the user handset. The most common techniques involve signal strength, angle of arrival (AOA), and time difference of arrival (TDOA).

Measuring signal attenuation operates on the principle that a mobile phone signal's power dissipates rapidly in all directions. So if the transmitted signal power of the mobile phone were known and the signal power were measured at another point, distance could be estimated using one of several propagation models.

Measuring the AOA requires installation of an antenna array at each of several cell site locations. When several cell sites can determine their respective AOAs, wireless telephone location can be estimated from the point of intersection of projected lines drawn out from the cell sites at the angle from which the signal originated.

TDOA is similar to a radar system. TDOA systems operate by placing location receivers at multiple sites over a wide geographical area, with each of the sites having an accurate timing source. When a signal is transmitted from a mobile device and received at the antenna sites, it is time stamped. The differences in time stamps are then combined to produce intersecting hyperbolic lines from which the location is estimated.

Performance Analysis of Incident Detection by Wireless Phone: The study also performed a probabilistic analysis of incident detection performance through wireless phone reports. This performance was measured as a function of wireless phone market penetration, percentage of users willing to report an incident, probability of receiving false calls, traffic volume, and number of required calls to verify an incident. To provide a benchmark, this performance was compared with incident detection via police patrol cars circulating through the highway system. To determine the time to detect an incident, the concept of random incidence was used. Some sample numerical results are provided in the following sections.

No False Alarms or Erroneous Calls: Figure 2-1 depicts the results of the analysis for different market penetration of wireless phones. The abscissa is time in minutes, and the ordinates show the cumulative distribution function for an incident to be reported within a certain time. The same results are shown and can be compared for incident detection by patrol cars in a freeway network 60 miles in length. Figure 2-2 shows the cumulative distribution function of time-to-detect for *n* cruising patrol cars.

Considering the Effect of False Alarms: To incorporate the effect of false reports in incident detection by wireless phones, it was assumed that a minimum number of consistent calls are required to verify an incident. This number can be varied based on the accuracy of the information received and on past experience at each traffic control center. Figure 2-3 depicts the 95th percentile of time to receive the required number of consistent calls to verify an incident. In order to derive these results, an Erlang distribution is assumed for time to receive *n* consistent calls.

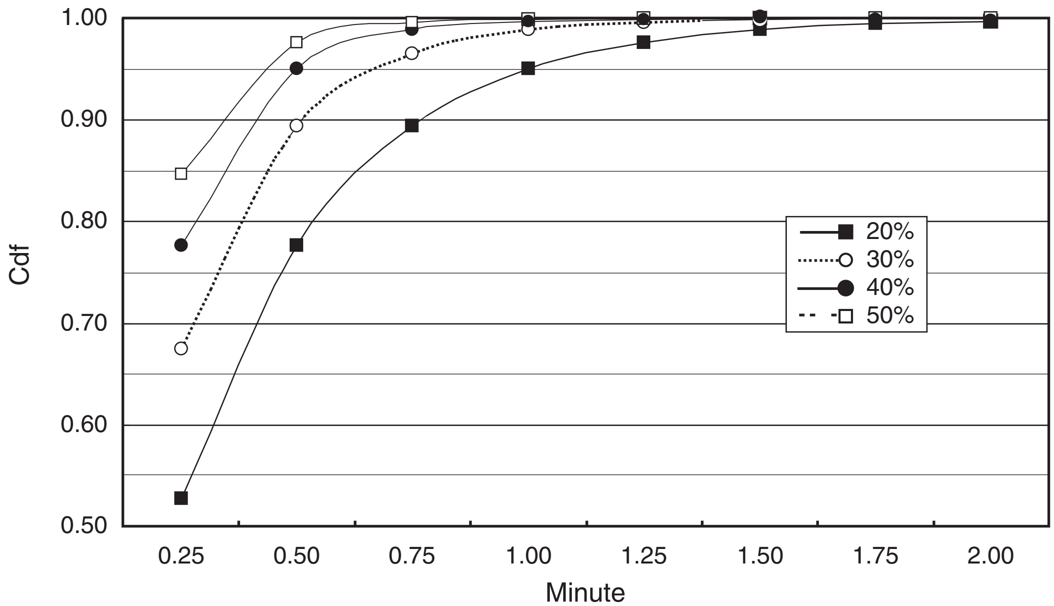

Figure 2-1 Cumulative distribution function of time until an incident is reported by wireless phone callers for different market penetration

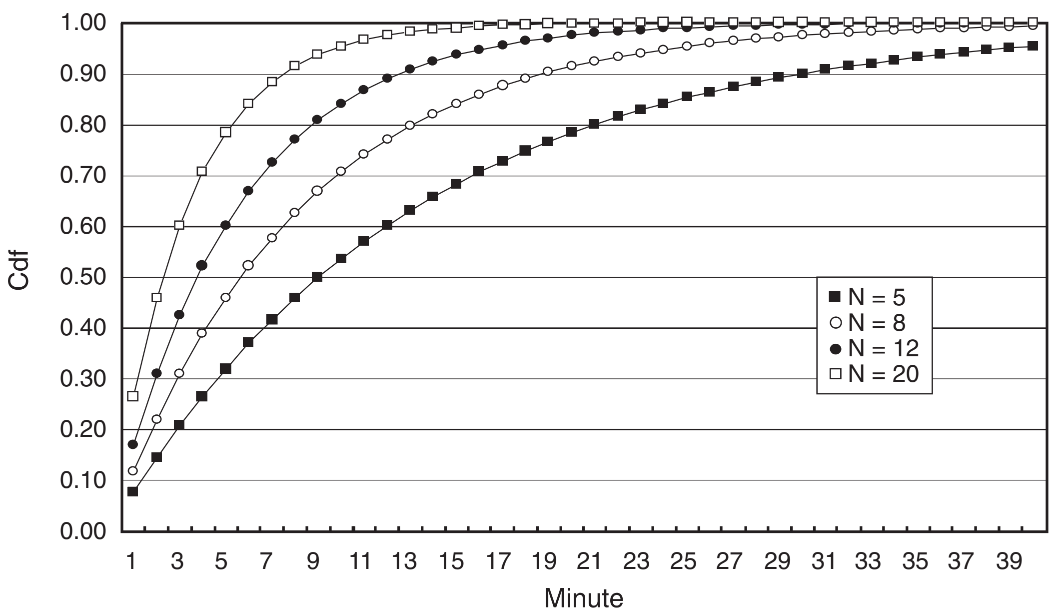

Figure 2-2 Cumulative distribution function of time-to-detect for n *cruising patrol cars*

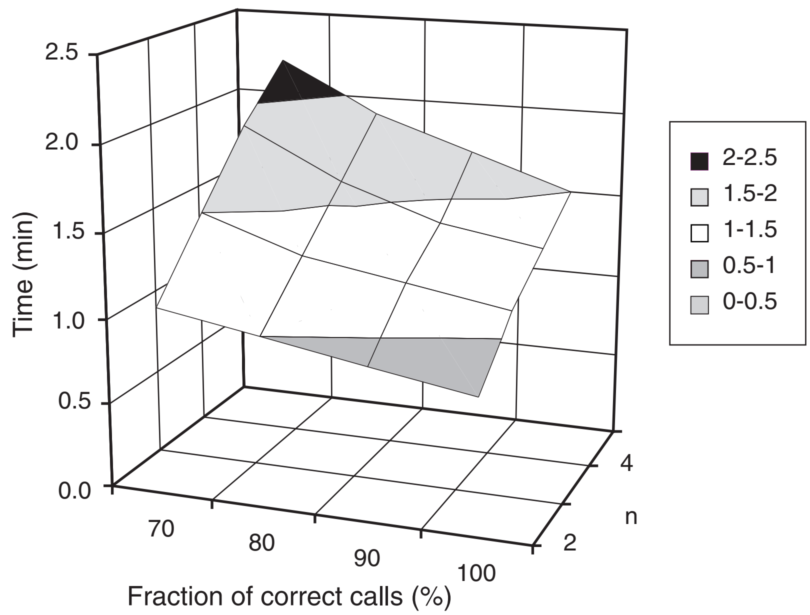

Figure 2-3 95th Percentile of time to receive n *consistent calls to verify an incident*

The analysis confirms the huge potential of incoming mobile phone calls as a primary source of incident detection information. Simple rules can be applied to virtually eliminate incorrect or prank calls and greatly increase the reliability of the system. There would be no significant deterioration in the likelihood of detection within a couple of minutes. To tap this potential and improve its performance, public education messages could be adopted to educate motorists to assist in traffic management schemes.

2.1.1.5. Sensor Fusion

Sensor fusion is a method employed to obtain more complete, accurate, and efficient incident detection performance. This method integrates data obtained from all available detection sources and points in time. For this project, a holistic and integrated incident detection model has been proposed and will be implemented. This model is expected to enhance the utilization of existing sources, reduce detection delays, and improve overall incident detection performance with the help of historic incident databases and experienced TMC operators' input.

Typical traffic management programs usually consist of conventional systems and automatic incident detection (AID) systems. Conventional incident detection systems consist of police patrolling (PP), motorist reports via cellular phone or call boxes, and surveillance cameras. For a majority of AID systems, an incident usually is not detected until the resulting shock wave travels to the upstream detector station where the AID algorithm detects the change in traffic patterns.

To provide a timely and appropriate emergency response to an incident, TMC operators must obtain accurate information about the location, type, severity, and scale of an incident. Sensor fusion can bring the advantages of individual sensors into one sensor system, thereby helping operators extract this information. Generally, AID systems, using conventional sensors, can detect an incident faster than other sources. If there are surveillance camera systems set up, the incident can be confirmed by visual observation, with related information easily obtained. If no visual confirmation system is available near the incident location, a neural network assessment based on the incident-related data can predict the incident type, severity, and magnitude of traffic impact. Reports from the highway patrol are also sources of information and are more reliable and accurate than civilian cellular phone calls. Cellular phone calls cannot be ignored, however, because of their increasing abundance in traffic networks. Currently, individual sensors are not integrated into a formal systematic detection and management procedure at most state TMSs. The fusion of information from these sensors has the potential to greatly reduce the detection time of incident detection algorithms and is one of the goals of this research. To this end, a sensor fusion framework has been developed and is graphically represented in Figure 2-4.

The combination of sensors and algorithms will integrate the efficiency of automatic sensors and cellular phones with the reliability of police/probe vehicle reports to create a highly effective incident detection program. This model is expected to enhance the utilization of existing sources, reduce detection delay, and improve overall incident detection performance with the help of a database of incident history and TMC operator experience. It is believed that this research will result in an incident detection logic that is more effective than current approaches. This logic will ultimately lead to faster detection of (and response to) incidents; it will also reduce congestion costs and save lives.

2.1.2. Algorithms

Access to traffic measurements through various sensors, in and of itself, is of no benefit to incident management. Only when coupled with algorithms to process data do traffic measurements become useful. Though there exists a formidable amount of research and literature on detection algorithms, they all share a common characteristic. It had already been acknowledged over 20 years ago (May 1975) that "detection of incidents . . . depends totally on disturbances or sudden changes in traffic conditions." The magnitude of these disturbances, of course, depends on prevailing conditions, such as traffic flow and speed, severity, and location of the incident. Various algorithms developed to operate under these varying conditions have over the years been classified into subgroups. A recent Federal Highway Administration (FHWA) document (Gordon 1996) cites six distinct algorithm classes, as discussed in the following sections.

2.1.2.1. Individual Algorithms

Incident detection algorithms, as mentioned before, perform pattern recognition. When an incident occurs, especially if it is capacity reducing, the bottleneck results in heavy congestion upstream and a very light concentration downstream. Some algorithms look for a discrepancy in speeds, volumes, or occupancies between upstream and downstream detectors. Others look at the output of one detector only. Neural networks train themselves to recognize incident patterns in traffic data, and algorithms based on fuzzy logic give a probability of incident occurrence. All algorithms need a steady stream of sensor data, and most give binary output (except for fuzzy algorithms) of incidents or no incidents.

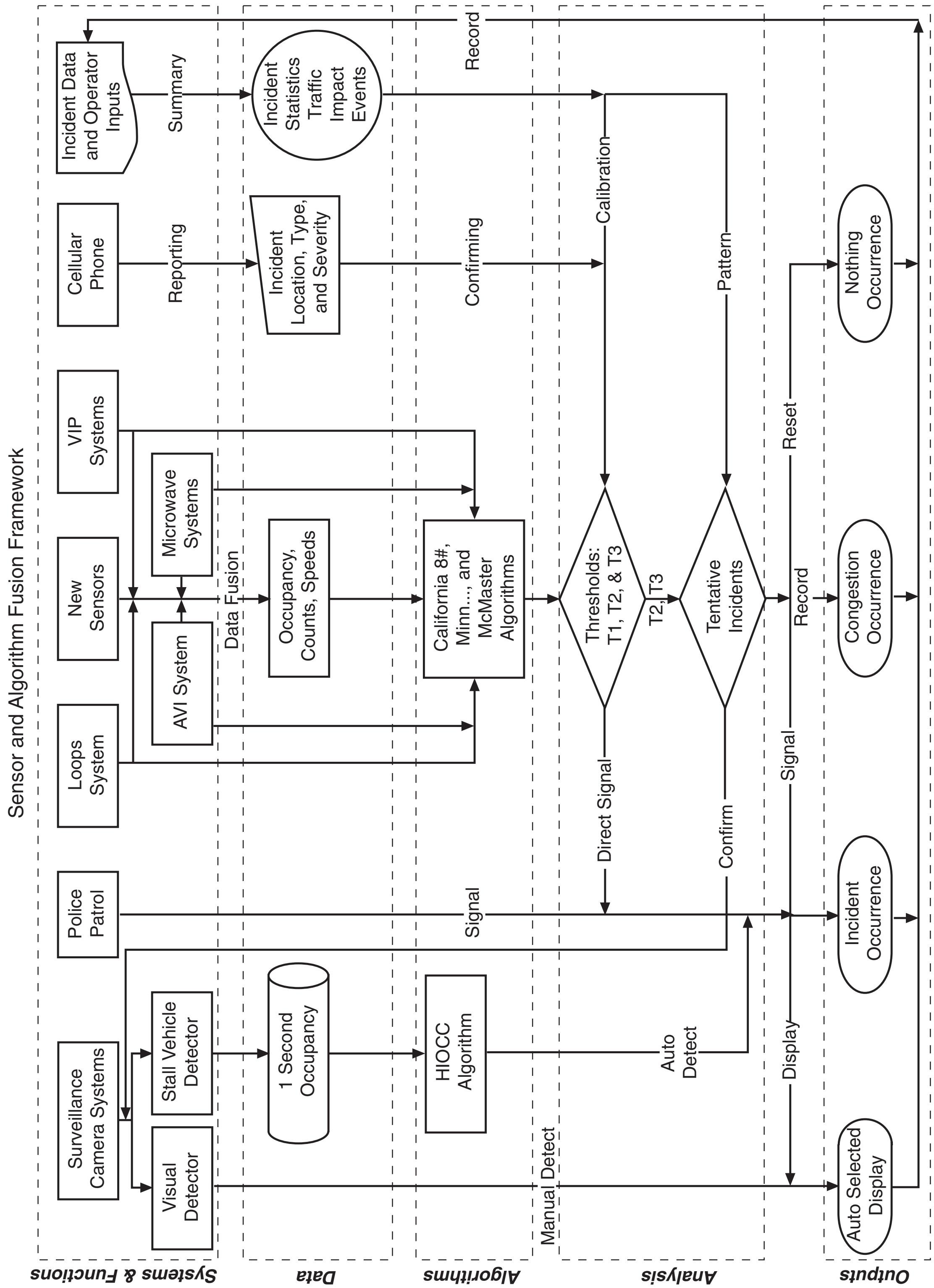

Figure 2-4 Sensor and algorithm fusion framework

Algorithms are sensitive to data resolution and aggregation. The most sensitive algorithms will use data with very small time ranges, e.g., 1-second detector outputs. The difficulty here lies with the high variance of traffic data, and with the probability that an algorithm would confuse recurring congestion with nonrecurring congestion. If, on the other hand, algorithms operate on the basis of averaged data (5 to 15 minutes), the data spikes become smoothed. This averaging of data, however, increases the time to detect an incident and can even lead to missed incidents. For this reason, many algorithms (based on detector data) operate on the basis of 20- or 30-second frequency detector outputs.

2.1.2.2. Algorithm Fusion

As is the case with sensors, many algorithms have strengths in certain traffic conditions. Most algorithms perform best in low-to-medium traffic volumes, while some are tailored specifically to high volumes. In many cases, algorithms compare traffic data to permanent thresholds that really should change as traffic flow changes. Detector loops work in all conditions but frequently break down or provide erroneous data. In all these cases, it would be advantageous to have available algorithm outputs. Then, using a weighting or voting scheme, the algorithm outputs can be combined to give a total incident score, or probability, as shown in Figure 2-5. Alternatively, the typical incident/nonincident binary output can be provided.

Algorithm fusion is an approach that combines existing algorithms to achieve the advantages of different algorithms. Algorithm fusion has inherent advantages over existing algorithms and costs very little. Algorithm fusion can be implemented easily because individual algorithms use similar data inputs, such as 20- or 30-second occupancy, vehicle counts, and average speed. Thus, no additional traffic data collection and system reconfiguration efforts are needed. Because of the increasing power of computers, no "perceivable" time lag appears in incident data testing for different algorithms. Algorithm fusion will be developed and evaluated based on the same data sets as used with individual algorithms.

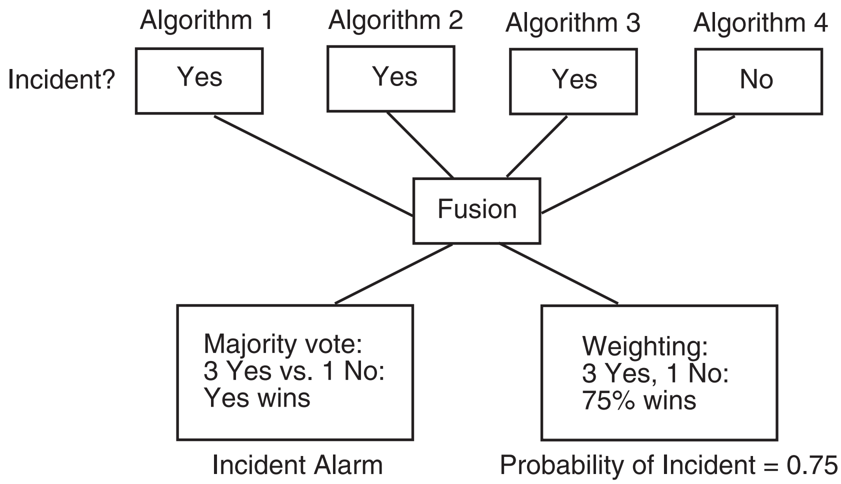

Figure 2-5 Combined algorithm outputs showing probability score

2.2. VERIFICATION AND RESPONSE

As mentioned in Chapter 1, the primary objectives of incident management include detecting, verifying, and clearing incidents as soon as possible to minimize traffic disruption and maximize safety. In addition, a complete incident management program should include methods by which motorists can be informed of incidents, so that they can alter their travel routes. A complete incident management program is shown in Figure 2-6.

The tasks involved in total incident management, outside of incident detection, are not the focus of this research, but are nonetheless equally important. Because the goal of this research is to minimize the impact of a traffic incident, the importance of incident verification and response must be stressed. Once a detection algorithm has identified an incident pattern, the incident must be verified. Currently, this verification occurs via surveillance cameras or mobile sources (cellular callers, highway patrol, and tow trucks), with this method of verification expected to continue in the future. What will probably change at some point is the method by which an incident is verified and the time that is required for that verification. Once an incident has been detected, one can search for the location manually or speed the process through automatic location. For example, software can be written to activate the camera closest to the incident, automatically panning, tilting, and zooming in on the incident. San Antonio's TransGuide employs this technique. The system automatically activates the nearest camera then leaves the fine tuning to the operator.

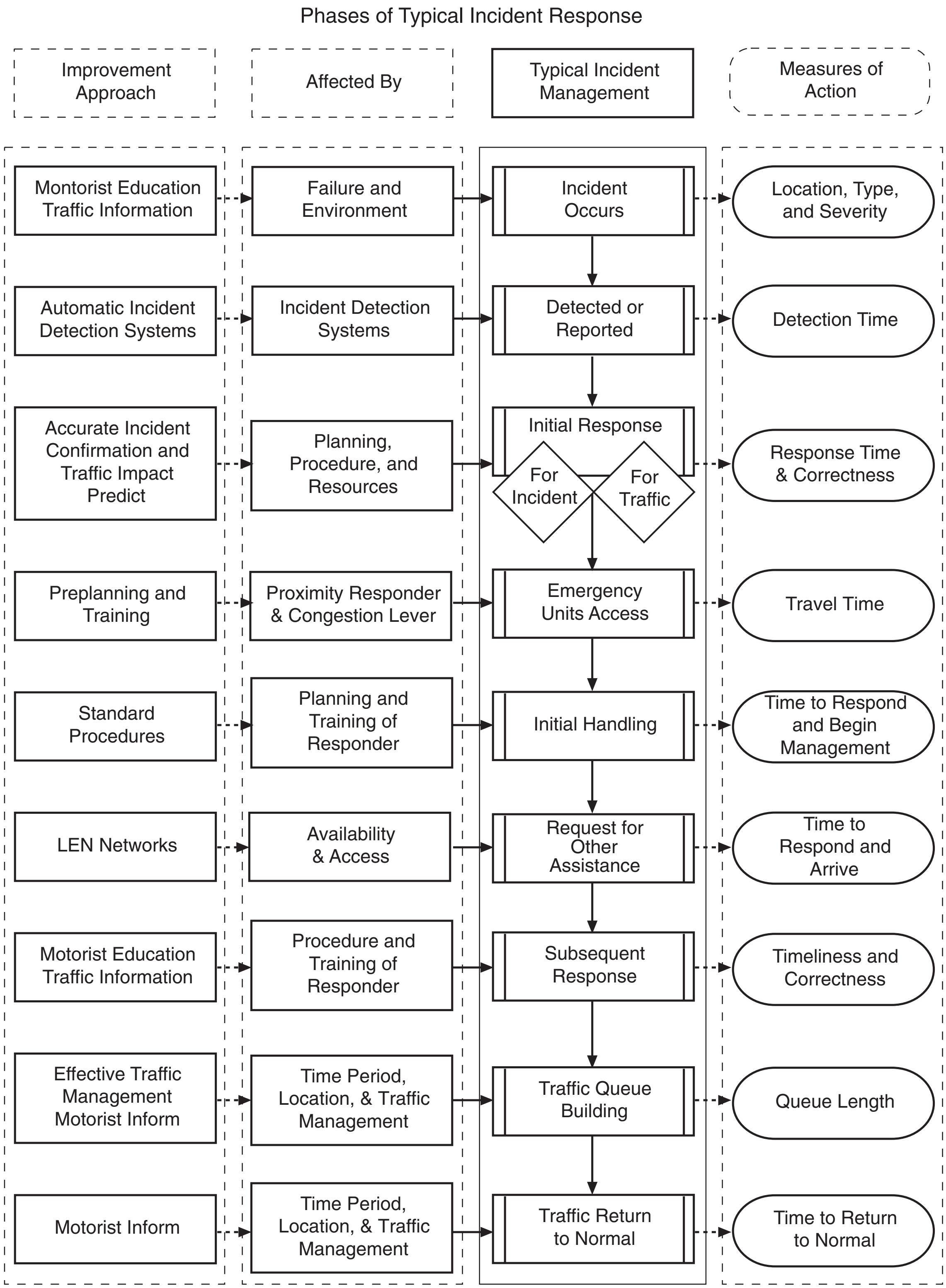

Figure 2-6 Phases of typical incident response

Once the operator verifies the incident, an appropriate response must be taken, and this is decided by the TMC. Motorists must be notified, appropriate emergency response agencies must be contacted, and traffic control measures must be implemented. In conventional TMCs, this response comes in the form of lane control signals, dynamic message signs, and traveler information systems. Management relies on incident detection as the first link; however, quick verification and appropriate responses are equally important in minimizing travel delay and maximizing safety.

2.3. EVALUATION CRITERIA

In an age when the size of government entities and private industries is shrinking, performance evaluations are becoming more and more common. The need for effective and informative performance measures has never been greater. In the process of reviewing literature for this research, it became apparent that not only should performance measures be effective and informative, but they also need to be *consistent*. Without consistent performance measures, traffic management procedures and results cannot be compared across regions. The following sections identify performance measures for incident detection algorithms.

2.3.1. Detection Rate

The detection rate (DR) is the percentage of total capacity-reducing incidents detected during a specified time period.

2.3.2. False Alarm Rate

The false alarm rate (FAR) is the percentage of *total* false incident alarms occurring during a time period; that is, the detection algorithm detects an incident that does not exist.

2.3.3. Mean Time-to-Detect

The mean time-to-detect (TTD) is the average time an algorithm takes to detect incidents. It is measured as the mean delay between the *apparent* occurrence of an incident and its detection, averaged for all incidents detected over a period of time.

2.3.4. Relations between Criteria and Trade-offs

For all algorithms, there is a trade-off between DR and FAR. As the sensitivity of an algorithm is increased, the probability that it will detect traffic disruptions that are not incident-related is also increased. Analogously, if a car alarm's sensitivity is high, it is going to detect very slight disturbances, many of which are not caused by would-be thieves. This implies positive correlation; as the DR rises, so does the FAR. For a given algorithm, this inherent positive correlation between DRs and FARs can be detrimental to the effectiveness of the incident-management system because the desired low FAR is coupled with a low DR. The sensitivity of detection algorithms usually is a function of the detection thresholds used.

There are also some resources that detection algorithms should tap, but rarely do. First, incident histories for a roadway segment present a reliable indication of future incidents. One should not disregard historical incident information when designing detection algorithms. Similarly, researchers in the past have not been attentive to the experience of TMC operators, whose job it is to search for these incidents throughout the day. Their experience should be, to the greatest extent possible, incorporated formally into a robust incident detection algorithm.

CHAPTER 3. REVIEW AND SYNTHESIS OF ALGORITHMS AND THEIR PERFORMANCE

The development of a strategy for future incident management must start with a careful assessment of the current state of the art in incident management methods. Motivation for this research, in fact, stems from a need to identify the best incident detection methods. With this in mind, the following sections summarize the most common detection algorithms, followed by an assessment of their performance.

3.1 ALGORITHM CLASSES

Many algorithms have been proposed to process traffic data and incident patterns. Although there is some overlap between categories, algorithm classes have been proposed. These classes consist of comparative, statistical, time series, theoretical models, and other algorithms, as discussed in the following sections (Picado et al. 1997).

3.1.1. Comparative Algorithms

All incident detection algorithms, in some form or another, are comparative algorithms. That is, they compare the current traffic conditions to a prespecified condition or threshold and base their incident decisions on that condition. The detection algorithms referred to in this report as "comparative" are those that make a direct comparison between current traffic stream measurements and predetermined thresholds. They do not smooth, filter, or process the detector data prior to input into the algorithm. These algorithms, developed by Payne and Tignor (1978) and later by Levin and Krause (1979), rely on the principle that an incident is likely to cause a significant increase in upstream occupancy while simultaneously reducing the occupancy downstream. An incident is detected when the following quantities exceed their respective thresholds:

- the absolute difference between upstream and downstream occupancy,
- the above quantity, measured relative to the upstream occupancy, and
- the difference in downstream occupancies that has been significant over the past two time periods.

A typical algorithm includes tests to distinguish between recurring and nonrecurring congestion; these tests include isolation of shock waves and a persistence test. Within the family of comparative algorithms, Algorithm No. 7 (Payne and Tignor 1978) is a descendant of the California algorithm, replacing the temporal downstream occupancy difference in the third test of the California model with the present downstream occupancy measurement. Algorithm No. 8 is the most complicated form of the comparative family in that it incorporates refining functions to deal with compressive waves. These functions seek to reduce the false alarms produced by compression waves.

Because they rely on static thresholds (i.e., they cannot adjust to the traffic level), comparative algorithms are incapable of handling fluctuating traffic demands efficiently. These algorithms, which work best under moderate-to-heavy traffic conditions, readily suffer from simultaneously occurring compression wave traffic patterns.

3.1.2. Statistical Algorithms

Statistical algorithms are so named because they are designed to detect significant differences between observed detector data and predicted traffic characteristics.

Teng et al. (1997) proposed an algorithm that assumes that traffic variables are independently and identically distributed, and then distributes them according to a normal probability density function. The algorithm calculates the log-likelihood of normal and incident conditions based on speed, volume, and occupancy measurements.

These algorithms do not limit themselves to application in incident detection. Mahmassani et al. (1997) developed a model that combines prior probabilities of incidents (based on historical data) with the probabilities of a current incident (based on short-term autoregressive integrated moving average [ARIMA] forecasts of traffic flow) to signify incident alarms.

3.1.2.1. Standard Normal Deviate

The standard normal deviation algorithm (Dudek and Messer 1974) calculates the mean and standard deviation of occupancy for the last 3 to 5 minutes and detects an incident when the present value differs significantly from the mean in units of standard deviation.

Stephanedes and Chassiakos (1993) developed a similar algorithm that used the standard normal deviate of a traffic variable, namely, occupancy and energy, which is a function of volume and speed.

3.1.2.2. Bayesian Algorithm

In an attempt to improve the significance of incident alarms, Levin and Krause (1978) observed historical probability distributions of traffic variables under both incident and incident-free conditions. Next they proposed the use of Bayes' rule to derive optimal thresholds. The application of Bayes' rule in thresholds was found to be too complicated, insofar as it requires a large incident database and complicated, station-by-station calibration. Furthermore, this application doesn't allow for much improvement and results in a high detection time.

3.1.3. Time-Series Algorithms

Time-series algorithms consider the recent history of a traffic variable and employ statistical forecasting of traffic behavior to provide short-term traffic forecasts. Significant deviations between observed and forecast values are attributed to incidents.

3.1.3.1. HIOCC Algorithm

As opposed to the previous algorithms, which for the most part use aggregated traffic data averaged over 30 to 60 seconds, the HIOCC algorithm developed by Collins et al. (1979) for the British U.K. Transport and Road Research Laboratory (TRRL) relies on 1-second occupancy data. The algorithm seeks several consecutive seconds of high detector occupancy in order to identify the presence of stationary or slow-moving vehicles over individual detectors. The main advantage of this algorithm is that it can detect stopped objects in the detector location or in the sight view of video cameras. This method lacks an ability to distinguish incidents from other congestion-producing traffic phenomena.

3.1.3.2. Double Exponential Smoothing and the ARIMA

Stephanedes and Chassiokos (1993) have extensively researched smoothing and filtering applications. They developed an algorithm that examines smoothed spatial occupancy between detector stations based on volume and occupancy measurements. They also developed a series of detector logic with smoothing (DELOS) algorithms based on average, median, and exponential smoothing.

The double exponential algorithm (Cook and Clevelend 1974) performs a double exponential smoothing of traffic occupancy to forecast occupancy and identifies as incidents the calibrated deviations. The same idea characterizes the autoregressive integrated moving average (ARIMA) algorithm, in which an ARIMA model provides short-term forecasts of the state variable (traffic occupancy) and the associated 95 percent confidence limits (Ahmed and Cook 1982). An incident is detected when observed occupancy values appear outside the confidence limits.

3.1.4. Theoretical Models

Typical algorithms use only single or dual detector outputs to make a decision, though other methods take advantage of insights gained from research in traffic-flow modeling. Willsky et al. (1980) proposed using macroscopic traffic modeling to describe the evolution of spatial-average traffic variables (velocities, flows, and densities). Thus, researchers were able to capture the dynamic aspect of traffic phenomena to alleviate false alarm problems.

Cremer (1981) has proposed a similar approach applicable to congested cross-country freeways in Europe, where detectors are located several kilometers apart. Whereas Willsky et al. model an incident as having a capacity-reduction effect, Cremer proposes that detection can be improved by modeling the attenuation of the road capacity with an additional (fictitious) volume input at the location of the incident. Although scientifically appealing, these two methods did not attract the interest of practitioners. The lack of interest was probably a result of the complexity of the methods and of the extensive data requirements. These restrictions limited testing of the methods to a small number of simulated incident patterns.

3.1.4.1. McMaster Algorithm

Unlike other algorithms that primarily use occupancy data, the McMaster algorithm is based on a two-dimensional analysis of the traffic data (Persaud et al. 1990). In particular, it proposes separating the flow-occupancy (vehicle counts) diagram into four areas corresponding to different traffic conditions. Incidents are detected after observations of specific changes in traffic conditions in a short time period. This approach requires calibration of the boundaries separating different traffic conditions — algorithm thresholds — individually for each station, as volume-occupancy characteristics vary across a station. Simplicity of design and potential for improved detection performance are the major advantages of the algorithm. However, excessive calibration requirements limit its use.

3.1.5. Other Algorithms

3.1.5.1. Human Decisions

Police patrolling (PP) and motorist assistance programs (MAPs) are the widest incident detection approaches. Generally an incident is detected and verified immediately when it is observed by emergency personnel. Incident information is relayed by staff, who prescribe proper response procedures. The detection mean time of PP depends on staffing levels; that is, the more officers dispatched, the sooner the incident is detected. With typical staffing levels, PP and MAPs are not effective as sole detection mechanisms.

3.1.5.2. Video Surveillance/Video Image Processing

The use of surveillance cameras can also be considered as a detection algorithm. The main advantages of surveillance cameras are similar to those of PP. An incident in a camera's field of view is visually detected and verified immediately. Incident severity and traffic impacts are observed and responded to by adequately trained traffic management center (TMC) operators. Surveillance cameras, like other conventional incident detection methods, however, are not always reliable. In complex networks, missed detections and detection time are high. Moreover, visual detection is labor-intensive and inefficient.

The AUTOSCOPE Incident Detection Algorithm (AIDA) takes advantage of temporal variations of traffic characteristics in addition to spatial ones. It looks for rapid breakdowns in traffic flow, such as sharp speed drops or occupancy increases, and speed thresholds for determining congestion levels. A speed trap is placed in each lane of traffic, spaced as far apart as possible (200 to 300 ft) to indicate speed changes within the field of view.

AIDA was later improved to include ancillary information provided by video detection. This information included stopped vehicles and shock wave signature recognition. In order to detect stopped vehicles on the shoulders or in the travel lanes, a new type of detector was developed, one called the *stopped vehicle detector*. It detects stopped vehicles within the camera's field of view. The user can place many virtual stopped vehicle detectors interactively on the video monitor and set location and lane-specific thresholds, which, if exceeded, will generate an alarm. Recently Michalopoulos reported an 81 percent incident detection rate with no false alarms on the Gowanus Expressway in Brooklyn, New York (1997).

Japanese researchers (Tsugie et al. 1994) used television cameras that experimented with three different accident detection algorithms. The researchers concluded that the best method in respect to *detection instantaneousness* (least elapsed time from occurrence to detection) is to perform a tracking process on each vehicle. The method provided an incident acknowledgment time of 8 minutes and detected 69 of 79 accidents automatically. The study also found that if the optimum camera installation height (3.3 ft, 131-to-164 ft range for two to three lanes of traffic) can be ascertained through measuring certain traffic volume parameters, the traffic count and speed can both be measured with at least a 90 percent accuracy. Particularly useful was the ability to continuously retain eighty frames of video in memory and to send it to a traffic control center for review. This function would facilitate incident verification by the TMC operator and would provide a prediction of the range and severity of the accident for incident clearance.

3.1.5.3. Neural Networks

A concern of incident detection is the recognition of certain traffic patterns, a task particularly suited to neural networks. The scope of this research does not include the investigation of neural network theories, though some basic explanation is warranted. At the most basic level, signals are input to the neural network, which has previous data, and the signals are weighted and propagated to an output signal, suggesting either incident or nonincident conditions.

The difficulty with neural networks lies in their data-hungriness and their time-to-detect (TTD). The neural networks must be trained to recognize uncongested and congested conditions, both recurring and nonrecurring. Such recognition takes considerable data, time, and personnel with neural network expertise, all of which are in short supply in typical transportation departments. Neural networks pose a problem in research as well. In this literature review, neural network results have been found to be artificially high. In most cases this finding is attributed to an algorithm test based on the same data used to train the algorithm. In addition, neural networks typically take much longer than direct comparative algorithms in recognizing and verifying incident patterns.

Dia and Rose (1997) built a multilayer feed-forward (MLF) neural network, trained it on a set of incidents, then implemented it with a back-propagation training algorithm. As with many of these algorithms, they found the best results when the algorithm was implemented with a persistence check (in this case two time intervals). Ivan (1997) fused a detector algorithm and a probe vehicle algorithm with an MLF neural network and then trained it with simulated data. Abdulhai and Ritchie (1997) attacked the issue of neural network transferability, combining a neural network incident detection algorithm with an output processor, based on Bayesian logic. Ritchie and Cheu (1993) applied an MLF neural network to data obtained from a microscopic traffic simulation model using 30-second volume and occupancy measurements. Simulated training data were also used on an MLF neural network, then compared to other time-series algorithms (Stephanedes 1994).

ANNs can bring short-term historic data (day of the week, incident frequency, and local incident patterns) into the decision-making process to enhance the performance of existing detection systems. ANNs hold much potential for incident detection application. More research is necessary using real-time freeway data to realize this potential and reduce detection time.

3.1.5.4. Fuzzy Algorithms

Fuzzy logic is used to model sensor data and combine information to detect incidents. Using fuzzy logic approaches will eliminate sharp decision thresholds and use membership functions to represent the degree of possibility for an incident.

Chang and Wang (1994) applied fuzzy theory to California algorithm No. 8 for use in high-volume conditions. Japanese researchers proposed a new method using image processing techniques and fuzzy theory (Kimachi et al. 1994) that tried to predict an incident by detecting abnormal behavior of a vehicle. First, this algorithm defined a behavioral feature, in this case the angle between the normal optical flow and an abnormal one. Then it defined three other features: size, velocity, and correlation value. These features were fuzzy-integrated to obtain *certainty*. In the sequence, the product of *behavioral feature* and *certainty* was defined as *behavioral abnormality*.

Fuzzy logic was integrated with Adaptive Resonance Theory (ART) to map a set of input patterns to a set of categories, similar to a neural network (Ishak and Al-Deek 1997). The algorithm was trained on 33,342 different traffic patterns and worked best when trained on speed and occupancy.

3.2 PERFORMANCE ASSESSMENT

The results from many of the incident detection algorithms discussed above have been compiled in the following figures. Note the obvious relationship between detection rate (DR) and false alarm rate (FAR). For the FAR to decrease, so must the DR, with the trade-offs changing in a logarithmic fashion. For that reason, a logarithmic regression curve has been added to the graphs based on the mean of the algorithm results. These graphs are an indication of what transportation management centers ought to expect from their incident management programs. In the final report for this research project, the individual algorithm results will be displayed and separated according to algorithm class for a better comparison. Given the previous discussion of the inflated results obtained from neural networks and the unsatisfactory results of some of the older algorithms, a separation by class will provide more information.

In addition, one can easily identify the trade-offs between FARs and detection time. The accuracy of a detection algorithm, in part, depends on how much time the algorithm is given to identify patterns; this trade-off is shown in Figure 3-1. Low detection times result in higher FARs than higher detection times.

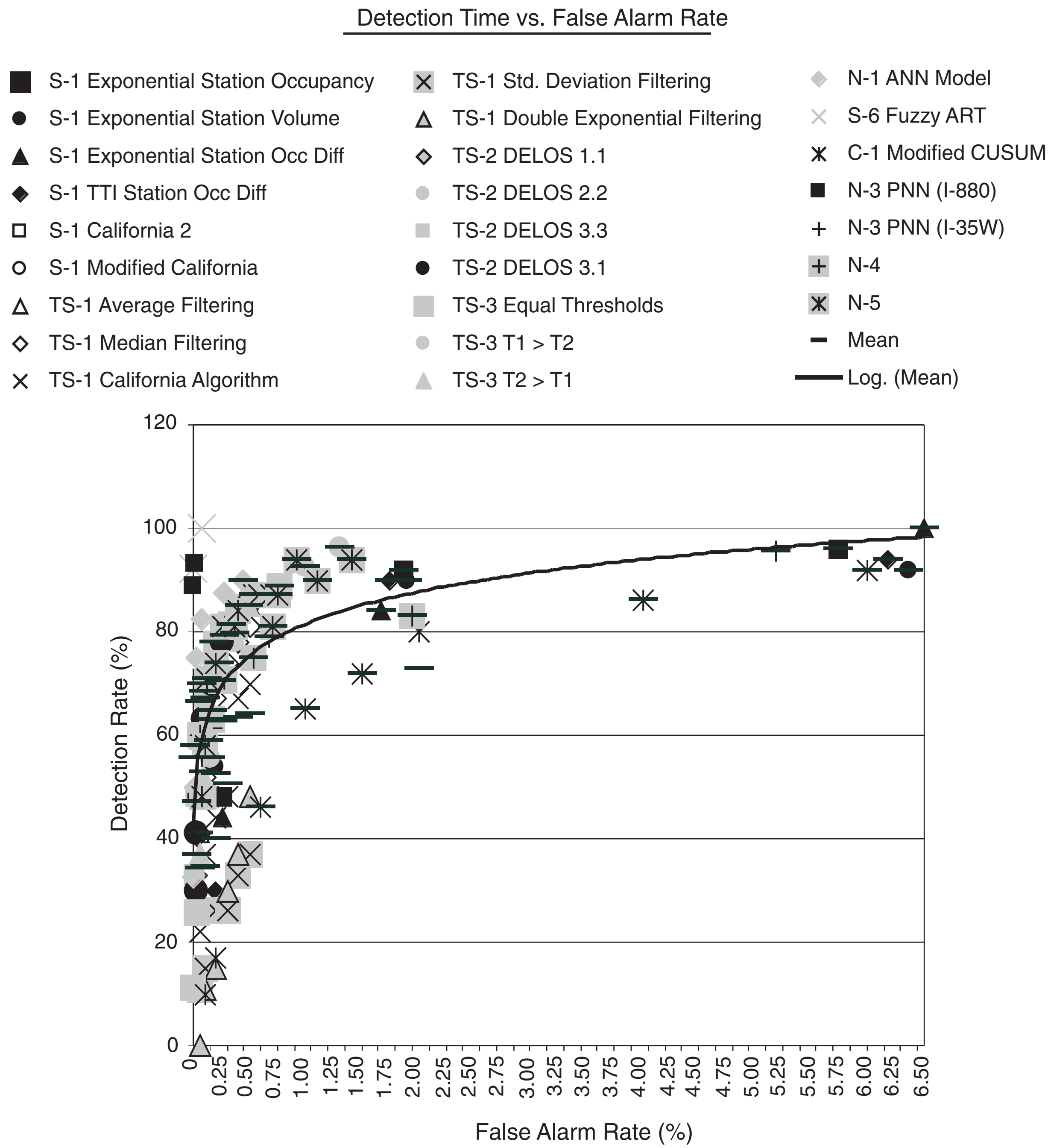

Figure 3-1 Performance assessment

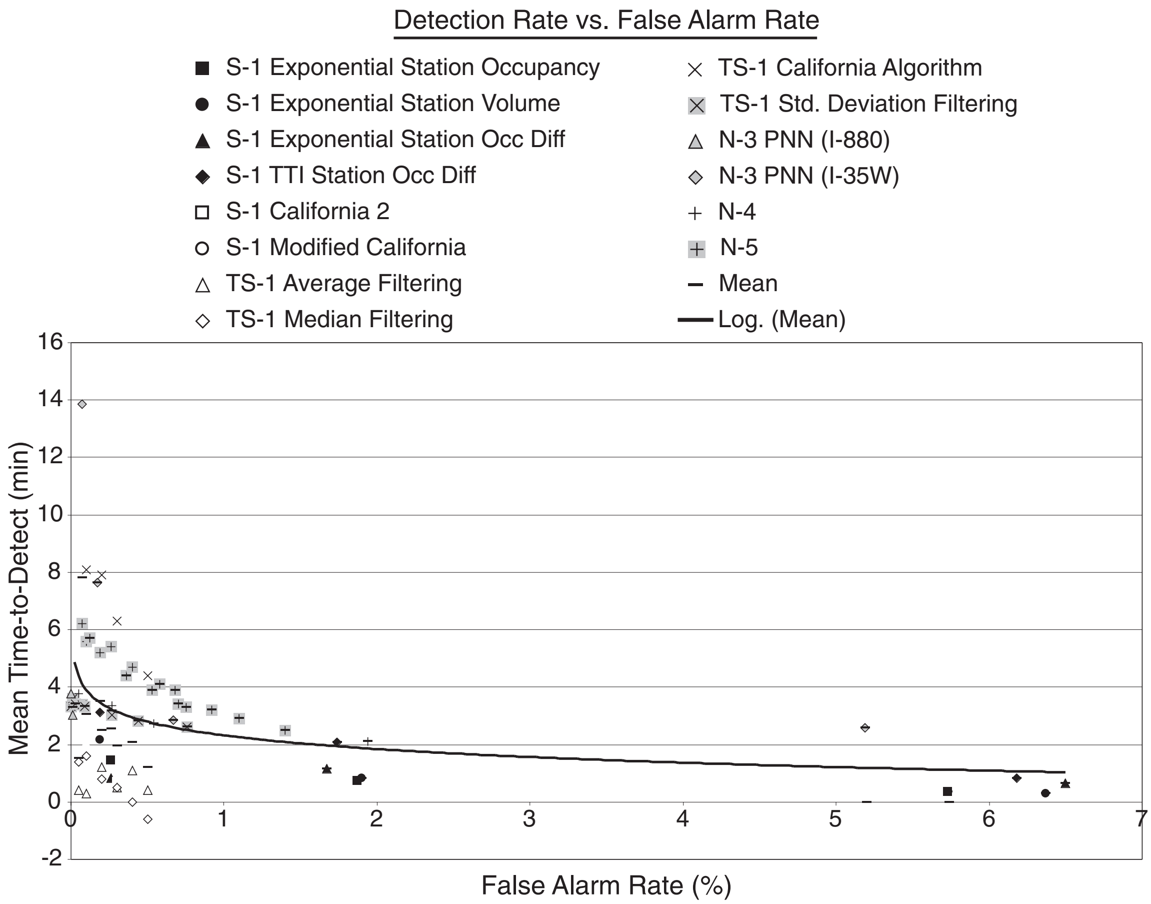

Figure 3-2 Performance assessment

CHAPTER 4. APPLICATIONS

Table 4-1 is a sampling of current traffic and incident management systems in place in the United States.

Table 4-1. Currently existing incident detection systems in major cities

Name	Location	Scope	Implementation Time	Sensors	Algorithms	Performance Reported	Other Systems	Reference
Gulf Freeway	Houston	14 CCTV	1967	CCTV	Manual Surveillance		Police Patrol, Call Box	(Goolsby 1967)
San Francisco	SF–Oakland Bay Bridge		1971–1974	CCTV Magnetic	Manual Surveillance			(MacCalden 1984)
AUTOSCOPE	Minneapolis		1984–	Loop, VIP	Comparative, Minn. and DELOS			(Michalopoulos et al. 1990)
TranStar	Houston	209 miles	1989–1998	Loop, CCTV, AVI	Manual, surveillance, and cellular	12% reduction in nonrecuurent congestion; 3% reduction in recurrent congestion	MAP, police, traffic service	(McCasland 1998)
TransGuide	San Antonio	27 miles	1992–1994	Loop, Surveillance Camera (SC)	Manual and Comparative	95%, 1%		
New York	New York		1994–	Loop, Microwave				
Colorado Springs	I-25 along the west side of Colorado Springs	10 miles	1995–	Loop, SC	SC is triggered by the loop detectors			(Merritt and Stadler 1995)
Pennsylvania	I-95 through metropolitan area	12 miles	1995–	CCTV	Manual Surveillance			(Gangisetty and May 1995)

4.1 TEXAS DEPARTMENT OF TRANSPORTATION IMPLEMENTATIONS

Various traffic management centers (TMCs) and their approaches toward incident management have been investigated in Texas. San Antonio's TransGuide (developed by Allied Signal and maintained by the Southwest Research Institute), Houston's TranStar (developed by Lockheed Martin), Fort Worth's TransVision (also designed by Lockheed Martin), and the advanced traffic management system (ATMS) being developed in Dallas by the Texas Transportation Institute (TTI) and in Austin and El Paso by the Texas Department of Transportation (TxDOT) have all been investigated for their incident management methods.

In San Antonio, the TransGuide TMC is part of an intelligent transportation system (ITS) model deployment initiative and is one of the premier advanced TMCs in the country. TransGuide's goal is to detect freeway incidents within 2 minutes of occurrence and to initiate a preplanned response within 15 seconds. The system is built on a complete digital communications network using the communication standard SONET, a fully redundant fiber optic network, a state-of-the-art fault tolerant computer system, software developed to POSIX standards, and field equipment consisting of changeable message signs, lane control signals, loop detectors, and surveillance cameras (ITS Joint Program Office 1998).

TransGuide is the subject of an ITS operational test to evaluate the freeway management system design for cost-effectiveness and benefits while using TransGuide's on-line test bed to provide a direct comparison of several incident detection algorithms. TxDOT, AlliedSignal Technical Services Corporation, Southwest Research Institute, TTI, and the Federal Highway Administration (FHWA) are partners in this operational test. The evaluation of the freeway management system has been completed, though the incident detection algorithms are still being tested. Currently, a simple speed or occupancy threshold forms the basis for incident alarms. Incidents can also be reported by courtesy patrol vehicles. TxDOT has been operating a courtesy patrol for several years, the primary purpose of which has been to help stranded motorists. With the TransGuide system on-line, the courtesy patrol will expand efforts on traffic control during incidents.

Designated as one of four ITS priority corridors, TranStar was built in Houston as a multi-agency complex. Members of this complex include the Houston Police Department, Houston METRO, TxDOT, the city and county, and other emergency management personnel. To gather traffic data, the complex primarily uses AVI cards and readers: 227 miles of freeways and 74 miles of high-occupancy vehicle lanes in Houston are covered by AVI readers, and over 400,000 travelers use the AVI cards daily. TranStar also has single and double trap loop detectors and 234 surveillance cameras.

In terms of incident detection, Houston relies on its motorist assistance program (MAP). Nine deputies per shift operate eighteen MAP vehicles, patrolling separate freeways. All incidents are reported within 10 minutes of occurrence (Allen 1998). The AVI readers provide a second tier in the detection hierarchy. AVI readers report average speeds, and if traffic operators in TranStar perceive a problem, they can investigate it. The difficulty here is that the incident must occur between AVI readers and must cause a large enough disturbance to be visible. Surveillance cameras also provide traffic images that are monitored by operators. An incident may be observed through these cameras. Finally, detector loops provide traffic volumes to supplement TranStar's traffic conditions' display (suddenly changing volumes can signify an incident). No formal automatic incident detection (AID) algorithm exists in TranStar.

Fort Worth is in the process of building its TransVision traffic management system. As of January 1997, the system was one-third complete and included thirty-eight closed-circuit TV (CCTV) cameras, eight compressed video cameras, and 1,269 loop detectors. Incidents are detected primarily (as they are in Houston) by a fleet of five courtesy patrol vehicles. The courtesy patrol operates 24 hours a day patrolling approximately 150 miles of freeways. In 1996 the patrol assisted almost 7,000 motorists and provided traffic control for 600 incidents. No formal incident detection algorithm exists as of yet; however, part of the TransVision plan is to implement a multi-algorithm incident detection scheme based on the California algorithm No. 8, the McMaster algorithm, and TxDOT's TransGuide algorithm (Abukar 1997).

The City of Dallas also relies on a courtesy patrol that has five vehicles per shift. As of this summer, the city had planned on having forty-two surveillance cameras and twelve compressed video cameras. The city also has a satellite TMC, where camera images are fed to a small staff of operators.

According to the ITS Joint Program Office (1997), the Austin ITS early deployment project is complete. TxDOT and the City of Austin have been the lead agencies for this project. A focus on incident management and a multi-agency management center have emerged as top priorities. A TxDOT courtesy patrol became operational in January 1997.

Five new full-time positions and an additional $350,000 were allocated to the Austin District during fiscal year 1997 in this effort to assist motorists and provide traffic control during incidents.

In El Paso, TxDOT is currently deploying a freeway management system on IH-10 and on US 54. A TMC is being proposed at the new TxDOT district grounds. TxDOT also operates a courtesy patrol along IH-10 and US 54 to assist stranded motorists and to facilitate incident response.

CHAPTER 5. CONCLUSION AND FURTHER WORK

The foremost objective of this research is to analyze and rank existing incident detection methodologies (taken individually and in combination). This analysis includes combining various sensors and incorporating operator expertise. Common detection algorithms, together with emerging technologies such as cellular phones and neural networks, are being explored and tested.

As described in previous chapters, these algorithms or combinations thereof use detector data as input. These data can come from individual sensors or from a combination of "fused" sensors. The input into the incident detection algorithms, whether such input be speed, occupancy, or volume, can be simulated to reproduce incident conditions. However, it is crucial that these algorithms function using actual, real-time data as well. For this purpose, data are being extracted from the traffic databases from the San Antonio TransGuide traffic management center (TMC) and from the FSP experiment conducted by the California Partners for Advanced Transit and Highways (PATH). Databases are being constructed using data from both incident and nonincident conditions. An essential step in specifying the best incident detection system is to identify the functions, limitations, and capabilities of the TMC monitoring system, its detection components, their functional relations, and the forms and nature of the data.

To date, various sensor technologies and incident detection algorithms have been observed and screened based on literature review and limited testing. In addition, algorithms are being coded based on equations and parameters described in the literature. Data are being collected from TransGuide and the California PATH FSP project.

Once the data have been collected, they will be individually tested and ranked, based on the false alarm rate (FAR), detection rate (DR), and detection time (DT). An algorithm fusion framework will be developed and all algorithms and sensors will be ranked based on the formal multi-objective methodology in this study. The overall results from the study will include an analysis of the state of the art in incident management (generally and specifically in Texas), a ranking of existing systems, recommendations for implementation, and a selection procedure for future use by the Texas Department of Transportation (TxDOT) and other state agencies.

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