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Incident Detection Algorithm Evaluation

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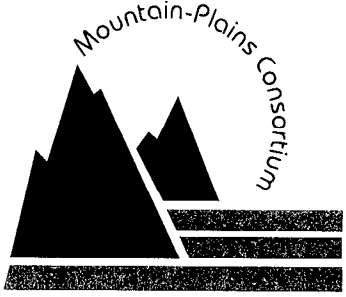
March 2001



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INCIDENT DETECTION ALGORITHM EVALUATION

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LIST OF ACRONYMS

AI	Artificial Intelligence
AID	Automatic Incident Detection
APID	All Purpose Incident Detection
ARIMA	Auto Regressive Integrated Moving Average
ATMS	Advanced Traffic Management System
DELOS	Detection Logic with Smoothing
DES	Double Exponential Smoothing
DOT	Department of Transportation
DR	Detection Rate
FAR	False Alarm Rate
FCC	Federal Communications Commission
FRESIM	Freeway Simulation
GPS	Global Positioning Satellite
HIOCC	High Occupancy
MLF	Multi-Layer Feed-forward
PATREG	Pattern Recognition
PE	Processing Element
PSAP	Public Safety Answering Point
PTZ	Pan/Tilt/Zoom
SND	Standard Normal Deviate
SSID	Single Station Incident Detection
TOC	Traffic Operations Center
TRRL	Traffic and Road Research Laboratory
TSC	Traffic Services Corporation
TTD	Time To Detect
UDOT	Utah Department Of Transportation
UHP	Utah Highway Patrol

EXECUTIVE SUMMARY

This research examines a range of incident detection technologies to determine a recommended combination of approaches for use in the Utah Department of Transportation's (UDOT) Advanced Traffic Management System (ATMS). The technologies that were examined are computer-based automatic Incident Detection (AID), Video Image Processing (VIP), and detection by cellular telephone call-ins.

Three performance measures are generally used in incident detection technology analysis: time to detect, false alarm rate, and detection time. A direct comparison of the performance of the computer-based algorithms is difficult because both the measures of effectiveness and how an incident is defined are inconsistent throughout the literature. The values are given as reported in the literature. The number of false alarm rates have been normalized by applying false alarm rates to the number of detector stations in the UDOT ATMS area (87 detectors). The results indicate that among the algorithms implemented outside of the laboratory environment, the All-Purpose Incident Detection (APID) algorithm performs well, giving about eight false alarms per peak hour (on the ATMS network) with 2.5 minutes to detect and an 86 percent detection rate. Inside the laboratory, the new neural network method also performs well with two false alarms per peak hour on the ATMS network with about 1 minute to detect and an 89 percent detection rate. Incident detection by video image shows promise with 0.03 false alarms per hour, 20 seconds to detect, and a 90 percent detection rate. The video image detection system has several advantages over the traditional inductive loop systems because it can detect incidents anywhere in its field of view, including the emergency lanes.

Increased use of Cellular telephones has made them the primary means of incident reporting. They also have made many of the computer-based algorithms obsolete because incident reports from them are received more quickly and accurately than automatic algorithms can detect incidents.

This project originally was scoped to include a rigorous testing of several computer-based algorithms. The project's Technical Advisory Committee (TAC), however, redirected this work to look more closely at the impact of cellular telephones in incident detection.

Cellular telephone technology will continue to impact the power and speed with which incidents are detected. The Federal Communications Commission has mandated that all cellular telephone service providers give the name, number, and location of a cellular telephone caller to the Pubic Safety Answering Point by October 2001, for when that caller dials 911. This information will be helpful to identify locations of traffic incidents. The number of cellular telephones in use also is increasing. UDOT has placed several "Highway Help Cellular "*11" signs on Utah Highways and Interstates. Before more of these signs are placed on the freeways to enhance incident detection time, a public awareness program should be instituted. The *11 calls are answered by the Highway Patrol dispatch center in the Traffic Operations Center, which is not able to dispatch emergency medical services needed in major accidents. While both 911 and *11 are on the freeway signs, public perception does not differentiate between the two.

Incident detection by cellular telephones will continue to be the primary means of incident detection. Because the ATMS already possesses the APID and Double Exponential Smoothing (DES) algorithms as part of the Navigator software, they should be enabled and calibrated as a secondary form of incident detection.

Other forms of incident detection can be evaluated from the ATMS. The neural network method and the video image processing method likely could be modified to work with existing ATMS equipment.

CHAPTER 1. INTRODUCTION

Freeway incidents cause injury, traffic congestion, increased environmental pollution, and cost millions of dollars every year in user-delay, cost, vehicular damage, and personal injury. Engineers and transportation officials have dedicated substantial resources in the past years to find better ways of preventing freeway incidents from occurring and managing them when they do. When there is an incident, minimizing the response time (the time from when an incident occurs to the time that emergency crews arrive on the scene) is crucial in several aspects. The most important is the treatment of injuries. The faster treatment arrives, the greater the survival rate of serious injury during an incident. Second, clearing the incident quickly minimizes the traffic flow disruption and the potential for secondary incidents.

Automatic incident detection (AID) has been considered a method for quickly detecting potential incidents. The technology has been in the research, development, and testing stages since the 1970s. During that time, many incident detection methods and algorithms were developed. Past experience has shown that when a traditional AID system is installed, the number of false alarms have become such a problem that traffic operations centers stop using them altogether. Other systems have a poor enough detection rate that operators are unable to rely on the system as their primary method of incident detection.

As part of the I-15 reconstruction project, the freeway network in the Salt Lake valley has been instrumented with an advanced traffic management system (ATMS). As part of the project, 87 sets of inductive loop detectors spaced at 800 meters and traffic monitoring video cameras have been installed. Also, the Utah Department of Transportation (UDOT) has acquired the base software used in the Atlanta, Ga., TOC. This software already has two automatic incident detection algorithms. Also, a UDOT management team has been formed and other local agencies have or are in the process of organizing their own incident management teams.

Several of these facts or circumstances have caused UDOT to ask questions about automatic incident detection. The questions were later formulated into the objectives of this project. They are:

1. Qualitatively evaluate and recommend an incident detection algorithm or algorithms for the UDOT ATMS.

2. Investigate the impacts of cellular telephones on incident detection and propose a strategy for future implementation.

By examining available literature and studies on incident detection algorithms and methods, a discussion of each algorithm is provided along with its reported performance, installation experience and deficiencies. Also provided are comments from other Traffic Operations Centers (TOCs) and consultants who have installed such systems around the nation. A comparison of the algorithms is provided, adjusting the performance measures to reflect how algorithms would perform on the Salt Lake Valley freeway network.

Over the last decade, more and more drivers carry cellular telephones. This has greatly impacted incident detection. In this research, we address how UDOT may be able to make incident detection by cellular telephone work to its advantage.

Incident detection by video image processing is a new technology that varies from traditional inductive loop detection technology. A discussion of the state of this technology provides ideas about how it might be used within the ATMS coverage area.

The majority of freeway incidents in the UDOT ATMS area are detected by cellular telephone call-ins. After the initial call, the accident is verified. This is done in one of two ways. Either the TOC operators verify the accident using the traffic monitoring video cameras, or a highway patrol officer must verify the site in person. Personal verifications are required in areas without video coverage, or areas outside of the planned coverage area. Highway patrol vehicles are scheduled to travel each freeway corridor at frequent intervals. The approximate mean time from the first call to the time that an emergency vehicle arrives on the scene is about four minutes.

The TOC operators also have a speed map of the freeways in the ATMS that contributes to incident detection. The map shows the speeds measured from the fixed speed detectors located approximately 800-meter intervals on the freeway network. The speed map color codes specific freeway links according to speed. Operators monitor the map and check on locations where speed is diminishing to check for incidents. UDOT also has an incident management team, which is responsible for coordinating incident clean-up activities, doing incident verifications, and even minor disabled vehicle repair or towing.

CHAPTER 2. MEASURES OF PERFORMANCE

Three parameters consistently have been used to measure the performance of incident detection algorithms. Unfortunately, how they are defined from study to study is not consistent. The parameters are detection rate (DR), false alarm rate (FAR), and time to detect (TTD).

Detection Rate

The detection rate generally is considered the ratio of the number of detected incidents to the total number of incidents. This varies according to the definition of an incident. Some studies count any stalled vehicle to be an incident, regardless of location, while others only count lane-blocking incidents. Those who belong to the latter group generally have reported higher detection rates because shoulder incidents often do not cause sufficient disruption in traffic flow to trigger an alarm.

Time to Detect

Time to detect is defined as the time from when the incident occurs until it is detected. This does not include the time taken to verify the incident. Algorithms will often adjust the persistence of the alarm. This persistence determines the number of time intervals that incident level flow disruption must exist before an alarm is raised. Most algorithms use 20- or 30-second time intervals. For most research results, the time to detect is assumed to have been calculated based on peak hour volumes. The basis for the calculations, however, generally was not provided with the reported performance results. It is possible that the reported TTD for installed systems is based on peak and off-peak period flows while the TTD for laboratory tests generally is based on peak volumes.

False Alarm Rate

The false alarm rate is most often defined as the percentage of incorrect detection signals relative to the total number of algorithm decisions. Most algorithms make one decision per detector station each

time interval. The reporting of this value is inconsistent in the literature due to the many ways it can be calculated. Given the above definition, small false alarm rates are reported. The number of decisions and the total number of detector pairs in a network can cause many false alarms in a short time. Others make relatively few decisions over a period of time creating a high percentage of reported false alarms. Another definition used is the number of false alarms per time frame, per station.

The values of these measures are interdependent. Generally, increasing the performance of detection rates, the false alarm rate also will rise. Similarly, if false alarms are decreased, then the sensitivity of the algorithm is reduced as a whole and the detection rate falls. In general, the longer an algorithm is given to analyze data, the better results it will give. This means that by increasing TTD, both the DR and FAR improve. Because of this dependency, most reports give a range of DR, FAR, and TTD to describe the performance of an algorithm. These values must be calibrated for each specific installation to balance the tolerable number of false alarms with an acceptable time to detect and detection rate.

The original intent was to compare the performance reports for each of the algorithms according to the three parameters. It quickly became evident, however, that most of the studies use different combinations of the definitions and do not always explicitly state what definitions they use. This makes a direct comparison of each algorithm rarely possible and likely to be inaccurate because each site has its own number of detectors, detector spacing, time intervals, geometry, and recurrent congestion characteristics. To compare 100 percent detection rate for an algorithm tested on only eight detectors to an algorithm tested on 500 detectors, with a rate of 68 percent is not reasonable.

Instead of attempting a direct comparison of performance measures, each set of performance measures is given as reported. The definitions of the measurement methods are given where they are reported.

CHAPTER 3. ALGORITHM DESCRIPTIONS

Four main types of computer-based algorithms have been developed in the last 30 years: (1) pattern recognition, (2) catastrophe theory, (3) statistical, and (4) artificial intelligence. While pattern and statistical based algorithms were first created in the 1970s, artificial intelligence is the newest and least mature of the four.

Some of these methods also are applied to incident detection using video image processing. Because this technology does not neatly fit into any of the four categories, it is treated on its own in section 3.5.

New programs or technologies incorporate several of the established incident detection algorithms through a decision support system. For example, if five algorithms are incorporated, the decision support framework may trigger an incident if three of the five algorithms "agree." Examples of these algorithm "groups" are proposed by Sheu and Ritchie (2000), Levin et al. (1979), and Cohen and Ketselidou (1993).

In our literature search, we also encountered several documents and articles that support incident detection research and evaluation. Examples are simulation programs, evaluation frameworks, and full reviews of incident detection technologies (Dougherty, Chen, and Montgomery 1998; Madanat et al. 1996; Kan, Krogmeier, and Doerschuk 1995; Kang, Ritchie, and Jayakrishnan 1998; Parkany and Bernstein 1998; Miller and Abkowitz 2000; Sullivan 1997; Solomon, 1991) Kan, W.Y.; Krogmeier, J.V.; Doerschuk, P.C. *Sensor Signal Processing for IVHS Applications.* 1995.

Pattern-Based Algorithms

Pattern-based algorithms are the most common algorithms in current operation. They work from occupancy, traffic volume, and traffic flow information that usually is collected from inductive loops. By identifying patterns in the data that are not considered "normal" for a stretch of road, potential incidents are recognized. This method requires preset thresholds that define normal interrupted flow. Anything

outside of "normal flow" should set off an alarm. Setting these thresholds is difficult and time consuming. This step should not be treated lightly to ensure the best performance.

The California Algorithm

One of the first to be developed, the California algorithm — sometimes referred to as Traffic Services Corporation-TSC algorithm 2, continues to be the algorithm most others use as a basis of comparison. The algorithm tests for an incident using three tests on the measured occupancy from two adjacent detectors. A potential incident is declared when values from the three tests surpass preset thresholds. The three tests are defined as follows:

1. The difference between the upstream station occupancy (OCC_i) and the downstream station occupancy (OCC_{i+1}) is checked against threshold value T_1. If the threshold value is exceeded, then proceed to step two.

2. The ratio of the difference in the upstream and downstream occupancies to the upstream station occupancy $(OCC_i - OCC_{i+1})/OCC_i$ is checked against threshold T_2. If this threshold is exceeded proceed to step three.

3. The ratio of the difference in the upstream and downstream occupancies to the downstream station occupancy $(OCC_i - OCC_{i+1})/OCC_{i+1}$ is checked against threshold T_3. If this threshold is exceeded, a potential incident is indicated and step two is repeated. If this threshold is again exceeded, a potential incident is flagged.

An incident state is terminated when threshold T_2 is no longer exceeded. The thresholds are calibrated from empirical data.

Although the California algorithm is straightforward, it requires the laborious calculation of thresholds for each location where it is installed. In large networks, separate thresholds must be calculated for different road geometries (i.e. ramps, weaving sections, hills, etc.). Due to its simple nature, its performance is not as good as that of later revisions or new techniques (Stephanedes and Hourdakis, 1996). It is a sound algorithm that is used in many locations.

TSC Algorithm 7

After further research into the subject, Payne and Tignor (1978) published 10 new algorithms based on the original California algorithm. The two that performed best are TSC 7 and TSC 8. The TSC 7 algorithm replaces the use of relative temporal differences in downstream occupancy values with downstream occupancy measurements. By doing this, recurring compression waves, common in heavy traffic, do not give off false alarms. It was found that simple downstream occupancy data that dropped below a certain threshold, usually 20 percent, was more indicative of an incident.

Along with the change in parameters, a persistence check was added to the basic algorithm that required that traffic discontinuity continue for a specified period of time before an incident was declared.

TSC Algorithm 8

This was the most complex algorithm to come from the modified California series and also is the best performer (Cohen and Ketselidou 1993). This algorithm provides a repetitive test for compression waves. These waves result in traffic slowdowns that move upstream and may produce momentary stoppages of traffic in heavy flows. By analyzing data, compressions can be detected and alarms are suppressed for up to five minutes at upstream locations. This way normal traffic congestion is less likely to give false alarms. This algorithm categorizes traffic data into nine different states and requires five different threshold values to be calibrated.

APID Algorithm

The All Purpose Incident Detection (APID) algorithm was developed by Philip H. Masters as a component of the COMPASS software for use in Toronto's ATMS (Chang and Lin 1993). The APID algorithm is a combination of the various California algorithms along with a compression wave test routine and a persistence test routine. Unlike the California algorithms, it uses smoothed-occupancy as the detection variable to reduce false-alarm rates. The algorithm's goal was to provide excellent performance under all conditions, thus the "all purpose" acronym. The algorithm worked well under high

traffic volumes, but performed poorly under low traffic volumes (Masters, Lam, and Wong 1991). Results given in an off-line evaluation showed a 66 percent detection rate over 29 incidents (86 percent of incidents creating abnormalities in traffic flow) with a TTD of 2.55 minutes and a FAR of 0.05 percent per station. This algorithm was to be used in Atlanta during the Olympics, but never was put on-line. The algorithms are built into National Engineering Technology's (NET) Navigator software that was developed for Atlanta, Ga., and remains in place in the navigator software present at the GDOT and UDOT TOCs, although it has not been activated. The city of Boston, Mass., currently is planning to implement the APID algorithm on the Boston Tunnel Project with detector spacing at every 70m. (Swartz, 2000)

PATREG Algorithm

Developed in 1979 by the Traffic Road and Research Laboratory (TRRL), the Pattern Recognition Algorithm (PATREG) was designed to work in conjunction with the High Occupancy (HIOCC) algorithm (Collins, Hopkins, and Martin 1979). The algorithm functions by estimating travel times between detector stations, converting this to a speed, then checking the current speed against preset thresholds. If the speed falls out of the thresholds for a specified period of time, then an alarm is sounded. The travel times are determined by a complex cross-correlation technique that matches up-stream to down-stream flow measurements. The algorithm worked best in low to medium flows (1,500 vph). This is because at higher flows, traffic becomes too irregular to adequately match flow measurements. Flows are measured every second, and every 40 seconds a new speed is displayed for that section of road. This algorithm requires detector spacing at 1/3 of a mile minimum. This algorithm is quite outdated, as no new developments have been made since the early 1980s.

Catastrophe Theory

Catastrophe Theory takes its name from the sudden discrete changes that occur in one variable of interest while other related variables are exhibiting smooth and continuous change (Persaud and Hall

1989). These variables are speed, flow, and occupancy. When speed drops dramatically without a corresponding increase in occupancy and flow, the alarm sounds. In this regard, Catastrophe Theory based algorithms are able to differentiate between incidents and recurring congestion. Congestion builds up slowly, while incidents cause a sudden queue to develop and drastic changes in speed to occur. The algorithms exploit this phenomenon. The difference between Catastrophe-based and pattern-based algorithms is that pattern-based methods rely on individual variable and pre-set thresholds, while the catastrophe method uses multiple variables and compares them to previous trends in data for recurrent congestion. The only type of algorithm that fits into this classification is the McMaster algorithm (Persaud and Hall 1989).

McMaster Algorithm

The theory is based in sudden changes that occur in one variable of interest while other related variables exhibit smooth and continuous change. This can be applied to incidents by looking at the relationships between speed, flow, and occupancy. The algorithm functions are based on data from a single detector station (Antoniades and Stephanedes 1996).

Using historical data, a flow-occupancy and speed-occupancy charts for the Burlington Expressway, near McMaster University, were created (Forbes, 1992). Figure 3.1 shows an example of these charts.

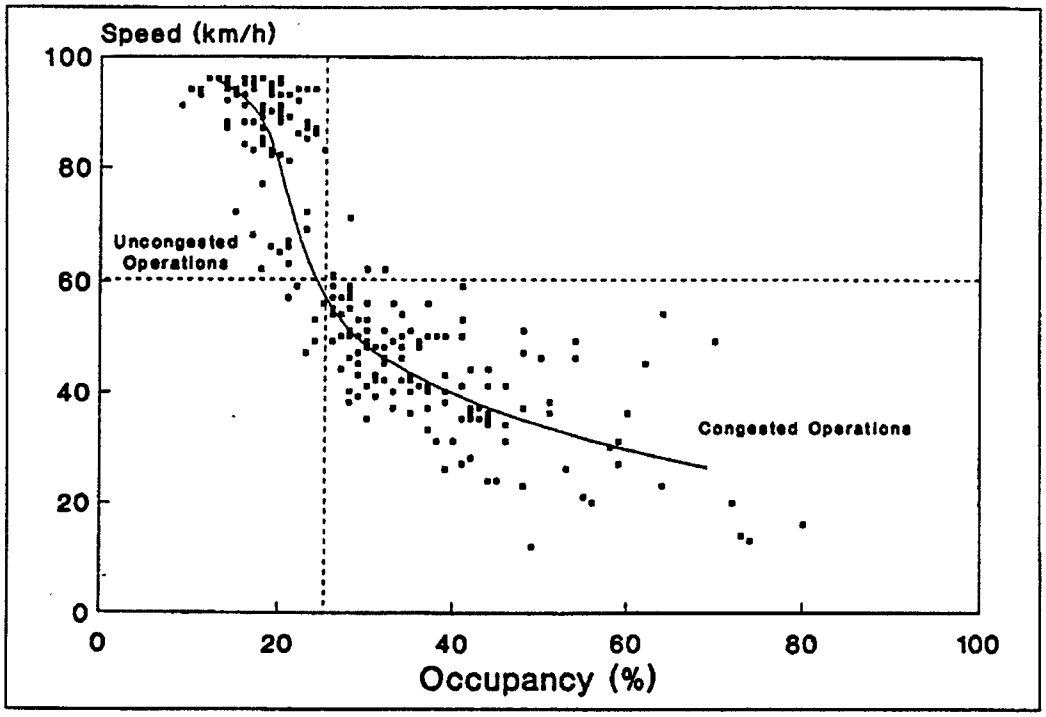

Figure 3.1 Speed/Occupancy Graph used by the McMaster Algorithm
Source (Forbes 1992)

This chart gives parameters for recurrent congestion. Thresholds for incidents were calibrated from this data. New charts must be made for each section of freeway where the algorithm is implemented.

The algorithm uses data illustrated by these charts by breaking it into ranges. When traffic patterns fall into a range that describes incident conditions for a preset number of intervals, an alarm is sounded. Initial tests of this algorithm were not encouraging, but as the algorithm evolved and the thresholds became more complex, results improved (Persaud, Hall, and Hall 1990). The best data had extremely low FAR, but high TTD (about two minutes).

Statistical Methods

Statistical methods compare real time traffic data with data forecasts. Algorithms model the actual traffic patterns, using time series data, and create a forecasted range of values. Any unexpected changes in traffic, compared to the forecasted traffic flows, are then classified as incidents. The advantage

to this method is that large amounts of data need not be gathered before the algorithm is implemented. Algorithms that fit into this category are the High Occupancy (HIOCC) algorithm (Collins and Martin 1979), smoothing (DELOS) model (Chassiakos and Stephanedes 1993), the Bayesian algorithm (Levin and Krause 1978), Auto-Regressive Integrated Moving-Average time series (ARIMA) algorithm (Ahmed and Cook 1982), Standard Normal Deviates (Dudek, Messer, and Nuckles 1974), and filtering models (Chassiakos and Stephanedes 1993).

HIOCC Algorithm

The TRRL developed this algorithm in conjunction with the PATREG algorithm. The premise of the HIOCC algorithm is that traffic will stop or slow considerably if there is an incident. The algorithm takes occupancy data every tenth of a second, and gives a value of 0 to 10 for every second of time. Zero means no vehicles have occupied the sensor that second, and 10 means the sensor was occupied the entire second. If two values of 10 are given consecutively, an alarm is sounded. The algorithm also is designed to terminate an alarm. It does this by taking the smoothed values of occupancy over the last five minutes of pre-alarm data and comparing it to the instantaneous smoothed occupancy values. When the instantaneous values drop below the pre-alarm levels, the algorithm is terminated. The smoothed instantaneous occupancy value is raised artificially in practice to prevent the alarm from premature termination. Field results from M1 and M4 in London, along with the Boulevard Peripherique in Paris, show the algorithm works well under congested conditions, but its effectiveness in light to moderate flows is yet to be seen (Chang and Lin 1993). Given the nature of the algorithm, performance is expected to drop in light flows. Actual numbers from seven stations along a two-mile stretch for 18 months of data show 10 of 11 incidents detected and 130 false alarms, seven of those with no apparent slow-down of traffic. A false-alarm rate is difficult to obtain solidly, because slow-moving vehicles initiated one third of the false alarms.

ARIMA Algorithm

ARIMA models are used to provide short-term forecasts of traffic occupancies and the associated 95 percent confidence intervals. These low-order linear models do this by taking observed data from three previous time intervals and predicting current conditions. If current conditions fall out of the range predicted by the model, an alarm is sounded. This algorithm was tested in several field tests. In an off-line test, the following performance was reported (JHK and Associates 1993):

Detection Rate:	100%
False alarm rate:	2.6%
Mean-time-to-detect:	0.58 min.

In a different test, the algorithm was compared to the DES and California algorithms (JHK and Associates 1993). With false alarm rates adjusted to one percent for all of them, the ARIMA model out performed them in detection rate and time to detect. This algorithm performs well under moderate and heavy traffic flows, but is questionable under light flows. It also is quite simplistic in its modeling characteristics, and therefore cannot account for many complexities associated with traffic behavior. The algorithm assumes stability from day to day, and its parameters are defined from one set of field data. Items such as day-to-day changes in traffic flow, weather conditions, construction, and other variables all thwart the performance of this algorithm. Because of these limitations, this algorithm is not used, and work to improve it has not been done. Improvements would include a test for outlying data points and multivariate time-series models, instead of the single variable set-up.

SND Algorithm

Texas Transportation Institute (TTI) developed this algorithm in 1974 for use on the Houston Gulf Freeway (I-45) (Dudek, Messer, and Nuckles 1974). The Standard Normal Deviate (SND) algorithm uses simple statistical analysis to determine a SND. SND is the current control variable minus the mean, all divided by the standard deviation. The mean and standard deviation of the control variable are determined from historical values. If the current occupancy value computes an SND value outside of

preset thresholds, an alarm is sounded. Persistence checks can be applied to reduce false alarms. An off-site evaluation performed by the designers showed results of 92 percent detection rate with a time to detect of 1.1 minutes and a false alarm rate of 1.3 percent. The most critical aspect of this algorithm is determination of the thresholds, a process that is not well defined. Further, detector spacing is an issue, since the algorithm relies on shock waves passing over detectors.

DES Algorithm

The double exponential smoothing (DES) algorithm was first developed in 1974 by Cook (1974). This statistical method is similar to the SND method, but uses a more complicated forecasting method. The smoothing aspect of the algorithm weighs recent traffic measurements more heavily than past measurements. In this way, changes in weather or volumes do not set a false alarm as readily. The double exponential algorithm smoothes data according to the following relations:

$S_1(t) = x(t) + (1 - \quad . \quad S_1(t-1);$

$S_2(t) = S_1(t) + (1 - \quad . \quad S_2(t-1);$

Where:

A smoothing constant determining the weight of past data

S_1= The first set of smoothed data

S_2= The second set of smoothed data

The smoothed set of data then is used to construct a tracking signal, which indicates deviation of the traffic measurement from the normal trend. Zero indicates no change, large values tend to indicate a possible incident. Cook tested the algorithm in 1974 using 13 different variables. Volume and occupancy yielded the best results. Busch and Fellendorf (1990) found that a speed discontinuity index also yielded good results.

Due to its simplicity, the algorithm is frequently used for comparison in other studies. A form of this algorithm also was developed for use in the COMPASS software to work with the APID algorithm. This particular version of the DES algorithm has the tracking signal computed by dividing cumulative

error of the variable by the current standard deviation. A predetermined threshold value for the tracking signal determines when an alarm is sounded. This algorithm is useful due to its simplistic nature and because no calibration is needed. Acceptable performance also has been repeatedly reported for this algorithm. Overall this is a useful, but simple algorithm.

Filtering Models

Chassiakos and Stephanedes (1993) developed the DELOS (Detection Logic with Smoothing) algorithm. The algorithm is designed to be simple because researchers determined that highly specific tests are not easily transferable, due to the amount of work that goes into determining thresholds for them. They wanted to design an algorithm that could be easily adapted to different locations.

The backbone of the algorithm is a moving average filter, which manipulates raw data before it is sent to the algorithm for calculation. The algorithm itself detects incidents through a high spatial occupancy difference between adjacent stations. The difference between this and standard pattern-based algorithms is that DELOS uses a three-minute average of the spatial occupancy instead of one-time interval. Also, the occupancies for the previous five minutes are stored. Large differences between the two values indicate an incident.

This logic can differentiate between an incident and recurring congestion by comparing the smoothed occupancy over a longer time interval. This method yields excellent DR and FAR rates, outperforming the California #7 algorithm in several comparisons conducted on Minnesota and California freeway data sets (Stephandes 1993). The drawback, however, is the considerable amount of time it takes to detect incidents due to the three-minutes necessary to average data. Subsequently TTD is over three minutes. This algorithm would be a good choice if the time to detection was not a large concern, as it is easy to implement and has a low false alarm rate coupled with high detection rates. Sample performance measures, from I-35 in Minnesota show an 80 percent DR with 0.35 FAR.

Bayesian Algorithm

This algorithm uses differences in occupancy between two detectors, similar to the California-based algorithms, but then takes this and applies Bayesian statistical differences to compute the probability that a large difference in occupancy is caused by an incident or recurrent congestion (Levin and Krause 1979). Three databases of information are needed for this to work: incident-free data for the stretch of road, incident data, and the highway patrol log, which lists the type, location, and severity of incidents. All historical information then is analyzed, and a statistical range is set up to determine if a given occupancy difference is incident-caused or incident-free. One large difference between this and other algorithms is that instead of either a yes or no result, percentage results can be given showing the probability of an incident. The version of the algorithm tested had a probability threshold and when this was exceeded, an alarm was sounded. Off-line results of this algorithm were good with for detection rates and false alarm signal, but the TTD was high due to the time needed to verify the incident. Reported off-line results from the J. F. Kennedy Expressway show a DR of 100 percent, FAR of 0 percent, and a TTD of four minutes.

SSID Algorithm

The Single-Station Incident Detection algorithm (SSID) uses a statistical T-test to analyze the temporal difference in occupancy at a single detector station (Antoniades and Stephanedes 1996). The occupancies during the 10 previous time intervals are averaged, and the standard deviation also is calculated. The T-test is used to find confidence limits around the mean. When a new interval is read, the value is compared to the standard deviation and confidence limit. An alarm is sounded if the new mean divided by the maximum allowable mean (determined from confidence limits) is greater than 1.015 and if the new mean minus the previous mean is greater than 75 percent of the standard deviation. This algorithm was tested on I-35 in Minneapolis and yielded a 100 percent DR and a 0.2 percent FAR. TTD was not reported, but would be in the range of one to three minutes, since two time intervals of queued traffic on the loop would be required to set off the alarm.

Artificial Intelligence

Artificial Intelligence (AI) is a recent development of AID algorithms. These algorithms detect incidents by either a rule-based algorithm or an algorithm that has "learned" to recognize incident patterns. Neural Network (Stephanedes 1995) and Fuzzy Set Logic (Chang 1994) are the main AI applications that have been applied to AID.

Neural Networks

In the early 1990s, researchers at the University of California, Irvine, showed the feasibility of using artificial neural networks for incident detection (Ritchie and Cheu 1993). A neural network is an algorithm modeled after the neural structure of a human brain. Information is distributed along many parallel paths to simple processing elements (PEs). A PE is a node where many input signals from other PEs can be processed, and several outputs sent to more PEs. The signal can be weighed, depending on its relevancy to the PE it is being sent. Automatic incident detection networks usually are multi-layer, feed-forward structured (MLF). The MLF consists of three layers, the input layer that takes data from loop sensors, intermediate layer that processes data, and the output layer, which gives an incident or incident-free signal. Training of the network must be done before implementation. Through trial and error, the network "learns" the appropriate weights to apply to the inputs and outputs. Supervised training involves letting the network know if its output matches the correct condition, while unsupervised training has the network finding patterns in data and producing consistent output for the input values. Most work on neural networks applied to AID was done in the early nineties by the University of California, Irvine and University of Minnesota (Dia and Rose 1997, Geng and Lee 1998). Initial results were promising, with all three measures of performance better than those displayed by the California algorithm in use in Orange County. The neural network algorithm had a detection rate of 85 percent, with a false alarm rate of 0.075 percent and a detection time of three minutes. This was much better than the on-line values of the California algorithm, taken from data at more than 800 detector stations in California. A detection rate of 0.075 percent equaled one false alarm every 11 hours for the data set tested. The University of

Minnesota's study tested a MLF network with 35 detector stations. The same data set that was used for training also was used to test the algorithm. The results were not as good as the University of California's study, but still promising. The Neural Networks were just beginning to be developed, but no further research or deployment has been done on the subject in recent years. With more work and a few actual sites in use, this would be a good choice for an algorithm. It is not recommended for implementation because on-line performance has yet to be documented.

Fuzzy Set Algorithm

As its name implies, this algorithm does not give a clear "incident" or "no incident" signal, rather it gives the likelihood for an incident. The fuzzy logic is designed to approximate reasoning when data is missing or incomplete. In this algorithm, the fuzzy set logic is applied as a supplement to the California #8 algorithm (Chang 1994). Although early research has been promising, no actual results have been determined. The fuzzy logic also requires extensive calibrating to define the logic boundaries. The best definition of this algorithm is a pattern-based algorithm with artificial intelligence technology in the decision tree process. It has not been fully developed and tested.

Video Image Processing

Incident detection using video image processing has several distinct advantages over inductive loop-based technology (Blosseville, Morin, and Locegnies 1993). Inductive loops only are capable of gathering traffic flow data at a point. Video image technology can provide this as well as information about traffic flow at a higher level. It can measure travel times, average speed, and detect stalled or stopped vehicles within the detection zone. It has been successfully used to accurately detect shoulder incidents (Blosseville, Morin, Locegnies 1993).

Two video incident detection technologies, TRAFICON (Versavel, 2000) and NESTOR (*) have the capability to use many existing pan-tilt-zoom traffic monitoring CCVT cameras. This requires each

camera to have one or more "home" positions when used for incident detection. While an operator wishes to pan, tilt, or zoom the view, the operation of the incident detection algorithm is suspended. Blosseville, Morin, and Locegnies (1993) tested video image incident detection on a 1.7 km long corridor in France. They tested several scenarios and compared them with the recorded video from each camera. Table 3.1 summarizes the results of the study.

Table 3.1 Results of Video Imaging by Incident Detection

	Traffic Lanes (TL)		Emergency Lanes (EL)	
	Approaching	Moving Away	Approaching	Moving Away
Detection Rate	88 %	91 %	79 %	85 %

False Alarm Rate	3%
False alarm frequency	0.2 per camera per 24 hr.'s
Average Detection Time (TL)	22 seconds
Average Detection Time (EL)	63 Seconds

Source: (Blosseville, Morin, and Lochegnies 1993)

An Autoscope video detection system is reported to have detected 80 percent of all incidents with only a 3 percent false alarm rate (False alarms to total number of alarms) (Michalopoulos, Jacobson, and Anderson 1993). Through the use of incident detection algorithms, the system also detected incidents almost two miles away, well outside the range of the camera's vision.

CHAPTER 4. ANALYSIS OF ALGORITHMS

Limitations of Computer-Based Incident Detection

No matter how complex or evolved an algorithm is, it never can fully mimic and comprehend the dynamic nature and changes associated with traffic flow. This random variation in traffic flow patterns is what causes most AID technologies to fail.

There are two main problems with computer-based algorithms. The first is that the time to detect is usually too long to be useful. Second, the number of false alarms is sufficient to irritate operators and usually either causes them to ignore the alarms, or turn them off altogether, as demonstrated in other TOCs. For most algorithms, the TTD ranges from 30 seconds to more than five minutes, with typical times being about two minutes. In a study done on filtering techniques, TTD was reported against the time noted in an engineer's logbook. The engineer detected incidents through the video coverage of the street network in the TOC. In 27 incidents, the engineer detected the incident before the algorithm (Stephanedes and Chassiakos 1993). In a separate evaluation for the McMaster algorithm in Toronto, an operator with live video of the network detected incidents an average of two minutes before the algorithm (Hall and Shi 1993). Operators in traffic operations centers that have video coverage of the freeway network generally will detect incidents more quickly than a computer-based algorithm.

Another problem associated with algorithms is the number of false alarms given, although false alarm rates of less than 1 percent commonly are reported. This can be misleading from the actual number of false alarms sounded. A false alarm rate of 0.1 percent, based on false alarms per decision made, would be unacceptable in a system the size of Chicago, which has more than 600 stations. An alarm would be given more than once a minute (Hall and Shi 1993). The Boston Tunnel project determined that an operator would tolerate 10 false alarms per hour before completely ignoring or shutting the detection system down (Swartz 2000). For large networks, the rates calculated, based on the number of algorithm calculations must be near 0.0001 percent. Few algorithms can achieve this level of performance at all, and usually do so at the expense of detection rates and time to detect. Levin (1979) stated that reducing

the FAR was the most difficult challenge of incident detection technology. The Salt Lake City ATMS area currently has 87 detectors planned for the I-15 and I-215 network. This network would require a false alarm rate of less than 0.0006 percent to yield 10 false alarms per hour based on a calculation per detector pair every 20 seconds.

The data source for most algorithms is from inductive loop detectors. An automatic incident detection algorithm only can be effective when flows are heavy enough that traffic is substantially interrupted by an incident. Traffic incidents in low flows and shoulders incidents do not usually cause enough disturbance to the flow to be recognized. Several papers acknowledge this flaw and consequently leave out all shoulder incidents from the reported detection rates. This limits the usefulness of computer-based algorithms, which are powerless to help in these circumstances and are thus limited in their usefulness.

At any given time, a system of inductive loop detectors will have some loops that are in need of repair. Although stationary freeway loops may experience less down time than the standard intersection stop-line and queue detectors, they still have maintenance problems. This has several implications for an AID system. Since most algorithms use a pair of detectors, this normally would cause one or two pairs to be down. If the algorithm is sophisticated enough, it should take the "new" adjacent pair of detectors and continue its calculations. For this section of roadway it will take approximately two times longer for the incident-induced queue to build sufficiently to trigger an alarm. Less sophisticated algorithms may not deal with the down detector at all. In the reviewed literature, JHK and Associates (1993) included a discussion of the various methods that can be used to determine whether or not a detector is functioning. There was, however, no discussion on how the various algorithms cope after a detector is found to be faulty. Chang and Lin (1993) comment that the APID algorithm is sensitive to loop detector failures, but offer no insight into the extent of the sensitivity.

Many of the algorithms are based on preset thresholds calibrated from "normal flow" conditions. When the conditions change, the algorithm performance likely will degrade on one or more of the measures of performance. The algorithms that follow trends rather than thresholds will theoretically

perform as well as in "normal" conditions. Video image processing algorithms also will degrade as visibility decreases. This also will affect the ability of operators to verify incidents through CCTV systems. Little or no discussion was provided for this problem in the collected AID systems literature.

Chang and Lin (1993) review weather sensitivity reports for some algorithms. The comments are, however, not qualified by performance statistics and in some cases they do state that further investigation is required. The comments are provided here for information. The APID algorithm showed robustness in varying weather conditions, but further testing was required. The McMaster algorithm was reported to suffer an increase in false alarms during a snowstorm. The Bayesian method is also reported to be sensitive to weather conditions. The SND and DES algorithms can tolerate moderate variations in weather conditions. Image processing technology as it is applied to incident detection also can be affected by weather and lighting conditions.

Comparison of Results

A direct literature-based comparison of algorithm performance is not possible, due to differences in testing different methods, networks, data sets, and calculation methods. The only way to accurately compare algorithm performance would be to test them side-by-side in a controlled environment. In the literature, some algorithms were tested with recorded data, some with real-time data, and others with simulated data. The number of detectors ranged from as few as eight to as many as 500. Table 4.1 shows the reported performance for the algorithms. Although these reported performance measures are known to be incompatible, they are provided as a summary of reported findings. Each false alarm rate is shown as an approximate hourly false alarm rate for the Salt Lake freeway network of 87 detectors.

Table 4.1 Summary of Algorithm Performance

Name	DR (%)[a]	TTD (min)[a]	FAR (%)[a]	FAR basis[b]	Installations	Projected SLC Network false alarms per hour
APID	86	2.50	0.05%	Calc	Toronto, Boston	7.74
DES	92	0.70	1.87%	Calc	Toronto	289.48
ARIMA	100	0.40	1.50%	Calc	Laboratory	232.20
Bayesian	100	3.90	0%	n/a	Laboratory	0.00
California	82	0.85	1.73%	Calc	California, Chicago, Texas	267.80
Low-Pass Filter	80	4.00	0.30%	Calc	Laboratory	46.44
McMaster	68	2.20	0.0018 %	Calc	Minnesota	0.28
Neural Networks	89	0.96	0.012%	Calc	Laboratory	1.86
SND	92	1.10	1.30%	Calc	Not Known	201.24
SSID	100	not reported	0.20%	Calc	Laboratory	30.96
TSC #7	67	2.91	0.134%	Calc	California, Chicago, Texas	20.74
TSC #8	68	3.04	0.177%	Calc	California, Chicago, Texas	27.40
Video Image Processing[c]	90	0.37	3.00%	Tot	France	0.03
Cellular Telephones[d]	100	-	5.00%	Tot	n/a	0.005

[a] Please note that not all values may not have been measured in the same way.

[b] (calc) means the measurements likely were based on the total number of calculations (assumed to be every 20 seconds per detector pair). (tot) indicates that this is based on the total number of alarms per location (assumed to be four freeway incidents per day in the ATMS coverage area)

[c] Only the values for the main traffic lanes were used, leaving out the values for emergency lane (shoulder) detection.

[d] Information for Cellular telephones based on an interview (Ranson 2000). Two incidents are assumed to occur per peak period and 40 peak periods each month. False alarms are "ghost calls," or people calling in incidents that don't exist. This value was reported to be about four per month (Ranson 2000).

Of the inductive loop computer-based algorithms, the trade-off between performance values is evident in the reported values. The Bayesian algorithm, for example, detects all incidents and has no false alarms, but has the highest value for TTD. The inconsistency in false alarm rate calculations also is evident here. Although a 20-second calculation interval is assumed, some of the algorithms may apply a 30-second interval and not report this value. Very high and low values for FAR are seen in several of the algorithms. For several of the algorithms, the calculation method or the definition of an "incident" were not reported. Where the calculation method is not stated, it was assumed that all FAR values under 2 percent were calculated based on the per calculation method, rather than the per total false alarms method.

Of the loop-based algorithms that have testing experience outside of the laboratory, the APID and DES algorithms stand out as being superior. APID reports a DR of 89 percent, a TTD of 2.5 minutes and a FAR of 0.05 percent, which is slightly more than seven false alarms per hour in the peak period. The DES algorithm shows a much faster TTD at 0.7 minutes and a higher detection rate at 91 percent, but shows a great number of false alarms. If the DR and TTD thresholds were loosened, it is likely that the number of false alarms would be substantially reduced.

The McMaster algorithm also reports good performance values. This algorithm, however, does not take advantage of the spatial and temporal changes in traffic flow values because it bases its calculations on the data from a single detector. These calculations therefore are based on temporal variations only. This algorithm may be more appropriate at remote locations or where more complete detector coverage is not available. If the special component of the calculation is to be used, close detector spacing is recommended. Where this is not possible, or detector spacing is distant, this algorithm could be considered.

Of the algorithms tested only in the laboratory, the Neural Networks method appears to have the most balanced performance values with a DR or 89 percent, a TTD of 0.96 minutes and an FAR of 0.92. Most of the other algorithms tested only in a laboratory seem to have been calibrated to give maximum detection rates, which resulted in unreasonable values for FAR and TTD.

The video image processing system and the cellular telephone reporting have similar performance values. Both of these outperform the loop-based detection systems by a large margin. The time to detect an incident using cellular telephones is not known exactly, but it is generally very short (Ranson, 2000).

CHAPTER 5. INCIDENT DETECTION BY CELLULAR TELEPHONES

Over the last 10 years, ownership of cellular phones has grown tremendously. In 1990, there were 5,283,000 U.S. subscribers to cellular service. Today that number is estimated to be more than 100 million (Mussa and Upchurch 2000). This increase has led to many people being able to report traffic incidents over their phone. As ownership continues to grow, the detection times and rates will continue to improve. The diminishing volume of research in automatic incident detection in attributed, in part, to the increasing impact that cellular telephone saturation has made.

Currently in the SL Valley, when a caller wants to report an incident, they will either call (911) or the cellular highway help number (*11). Figure 5.1 shows how a call normally is processed. It is important to note that when a call is placed using the *11 number, it is directed to the Utah Highway Patrol (UHP) dispatch area in the TOC. At that location, they currently are not able to dispatch all emergency services – notably medical emergency service. Therefore, if the reported incident has any potential injuries, the call must then be forwarded to the main UHP dispatch center or to a 911 call center.

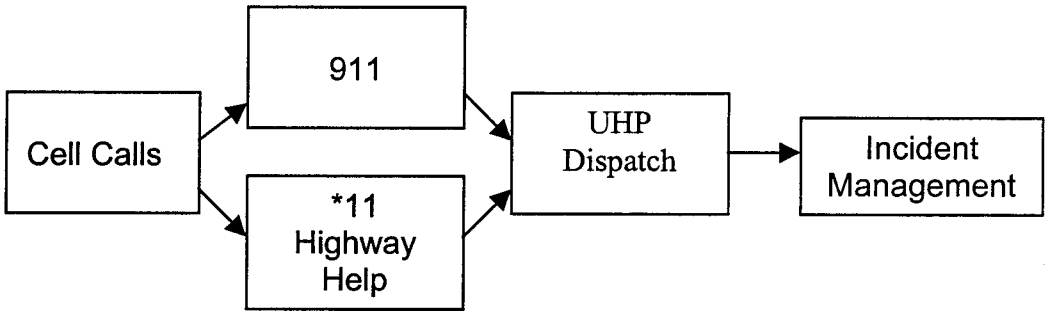

Figure 5.1 Current Incident Reporting Call Path

Literature on Cellular Telephones and Incident Detection

Mussa (1997) analyzed the performance of cellular phones in incident detection by considering the percent of drivers with cell phones, incident severity, and traffic volume. In all but the lightest flow, the cell phones reach 100 percent detection rates and have minimal detection times.

Mussa and Upchurch (2000) conducted a series of simulations to determine the effects of varying the number of cellular telephone customers willing to use their phones to report an incident. They compared this to a computer-based automatic incident detection algorithm. Simulation scenarios were run for low, medium, or heavy traffic encountering shoulder, 1-lane, or two lane incidents were using the FRESIM (Freeway Simulation) software. It was found that higher volumes corresponded to lower detection times, and one and two-lane incidents received more calls than shoulder incidents. It is important to note that nearly all shoulder incidents were reported. Automatic incident detection algorithms generally cannot detect shoulder incidents because they often do not sufficiently disrupt traffic flow.

The results of the simulations were much better than any algorithm, even with conservative input parameters. If 10 percent of drivers have a phone and 10 percent of those are willing to call in (1 percent of drivers calling), 80 percent of the incidents are detected within five minutes. If the percentages increase to 25 percent of people owning cellular telephones and 40 percent of those willing to call (10 percent of drivers calling), all incidents are reported within 1.5 minutes. False alarms, in the form of prank calls or faulty information do occur, but not nearly on the same scale as false alarms given by algorithms.

Much attention recently has been given to the danger of using cellular telephones while driving. Reed and Green (1999), explore these effects by measuring lateral speed of the vehicle in the traffic lane (weaving within the lane) during normal driving and while dialing on a keypad. A 43 percent increase in lateral speed was found if the driver was dialing a keypad. The risk of encouraging the use of cellular phones for incident detection is that the number of unsafe drivers on the road will increase.

One new technology explores the use of cellular telephones as probes to measure travel time along a major freeway corridor in Texas (Balke, Dudek and Mountain 1996). The results of this report are, however, pessimistic and inconclusive.

Enhanced Cellular 911 Service

The Federal Communications Commission has mandated that all cellular telephone service providers implement Enhanced 911 Service (E911) (FCC 1999). The requirement consists of two phases. Phase One requires carriers to provide caller's location to within 300 meters and the caller's telephone number to the Public Safety Answering Point (PSAP). The deadline for implementation of this phase was April 1, 1998. Phase Two simply requires a more specific location to be provided. The Phase Two implementation deadline is October 1, 2001. The location of a caller is helpful to incident management teams and could be used to improve their detection and response times. It is possible that this may help screen out some false alarm calls though the separation of the caller location and the accident location reported.

Two technologies are available that provide a caller's location. The first technology uses a triangulation procedure between two adjacent cellular telephone towers. This technology does not require any modification to the phones. Two-way pagers also can be located using this technology. An engineer at a local cellular telephone service carrier said that although this technology is in place, it is too lengthy to be useful. He said that they are working quickly to discover new methods for speeding the process up by the October 1, 2001 deadline. The second technology, called the handset method, uses a small Global Positioning Satellite (GPS) unit in each handset. The only problem with this technology is that by the deadline, there will be many users that still are using older cellular phones, which do not have the GPS technology.

The location technology is important to incident detection because callers on the road do not always know where they are. While they generally can give an approximation of the incident, unless it occurs within camera coverage, details are not always available.

A disadvantage of cellular telephones in incident detection is the multiple reporting of incidents and locating of incidents. Until emergency vehicles arrive on scene, calls can continue to come in to report the same incident (Ranson 2000). During the tornado of 1999, the entire cellular network became

jammed to due cellular calls. A recent interview with a local cellular provider, however, revealed that cell saturation quickly is becoming a minor problem as new digital technology replaces analog methods.

Highway Help: Cellular *11

Several Highway Help signs are in place on Utah freeways. Most are located along the freeway system near major junctions (see Figure 5.2). Several signs have been displaced due to construction. An example sign located on I-80W between Foothill Blvd. and 1300 E. is shown in Figure 5.3. Currently, all calls to *11 are taken by the Highway Patrol Dispatch center located within the UDOT TOC.

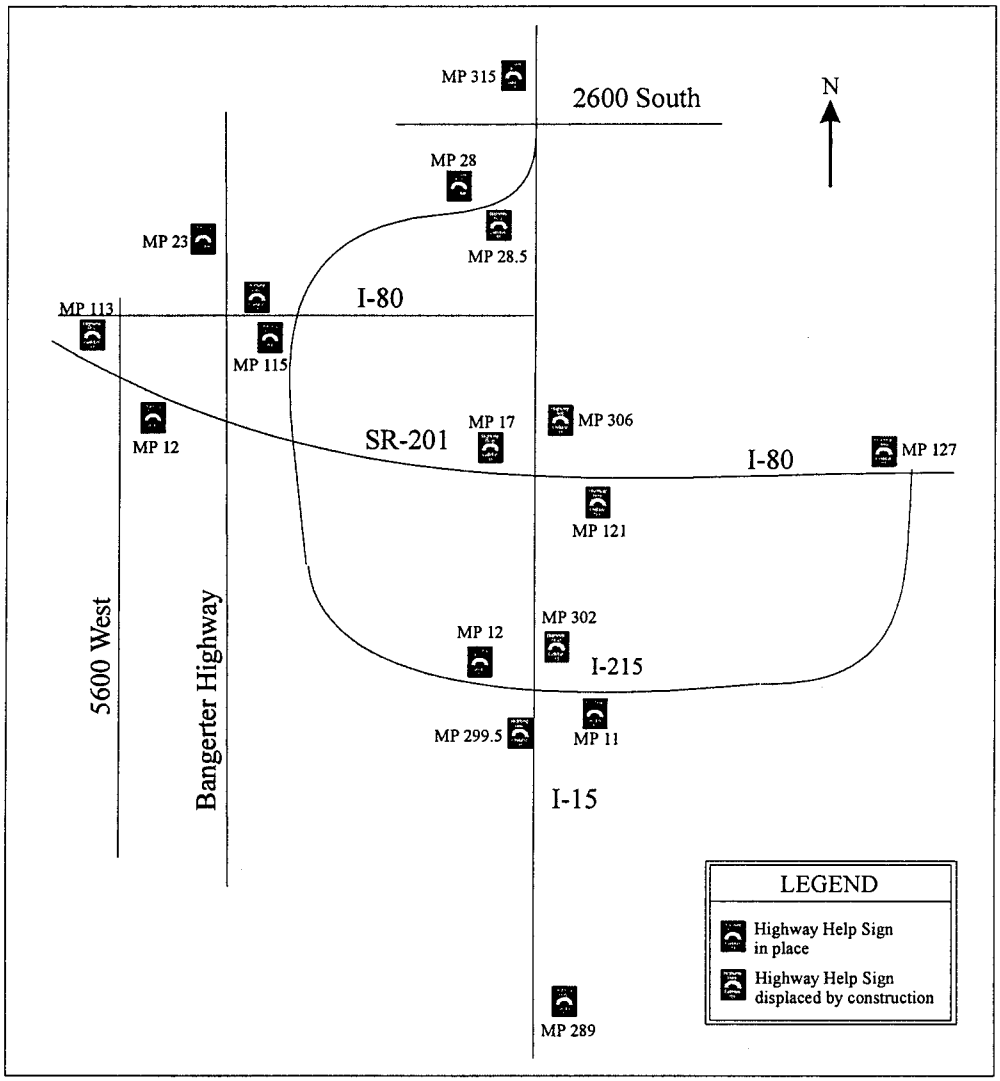

Figure 5.2 Highway Help Sign Locations

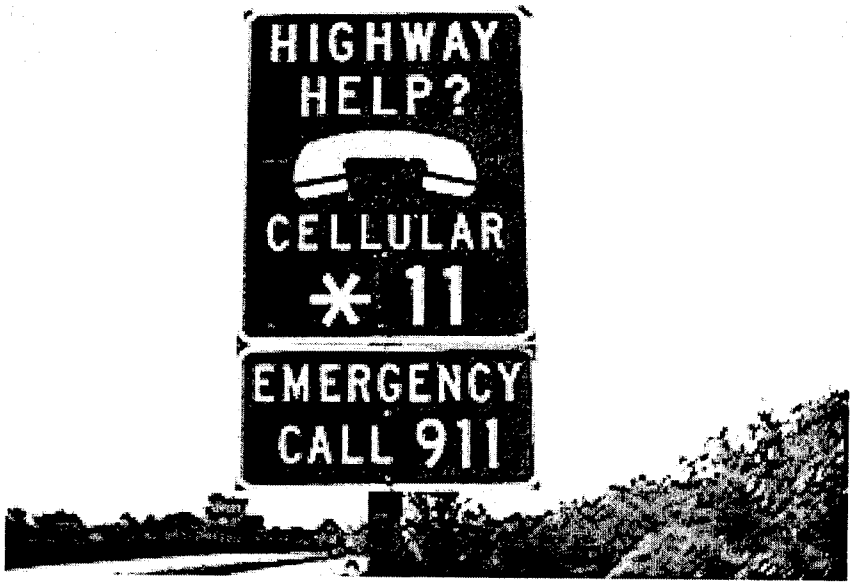

Figure 5.3 Highway Help Sign

An average of 4,000 calls per day are received at the Highway Patrol Call Center located in the UDOT TOC (Rueckert 2000). Estimated percentages of call types are presented in Table 5.1.

Table 5.1 Call Types received by the *11 Cellular Highway Help Number

Percentage	Call Type
30%	Incidents
50%	Road Debris / Disabled Vehicles / Reckless Driving
20%	Road Condition Inquiries / Business Calls

Source: (Nelson 2000)

It is important to note that because the highway patrol cannot dispatch medical emergency services from their facility, they did not intend this number and facility for the purpose of directing callers to call in about major incidents. The reason for this is that from their facility they are not able to dispatch medical emergency services.

On July 21, 2000, the FCC approved the U.S. Department of Transportation's request for a three-digit traveler information telephone number, "511." This number functions similarly to the emergency

"911" number. The intention of the number is to replace approximately 300 existing numbers throughout the states so people can acquire traveler information anywhere in the U.S. The FHWA has offered up to $50,000 for each state to convert existing numbers to "511."

Recommendations for Cellular Incident Detection

Based on the review of available AID technologies and the impacts of cellular phones, the conclusion reached is that cellular phones are more accurate, quicker, and have less false calls than AID.

The reemergence of call boxes also is valuable — only cellular and solar powered, as opposed to traditional boxes (Ullman 1999). Those without cellular telephones would benefit from the technology by being able to place an emergency call from a box.

CHAPTER 6. CONCLUSION AND RECOMMENDATIONS

This research reviewed various technologies and algorithms for incident detection to determine the most potentially beneficial system to the Salt Lake Valley. The results from algorithm performance reviews and conversations with other DOTs and cities using incident detection revealed that cellular phone technology has made much of the computer-based incident detection technology obsolete.

The findings of the algorithm review indicate that the majority of the techniques rely on inductive loop detection to collect speed, occupancy, flow or other measures. These are used to create thresholds that determine the bounds of "normal" flow. When flows exceed these thresholds, a potential incident is reported. The traditional problem with automatic incident detection is balancing the ability to detect an incident in a timely manner while minimizing the number of false alarms. If the thresholds are too restrictive, then false alarms increase. If the thresholds are too lax, the time to detect the incident increases. Finding this balance is difficult and has resulted in many of the installed incident detection algorithms being turned off by the TOC operators.

Another issue is that many of these algorithms are tested and installed with close detector spacing, typically 70 m, to provide timely incident detection. UDOT freeway detector spacing is 800 m making detection a much longer process.

The most widely implemented algorithm is the California series (California, TSC #7 and TSC #8), which have been used in California, Texas, and Chicago. Based on results from these installations, the time to detection is three minutes with a 68 percent detection rate. APID is an enhanced version of the TSC #8 algorithm. It is shown as the most effective algorithm in the field with installations in Toronto and Boston. Its performance is reported as an 86 percent detection rate and a 2.5-minute time to detect. For Salt Lake Valley 87 detectors, it is estimated that the California algorithms would produce 21 false calls per hours and the APID would produce eight false calls per hour during the peak periods.

Other methods that have been simulated, but not installed, have shown promising results. The neural network method has been modeled to provide 89 percent detection in 0.96 minutes with a false alarm rate that translates into two false alarms per hour on the Salt Lake network during the peak period.

While the incident detection has shown promising results in the past, the use of video coverage on the freeway systems and ever-expanding use of cellular phones has made the need for incident detection less important. Incident detection algorithms rely on congestion to trigger preset thresholds. In low flow conditions, algorithms perform poorly because the incident may fail to disrupt traffic sufficiently to trigger the thresholds. This means the algorithms are most suited for high flow conditions. This also is when many drivers are available with cellular communication. The result is that other drivers are calling in incidents seconds after they happen and minutes before the algorithms can detect the onset of congestion.

Based on these findings, it is recommend to UDOT that cellular telephone technology be used as the primary form of incident detection. APID and DES algorithms that are already embedded in the GDOT software, however, should be activated and calibrated as a backup to cellular telephones.

If UDOT wish to test and compare any of the other computer-based algorithms, the TOC will be an ideal setting. In particular, the artificial intelligence methods and the video image processing methods seem promising and should be evaluated further.

REFERENCES

Ahmed, S.A., Cook, A.R. Application of Time-Series Analysis Techniques to Freeway Incident Detection. *Transportation Research Record 841,* TRB, National Research Council, Washington D.C., 1982.

Antoniades, Charalambos N.; Stephanedes, Yorgos J. Single-Station Incident Detection Algorithm (SSID) for Sparsely Instrumented Freeway Sites. *Transportation Engineering,* 1996.

Blosseville, J.; Morin, J.; Lochegnies, P. Video Image Processing Application: Automatic Incident Detection Freeways. *Proceedings of the Pacific Rim Trans Tech Conference,* July 25-28, 1993. (69-76).

Busch, Fritz; Fellendorf, Martin. Automatic Incident Detection on Motorways. *Traffic Engineering & Control* Vol. 31 No. 4 (221-227), 1990.

Chassiakos, Athanasios P., Stephanedes, Yorgos J. Smoothing Algorithms for Incident Detection. *Transportation Research Record 1394 (8-16)* TRB, National Research Council, Washington D.C., 1993.

Chin-Ping Chang, Edmond. Fuzzy Systems Based Automatic Freeway Incident Detection. *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics* (1727-1733), 1994.

Chin-Ping Chang, Edmond; Wang, Su-Hua. Improved Freeway Incident Detection Using Fuzzy Set Theory. *Transportation Research Record 1453 (75-82)* TRB, National Research Council, Washington D.C., 1994.

Cohen, Simon; Ketselidou, Zoe. A Calibration Process for Automatic Incident Detection Algorithms. *Microcomputers in Transportaton* (7-254), 1993.

Collins, J.F., Hopkins, C.M., and Martin, J. A. . Automatic Incident Detection—TRRL Algorithms HIOCC and PATREG. Supplementary Report 526, Transport and Road Research Laboratory, Crowthorne, England, 1979.

Cook, Allen R. Management of Urban Freeway Traffic. *Canadian Journal of Civil Engineering* Vol.1 No.2 (141-149) Montreal, Quebec 1974.

Dia, Hussein; Rose, Geoff. Development and Evaluation of Neural Network Freeway Incident Detection Models Using Field Data. *Transportation Research Part C.* Vol.1, Number 3 (203-217) 1997.

Dougherty, Mark; Chen, Haibo; Montgomery, Frank. Principle Components Analysis Based Incident Detection. *Applications of Advanced Technologies in Transportation.* 1998. (51-58).

Dudek, C.L., Messer, C.J., Nuckles, N.B. Incident Detection on Urban Freeways. *Transportation Research Record 495.* TRB, National Research Council, Washington D.C., 1974.

Federal Communications Commission. *FCC acts to promote competition and public safety in enhanced wireless 911 services.* Washington, DC. 1999.

Forbes, Gerald J. Identifying Incident Detection. *Institute of Transportation Engineers (ITE).* Vol. 62 (17-22), 1992.

Geng, Jason; Lee, T.N.; Freeway Traffic Incident Detection Using Fuzzy CMAC Neural Networks. Published by IEEE, 1998. (1164-1169).

Hall, Fred L., Shi, Yong., Atala, George. Off-Line Testing of the McMaster Incident Deteciton Algorithm Under Recurrent Congestion. *Transportation Research Record 1394 (1-7),* TRB, National Research Council, Washington D.C., 1993.

JHK & Associates. Bay Area Traffic Operations System Incident Detection Algorithms Report. January 1993.

Kang, Seungmin; Ritchie, Stephan G.; Jayakrishnan, R.; Prediction of Short-term Freeway Traffic Volume Using Recursive Least Squares and Lattice Filtering. *Applications of Advanced Technologies in Transportation,* 1998. (255-263).

Levin, Moshe., Krause, Gerianne M. Incident-Detection Algorithms, Part1. Off-Line Evaluation, *Transportation Research Record 722 (49-64),* TRB, National Research Council, Washington D.C., 1979.

Levin, Moshe., Krause, Gerianne. Incident Detection: A Bayesian Approach. *Transportation Research Record 682 (52-58),* TRB, National Research Council, Washington D.C., 1978.

Madanat, Samer M.; Teng, Hua-Liang; Liu, Pen-Chi. A Sequential Hypothesis-Testing Based Freeway Incident Response Decision-Making System, *Transportation Engineering Technologies*, 1996. (286-291).

Masters, Philip H., Lam, Joseph K., Wong, Kam. Incident Detection Algorithms for COMPASS – An Advanced Traffic Management System. *Vehicle Navigation & Information Systems Conference Proceedings: 1991,* (295-310). Warrendale, PA., 1991.

Michalopolous, P.; Jacobson, R. Field Implementation and Testing of Machine Vision Based Incident Detection System. *Transportation Research Record 1394 (1-7),* TRB, National Research Council, Washington D.C., 1993.

Miller, Charles; Abkowitz, Mark. A Decision-Support for Highway Incident Management System Development. *79th Annual Meeting of the Transportation Research Board,* Washington D.C., 2000.

Mussa, Renatus N. Evaluation of Driver-based Freeway Incident Detection *ITE Journal,* March 1997. (33-40).

Mussa, Renatus N., Upchurch, Jonathon E. Simulator Evaluation of Incident Detection Using Wireless Communications*79th Annual Meeting of the Transportation Research Board,* Washington D.C., 2000.

Nelson, Cindy W. 2000. Interview by Dan Moore. Utah Highway Patrol Office in the Utah Department of Transportation Traffic Operations Center. 23 June, 2000.

Parkany, Emily; Bernstein, David. Design of Incident Detection Algorithms Using Vehicle-to-Roadside Communication Sensors. *Transportation Research Record 1494 (67-74)*. TRB, National Research Council, Washington D.C., 1995.

Payne, H.J. and Tignor, S.C. Freeway Incident Detection Algorithms Based on Decision Trees with States. *Transportation Research Record 682, (30-37)*. TRB, National Research Council, Washington, D.C., 1978.

Persaud, Bhagwant N., Hall, Fred. Catastrophe Theory and Patterns in 30-second Freeway Traffic Data – Implications for Incident Detection. *Transportation Research–A, Vol. 2, (103-113)*. Pergamon Press, Great Britain, 1989.

Persaud, Bhagwant N.; Hall, Fred L.; Hall, Lisa M. Congestion Identification Aspects of the McMaster Incident Detection Algorithm. *Transportation Research Record 1287,* 1990. (167-175).

Ranson, Tom. 2000. Interview by Ryan Kump and Blake Hansen. Utah Department of Transportation, Salt Lake City, 2 February.

Reed, Matthew P.; Green, Paul A. Comparison of Driving performance on-road and in a low-cost simulator using a concurrent telephone dialing task. *University of Michigan, Transportation Research Institute.* 1999.

Ritchie, Stephan G.; Cheu, Ruey L. Simulation of Freeway Incident Detection Using Artificial Neural Networks. *Trasportation Research Part C. Volume 1, (313-331)*. Pergamon Press Ltd. New York, NY 1993.

Rueckert, Chris. 2000. Interview by Ryan Kump. Utah Highway Patrol office in the Utah Department of Transportation Traffic Operations Center. 23 May 2000.

Sheu, Jiuh-Biing; Ritchie, Stephen G. A Sequential Detection Approach for Real-Time Freeway Incident Detection and Characterization. *79th Annual Transportation Research Board Meeting* 2000.

Solomon, Marc. A Review of Automatic Incident Detection Techniques. *ADVANCE Program Technical Report* ADVANCE 1991.

Stephandedes, Yorgos J., and John Hourdakis. Transferability of Freeway Incident Detection Algorithms. *Transportation Research Record 1554 (184-195),* TRB, National Research Council, Washington D.C., 1996.

Stephanedes, Yorgos J., Chassiakos Athanasios P. Low Pass Filter For Incident Detection. *2nd International Conference on Applications of Advanced Technologies in Transportation Engineering.* ASCE. (101-105). 1991.

Stephanedes, Yorgos J., Chassiakos, Athanassios P. Freeway Incident Detection Through Filtering. *Transportation Research-C. Vol. 1 Number 3, (219-233).* Pergamon Press Ltd. Great Britain 1993. pp. 219-233.

Stephanedes, Yorgos J., Liu, Xiao. Artificial Neural Networks for Freeway Incident Detection. *Transportation Research Record 1494 (91-97),* TRB. National Research Council, Washington D.C., 1995.

Sullivan, Edward C. New Model for Predicting Freeway Incidents and Incident Delays. *Journal of Transportation Engineering. Vol. 123, (267-275). ASCE.* 1997.

Swartz, John. Engineer in charge of incident detection within the Boston Tunnel Project. Interview by author. Teleconference call from Boston to Utah, February 29, 2000.

Ullman, Gerald L. An Assessment of Potential Use and Benefits of a Statewide Call Box System in Texas. *Texas Transportation Institute,* College Station, TX, 1999.

Versavel, J. 2000. Sparing lives, saving time: a unified approach to automatic incident detection. *Traffic Technology International.* Issue: The 2000 International Review of Advanced Traffic Management. (189).

BIBLIOGRAPHY

Balke, Kevin; Dudek, Conrad L; Mountain, Christopher E Using Probe-Measured Travel Times to Detect Major Freeway Incidents in Houston, Texas. *Transportation Research Record 1554,* 1996.

Cheu, Ruey L.; Recker, Wilfred W.; Ritchie, Stephen G. Calibration of INTRAS for Simulation of 30-sec. Loop Detector Output. *Transportation Research Record 1457 (208-215),* TRB, National Research Council, Washington D.C., 1991.

Cheu, Ruey-Long. Freeway Traffic Prediction Using Neural Networks. *Applications of Advanced Technologies in Transportation,* 1998. (247-254).

Gall, Ana I.; Hall, Fred L. Distinguishing Between Incident Congestion and Recurrent Congestion: A Proposed Logic. *Transportation Research Record 1232 (1-8),* TRB, National Research Council, Washington D.C., 1989.

Hellinga, Bruce; Knapp, Geoff. AVI Based Freeway Incident Detection. *Presented at the 79th Annual Transportation Research Board Meeting.* 1999.

Hourdakis, John; Chassiakos, Athanassios P.; Preliminary Features of a Decision Support System for Incident Detection. *Transportation Engineering Technologies,* 1996. (227-232).

Hsiao, Chien-Hua; Lin, Ching-Teng; Cassidy, Micheal. Application of Fuzzy Logic and Neural Networks to Automatically Detect Freeway Traffic Incidents. *Journal of Transportation Engineering.* Vol. 120, Number 5, 1994. (753-771).

Ishak, Sheriff S.; Al-Deek, H.M. Freeway Incident Detection Using Fuzzy ART. *Applications of Advanced Technologies in Transportation,* 1998. (59-65).

Kuhne, Reinhart D. Design of a Freeway Control System Based on Artificial Intelligence Methods for Travel Time Detection. *Fourth International Conference on Applications of Advanced Technologies in Transportation Engineering,* 1995. (439-443).

Lamble, Dave; Tatu Kauranen; Matti Laakso; Heikki Summala. Cognitive Load and Detection Thresholds in Car Following Situations: Safety Implications for using Mobile (Cellular) Telephones while Driving. *Traffic Research Unit:* Helsinki, Finland, 1999.

Madanat, Samer M.; Cassidy, Michael J.; Teng, Hua-Liang. Decision-Making System for Freeway Incident Response Using Sequential Hypothesis Testing Methods, *Transportation Research Record 1554 (228-235),* TRB, National Research Council, Washington D.C., 1996.

McKnight, James A; McKnight, Scott The Effect of Cellular Phone Use upon Driver Attention. *National Public Services Research Institute* 1991.

Mussa, Renatus N. Modeling Detection of Incidents by Drivers. *Transportation Research Part–C.* 1998. (129-139).

Nathanail, Teti; Kostas, Zografos. Simulation of Freeway Incident Detection Using Artificial Neural Networks. *Vehicle Navigation & Information Systems Conference.* Institution of Electrical and Electronic Engineers, 1994. (2683-2686).

Okutani, Iwao. Dynamic Prediction of Traffic Volume through Kalman Filtering Theory. *Transportation Research –B.* Vol. 18B No. 1, 1984. (1-11).

Park, Byungkyu. Clustering Based RBF Neural Network Model for Short-term Freeway Traffic Volume Forecasting. *Applications of Advanced Technologies in Transportation.* 1998. (280-287).

Payne, Harold J., Development and Testing of Operational Incident Detectionn Algorithms: Executive Summary. Federal Highway Administration, ITS Research Division. Turner-Fairbank Highway Research Center. 1997.

Peeta, Srinivas; Das, Debjit. Continuous Learning Framework for Freeway Incident Detection. *Transportation Research Record 1644 (124-131),* TRB, National Research Council, Washington, D.C., 1998.

Ritchie, Stephen G.(Univ. of California); Stack, Robert. A real time expert system for freeway incident management in Orange County, CA. *Proceedings of the Fifth International Conference on Computing in Civil and Building Engineering.* ASCE. 1993. (607-613).

Skabardonis, Alexander; Chira-Chavala, Ted; Rydzewski, Daniel. The I-880 Field Experiment: Effectiveness of Incident Detection Using Cellular Phones. CALIFORNIA PATH PROGRAM; Institute of Transportation Studies.University of California Berkley. 1998.

Sugimoto, Futoshi., Toyabe Toru. An Analysis of Human Error in Skill Task and Visual Recognition. Toyo University. Department of information and Computer Sciences.

Sullivan, Edward C. Estimating Accident Benefits of Reduced Freeway Congestion. *Journal of Transportation Engineering.* Vol. 116. Num. 2 (167-181). ASCE. 1990.

Tavana, Hossein, Mahmassani, Hani S., Haas, Carl C. Effectiveness of Wireless Telephones in Incident Detection. *Transportation Research Record 1683.* 2000. (31-37).

Versavel, Jo, Boucke, Bart. Video for Traffic Data and Incident Detection for Traficon. *Applications of Advanced Technologies in Transport.* 1998. (33-40).

Violanti, John M. Cellular Phones and Fatal Traffic Collisions. *Rochester Institute of Technology* 1997.

VRPA Technologies. Evaluation of the Enhanced Traffic Monitoring Program—"Smart" Call Box Pilot Program. VRPA Technologies. 1999.

Zifeng, Jiang. Macro and Micro Freeway automatic Incident Detection Methods Based on Image Processing. IEEE. 1997. (344-349).