EVALUATION OF AID SYSTEMS USING THE AID CAAT

EVALUATION OF AUTOMATIC INCIDENT DETECTION SYSTEMS USING THE AUTOMATIC INCIDENT DETECTION COMPARISON AND ANALYSIS TOOL

By

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ABSTRACT

This thesis presents a new testbed for Automatic Incident Detection (AID) systems that uses real-time traffic video and data feeds from the Ministry of Transportation, Ontario (MTO) COMPASS Advanced Traffic Management System (ATMS). This new testbed, termed the AID Comparison and Analysis Tool (AID CAAT), consists largely of a data warehouse storing a significant amount of traffic video, the corresponding traffic data and an accurate log of incident start/end times. An evaluation was conducted whereby the AID CAAT was used to calibrate, and then analyze the performance of four AID systems: California Algorithm 8, McMaster Algorithm, the Genetic Adaptive Incident Detection (GAID) Algorithm and the Citilog - VisioPAD. The traditional measures of effectiveness (MOE) were initially used for this evaluation: detection rate (DR), false alarm rate (FAR), and mean time to detection (MTTD). However, an in-depth analysis of the test results (facilitated by the AID CAAT) revealed the need for two additional MOEs: False Normal Rate and Nuisance Rate. The justification and sample calculations for these new MOEs are also provided. This evaluation shows the considerable advantages of the AID CAAT, and also suggests the strengths and weaknesses of the AID systems tested.

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1.0 Introduction

1.1 Research objectives

The purpose of this research is to develop a testbed to analyse and compare the operation of Automatic Incident Detection (AID) algorithms and platforms (i.e. AID Systems) and to conduct an evaluation on four AID Systems. Development of an AID comparison and analysis tool (AID CAAT) entails two key development initiatives: a) the development of a means to collect and store video and traffic data suitable for the purposes of testing and, b) the development of a user interface to set-up and run tests and to generate reports based on the prescribed measures of effectiveness. The purpose of the evaluation is to demonstrate the effectiveness of the AID CAAT and to better understand the pros and cons associated with the various AID System techniques in real-world circumstances.

1.2 Background

Freeway incidents cost North Americans billions of dollars a year in lost productivity, property damage, and personal injuries (Mahmassanni, Haas, Zhou, and Peterman, 1999). Incidents account for more than 60% of urban freeway congestion (Lindley, 1987). In a 1996 report, the Federal Highways Administration (FHWA) projected that by the year 2005, incidents will cause 70 percent of all urban freeway congestion costing road users as much as $35 billion (Gordon, 1996). Intelligent Transportation Systems (ITS) and specifically Advanced Traffic Management Systems (ATMS) play a crucial role in mitigating this problem.

The primary responsibilities of an Advanced Traffic Management System (ATMS) are to detect and verify traffic incidents as quickly as possible, to reduce incident response/clearance times, and to disseminate traffic information to the public. AID systems should play an integral role in achieving these objectives. However, many transportation agencies are looking towards other alternatives such as incident call-in-centres and freeway patrollers (Mussa and Upchurch, 2001). The migration away from the traditional AID systems is occurring because in real-world AID system deployments, the rate of false alarms is too high and/or the incident detection rate is too low. There exists a trade-off between the AID system's ability to detect incidents, the rate of false incident detections, and the speed at which the AID systems detect incidents. In addition, there are costs associated with deployment and maintenance of AID systems (e.g. traffic sensor infrastructure, software development) that transportation agencies must consider when deciding which AID system to use. These facts suggest that more rigorous testing is required of the existing AID systems to clearly understand their shortcomings, develop detailed implementation/deployment guidelines and to propose modifications to improve real-world AID system performance.

Much of the research done to date has focused on the introduction of newer algorithms with fairly rudimentary performance evaluations. The test conditions in these evaluations can vary significantly (e.g. traffic simulation vs. real-data testing, duration of tests, test location specifics, percentage composition of incident versus incident-free test data, inconsistencies with measures of effectiveness and environmental conditions) such that it is difficult to make a performance comparison among the various algorithms (Petty, Bickel, Kwon, Ostland, and Rice, 2000).

Further, the evaluation techniques used in prior research are often flawed due to practical limitations. For instance, traffic simulation models offer the flexibility to test AID algorithm performance under different circumstances (Hellinga, Rakha & Van Aerde, 1997). However, the ability of the traffic simulation model to accurately simulate incident traffic conditions has been questioned (Payne, 1997). Some researchers have used real traffic data (i.e. offline testing) in their evaluations. While this is the preferred technique, problems can occur as the incident logs developed by either traffic operators or local authorities often have inaccurate incident start/stop times. Moreover, the traffic video feeds that could be used to correct this inaccuracy are typically not recorded or made available to the researchers. Online tests have also been conducted in the past (i.e. the algorithm is set up and evaluated in an actual traffic operations centre), however the traffic video associated with false alarms is often neglected. These video segments could potentially provide valuable insight into the factors affecting the AID algorithms performance.

There is clearly a need for a new AID system testing platform that provides: a standardized set of measures of effectiveness, the means to record and store real traffic data and the corresponding traffic video, and the means to automatically log and provide reports on the performance of AID systems being tested.

1.3 Feasibility

Online testing and analysis is the preferred technique for evaluating AID systems, however opportunities are rare as there is the concern that such efforts may intrude on the daily operation of the traffic management centres. The exposure of AID systems to a real-world testing environment could potentially reveal opportunities for significant improvement and identify prospects for further research. The University of Toronto ITS Centre and Testbed provides a unique opportunity for developing the AID CAAT.

The ITS Centre and Testbed is a research facility geared towards the development of ITS technologies and traffic control strategies. It resembles a typical traffic control centre with access to real-time video and data from the Ontario Ministry of Transportation (COMPASS), and City of Toronto (RESCU). It houses a twenty monitor video wall, 26 PCs and two fileservers capable of storing up to one year of traffic data. The ITS Centre and Testbed provides an environment for the AID

CAAT to operate in a manner non-intrusive to the daily operations of the local transportation authorities.

At the onset of the research initiative to develop the AID CAAT, the ITS Centre and Testbed was incomplete and required some communication infrastructure in order to access the real-time video and traffic data feeds from COMPASS and RESCU. Consequently, the development of the AID CAAT included the completion of the ITS Centre and Testbed. That effort is also documented in this thesis.

1.4 Organization of the thesis

The remaining four chapters of the thesis are organized as follows:

Chapter 2 reviews the existing literature related to AID algorithms and systems and the testing methodologies/techniques used in the past. The need for the AID CAAT is clearly established.

Chapter 3 describes the approach to developing the AID CAAT in detail. A brief description of the ITS Centre and Testbed is provided along with a description of the design upgrades necessary in order to facilitate the AID CAAT. A detailed description of the AID CAAT software and database is also provided.

Chapter 4 provides the details on the evaluation conducted with a description of the AID system calibration process and the data sets used in the evaluation. The traditional measures of effectiveness are used in the evaluation along with the introduction of two new performance measures. A detailed comparative analysis is provided that describes the apparent strengths and weaknesses of the different AID system techniques.

Chapter 5 contains the summary, conclusion and recommendations for future research.

2.0 Review of Present Literature

2.1 Introduction

The purpose of this chapter is to provide the justification and functional requirements for the development of a testbed for AID systems via a review of previous research literature. The intent of the literature review is to: provide an understanding of the different types of AID systems, review the evaluations conducted previously, and provide the arguments for developing a standardized platform for comparing and analyzing AID systems. Following the literature review is a set of functional requirements for the development of the AID CAAT.

2.2 AID system research and development

Research in the field of AID system development, testing and comparative evaluation dates back to the mid 1960's. Using combinations of upstream and downstream traffic measures (volume, speed and occupancy) many algorithm techniques have been proposed. The systems developed to date can be grouped into five categories based on similarities in technique:

- comparative algorithms,
- time-series algorithms,
- theoretical models,
- artificial neural network algorithms (ANN), and
- video-based incident detection.

The comparative algorithms (for example Payne & Tignor, 1978, Levin & Krause, 1979) use several thresholds to detect an incident based on an increase in the upstream loop detector's occupancy and a decrease in the downstream loop detector's occupancy following the onset of an incident. The time-series algorithms (such as those by Ahmed & Cook, 1982, Cook & Cleveland, 1974, Collins, 1983, Stephanedes

& Chassiakos, 1993) use statistical indicators derived from the traffic measures to describe normal traffic conditions and declare an incident when a significant deviation occurs between observed and normal traffic condition measures. Theoretical models such as the McMaster algorithm (Gall & Hall, 1989) use the relationship between volume and occupancy to classify the upstream and downstream traffic measures into different states (e.g. uncongested, congested, and incident). Advances in video image-processing have led to video-based incident detection systems as an alternative to using data from loop detectors (Michalopoulos, Jacobson, Anderson & DeBruycker, 1993, Blosseville, Morin & Lochegnies, 1993). Most recently, ANN algorithms (such as those by Cheu, 1994, Abdulhai, 1996, Ishak & Al-Deek, 1998, Teng, Martinelli & Taggert, 1999, Abdulhai & Ritchie, 1999, Jin, Srinivasan & Cheu, 2002, Roy, 2002, Karim & Adeli, 2003) have been introduced that use historic traffic data of incident/normal conditions for the purposes of incident/normal traffic pattern classification. Typically, for each new technique presented, an evaluation and/or performance comparison follows in the literature.

2.3 Previous AID system evaluations

Many of the earlier evaluations of AID systems were conducted online using real-time traffic data in traffic operations centres (Dudek, Messer & Nuckles, 1974, Levin & Krause, 1979, Payne, Heifenbein & Knobel, 1976, Payne, Goodwin & Teener, 1975). In each of these earlier attempts, the authors identified the fact that their algorithms exhibited high false alarm rates due primarily to random fluctuations in traffic patterns. One shortcoming of these early evaluations is the lack of recorded traffic video to support their findings. For example, they made speculations as to the factors affecting AID algorithm performance, but without traffic video, they were unable to identify any potential means for mitigation.

With advances in computer technology, many traffic operations centres began recording and storing their traffic data. Traffic data sets such as the ones from California freeways I-880, I-405 and SR-22 were made available to researchers for the purposes of calibration and testing of their AID algorithms offline. These particular data sets contain a significant amount of incidents that were logged either by the traffic operators or by the local police. Researchers such as Koppelman et al., 1996, Martin et al., 2001, Stephanedes et al., 1996 and more recently Roy, 2002 used these data sets in their evaluations. While using this data, Roy identified a discrepancy between the operator/police logged incident start times and the perceived incident start time based on visual inspection of the data. It was found that the operators logged the incident start time 5-10 minutes after the incident appears in the data. Without an accurate log of incident start times, any values reported for time-to-detection are questionable. Further, the composition of these data sets (i.e. the amount of data reflecting incident conditions versus recurrently congested traffic conditions) can produce biased results. In the aforementioned study, Roy also indicated that the composition of the data sets from freeways I5, I405, SR55, SR57, SR91 and SR22 only consists of the incident data, the data 30 minutes prior to the incident and the data 15 minutes following (i.e. there is no true reflection of the actual recurrently congested traffic conditions at each of these sites). Given this observation, it is questionable as to whether or not the test results generated from the use of these data sets would reflect the actual performance of the AID systems in daily operation.

Dynamic micro simulation models have been used for the purposes of AID algorithm testing (Cheu, 1994, Abdulhai, 1996, Abdulhai & Ritchie, 1999, Cheu, Qi & Lee, 2002, Karim & Adeli, 2003). Traffic simulation models serve as a good tool for the development and testing of AID algorithms because they allow for testing under various conditions whereby the actual incident start/end time is known. However, Payne, 1997 concluded that it is very difficult for micro simulation models to accurately model incident conditions. They argue that driver behaviour under freeway incident circumstances is hard to predict and accurately model. By that same logic, traffic simulation models may also have difficulty in modelling recurrent congestion conditions (i.e. due to highly variant driver characteristics and behaviour). Given these considerable concerns, the results reported by researchers using traffic simulation models may not necessarily reflect their AID algorithm performance in the real-world context. Further, micro simulation models cannot be used to test video-based AID systems.

Video-based AID systems are still relatively new to North American traffic operations centres in that there is not yet wide-scale deployment. There have been a couple of video-based AID systems evaluations (Michalopoulos, Jacobson, Anderson & DeBruycker, 1993, Blosseville, Morin & Lochegnies, 1993) however, no side-by-side comparisons with inductive loop-based systems have been made to date.

2.4 Inconsistencies associated with the typical measures of effectiveness

The detection rate (DR), false alarm rate (FAR), and mean time to detection (MTTD) are commonly used throughout the previous research literature as the basis for assessing and comparing the performance of AID systems. However, there are a number of inconsistencies in how these MOE are implemented throughout the research literature. In principle, these performance measures are calculated as follows:

$$\textit{Detection Rate (DR)} = \frac{\textit{the total number of correct incident detections}}{\textit{the total number of incidents in the data set}} \qquad \textit{(Eq. 2.1)}$$

$$\textit{False Alarm Rate (FAR)} = \frac{\textit{the total number of false incident observations}}{\textit{the total number of observations in the test data set}} \qquad \textit{(Eq. 2.2)}$$

$$\textit{Mean Time to Detection (MTTD)} = \frac{\sum(\textit{AID incident start time} - \textit{actual incident start time})}{\textit{the total number of incidents detected}} \qquad \textit{(Eq. 2.3)}$$

One of the largest discrepancies between evaluations stems from the respective author's definition of an incident. For example, some authors choose to distinguish incidents that occur in the freeway shoulder or during off-peak hours (e.g. Stephanedes & Hourdakis, 1996, Stephanedes & Chassiakos, 1996) because of the minimal impact that they have on traffic (i.e. undetectable by most AID algorithms). Some researchers (such as Payne et al, 1977, Hall, Shi, Atala, 1993) include these types of incidents which may account for their reporting lower DRs.

Further, inaccurate incident start/end time logs can significantly affect the calculation of the three performance measures. Per equation 2.1, DR is a function of the actual incidents within the data set (i.e. as defined by the start and end times). As shown in equation 2.2, FAR is a function of the number of false incident observations (i.e. as defined by the number of incident declarations made at time segments outside of the actual incident start and end times). Per equation 2.3, MTTD is directly a function of the actual incident start time. Operator logged incident start and end times, cannot be validated without the corresponding video. Moreover, while the incident start and end times can be discerned via manual inspection of the data, this task is complicated without having the traffic video.

In the research literature, there are variances in how FAR is calculated resulting in significant differences in the values reported. Payne et al, 1976 suggested that in order to provide some operational context to FAR, this performance measure should be presented as FAR/hour. This technique, though appropriate because it compensates for variances in the volume of data used in the test, yields a far lower FAR value. Some researchers do not use this technique making it difficult to make direct comparisons (e.g. Martin, Perrin & B. Hansen, 2001, Roy, 2002, Karim & Adeli, 2003).

Clearly, there are a number of inconsistencies associated with the use of these performance measures. These problems are due to variations on the definition of an 'incident event', inaccurate logging of incident start/end times, and inconsistencies with respect to the application of the performance measures (e.g. FAR). Some of the inconsistencies could be alleviated through the use of a consistent definition of an 'incident event'. Further, traffic video recordings could be used to accurately and consistently log the actual incident start and end times. In addition, if the incidents were logged to a database via their start/end times, therein lies the possibility to uniformly apply the performance measure calculations to all AID systems being tested.

2.5 Need for the AID CAAT

For the practitioner surveying this previous research, no single, clear-cut, AID algorithm approach appears to stand out as the best. The problem is due in part to the fact that the test conditions vary significantly in each study (e.g. traffic simulation vs. real-data testing, duration of tests, and test location specifics) such that it is difficult to make a performance comparison between the various algorithms (as identified by Petty, Bickel, Kwon, Ostland, and Rice, 2000). In addition, poor composition of the test data in previous evaluations may have led to the reporting of results that do not necessarily reflect the operation of the AID system in the real-world. Further, there are inconsistencies with respect to the application of the traditional measures of effectiveness from one evaluation to another.

There is a need for a new testing platform that allows for comparative analyses between the AID system techniques. In addition, the development of a testing/calibration data set that contains a significant amount of incident data and recurrently congested data reflecting normal circumstances is crucial to this effort. Given the various issues and concerns mentioned with regards to previous evaluations and testing methodologies, the functional requirements for the new testing platform can be defined.

2.6 Summary

The review of previous research literature raises significant enough questions to warrant further and more rigorous testing of AID systems. The AID CAAT is proposed as a new testbed to facilitate this need. Identification of the deficiencies with previous evaluations helps in clearly identifying the functional requirements and key features necessary for this new testbed. The following chapter details the design for the AID CAAT in fulfilling the functional requirements specified.

3.0 The Approach

3.1 Introduction

The purpose of this chapter is to provide a detailed description of the AID CAAT and the design for the hardware and software required to facilitate its operation. The AID CAAT was the first application of the University of Toronto – ITS Centre and Testbed (ITS Centre) to make full use of the real-time video and traffic data feeds offered by the MTO – COMPASS and City of Toronto – RESCU systems. As a result, the AID CAAT's functional requirements became the driving force behind the design changes proposed for the ITS Centre. In describing the overall approach taken to develop the AID CAAT, this chapter is divided into four major sections: functional requirements for the AID CAAT, modifications to the ITS Centre design in preparation for the AID CAAT, the AID CAAT system design, and using the AID CAAT.

3.2 Functional requirements for the AID CAAT

Prior to designing the AID CAAT in detail, it is necessary to identify the functional requirements for the system. The AID CAAT's functional requirements identify specific features of the testbed that should alleviate the inconsistencies associated with previous evaluations conducted by other researchers. The following key functional requirements are identified for the AID CAAT.

- *The AID CAAT should allow for the specification of test areas (i.e. from traffic sensor station A to X)* – The length of the test area, freeway geometry and freeway grade all potentially affect the performance of the AID system. In order to conduct controlled experiments with AID systems, the researcher needs to have the ability to test the AID systems on specifically defined segments of freeway.
- *The AID CAAT should be capable of simultaneously testing and logging the operation of each of the AID systems* – If the specific evaluation requires online

testing (i.e. real-time video or data is fed to the AID system and the performance is checked afterwards), then the AID CAAT must have the ability to simultaneously serve the real-time data to each of the AID systems being tested and record their results.

- *The AID CAAT should be capable of viewing the recorded freeway traffic video corresponding to both correct incident detections and false alarms* – This feature is critical as it allows for the accurate assessment of the incident start time for calculation of DR and TTD. Moreover, it facilitates the testing of video-based AID systems. In addition, video pertaining to false alarms may prove valuable in understanding the factors that affect the performance of the AID systems.
- *The AID CAAT should allow for the development of a user defined, confirmed incident log based on the recorded video* – The AID CAAT needs to record video from the entire test period to allow the researcher to accurately log incident start and end times as a ground truth for testing purposes.
- *The AID CAAT should include a database component that maintains the AID algorithm performance records* – This feature is important as it allows for the generation of automatic routines, using standard database queries, to calculate the performance measures. It would also facilitate the addition of qualifications to the performance measures (e.g. incidents not caught by the AID systems that occurred during off-peak hours).

3.3 The ITS Centre and Testbed

The ITS Centre was originally proposed to obtain and display twenty real-time video feeds from the local transportation agencies. Specifically, ten CCTV camera feeds were to come from the COMPASS system and similarly ten from the RESCU system. In addition, the ITS Centre was to receive real-time traffic data feeds and the capability for remote camera selection. The traffic data was to be stored in a large data archive capable of maintaining up to one year's worth of data. A VCR was proposed for the purposes of short-term video storage and for presentations in the lab. The following sections detail the modifications required to facilitate the AID CAAT.

3.3.1 Communication design topology

When the research initiative to develop the AID CAAT started, agreements were in place with the MTO and the City to provide access to the video and data. An agreement was also in place with Toronto Hydro to construct the fibre optic cable link between COMPASS, the University of Toronto, and RESCU. However, additional communications infrastructure was required in order to transmit the video and data over the fibre optic communication links. In order to determine the most suitable equipment for this task, a communication network design was required that met the needs of both the ITS Centre and moreover the AID CAAT.

Toronto Hydro was to provide two, single pair, single mode, fibre optic links: one 33km link from the ITS Centre to the MTO, and one 28km link from the ITS Centre to the City's RESCU Traffic Operations Centre. The communications room of the ITS Centre had Bell communication facilities in place making it fairly simple to implement voice-grade or Digital Subscriber Link (DSL) communications if necessary. With these facilities in place, a "one-way" communication design was initially proposed as the means to receive video and data from COMPASS and RESCU.

The "one-way" communication design proposed the utilization of two communication technologies. As shown in Figure 3-1 below, the video would be transmitted over the fibre optic path via a video multiplexer and demultiplexer with the camera selection and traffic data over two 128kbps DSLs. In this design topography, the camera video channels and traffic-data feed in to the ITS Centre while the two camera-selection data links feed out to the MTO and City. This technique was initially proposed as the Ministry and the City already had significant implementation experience of this nature for other traffic video/data subscribers (e.g. television media, radio).

There were a number of problems associated with this design in the context of the proposed AID CAAT. The FDVM products surveyed at the time provided very high quality video, however they were only capable of carrying nine camera channels per fibre whereas ten channels were required. In addition, given the significant length of the communications path, signal repeaters would have been required thus increasing the cost for this alternative. Separate leased communication lines would have been required for the traffic-data feed and remote-camera-selection operations. The costs for the service and maintenance for these four communication lines also had to be considered.

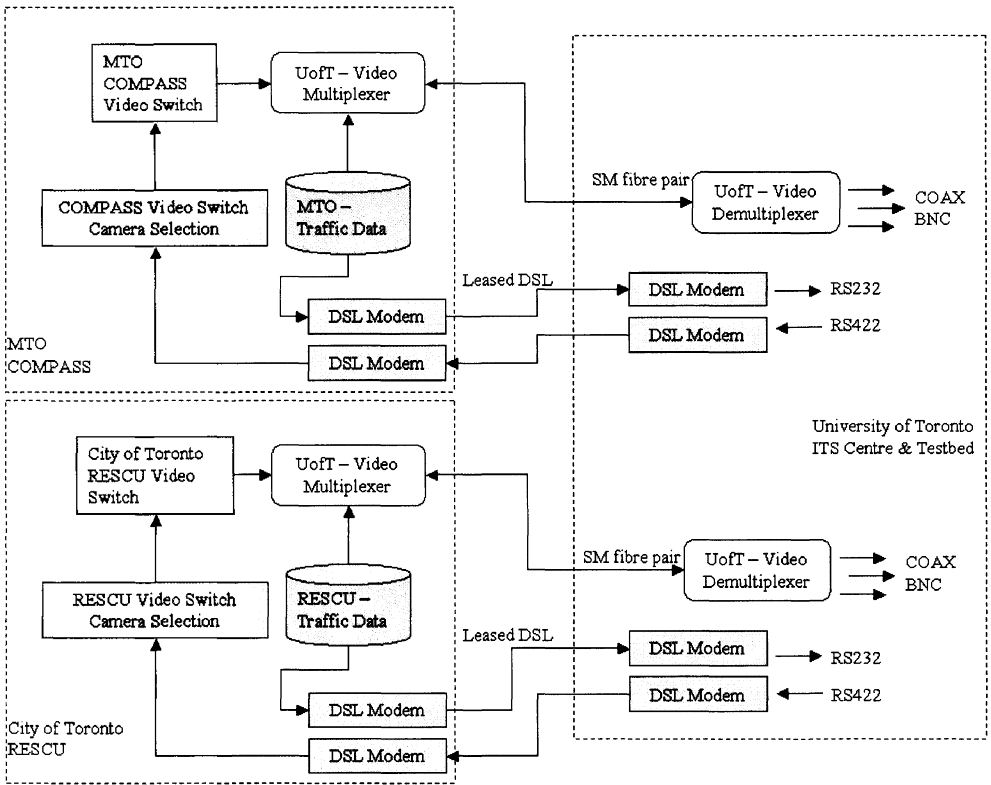


Figure 3-1 The initially proposed one-way communication design

Further, the AID CAAT requires a high bandwidth data link to ensure fast, if not instantaneous transmission of traffic data. Given the significant amount of data anticipated from COMPASS and RESCU (i.e. traffic data at the finest resolution – 20 seconds, for each inductive loop within each station), the 128kbps DSL would not have sufficed. In addition, the AID CAAT requires very high quality video for testing video-based incident detection systems. These system requirements became the motivation to develop a more robust communication design topography. I proposed the use of a ubiquitous drop/insert communication ring.

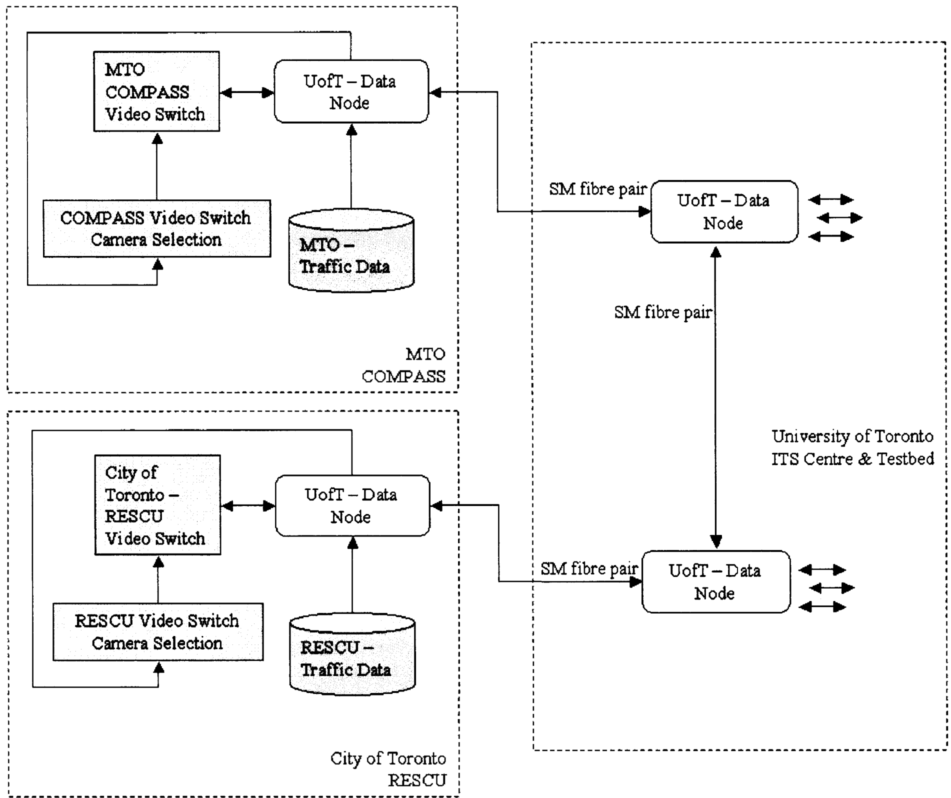


Figure 3-2 The ubiquitous drop/insert communications ring design

As shown in Figure 3-2 above, the ubiquitous drop/insert ring is comprised of four data nodes interconnecting the three centres. As the name implies, data can be "inserted" or added at any node on the ring. Similarly, data can be "dropped" or extracted at any node along the ring. Unlike the one-way communication design, the CCTV video is digitised and combined with the traffic data and remote camera selection control data such that there is no need for any additional communication lines. This design topology makes far more efficient use of the fibre optic bandwidth. The "off-the-shelf" data node products available possess data throughput capacities ranging from 400Mbps to 2Gbps (i.e. well in excess of the University's current needs).

Upon deciding to proceed with the new communications design, an extensive product search was conducted to source the data nodes that would be used. A detailed cost vs. features comparison was conducted and the Siemens Open Transport Network product (OTN) (Siemens Canada, Mississauga, Ontario) was selected, as it was best suited for this specific design. The University acquired the data node equipment and with the combined assistance of the Siemens, Toronto Hydro, COMPASS and RESCU technical staff, the system was made operational. The communications network was brought officially online March 31st, 2003 at a ceremony officiated by then Federal Transport Minister, Hon. David Collenette.

3.3.2 ITS Centre developments in support of the AID CAAT

The functional requirements for the AID CAAT necessitated the development of two additional components for the ITS Centre. These new components were designed in a generic fashion such that they could be reused for other research projects. The two new components listed below are described in detail in the following sections.

- The Central Database Server – The central database server stores all the traffic data received from COMPASS and RESCU.

- The Digital Video Recording System (DVRS) – The DVRS records all of the real-time video feeds from COMPASS and RESCU.

3.3.3 The Central Database Server

Traffic data from COMPASS and RESCU are fed into the ITS Centre and stored in this central database server. The data provided from the traffic operation centres includes freeway vehicle detector station (VDS) data – volume, speed and occupancy, changeable message sign (CMS) messages and operator logged incidents.

The central database server is an IBM Netfinity 5600 server with a 933MHz Pentium III processor. Currently the server is running Windows 2000 Server and MySQL Database Server. A specialized program was developed that listens to the serial ports where real-time traffic data from COMPASS and RESCU are being fed, and logs the traffic data into the database. As a side product, it also generates web pages to allow easy visualization of the real time data. The central database server can be accessed by any of the machines on the ITS Centre network or via the Internet.

3.3.4 The Digital Video Recording System

To adequately meet the needs of the AID CAAT, a digital video recording system (DVRS) was developed to replace the originally proposed VCR. An extensive product literature search was conducted to find off-the-shelf DVRS equipment capable of storing multiple video channels, at high quality, for long durations of time. While a few product alternatives were found, the combined cost of the necessary equipment was in excess of $100,000. The University did not anticipate this expenditure and it became necessary to pursue other alternatives.

An in-house DVR system was developed comprised of video capture software, PCs, and off-the-shelf computer components. In order to simultaneously record twenty video feeds, 10 PCs were required with two video-capture cards in each. Each of the 10 PCs had 120GB hard drives installed to store approximately two weeks of video data (i.e. one week per video channel). Given the constraints of the computer's processing power, it was not possible to view recorded video at the same time that the PC is recording live video. Thus, a "Master" DVR (MDVR) was proposed as an independent server to the stored video files.

The MDVR PC includes a 240GB hard drive, a DVD burner, and a video card capable of VGA to NTSC video conversion. The MDVR allows for the playback of recorded video on any of the ITS Centre computers or the main room projector. The 10 DVR PCs are networked together via a local switch with the MDVR PC acting as a gateway to the ITS Centre local area network and the Internet. In this design, the AID CAAT is capable of controlling the complete DVRS remotely.

3.4 The AID CAAT Software

As the name implies, the AID CAAT is a comparison and analysis tool that facilitates the process of rigorous online and offline testing of AID algorithms and systems using real traffic data and video. The AID CAAT itself is a series of software components that make full usage of the central database server, and the DVRS via a remote and/or local network interface. The five software elements comprising the AID CAAT are:

- The AID CAAT Graphical User Interface
- The AID CAAT Database
- The AID CAAT Report-Scripts Library
- The AID CAAT Dispatcher
- The AID Algorithm/System Interface

The following sections describe each of the software components in more detail.

3.4.1 AID CAAT Graphical User Interface

The AID CAAT Graphical User Interface (GUI) is the central software that allows the user to assess and interact with all of the other software components. It offers the user a fairly user-friendly environment to register AID algorithms/systems on the AID CAAT, create and run tests, view ongoing tests real-time, replay tests conducted previously, and create reports regarding either the test traffic data or the performance of the AID algorithms/systems.

3.4.2 AID CAAT Database

The AID CAAT Database is a database of tables pertaining specifically to the AID CAAT operation. In general, the AID CAAT Database contains tables pertaining to the registered AID algorithms/systems, test areas, confirmed incident logs, and traffic state classifications as logged by the AID algorithms/systems being tested.

The AID CAAT Database physically resides on the central database server and hence, each of the tables and variable fields can be accessed both locally and remotely. Table 3-1 below describes each of the tables in the AID CAAT Database in more detail:

Table 3-1 AID CAAT Database Table Descriptions

Table Name	Variable Fields	General Description
algorithms	algorithm_id description icon host_ip	This table contains all the information pertaining to the AID systems registered on the AID CAAT. While some of the variables are optional (e.g. **icon**), the **host_ip** variable is the most important as the system uses this address to forward traffic data during a test.
stationpairs	stationpair_id us_vdsid ds_vdsid	The "station pair" is the basic unit of study in the AID CAAT and is a reference for the specific highway segments being examined. This table contains the information pertaining to upstream and downstream traffic sensor stations defining each highway segment.

testareas	testarea_id testname description locationmap running starttime endtime	This table contains all the information pertaining to test areas specified by the user. Each test area is comprised of a set of **stationpairs** with all other variables being optional.
confirmedincidents	confirmedincident_id stationpair_id starttime endtime	This table contains the location and start/stop times for each of the incidents (confirmed via the CCTV recordings) within the traffic data. After a test is complete, the user can view the recorded video and fill in this table via the AID CAAT GUI software.
algorithmresults	algorithmresult_id aidalgorithm_id stationpair_id timestamp trafficstate interpretation	This table contains interval-by-interval traffic-state classifications for each AID system for each test conducted. The **algorithmresults** table is queried against the **confirmedincidents** table to assess the AID system performance.
mtocameras	cameraurl mtocamera_id camerafile cameraname	This table stores information regarding the COMPASS CCTV cameras available for use on the system.
stationpairmtocamera	stationpair_id mtocamera_id	This is a "join" table that relates CCTV cameras to **stationpairs.** The **camera_id** values relate to the actual camera channel numbers used by the MTO.
algorithmtestareas	algorithm_id lasttimestepsent testarea_id	This is a "join" table that is used by the system to indicate the algorithms are assigned to each test area.
testareastationpairs	testarea_id stationpair_id	This is a "join" table used by the system to link station pairs with specific test areas.

3.4.3 AID CAAT Report Scripts Library

The AID CAAT has the capability to provide reports on the test traffic data statistics (e.g. 24hr volume plots, 24hr volume vs. occupancy plots, number of incidents in the data set, severity of incidents, weather conditions) and on AID system performance (e.g. detection rate, false incident rate, mean time to detection) via the

Report-Scripts Library (RSL). The RSL file directory consists of a generic set of Personal-Home-Page Hypertext Pre-processor (PHP) scripts that generate these standard reports as Hypertext Mark-up Language (HTML) pages that can be viewed locally, remotely and/or printed to hard copy. These PHP scripts access and process the necessary data from the central database sever via standard SQL queries. While this process can be done manually, the AID CAAT GUI provides a simple means for the user to select and generate reports from the RSL. It is foreseeable, that the user may require a report beyond the scope of the standard RSL. Through combined use of PHP and the MySQL central database server the user has the option of generating new reports. Once the new report is generated using PHP script and then copied to the RSL directory, the new report will automatically appear as an option in the AID CAAT GUI software. Conversely, deleting report-PHP files from the RSL will result in the automatic removal of that specific report option from the AID CAAT GUI.

3.4.4 AID CAAT Dispatcher

The AID CAAT Dispatcher is a separate process that serves the traffic data to the registered AID algorithms/systems then listens and records the respective traffic state classifications to the '**algorithmresults**' table. The Dispatcher is designed to facilitate offline testing, online testing and combinations of both via the user-defined test start and end times as described below.

- **Offline testing** – By setting the test start/end times in the past, the dispatcher will automatically serve this historic data to the prescribed AID algorithms.
- **Online testing** – By setting the test start/end times to future dates, the system will wait until the traffic data pertaining to the start time arrives in the central database server and proceed with the test.
- **Offline/Online testing** – It is also possible to specify the start time in the past and the end time in the future. In doing so, the Dispatcher will serve the historic data

automatically until it reaches the current time. As new data arrives, it will continue to serve until the end time data arrives and the test is complete.

While all other AID CAAT software modules can be started or stopped (e.g. the AID CAAT GUI) it is critical for the Dispatcher to remain running at all times. If the Dispatcher is stopped, the system will not serve traffic data and consequently, traffic state classifications cannot be logged.

3.4.5 AID CAAT AID System Interface

The AID System Interface is the software module that physically links the Dispatcher to each of the respective AID algorithms/systems being tested. For each AID algorithm/system being tested, a separate unique AID System Interface needs to be coded. The AID System Interface itself is a generic set of Java code that can be readily modified. It is important to note that while the Interface is coded in Java, the AID algorithms/systems themselves can be coded in any format (e.g. Fortran, C, C++, Visual Basic, Visual C, Java, J++).

3.4.6 Interaction between the AID CAAT Components

The AID System Interface, the Dispatcher and the Central Database Server all interact in order to serve traffic data to the test AID algorithms/systems and to log each of the traffic state classifications. The following outlines the steps required for the AID CAAT to serve traffic data to an AID algorithm as shown in Figure 3-3 below.

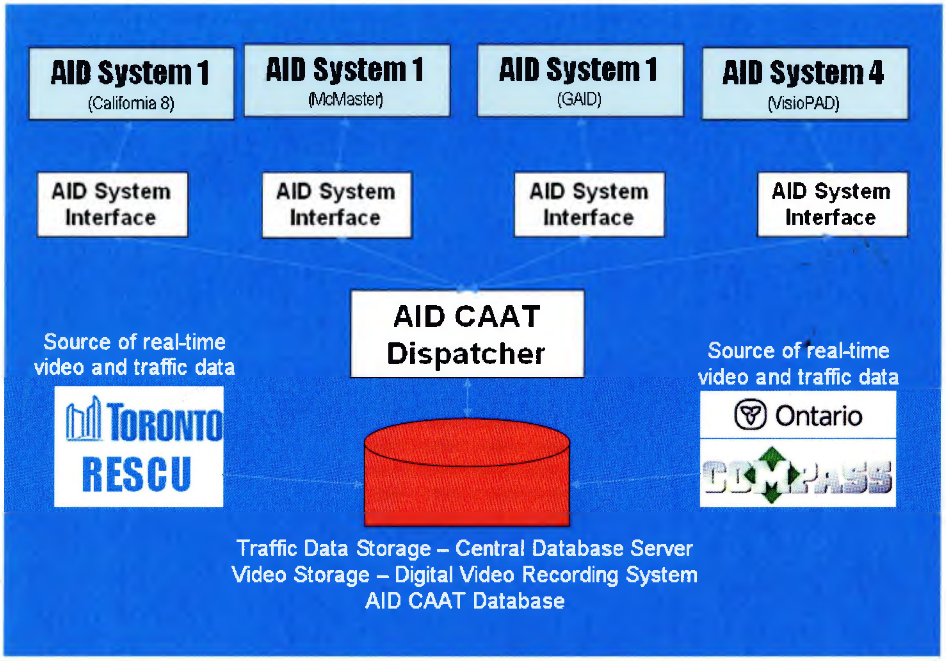


Figure 3-3 Schematic showing relationship between AID CAAT components

1. The AID CAAT Dispatcher looks for tests that have been started or underway in the AID CAAT Database.
2. The AID CAAT Dispatcher then reads the names of the VDS pairs that have been assigned to each test in the '**testareas**' table.
3. The AID CAAT Dispatcher then creates a vector of traffic data based on the actual traffic data values extracted from the central database server.
4. The AID CAAT Dispatcher then reads the location of the AID System Interface for each AID algorithm/system from the '**algorithms**' table.
5. The AID CAAT Dispatcher then creates multiple instances of the AID System Interface (i.e. one for each algorithm) and serves the identical vector of traffic data for each instance.

6. Each AID System Interface decodes the vector of traffic data and passes the required data (e.g. upstream/downstream volume, speed, occupancy) to it's respective AID algorithm/system.
7. The AID algorithm/system processes the traffic data and returns the traffic state classification (e.g. 1 = incident, 0 = normal) to the AID System Interface.
8. The AID System Interface returns the traffic state classification to the Dispatcher.
9. The AID CAAT Dispatcher writes the traffic state classification to the '**algorithmresults**' table with reference to the time, location, and AID system/algorithm that made the declaration.

3.5 Using the AID CAAT

The AID CAAT can be used for a wide variety of applications ranging from calibration, fine-tuning and testing of an AID system to quantitatively assessing the external factors that affect AID system performance. The system is designed to handle multiple tests simultaneously with the possibility of investigating different sets of AID systems on different sets of data. The AID CAAT can serve historic data and/or current data to any of the registered AID systems and allow the user to view the traffic state classifications both real-time and offline. The AID CAAT can also be used to generate standard AID system performance reports, generate test-data statistical reports, and generate custom-made reports as defined by the user.

3.5.1 Registering an AID System on the AID CAAT

Registering an AID System on the AID CAAT is a two step process which entails: coding a unique AID System Interface (in Java) and creating a "New AID System" using the AID CAAT GUI. Details with regard to the development of the AID System Interface are outlined in Appendix A.

Once this task is completed, the AID CAAT GUI can be used to create a new AID System. As shown in Figure 3-4 below, the AID CAAT GUI allows the user to enter values such as the name of the algorithm, a brief description of the algorithm, and most importantly the "Host IP". It is important to note that the "Host IP" field specifically requires the address of the unique AID System Interface and not the AID System itself. The user should enter the directory path and class name (e.g. AIDInterface) in this field. This interface also allows the user to assign an icon to the AID system. Though this feature is not mandatory, it is a useful reference aid as the icon will appear whenever the AID CAAT presents information pertaining to that specific AID system.

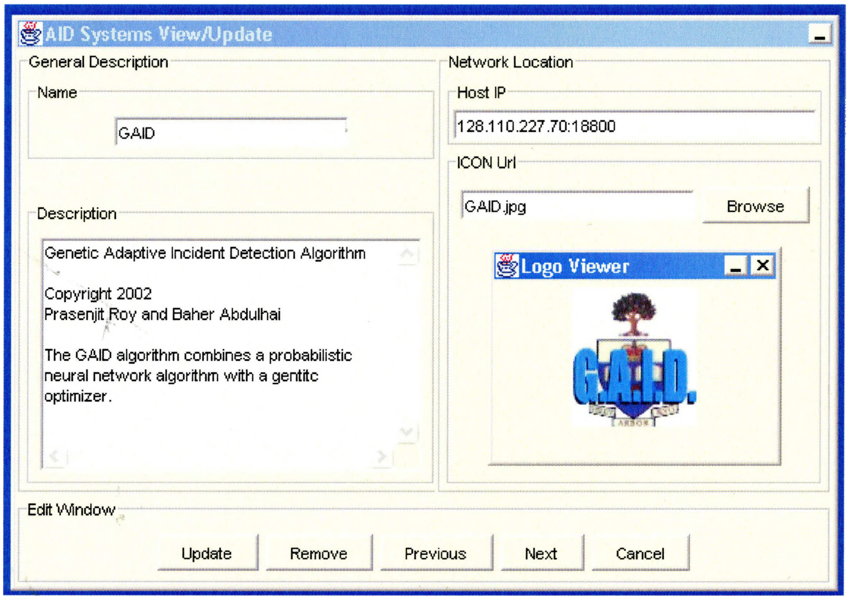


Figure 3-4 Registering a new AID system on the AID CAAT

3.5.2 Online and Offline Test Viewing

The AID CAAT allows the user to view any of the ongoing tests real-time as the AID systems receive and process the traffic data, and then return traffic state classifications.

Specifically, the AID CAAT online/offline viewer allows the user to change between viewing different tests and to display the following items as shown in Figure 3-5 below:

- the base map pertaining to the currently selected test;
- the real-time traffic data for the currently selected traffic sensor station pairs;
- the CCTV cameras pertaining to the currently selected traffic sensor station pairs;
- the AID system traffic-event-log window for the currently selected AID system pertaining to the currently selected traffic sensor station pairs.

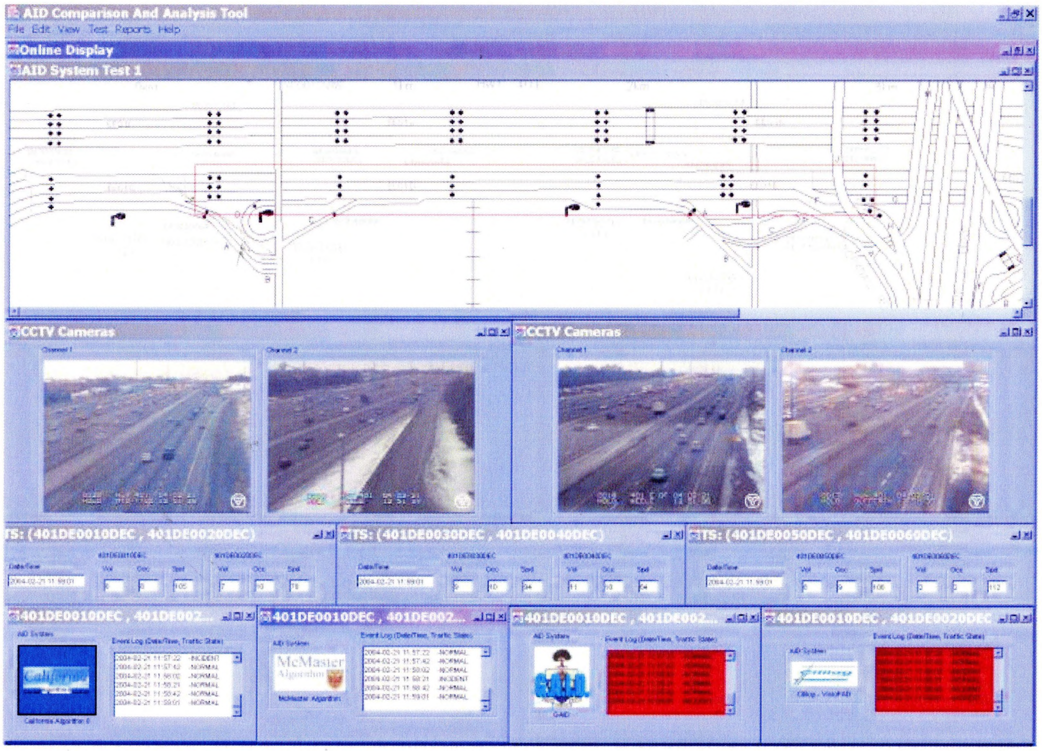


Figure 3-5 Screen shot from the AID CAAT online test viewing

3.5.3 Viewing Recorded Video & Recording Confirmed Incidents

The DVRS is always running and recording video from whichever cameras are defined by the AID CAAT. The user has the option of accessing and replaying video from any of the recorded video feeds through the AID CAAT GUI.

The AID CAAT requires manual confirmation and input of the confirmed incidents in order to automatically calculate the performance statistics such as detection rate, false alarm rate and mean time to detection. The AID CAAT GUI provides an interface for the user to log the exact dates and times that the incident started and ended.

3.5.4 Viewing Incidents and Incident Detections

Once a confirmed incident has been logged, the AID CAAT GUI can be used to generate a table displaying all the confirmed incidents within the AID CAAT Database. The log appears as a table with a "view" button appearing beside each entry. Clicking the view button will launch the recorded video pertaining to this incident playing one minute before and five minutes after the incident start/end times pre-specified by the user. An example is shown in Figure 3-6 below.

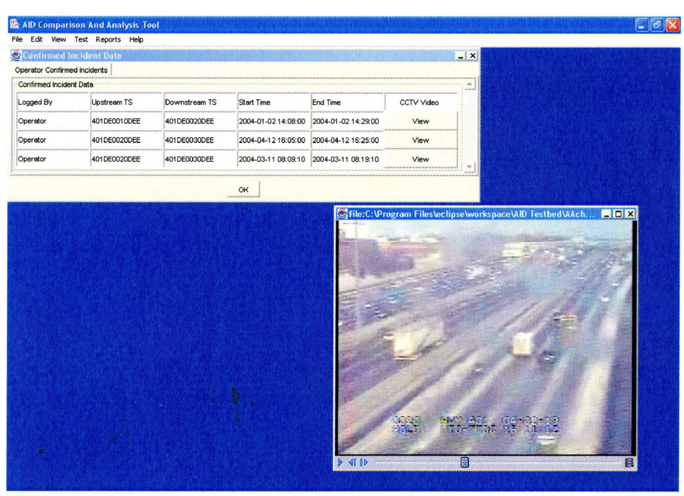


Figure 3-6 Viewing incidents logged on the AID CAAT

The video recordings are useful in determining the reasons surrounding missed incident detections (e.g. missed incident detection due to the incident having minimal impact on traffic). Similarly, the AID CAAT GUI allows the user to call and display tables showing all of the incidents detected by the AID systems. This feature is very useful for identifying the factors that cause false alarms.

3.5.5 Viewing Performance Statistics and Reports

One of the most important features of the AID CAAT lies in its ability to automatically generate reports. Through the use of advanced SQL queries to the Central Database Server and the AID CAAT Database, reports can be generated regarding the AID system performance and/or the test data.

A generic set of reports appears as menu options within the AID CAAT GUI. The AID CAAT allows for the development of customized reports. However, a basic set has been provided that reflects the traditional measures of effectiveness (detection rate (DR), false alarm rate (FAR), and mean-time-to-detection (MTTD)). Table 3-2 below summarizes the basic set of reports that can be generated by the system.

Table 3-2 Available Reports within the AID CAAT

	Report Classifications			
Report Type	Traffic Data	Confirmed Incident Data	Detected Incident Data	Performance Indices
Volume vs. Time	X			
Occupancy vs. Time	X			
Volume vs. Occupancy	X			
Speed vs. Density	X			
# of Incidents vs. Location		X	X	
# of Incidents vs. Time		X	X	
FAR vs. Location			X	
Standard MOEs				X
Incident Graphs				X

3.6 Summary

The AID CAAT was designed in a modular fashion to facilitate the testing of different types of AID systems (e.g. loop-based vs. video based). Moreover, the test data set can be easily changed (e.g. for testing AID algorithms that use probe-data), and the measures of effectiveness can be easily changed to meet the requirements of the specific test. With the completion of the AID CAAT and the new components of the ITS Centre, a pilot evaluation was conducted to demonstrate the effectiveness of the overall system.

4.0 The Pilot Evaluation

4.1 Introduction

In this chapter, a pilot test evaluation is presented to demonstrate the effectiveness of the AID CAAT in conducting a comparative analysis of AID systems. Four fundamentally different AID systems were chosen in order to illustrate the AID CAAT's ability to evaluate different types of AID algorithms and platforms. Specifically, the California algorithm 8, the McMaster algorithm, the Genetic Adaptive Incident Detection (GAID) algorithm, and the Citilog - VisioPAD were chosen for the evaluation.

This chapter is divided into five major sections: an overview of the evaluation and the calibration/test data used, a description of the algorithms and the calibration efforts undertaken, a description of the measures of effectiveness used in the evaluation, a comparative analysis of the test results, and a discussion summarizing the respective strengths and weaknesses of the four AID system techniques.

4.2 Evaluation overview

The pilot test was designed to evaluate the performance of four AID systems using real-time traffic video and data from the COMPASS system. The four AID Systems selected for the evaluation use significantly different techniques for incident detection (i.e. California 8 - comparative algorithm, McMaster - theoretical model, GAID - neural network classifier and Citilog-VisioPAD - video-based AID). The AID CAAT was instrumental in the evaluation process by providing the means for:

- collecting the CCTV video and traffic data for the test with incident start and end times logged via visual inspection of the recorded video;
- calibrating the algorithms prior to testing (using a different subset of the data than was used for testing);

- simultaneously serving traffic data to each of the AID algorithms while logging their respective responses; and,
- providing the final performance reports using the prescribed measures of effectiveness.

4.2.1 Definition of an incident

Prior to collecting data for the purposes of testing and calibration, it is imperative to provide a clear definition of an incident event. After discussion with MTO – COMPASS staff, it was agreed that an incident should be defined as any 'event' taking place on the freeway that causes a reduction in freeway capacity such as: vehicle collisions, stalled vehicles on the traveled portion of freeway, overturned vehicles and road debris. Stalled vehicles in the shoulder are only counted as incidents if it is perceived, via a review of the video recording or the traffic data, that they are causing a reduction in freeway capacity.

The onset or 'start-time' of the incident is the exact time at which the freeway capacity is reduced. The 'end-time' of the incident is the exact time at which the freeway capacity reducing incident is removed. For the video and traffic data collected by the AID CAAT, the incident 'end-time' can be clearly defined using the video recordings. Wherever the actual onset of the incident was not captured in the video recording, a standardized technique was employed to establish the 'start-time'. The technique depicted the incident on a graph of speed and occupancy versus time for the upstream traffic sensor station, as seen in Figure 4-1 below. At the onset of the incident, the speed drops sharply with a simultaneous surge in occupancy. For cases where there is no video, or the onset of the incident was missed, the last speed data point prior to the significant drop in speed is taken to be the onset of the incident.

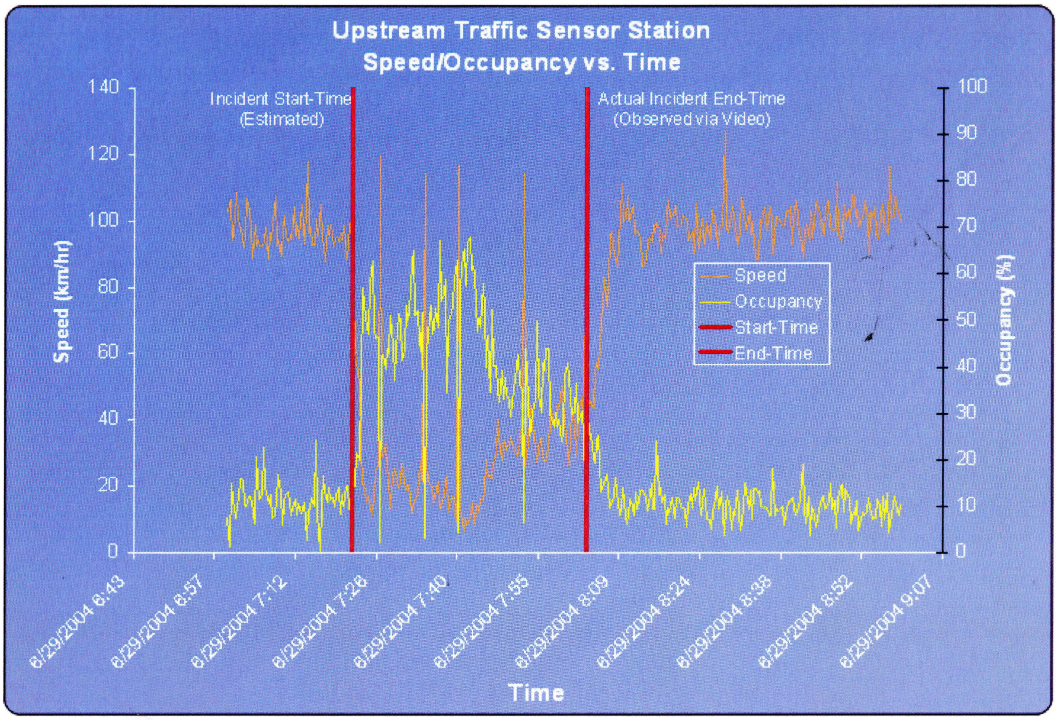


Figure 4-1 Incident depicted via upstream speed and occupancy

4.2.2 Measures of effectiveness

The AID CAAT's library of performance measures (i.e. Report Scripts Library (RSL)) contains the traditional measures of effectiveness: detection rate (DR), false alarm rate (FAR), and mean time-to-detection (MTTD). In addition, the "Percentage Correct Classification" (PCC) measures used by Roy and Abdulhai, 2003 were added to the AID CAAT's RSL.

Specifically, PCC refers to the percentage of correct incident classification (hereinafter referred to as $PCC_{Incident}$) and the percentage of correct normal classification (hereinafter referred to as PCC_{Normal}). Figure 4-2 below provides a sample calculation for DR, FAR, $PCC_{Incident}$, PCC_{Normal} and MTTD. Each of the rectangular boxes shown represents a traffic data-interval (i.e. discrete time interval from which volume, speed and occupancy data is polled). The AID systems can make decisions at an interval-by-interval basis however, in a real-world deployment, the traffic operator need only be alerted at the onset of the incident.

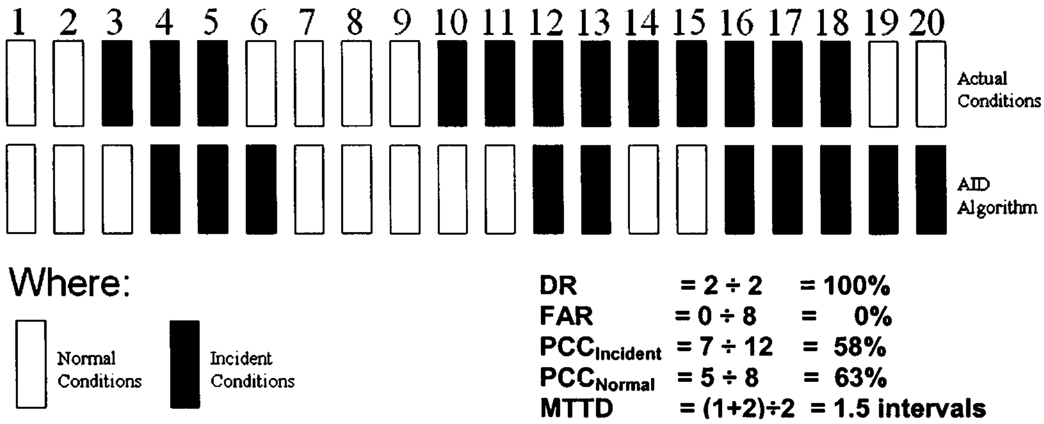


Figure 4-2 Measures of effectiveness - comparison of evaluation techniques

When conducting comparative evaluations of AID Systems, it is important that PCC measures be used appropriately. These measures are critical for the calibration of neural network – pattern recognition algorithms (e.g. GAID) to determine how well incident and normal traffic patterns are identified within the data. In contrast, it was found that the PCC measures are not a preferable means for calibrating comparative and theoretical type AID algorithms as described later in this chapter. Moreover, it is important to note that these measures do not necessarily reflect the AID system performance that would be experienced in a traffic operation centre.

In the above example, neither the traditional measures (e.g. DR and FAR) nor the PCC measures account for the fact that for the second actual incident, the AID algorithm prematurely assumed normal conditions and subsequently detected the same incident twice. This scenario would present a nuisance for traffic operators and should warrant further consideration depending on the frequency of occurrence. For this reason, two new measures of effectiveness are proposed:

$$Nuisance\_Rate = \frac{\sum (ID-1)}{AI} \qquad (Eq.\ 4.1)$$

Where:

ID = Number of times the same incident is declared by the AID system
AI = Total number of incidents detected by the AID system

and

$$False\_Normal\_Rate = \frac{\sum FND}{AI} \qquad (Eq.\ 4.2)$$

Where:

FND = Number of times the AID algorithm detects normal conditions before the end-time of the incident logged by the operator

From Figure 4-2 above, the NR would be: [(1-1) + (2-1)] ÷ 2 = 0.5 incident declarations per incident. The ideal NR would be equal to 0. The FNR would be: [0 + 1] ÷ 2 = 0.5 false normal declarations per incident. Similarly, the ideal FNR would be equal to 0. These new measures will be used wherever deemed appropriate in the calibration process and used throughout the comparative analysis.

4.2.3 Test traffic video and data sets

In order to yield test results that would reflect the AID system performance expected in a real-world deployment, it is imperative that the test data be representative of recurrently congested traffic conditions in addition to incident conditions. To meet this requirement, each of the test video and data sub-sets were uniquely chosen for each of the respective tests (e.g. DR and MTTD test, FAR test). The AID CAAT served as the user interface to scan and select the video (via video playback) and data (via graphs) from the Central Database Server (CDS) and the Digital Video Recording System (DVRS) to be used in each of the tests.

From the time that the ITS Centre was brought online, three video/data sets have been collected and/or developed as described in Table 4-1 below. Each data sub-set is stored on the CDS with incident date and time references stored within the AID CAAT database (i.e. for simplified, remote retrieval purposes). Where available, the corresponding video is stored on the DVRS with references stored, in a manner similar to the traffic data, on the AID CAAT database.

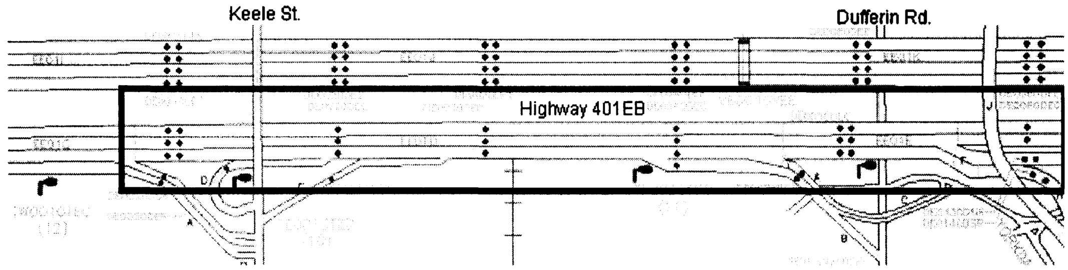
Table 4-1 Summary of the 3 Video/Data Sets

	Description
Video/Data Set 1 **Jan. 1st to February 12th, 2003**	• 130 incidents based on estimated start-times and operator-logged end-times • No corresponding video to confirm the 130 incidents • 14 days of incident-free traffic data from 6 traffic sensor stations (Highway 401 Keele St. – Dufferin Rd.) with corresponding video • Mixture of peak and off-peak traffic conditions • Various locations along Hwy. 401
	Description
Video/Data Set 2 **Feb. 8th to March 14th, 2004**	• 33 consecutive days of traffic data from 6 traffic sensor stations (Highway 401 Keele St. – Dufferin Rd.) • 7 incidents confirmed via video • Predominantly incident-free data
	Description
Video/Data Set 3 **June 14th to July 16th**	• 20 incidents confirmed via video recordings • Of the 20 incidents, there are only 2 cases where the incident start-time is caught on video, all others are estimated • The actual incident end-time is caught on video for all 20 cases • Each incident data segment includes 1hr prior to and 30mins following the incident itself • The incidents occur during both peak and off-peak traffic conditions • Various locations along Hwy. 401

The main requirement for the calibration data sub-set is that it be separate from yet representative of the test data sub-set(s) used in the actual comparative analysis. In addition, it should meet the calibration/training requirements of the AID systems themselves. While the McMaster Algorithm and California Algorithm 8 both require a moderate amount (e.g. 24 hours) of incident and incident-free data for calibration, GAID requires a significant amount of incident data for training purposes. The Citilog – VisioPAD primarily requires traffic video recordings from incident-free conditions to be trained on. Video Data Set 1 was selected for this purpose as it meets all of the above criteria.

In order to determine the most suitable data to test FAR and PCC_{Normal}, it is important to first hypothesize the factors causing false alarms. From this hypothesis, data can be selected that specifically tests the AID systems' capability to overcome these factors. For this comparative evaluation, the selection criteria were based on the hypothesis that false alarms occur primarily due to shockwaves and random fluctuations in congested traffic that appear to look like incidents in the traffic data (as previously identified by Payne and Tignor, 1978). Therefore, for the purposes of this evaluation, a significant amount of traffic data representing typical, recurrently congested traffic conditions were selected. Video/Data Set 2 was selected for this purpose as it best suits this criterion. The 7 video-confirmed incidents within this data set serve as a control. Further, the corresponding video provides the opportunity for further analysis into the factors affecting false alarms.

Figure 4-3 below depicts the segment of freeway where this traffic data was obtained. The dots represent the locations of the traffic sensor stations and the four cameras (for which there are video recordings) are shown on the south side of the freeway. This freeway segment also presents a geometric challenge for the AID systems in that the three lanes drop down to two (i.e. a freeway bottleneck) at the latter end of the segment.



N.T.S.

Figure 4-3 Data source for Video/Data Set 2 - Highway 401 eastbound collectors

The tests to determine DR, $PCC_{Incident}$ and MTTD require a significant amount of incident data with accurately logged incident start/end times and preferably with the accompanying video. Video/Data Set 1 contains a significant amount of incident data, however there is no corresponding video to confirm the incident start and end times. While there are video recordings for the incidents within Video/Data Set 2, the 7 incidents are not enough for a valid comparison of performance. Video/Data Set 3 was selected for this purpose as it was the best suited of the available data sub-sets.

4.3 Preparation of the AID Systems for testing

The AID CAAT was used to calibrate each of the three algorithms via offline tests primarily using Video/Data Set 1. A detailed description of the AID Systems themselves can be found in the Appendix B. The following sections provide a brief summary of the process undertaken to calibrate and prepare the AID systems for real-world testing.

4.3.1 Calibration of the California Algorithm 8

A brief description of the California Algorithm 8 is provided in Appendix B. Essentially, the California Algorithm 8 requires five threshold parameters to be calibrated. The AID CAAT and Video/Data Set 1 were used to calibrate the California Algorithm 8 using a technique described by Payne and Knobel, 1976. The thresholds are first estimated through an iterative trial and error process to maximize the detection rate without concern for the degree of false alarms. Next, the thresholds are fine-tuned to minimize the false alarm rate without reducing the optimum detection rate. The five thresholds that need to be calibrated are defined as:

- $OCCDF_{i,t}$ – The spatial difference between downstream and upstream occupancy (i.e. the delta between the upstream and downstream occupancy).
- $OCCRDF_{i,t}$ – The relative spatial difference between downstream and upstream occupancy (i.e. the spatial difference divided by the upstream occupancy).
- $DOCCTD_{i,t}$ – The relative temporal difference in downstream occupancy (i.e. the delta in occupancy over two time periods divided by the occupancy in the earlier time period).
- DOCC1 – The downstream occupancy is used to avoid classifying "tentative" incidents as actual incidents.
- DOCC2 – The downstream occupancy is also used to detect compression waves.

The AID CAAT was used to simplify the calibration process by simultaneously testing five "versions" of the California algorithm 8 (i.e. each with different parameters settings) at a time. The threshold values were fine-tuned, iteration-by-iteration, each time improving upon the best threshold set from the previous iteration. Table 4-2 below lists the top three sets of threshold values.

Table 4-2 Thresholds used in the California Algorithm 8

Threshold Set	DR (%)	FAR (%)	Threshold Values						
			$PCC_{Incident}$ (%)	PCC_{Normal} (%)	T1 OCCDF	T2 DOCCTD	T3 OCCRDF	T4 DOCC1	T5 DOCC2
1	*95*	*0.42*	*64*	*77*	*7.50*	*-0.25*	*0.30*	*27*	*30*
2	*94*	*0.33*	*62*	*78*	*5.60*	*-0.65*	*0.40*	*27*	*27*
3	*64*	*0.03*	*58*	*82*	*14.00*	*-0.35*	*0.65*	*28*	*30*

As described above, PCC was not used in the calibration process however, the PCC values are listed on Table 4-2 for the basis of discussion. Because the California algorithm 8 declares incidents based on occupancy-related thresholds being exceed (i.e. the transition to an incident), optimization should not be based on its classification capabilities. Rather, optimization of the California Algorithm 8 should be based on minimizing the FAR while maintaining an acceptable DR. Given this criterion, the second threshold set was used in the evaluation.

It is important to note that the following assumptions were made in the calibration of California algorithm 8.

- The traffic sensor occupancy measures were taken as an average over the entire station rather than on a lane-by-lane basis.
- The calibration parameters that were established based on the five traffic sensors within the test area were assumed to be applicable over the entire freeway network.

4.3.2 Calibration of the McMaster Algorithm

A brief description of the McMaster algorithm is provided in Appendix B. The McMaster algorithm requires calibration separately for lanes 1 and 2 (i.e. passing lane and next adjacent through lane) for each loop detector station. Specifically, the calibration exercise determines the coefficients for the lower bound of uncongested data (LUD) curve, the critical flow rate (V_{crit}), the critical occupancy, and the occupancy intersect for the line intersecting the V_{crit} line and the LUD curve (Hall et al., 1993). As the MTO had previously implemented the McMaster Algorithm, they were able to provide the coefficients for each of the stations for the purpose of this test as listed on Table 4-3 below. These parameters were verified via visual inspection of the parameters graphed on incident-free data from the corresponding stations in Video/Data Set 1.

Table 4-3 McMaster Calibration Parameters

Station ID		X^2 Coeff.	X Coeff.	K Const.	Critical Vol.	Critical Occ.	Intersect Occ.
Lane 1	10DEC	-0.67	-0.005	-2	6	29	15
	20DEC	-1.00	-0.008	-2	6	23	11
	30DEC	-0.78	-0.006	-2.9	6	23	11
	40DEC	-0.68	-0.005	-3.2	6	24	13
	50DEC	-0.78	-0.006	-1.8	7	22	13
	60DEC	-0.76	-0.005	-3	6	26	14
Lane 2	10DEC	-0.67	-0.005	-2	6	29	15
	20DEC	-1.01	-0.009	-2	6	23	11
	30DEC	-0.78	-0.006	-2.9	6	23	11
	40DEC	-0.69	-0.006	-3.2	6	24	13
	50DEC	-0.78	-0.006	-1.8	7	22	13
	60DEC	-0.76	-0.005	-3	6	26	14

In addition, the McMaster algorithm incorporates a persistence test before declaring an incident (INC – Incident Check) and before assuming normal conditions again (BTN – Back-to-Normal Check). The AID CAAT was used to conduct a series of trials using different values for INC and BTN on Video/Data Set 1 traffic data.

Table 4-4 below shows the test results for DR, FAR, $PCC_{Incident}$, PCC_{Normal}, NR and FNR. Case A shows the McMaster performance using INC = 3 and BTN = 2. Case B shows the performance using exactly the same test data and INC = 3 and BTN = 3. Whereas changing INC and BTN had no impact on DR, FAR, and PCC_{Normal}, there was an improvement in $PCC_{Incident}$, NR and FNR. Given this observation, the Case B parameters were used in the comparative analysis.

Table 4-4 McMaster Calibration - Comparison of INC/BTN Settings

Case	INC	BTN	DR (%)	FAR (%)	$PCC_{Incident}$ (%)	PCC_{Normal} (%)	NR	FNR
A	3	2	85	0.07	72	84	1.3	1.6
B	3	3	85	0.07	73	84	1.1	1.3

4.3.3 Calibration of GAID

A brief description of the GAID algorithm is provided in Appendix B. Implementation of the GAID algorithm requires the calibration of the 16 smoothing parameters (i.e. sigma values) associated with each of the inputs (Roy, 2002). GAID is inherently self-calibrating via its GAID-Optimizer component. The GAID-Optimizer uses genetic algorithms and historic traffic data to determine the optimal smoothing parameters for each loop detector station. As a result, preparation of GAID for real-world testing actually lies in the effort to prepare the training data set. For the pilot evaluation, GAID was trained using data from Video/Data Set 1.

The PCC measures are critical for calibrating GAID as illustrated on Table 4-5 below. Sigma sets A and B represent two (of the many) sets of smoothing parameters actually generated by the GAID-Optimizer during the calibration process. Using these sigma sets, GAID was tested on another independent incident (i.e. one that was not part of the training set of incidents) to yield the results shown on the table. In this example, $PCC_{Incident}$ is the only performance measure that clearly shows that Sigma Set B is a poor classifier. The DR could not have revealed this shortcoming because GAID (using Sigma Set B) still managed to detect the incident for a few intervals thus achieving a perfect DR score.

Table 4-5 Sample Calibration Results - GAID

σ Set	DR (%)	FAR (%)	$PCC_{Incident}$ (%)	PCC_{Normal} (%)	NR	FNR
A	100	0.03	92	84	0	1
B	100	0.02	7	84	0	1

It is important to note that theoretically, in a proper real-world implementation of GAID, the training process would be continuous with periodic operator input (i.e. confirming or denying incident detections). For the purpose of this test, the optimal set of sigmas, obtained via the training data set, were used throughout the testing process. A separate set of sigmas were obtained via the GAID-Optimizer and used for each traffic sensor station pair.

Table 4-6 below lists the actual sigma values used in the testing process for the first traffic sensor station pair.

Table 4-6 Sample sigma values used by GAID

σ_x	Value		σ_x	Value		σ_x	Value
1	4.343		7	2.946		13	2.105
2	2.644		8	0.569		14	1.075
3	3.195		9	1.710		15	4.680
4	2.570		10	3.371		16	3.652
5	1.117		11	3.728			
6	1.060		12	1.152			

To suppress false alarms due to random fluctuations in traffic measures, GAID uses Bayes' continuous updating of incident probability instead of a persistence check. In this technique, upper and lower incident-probability thresholds are required. If the incident-probability exceeds the upper threshold, an incident is declared. Conversely, the algorithm does not declare the end of the incident until the incident-probability falls below the lower threshold. For the actual test, GAID was tested using three different upper thresholds: 85%, 75% and 65% while the lower threshold was held constant for each scenario at 35%. The results for all three scenarios are presented in Tables 2 and 3, however GAID with the upper threshold setting of 75% (i.e. $GAID_{75}$) is considered the optimal configuration and used as a basis for comparison.

4.3.4 Calibration of the Citilog - VisioPAD

The VisioPAD is fairly simple to set-up and configure (i.e. once turned on, the system has its own built-in automatic learning/training process) (Toffin, 2001). The only configuration parameter of concern relates to the amount of time a vehicle is stopped before an incident is declared. This parameter directly impacts this AID system's false alarm rate and minimum time-to-detection. Calibration of the system simply involves a process of observing regular recurrent traffic patterns in order to determine the maximum time that vehicles typically are stopped. The AID CAAT was used to channel video from Video/Data Set 1 to the VisioPAD for this purpose.

During the early trials of calibration, the VisioPAD exhibited excessive false alarms. The AID CAAT video recordings confirmed that these false alarms were due to traffic on an arterial road caught within the traffic camera's field of view. Vehicles stopping at the arterial's signalized intersection resulted in false detections. To avoid significant bias in the test results, the false alarm rate test was conducted using a segment of freeway without any arterials in the field of view (i.e. Video/Data Set 2).

A number of timings were tested ranging from 10-120 seconds. The default setting on the VisioPAD is 15 seconds. Table 4-7 below shows the findings from the calibration effort.

Table 4-7 Calibration of Results for the VisioPAD

Threshold Setting (in seconds)	*FAR (percentage)*
10	*2.78*
15	*1.67*
20	*1.67*
40	*0.56*
60	*0*
120	*0*

From this analysis, a threshold setting of 60 seconds appeared to be the optimal in that it eliminated the FAR while still maintaining a reasonable minimum MTTD. Further, at this setting the VisioPAD would still be capable of incident detection because the average duration of the incidents in Data Set 1 is significantly longer at 45 minutes. As a result, the 60-second setting was carried forward to the pilot evaluation. The FAR calculation is based on the assumption of data arriving at twenty-second intervals (i.e. in order to make the number of observations relative to the AID algorithms being tested).

4.4 Comparative Analysis

The following sections detail the findings from the tests conducted. The test results reflect the performance of all four of the AID systems using Video/Data Set 2 and Video/Data Set 3. The AID algorithms used the traffic data and the VisioPAD used the video recordings.

4.4.1 Detection Rate, Nuisance Rate and False Normal Rate Test Results

The results of the Detection Rate, Nuisance Rate and False Normal Rate tests are shown in Table 4-8 below.

Table 4-8 Detection Rate, Nuisance Rate and False Normal Rate Test Results

AID System	*Detection Rate (DR)*	*Nuisance Rate (NR)*	*False Normal Rate (FNR)*
California 8	*90%*	*1.2*	*1.7*
McMaster	*85%*	*1.1*	*1.5*
$GAID_{75}$	*95%*	*0.7*	*1.1*
Citilog-VisioPAD	*100%*	*2.4*	*3.1*

The VisioPAD exhibited a 100% DR, however these incidents were not captured at the onset (i.e. the incidents occurred outside the field of camera view and the VisioPAD logged the detection at the time when the cameras were moved to the incident). Overall, the Citilog - VisioPAD appears to have the least desirable results of NR = 2.4 and FNR = 3.1. This may have been due to the fact that the duration for most of the incidents was long enough to warrant the system to detect each incident more than once.

Of the algorithms, $GAID_{75}$ exhibited the highest DR at 95% and the best NR and FNR score overall with an NR = 0.7 and an FNR = 1.1. These results show that GAID excels at identifying the incident patterns within the data.

The California Algorithm 8 had the second highest DR at 90%. However, this came at the cost of having the highest NR and FNR of the three loop detector based algorithms at NR = 1.2 and FNR = 1.7 respectively. These results suggest that the California Algorithm 8 suffers in its ability to determine the end of the incident.

The McMaster algorithm exhibited a DR of 85% with an NR of 1.1 and an FNR of 1.5. While McMaster's DR appears lower than that exhibited by the California Algorithm 8, this actually reflects McMaster's more conservative approach at distinguishing incidents. This observation came from the AID CAAT's Offline Viewer whereby the recorded incident video was viewed alongside the California Algorithm 8 and McMaster algorithm output windows. The California Algorithm 8 detected the same incident repeatedly without any identifiable reason from the video. In contrast, the McMaster algorithm's NR and FNR appeared to be caused by the police, an ambulance, and/or a fire truck arriving at the scene of the incident and closing additional lanes.

4.4.2 False Alarm Rate Test Results

The results of the FAR tests are shown in Table 4-9 below.

Table 4-9 False Alarm Rate Test Results

AID System	*FAR*
California 8	*0.35%*
McMaster	*0.07%*
$GAID_{75}$	*0.03%*
Citilog-VisioPAD	*0%*

Overall, the VisioPAD exhibited the lowest FAR at 0%. This is to be expected because the possibility of a vehicle being completely stopped during recurrent congestion for more than the VisioPAD threshold of 60 seconds is low. This is also evident in the video recordings of recurrent congestion in the test area.

The $GAID_{75}$ algorithm exhibited the second lowest FAR at 0.03%. As a pattern classifier, $GAID_{75}$ excels at separating shockwaves and random fluctuations in traffic from actual incident conditions. This observation is supported via a scan of $GAID_{75}$'s false alarm rate test through the AID CAAT Offline Viewer.

The McMaster algorithm had the third best FAR at 0.07%. It is interesting to note that the AID CAAT reported the McMaster algorithm exhibiting the majority of its false alarms between one particular traffic sensor station pair (See Appendix E). The recorded video from this test area shows that the freeway geometry (i.e. bottleneck) causes erratic traffic patterns to occur which appears to have affected McMaster's performance.

The California Algorithm 8 exhibited the highest FAR at 0.35%. It is evident from the AID CAAT Offline Viewer that the California Algorithm 8 has difficulty in distinguishing shockwaves in recurrent congestion from incidents.

The AID CAAT was used to generate a report correlating the time of day to the percentage of false alarms occurring (see Appendix E). It was interesting to note that the vast majority of the false alarms occurred during the peak hours. In sharp contrast, little or no incidents occurred during the off-peak hours. For this reason, it is important to note that the FAR results presented in Table 4-9 may be far lower than that actually experienced during peak hours. It was also interesting to note that while the California algorithm 8 and McMaster algorithm appeared to have problems at certain locations due to highway geometry, the GAID algorithm did not seem to have any location specific problems (i.e. GAID's false alarms occur fairly evenly from location to location).

4.4.3 Mean Time to Detection Test Results

The results of the MTTD tests are shown in Table 4-10 below. Overall, the California Algorithm 8 was the fastest at detecting incidents with a MTTD = 2.6 minutes. The McMaster algorithm had the second best MTTD of 4.4 minutes. The $GAID_{75}$ algorithm was close to the McMaster algorithm by detecting incidents with a MTTD = 4.9 minutes. The VisioPAD exhibited the longest MTTD. This is due primarily to the fact that the cameras were not facing the incidents when they first occurred.

Table 4-10 Mean-Time-To-Detection Test Results

AID System	*MTTD*
California 8	*2.6 mins*
McMaster	*4.4 mins*
$GAID_{75}$	*4.9 mins*
Citilog-VisioPAD	*9.6 mins*

4.4.4 Percentage Correct Classification

The results of the PCC tests are shown in Table 4-11 below. When comparing AID systems in the context of classification rate, both the incident and normal classification rates should be considered together.

Table 4-11 PCC Test Results

	$PCC_{Incident}$	PCC_{Normal}
California 8	*75%*	*69%*
McMaster	*68%*	*71%*
GAID₇₅	*72%*	*89%*
Citilog-VisioPAD	*64%*	*100%*

It is interesting to note that the Citilog-VisioPAD exhibited the lowest $PCC_{Incident}$. The irony of this is the fact that the Citilog-VisioPAD technically scored a perfect DR. This example emphasizes the fact that PCC performance measures should not be considered solely or taken out of context.

4.5 Overall AID system performance

Figure 4-4 below depicts the overall DR, FAR, MTTD performance of the four AID systems on a three dimensional graph.

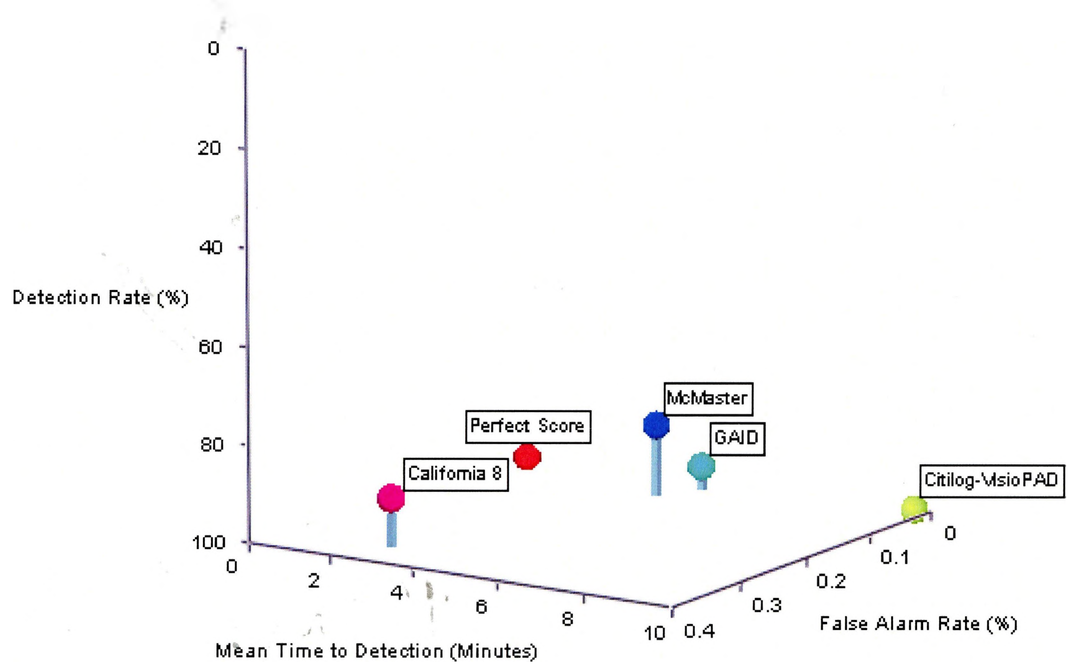


Figure 4-4 AID system overall performance

A perfect/ideal score of 100% DR, 0% FAR, and 0 minutes MTTD is indicated at the origin of the graph. In this representation, the closer the AID system points are to the origin, the closer they are to the ideal performance measures. The graph depicts the McMaster and GAID algorithms as being the closest to the ideal. The GAID algorithm exhibits a better DR/FAR than McMaster but, McMaster outperforms GAID in MTTD.

4.6 Discussion on performance issues and results

As an analytical tool, the AID CAAT provides valuable information (i.e. video recordings both of actual incidents, and of false detections corresponding to the traffic data) to provide insight into the operation of differing AID algorithm techniques. These observations could be used as a basis for further experiments to improve any identified shortcomings. Moreover, this information could be used as justification to develop new algorithms that leverage the superior features of those previously tested. The following summarizes the performance issues determined through the comparative analysis for each of the AID systems.

- The California Algorithm 8's technique of looking for thresholds (e.g. occupancy) to be met or exceeded resulted in it being the first to detect incidents. This sensitivity came at the expense of a high FAR. Moreover, its inability to distinguish incident from recurrent congestion resulted in the highest reported NR and FNR of the three loop-based algorithms.
- After observing both the video and the data collected, it was clear that the McMaster algorithm exhibited a superior ability to distinguish recurrent congestion from actual incidents in comparison to the California Algorithm 8. In the evaluation conducted, the McMaster technique successfully tracked the states of each loop station (e.g. from uncongested to congested) in a manner that results in noticeably less false alarms than the California Algorithm 8. This reduction in

false alarms comes at the expense of a higher (i.e. almost double) MTTD in comparison to the California Algorithm 8. Nuisance Rate and False Normal Rate appear to be very effective performance measures for calibrating McMaster's INC and BTN values and should be considered in future evaluations.

- The GAID algorithm's technique of training on location specific data gave it a definitive advantage in the comparative analysis with respect to its ability to minimize false alarms, nuisance detections and false normal detections. This ability comes at the marginal expense of an additional 30 seconds in MTTD relative to the McMaster algorithm. PCC was shown at the calibration stage to be a critical performance measure for calibrating this algorithm. It is recommended that more emphasis be placed on using PCC performance measures in future evaluations that involve comparisons between neural-network pattern recognition algorithms.
- The Citilog-VisioPAD exhibited a perfect detection rate score. However, it is important to note that this assessment is based on a test video set where only two incidents were caught at the onset (i.e. all other incident recordings were captured as they were ongoing). The results are still promising in that all incidents were captured by the Citilog and moreover, the FAR was 0% when tested over the 33 days of video recordings. The most important outcome of the Citilog evaluation is the revelation that the current MTO and City of Toronto practice of 1 km traffic camera spacing is inadequate for this type of AID system. Further, it was identified through the field trials that the positioning of cameras to avoid arterial roads (i.e. with signalized intersection) from the field of camera view is essential for this system. The cycle of stopped vehicles was observed as false detections during the calibration stage. Although this specific product is designed to work with pan-tilt-zoom cameras, static cameras are still recommended for this

operation to avoid inadvertently catching vehicles stopped at intersections within the field of camera view.

- Throughout the evaluation, it became evident that the more the algorithm technique uses location specific information (i.e. somehow taking into consideration the recurrent traffic congestion patterns at each specific location) the lower the degree of false alarms. Specifically, the California algorithm 8 technique has no mechanism to consider location specific traffic data and it resulted in having the highest FAR. In contrast, GAID, which used historic traffic data from each of the specific traffic sensors in the test area exhibited the lowest FAR.

4.7 Summary

The AID CAAT was successful in providing the means for a detailed comparative analysis of the four AID systems being tested. The pilot evaluation was designed to simply test the ability of the AID CAAT to evaluate different types of AID systems. In retrospect, because these AID systems are different in their operating principles, it is recommended that further testing be done to compare like-systems (e.g. neural-network pattern classifiers against neural-network pattern classifiers, or video-based against video-based AID systems).

The DR, FAR, and MTTD performance measures are still the best starting point for comparisons and evaluation. It is recommended, however that consideration be given to developing new performance measures, on a case by case basis, to meet the objectives of the specific test rather than being confined to the traditional measures. The AID CAAT was shown through this comparative analysis to be capable of accommodating any quantifiable type of performance measure.

5.0 Summary and Conclusions

5.1 Summary of research and contributions

At the onset of this research initiative, it was determined that there was a need for further, more rigorous testing of AID systems specifically in the real-world context. The AID CAAT and its supporting components within the ITS Centre and Testbed provide valuable tools that can facilitate this need. This research effort resulted in five key contributions as described below.

1. The AID CAAT itself provides a means for comparing and analyzing multiple AID systems simultaneously using real-world traffic video and data. The system was designed for remote access via the Internet such that others can conduct tests using the AID CAAT and achieve comparable results. Moreover, the design is transferable as the entire system can be readily duplicated in any traffic operations centre or research facility.

2. The development of the AID CAAT set in motion the initiative to upgrade the proposed communications system for the ITS Centre and to introduce two new systems for storage of the traffic video and data feeds. The new ITS Centre communications design implements centre-to-centre technology providing a high capacity video/data ring between the City of Toronto, the University of Toronto and the Ministry of Transportation, Ontario. This is the first centre-to-centre video/data communication link between the two traffic management centres and it uses a technology that neither agency had used before. The Central Database Server was developed and now provides real-time and historic traffic data locally within the ITS Centre lab and via the Internet. The Digital Video Recording System provides storage media for the traffic video with remote control and remote playback access via the Internet.

3. The pilot evaluation demonstrated the AID CAAT's ability to test all types of AID systems including: comparative algorithms, theoretical models, neural network-based algorithms and video-based AID systems. Moreover, it helped in identifying the strengths and weaknesses of the respective algorithms. It also provided some suggestions for better calibration of the AID systems.

4. The comparative analysis revealed the need for two additional measures of effectiveness to be considered: Nuisance Rate and False Normal Rate. These performance measures provide a new operational context for AID system performance not encompassed in the traditional measures of effectiveness. In addition, the comparative analysis test results provided valuable insights into the operation of the respective AID systems.

5. As a by-product of the evaluation, a high quality database consisting of video and data was developed that can be used for future calibration and testing of AID systems. This "gold-standard" database consists of three video/data sets containing accurate logs of incident start/end times and is more representative of typical daily traffic conditions than the testing data sets described by Roy, 2002.

5.2 Conclusions

The capability for analysis of AID system operation and performance is now greatly simplified via the AID CAAT. Tests can be conducted real-time or offline and the results can be confirmed via the recorded video. Moreover, the AID CAAT is designed in a modular fashion such that:

- any AID algorithm or system can be tested,
- the test data set itself can be easily changed (e.g. for testing AID algorithms that use probe-data), and

- the measures of effectiveness can be easily changed to meet the requirements of the specific test.

The pilot evaluation provided significant insight into the strengths and weaknesses of the respective AID systems and in some cases, suggested recommendations for measures to improve calibration. Specifically:

- California Algorithm 8 - is at a disadvantage in comparison to the other algorithms in that its technique is the least location specific (i.e. unable to accommodate for the recurrent congestion traffic patterns that that are unique to each location). Even after significant calibration efforts, the false alarm rate was still significantly higher than the other AID systems. The detection rate and false alarm rate are still the best measures to calibrate the California algorithm 8 (i.e. differences in threshold sets had minimal impact on the percentage correct classification, nuisance rate, and false normal rate).
- McMaster Algorithm – is more location specific than California Algorithm 8 (i.e. it's technique requires calibration parameters from each traffic sensor station) and hence, is shown to be better at distinguishing recurrent congestion (i.e. exhibiting a lower false alarm rate). It is good at distinguishing the onset of the incident (i.e. exhibiting the second best mean time to detection) but the test revealed that it lacks in its technique for determining the end of the incident in that it exhibits the second highest false normal rate. Nuisance rate and false normal rate are shown to be the best performance measures for determining the 'back-to-normal' persistence check values.
- GAID Algorithm – incorporates the most location specific technique hence, exhibits the lowest false alarm rate of the algorithm based systems tested. While it is marginally slower to detect incidents than the McMaster Algorithm, it is proficient at detecting the end of an incident (i.e. exhibiting the lowest false normal rate). The pilot evaluation showed that detection rate and false alarm rate

should not be used solely when calibrating this algorithm. The percentage correct classifications are shown to be the best performance measures for calibrating this algorithm.

- Citilog-VisioPAD – requires 100% video coverage of the proposed detection area (i.e. the MTO/City practice of 1km spacing is inadequate). Moreover, the location of the detection cameras should be placed in a manner to avoid arterials to avoid inadvertently detecting vehicles stopped at traffic signals. The Citilog is shown in the test to be proficient at detecting incidents when there are low traffic volumes (i.e. when there is no apparent incident pattern in the data).

5.3 Recommendations for further research

The findings of the pilot evaluation suggest that some combination of the AID system techniques may yield a more effective algorithm. In principle, McMaster and GAID could be combined to create a system that is both proficient at detecting the onset of an incident and detecting the end of the incident. The Citilog could be added to this system specifically for the purposes of detecting incidents during periods of low traffic volume. Given that the AID CAAT provides a real-world environment for testing both loop-based and video-based systems, it is recommended that it be used to develop and test this new system.

In addition, the AID CAAT could be used for researching the factors and issues surrounding effective deployment of the existing AID systems. Listed below are some potential opportunities for further research:

- A detailed analysis into the causes of false alarms and identification of potential measures for mitigation;
- A determination of how best to locate traffic sensors and polling frequencies in a manner that optimizes the balance between false alarms and time to detection without compromising the AID system's ability to detect incidents;

- A detailed analysis on how best to perform calibration on various AID systems while incorporating some form of cost function (e.g. costs for misclassification);
- A comparative analysis within a set of video-based AID systems (i.e. identifying the factors affecting performance and proposing a suitable set of performance measures); and
- A series of tests to compare and develop AID algorithms/systems that use data sets other than inductive loops (e.g. probe data, remote traffic microwave sensors).

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APPENDIX A – AID SYSTEM INTERFACE

In order to create a new AID System Interface, the user must create a Java class that is called via the traffic data vector and returns the traffic state classification using a Binary operator. The following is the generic template for developing the AID System Interface. The remark statements, denoted by '//', highlight the area where the user must write their own code.

```
import ca.utoronto.civ.its.aidtestbed.AIDAlgorithm;
import ca.utoronto.civ.its.aidtestbed.StationPairDataObject;

public class AIDInterface extends AIDAlgorithm
{
  public int classify(StationPairDataObject theData)
  {
    // String currentTimeStamp = new String();
    // String us_vdsid = new String();
    // String ds_vdsid = new String();
    // Vector upstreamVolume_us = new Vector();
    // Vector upstreamOccupancy_us = new Vector();
    // Vector upstreamVolume_ds = new Vector();
    // Vector upstreamOccupancy_ds = new Vector();
    // Vector upstreamSpeed = new Vector();
    // Vector downstreamVolume_us = new Vector();
    // Vector downstreamOccupancy_us = new Vector();
    // Vector downstreamVolume_ds = new Vector();
    // Vector downstreamOccupancy_ds = new Vector();
    // Vector downstreamSpeed = new Vector();
    // For example, to extract the downstream speed value use:
    // "theData.downstreamSpeed(lane#)"

    // Call your algorithm here and provide whatever values
    // are needed. The AID CAAT requires a 1 or 0 to be returned
        // integer 1=incident and 0=normal traffic conditions

     int incidentresult = 0;

        // Once your algorithm has returned a result, assign that
    // value to the int variable incident result

      return incidentresult;
    // returns the value back to the AID CAAT dispatcher
  }
}
```

This Java class can be developed using any simple text editor however, upon completion, it must be compiled using the Command Prompt interface instruction, "JAVAC name_of_file.java". The class name (e.g. AIDInterface) should be modified to reflect the name of the specific AID system to which it is intended to interface. The user may delete these remark statements prior to compiling the file.

APPENDIX B – DESCRIPTION OF AID SYSTEMS

The following sections provide brief descriptions of the four AID systems used in the pilot evaluation. The algorithms are described here in principle to assist the reader in understanding the calibration measures discussed in the main body of the thesis. The intricate details surrounding the modifications necessary for real-world implementation have been omitted to avoid infringing on the copyright/license-rights of the respective owners.

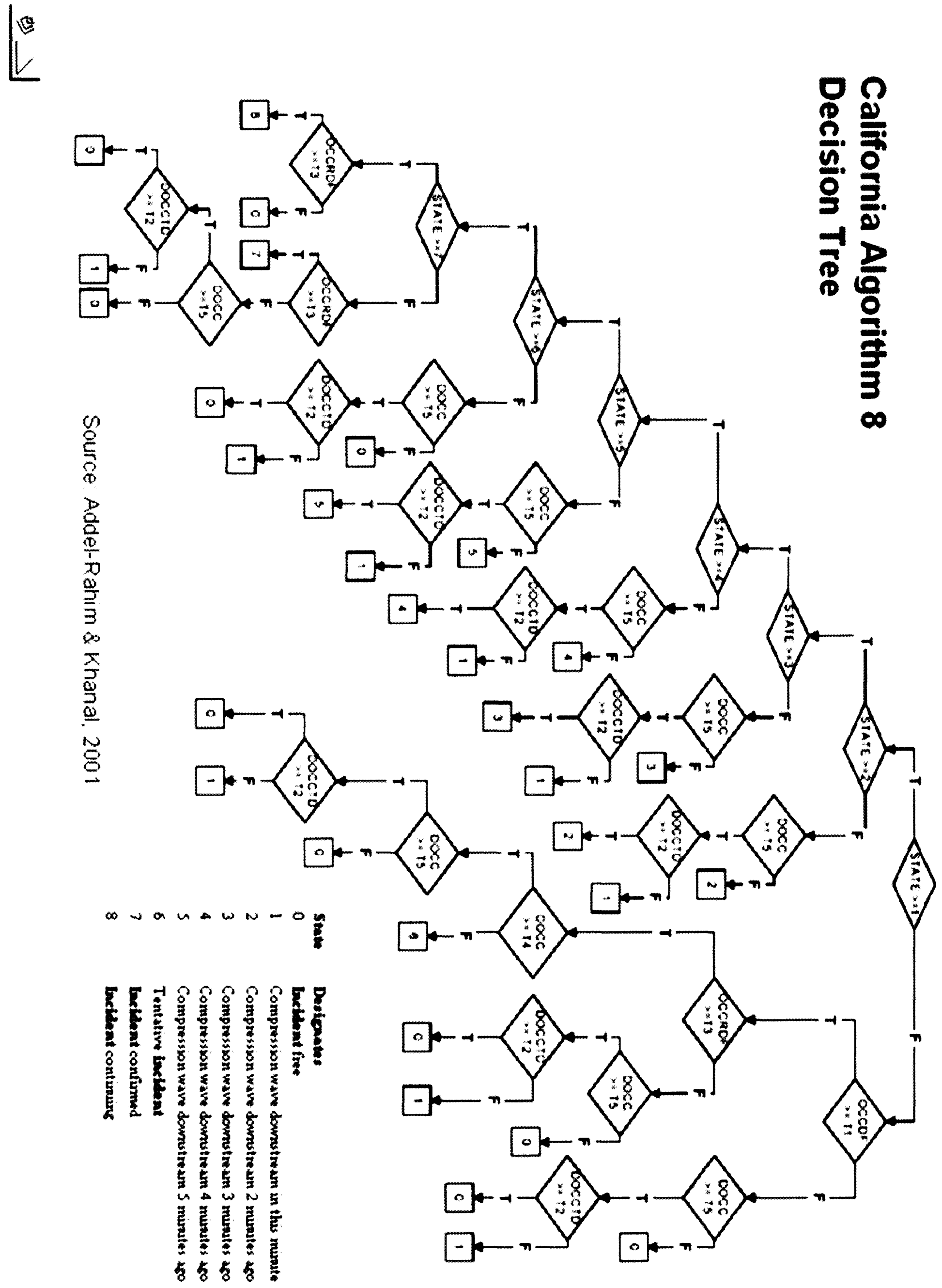
The California Algorithm 8

The California Algorithm 8 consists of a binary decision tree methodology that tracks the traffic conditions through eight possible states to detect incident-like traffic conditions while attempting to distinguish shockwaves and random fluctuations in the traffic patterns. The binary decision tree proposed consists of a series of tests that compare five primary traffic flow measurements against threshold values in order to distinguish recurrent from non-recurrent congestion. The five primary traffic flow measurements are described both in concept and mathematically in the table below.

Concept	Mathematical Formulation	
The spatial difference between downstream and upstream occupancy (i.e. the delta between the upstream and downstream occupancy).	$OCCDF_{i,t} =$	$(OCC_{i,t} - OCC_{i+1,t})$
The relative spatial difference between downstream and upstream occupancy (i.e. the spatial difference divided by the upstream occupancy).	$OCCRDF_{i,t} =$	$\frac{(OCCDF)}{OCC_{i,t}}$
The relative temporal difference in downstream occupancy (i.e. the delta in occupancy over two time periods divided by the occupancy in the earlier time period).	$DOCCTD_{i,t} =$	$\frac{(OCC_{i+1,t-6} - OCC_{i+1,t})}{OCC_{i+1,t-6}}$
The downstream occupancy is used to avoid classifying "tentative" incidents as actual incidents.	$DOCC1 =$	$DOCC_{i,t}$
The downstream occupancy is also used to detect compression waves.	$DOCC2 =$	$DOCC_{i,t}$

The calibration procedure for the algorithm requires the user to define the threshold parameters (T1, T2, T3, T4, and T5) for each of the five variables described above. With these parameters defined, the algorithm uses a binary decision tree to track the traffic conditions as shown in the diagram below.

Description of AID Systems - California Algorithm 8 (Cont'd)

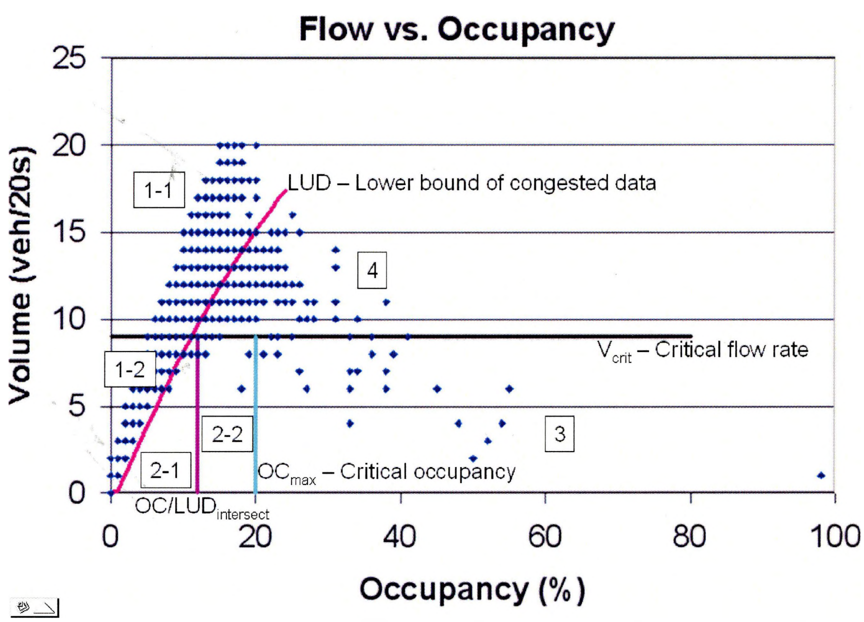


Description of AID Systems - California Algorithm 8 (Cont'd)

The algorithm processing starts in an incident-free state (i.e. state value = 0 per the above diagram). The OCCDF $_{i,t}$, OCCRDF $_{i,t}$, and the DOCC1 have to meet or exceed their corresponding thresholds (i.e. T1, T3, and T4) before a tentative incident is declared (i.e. state value = 6). per the above diagram, once a tentative incident is declared, if the OCCRDF $_{i,t}$ exceeds T3 in the next time interval, the incident is confirmed.

The McMaster Algorithm

The McMaster Algorithm uses the relationships between volume and occupancy at upstream and downstream traffic sensors to distinguish between recurrent and non-recurrent traffic congestion. It classifies traffic data through the use of a volume vs. occupancy graph that is divided into six traffic states (that is 1-1, 1-2, 2-1, 2-2, 3, 4) as seen in the graph below.



The operational parameters LUD, OC(max), OC/LUD(intersect), and V(crit) have to be defined by the user (usually via visual inspection of a 24 hour plot of the volume and occupancy). The McMaster algorithm provides a series of look-up charts that can be used to determine the traffic conditions depending on where the upstream and downstream volume/occupancy measures fall on the above graph.

Description of AID Systems (cont'd)

The GAID Algorithm

The Genetic Adaptive Incident Detection (GAID) algorithm uses historical traffic data reflecting both incident and non-incident conditions to classify current traffic data. Unique to this algorithm is its capability to calibrate itself at an ongoing basis. This feature can potentially resolve the problem of transferability that exists with other AID algorithms.

The concept of GAID comprises of two fundamental components: a probabilistic neural network (PNN) classifier and a genetic optimizer. The PNN classifier operates on the principle that if the probability density functions $f_k(x)$ can be calculated or estimated for all populations (i.e. incident or normal data sets) then by Bayes' optimal decision rule, the unknown sample x can be classified into class i if:

$$h_i c_i f_i(x) > h_j c_j f_j(x)$$

Where:
h_k = prior probability of appearance of random samples from population k
c_k = cost associated with the misclassification of a case that truly belongs to k

The probability density function for each class (incident/normal) is calculated using the modified Parzen equation:

$$f_k(y_1,\ldots,y_P) = \frac{1}{n_k}\sum_{i=1}^{n_k} e^{\sum_{j=1}^{P}\left(\frac{y_j - x_{ijk}}{\sigma_j}\right)^2}$$

Where: x_{ijk} denotes, j^{th} variable for the i^{th} vector of the training set for class k
σ_j is the smoothing parameter for the j^{th} dimension
n_k = the population size of the class

Per the above formulation, a vector of traffic data (e.g. upstream/downstream volume-speed-occupancy) is used to compare against the current data rather than single values. While any combination thereof could be used that properly describes the traffic conditions, for the purposes of this test the following 16 value input vector is used.

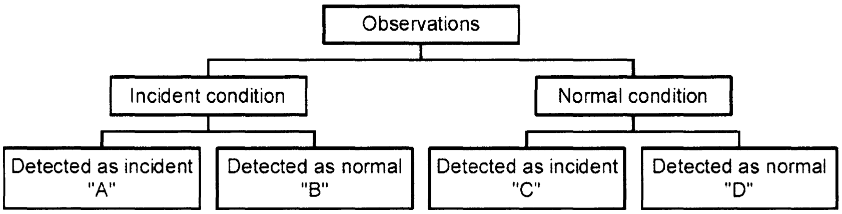
X_0	X_1	X_2	X_3	X_4	X_5	X_6	X_7
$O_{t-4, i}$	$O_{t-3, i}$	$O_{t-2, i}$	$O_{t-1, i}$	$O_{t, i}$	$V_{t-4, i}$	$V_{t-3, i}$	$V_{t-2, i}$

X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
$V_{t-1, i}$	$V_{t, i}$	$O_{t, i}$	$O_{t-1, i-1}$	$O_{t-2, i-2}$	$V_{t, i}$	$V_{t-1, i-1}$	$V_{t-2, i-2}$

Description of AID Systems - GAID (Cont'd)

Where:
V = volume,
O = occupancy,
i = upstream traffic sensor location,
t = current traffic data time interval

The vector of traffic measures used in the pilot evaluation is identical to that used by the authors of the GAID algorithm. In addition, a smoothing parameter σ_j is required for each of the 16 input variables. Through a simultaneous but, independent process, GAID uses its genetic optimizer to estimate the set of σs that maximizes the detection rate while minimizing the false alarms via the following formula:



$$f = \frac{A}{A+B} + \frac{D}{D+C}$$

Source: Roy, 2002

In the above formula, 'f' represents the Overall Classification Rate as a function of the incident and normal classification rates. Whenever this process calculates a new set of σs, it provides these values to the PNN classifier real-time.

The Citilog VisioPAD

The Citilog-VisioPAD (France) is a video-based AID system. While the mechanics behind the Citilog-VisioPAD are proprietary, the manufacturer does suggest that it does use a highly complex artificial intelligence algorithm to compare current/previous video frames. This technique allows the system to detect either stopped vehicles, slow moving vehicles, or vehicles moving the wrong way. While this particular product has been used on a variety of projects in Europe, at the time of the pilot evaluation, no formal test results were found.

APPENDIX C – DETAILED SUMMARY OF DATA SETS USED FOR CALIBRATION AND TESTING

The following tables list the incidents within each of the Video/Data Sets. Any fields that are denoted with a '-' represent values that could not be determined via visual inspection of the data. Times were corrected via visual inspection of the data.

Video/Data Set 1 Statistics

Incident No.	Date	Incident Location Upstream Station	*Corrected Start Time	*Corrected End Time	Duration	Operator Logged Start Time	Operator Logged End Time
1	20030102	401DW0040DWS	14:22:00	15:29:40	1:07:40	14:33:28	0:11:28
2	20030102	401DE0250DEC	17:23:00	18:08:40	0:45:40	17:12:26	0:10:34
3	20030102	401DW0010DWE	-	-	-	18:06:26	18:06:26
4	20030103	401DW0130DWC	-	-	-	7:01:04	7:01:04
5	20030103	401DE0370DEC	13:43:40	15:32:20	1:48:40	15:12:21	1:28:41
6	20030104	401DE0200DEE	8:54:40	9:22:40	0:28:00	8:53:48	0:00:52
7	20030104	401DW0070DWE	8:55:20	9:08:40	0:13:20	8:58:23	0:10:17
8	20030105	401DW0030DWE	13:59:00	15:22:20	1:23:20	14:43:00	0:39:20
9	20030104	401DE0120DEE	10:15:20	11:16:40	1:01:20	10:33:02	0:17:42
10	20030104	401DW0030DWS	18:37:00	19:19:00	0:42:00	18:49:25	0:12:25
11	20030104	401DW0070DEC	16:03:40	18:02:20	1:58:40	16:05:54	0:02:14
12	20030104	401DW0020DWE	-	-	-	16:13:00	16:13:00
13	20030105	401DW0020DWS	-	-	-	18:13:29	18:13:29
14	20030106	401DW0010DWE	-	-	-	7:54:10	7:54:10
15	20030106	401DW0060DEC	16:18:40	18:59:00	2:40:20	17:42:51	1:24:11
16	20030106	401DE0260DEC	-	-	-	19:10:34	19:10:34
17	20030107	401DE0100DEC	-	-	-	8:03:59	8:03:59
18	20030107	401DE0120DWC	15:57:40	16:58:40	1:01:00	15:58:21	0:00:41
19	20030107	401DE0130DWC			-	22:47:25	22:47:25
20	20030107	401DE0110DWE	0:12:20	0:32:40	0:20:20	0:20:00	0:07:40
21	20030108	401DE0250DEE	8:26:00	10:33:00	2:07:00	9:22:14	0:56:14
22	20030108	401DW0050DEC	-	-	-	14:57:25	14:57:25
23	20030108	401DE0100DEE	14:17:00	15:14:00	0:57:00	16:24:22	2:07:22
24	20030109	401DE0100DEC	8:39:40	9:06:00	0:26:20	7:48:29	0:51:11
25	20030109	401DE0250DEE	-	-	-	15:18:50	15:18:50

Video/Data Set 1 Statistics (Cont'd)

Incident No.	Date	Incident Location Upstream Station	*Corrected Start Time	*Corrected End Time	Duration	Operator Logged Start Time	Operator Logged End Time
26	20030104	401DW0110DWC	-	-	-	3:05:59	3:05:59
27	20030101	401DE0160DEE	-	-	-	3:25:57	3:25:57
28	20030101	401DW0200DWC	-	-	-	22:01:59	22:01:59
29	20030102	401DE0160DWE	20:38:40	21:32:00	0:53:20	20:47:41	0:09:01
30	20030103	401DW0170DWC	1:35:00	2:06:00	0:31:00	2:01:23	0:26:23
31	20030103	401DE0160DWE	5:16:40	6:23:20	1:06:40	5:51:25	0:34:45
32	20030103	401DE0200DWC	5:55:20	6:20:40	0:25:20	5:57:36	0:02:16
33	20030103	401DE0190DEE	-	-	-	10:09:42	10:09:42
34	20030103	401DW0180DWC	-	-	-	11:40:36	11:40:36
35	20030103	401DE0200DWE	12:30:00	13:50:40	1:20:40	13:25:16	0:55:16
36	20030103	401DE0380DEC	13:56:20	14:40:20	0:44:00	14:06:44	0:10:24
37	20030103	401DE0390DEE	13:47:00	14:42:40	0:55:40	14:08:16	0:21:16
38	20030103	401DE0100DEE	19:54:40	21:05:20	1:10:40	20:08:44	0:14:04
39	20030103	401DE0190DEE	22:14:20	-	-	22:13:58	0:00:22
40	20030109	401DE0120DEC	-	-	-	20:22:42	20:22:42
41	20030109	401DE0140DEE	22:00:00	22:52:00	0:52:00	22:07:00	0:07:00
42	20030109	401DE0100DEE	21:59:40	22:56:20	0:56:40	22:39:30	0:39:50
43	20030109	401DE0280DEE	23:16:00	23:48:40	0:32:40	23:24:24	0:08:24
44	20030110	401DE0260DEC	23:58:00	0:23:40	0:25:40	0:20:02	0:27:40
45	20030110	401DE0120DEC	5:50:20	7:19:20	1:29:00	5:55:38	0:05:18
46	20030110	401DE0070DEE	6:22:20	7:21:40	0:59:20	6:19:14	0:03:06
47	20030110	401DW0050DEE	6:58:40	-	-	7:26:01	0:27:21
48	20030110	401DE0140DEC	7:38:20	8:36:40	0:58:20	7:48:07	0:09:47
49	20030110	401DW0060DWE	-	-	-	14:34:54	14:34:54
50	20030110	401DW0030DEE	-	-	-	15:08:06	15:08:06

Video/Data Set 1 Statistics (Cont'd)

Incident No.	Date	Incident Location Upstream Station	*Corrected Start Time	*Corrected End Time	Duration	Operator Logged Start Time	Operator Logged End Time
51	20030110	401DW0030DWE	15:14:20	15:45:40	0:31:20	15:09:12	0:05:08
52	20030111	401DE0120DEE	15:24:40	-	-	15:32:26	0:07:46
53	20030111	401DE0280DEC	21:40:00	22:30:00	0:50:00	21:40:22	0:00:22
54	20030113	401DE0190DEE	8:49:00	9:23:00	0:34:00	8:58:04	0:09:04
55	20030113	401DE0110DWC	9:45:40	10:06:40	0:21:00	9:58:33	0:12:53
56	20030113	401DE0130DWE	-	-	-	15:40:50	15:40:50
57	20030113	401DE0340DEC	-	-	-	17:37:58	17:37:58
58	20030113	401DE0110DEE	17:44:00	18:47:40	1:03:40	17:56:14	0:12:14
59	20030114	401DW0100DWC	1:21:00	-	-	1:19:00	0:02:00
60	20030114	401DE0190DWC	9:18:00	9:45:20	0:27:20	9:19:15	0:01:15
61	20030114	401DE0070DEC	-	18:34:00	-	18:16:46	18:16:46
62	20030115	401DE0130DWC	9:00:20	9:29:40	0:29:20	9:21:27	0:21:07
63	20030115	401DE0200DEC	17:57:00	18:23:20	0:26:20	18:03:28	0:06:28
64	20030116	401DW0020DWE	-	-	-	7:25:23	7:25:23
65	20030116	401DE0280DWC	10:54:00	11:45:00	0:51:00	11:22:20	0:28:20
66	20030117	401DE0040DEE	7:20:00	8:20:00	1:00:00	7:27:13	0:07:13
67	20030117	401DE0190DEE	8:50:00	9:22:00	0:32:00	8:56:12	0:06:12
68	20030117	401DE0190DEC	15:17:00	15:44:00	0:27:00	15:18:28	0:01:28
69	20030117	401DE0120DWC	16:12:20	-	-	16:05:19	0:07:01
70	20030117	401DE0260DEC	-	-	-	17:27:55	17:27:55
71	20030118	401DE0080DEC	17:55:00	19:04:00	1:09:00	18:07:48	0:12:48
72	20030118	401DW0290DEE	-	-	-	23:13:46	23:13:46
73	20030119	401DE0010DEC	-	-	-	1:16:57	1:16:57
74	20030119	401DW0090DWC	3:42:00	4:00:00	0:18:00	3:43:33	0:01:33
75	20030119	401DE0080DEE	17:09:00	18:00:00	0:51:00	17:04:50	0:04:10

Video/Data Set 1 Statistics (Cont'd)

Incident No.	Date	Incident Location Upstream Station	*Corrected Start Time	*Corrected End Time	Duration	Operator Logged Start Time	Operator Logged End Time
76	20030119	401DE0270DEC	-	-	-	22:47:41	22:47:41
77	20030120	401DE0160DEC	2:43:20	3:20:00	0:36:40	2:49:28	0:06:08
78	20030120	401DE0060DEE	7:40:00	8:02:20	0:22:20	7:54:25	0:14:25
79	20030120	401DW0030DWE	10:17:00	11:56:00	1:39:00	10:30:25	0:13:25
80	20030120	401DW0090DEC	10:45:00	11:15:00	0:30:00	11:05:56	0:20:56
81	20030120	401DE0140DEC	11:44:00	13:11:40	1:27:40	11:45:24	0:01:24
82	20030120	401DE0290DWC	12:52:00	13:09:20	0:17:20	12:58:07	0:06:07
83	20030120	401DW0180DWC	14:40:00	18:45:00	4:05:00	14:42:44	0:02:44
84	20030120	401DE0120DEC	15:15:00	15:35:00	0:20:00	15:23:25	0:08:25
85	20030120	401DW0060DEC	-	-	-	16:28:00	16:28:00
86	20030121	401DE0280DWC	0:33:20	1:06:40	0:33:20	0:43:45	0:10:25
87	20030121	401DW0110DEE	6:46:00	7:26:00	0:40:00	7:18:28	0:32:28
88	20030121	401DW0040DWE	7:55:00	9:24:40	1:29:40	8:07:12	0:12:12
89	20030121	401DW0130DEC	8:00:40	9:22:20	1:21:40	8:13:38	0:12:58
90	20030121	401DE0200DEC	8:25:20	9:29:00	1:03:40	8:19:42	0:05:38
91	20030121	401DE0380DWE	8:46:40	9:14:40	0:28:00	8:54:34	0:07:54
92	20030122	401DE0400DWC	7:28:20	7:45:20	0:17:00	7:27:18	0:01:02
93	20030122	401DE0180DEC	9:51:40	10:35:00	0:43:20	9:52:44	0:01:04
94	20030120	401DE0160DEC	2:43:20	3:20:00	0:36:40	2:49:28	0:06:08
95	20030120	401DE0060DEE	7:40:00	8:02:20	0:22:20	7:54:25	0:14:25
96	20030120	401DW0030DWE	10:17:00	11:56:00	1:39:00	10:30:25	0:13:25
97	20030120	401DW0090DEC	10:45:00	11:15:00	0:30:00	11:05:56	0:20:56
98	20030120	401DE0140DEC	11:44:00	13:11:40	1:27:40	11:45:24	0:01:24
99	20030120	401DE0290DWC	12:52:00	13:09:20	0:17:20	12:58:07	0:06:07
100	20030120	401DW0180DWC	14:40:00	18:45:00	4:05:00	14:42:44	0:02:44
101	20030120	401DE0120DEC	15:15:00	15:35:00	0:20:00	15:23:25	0:08:25
102	20030102	401DE0160DWE	20:38:40	21:32:00	0:53:20	20:47:41	0:09:01
103	20030103	401DW0170DWC	1:35:00	2:06:00	0:31:00	2:01:23	0:26:23
104	20030103	401DE0160DWE	5:16:40	6:23:20	1:06:40	5:51:25	0:34:45
105	20030103	401DE0200DWC	5:55:20	6:20:40	0:25:20	5:57:36	0:02:16
106	20030119	401DE0080DEE	17:09:00	18:00:00	0:51:00	17:04:50	0:04:10
107	20030119	401DE0270DEC	-	-	-	22:47:41	22:47:41
108	20030120	401DE0160DEC	2:43:20	3:20:00	0:36:40	2:49:28	0:06:08
109	20030120	401DE0060DEE	7:40:00	8:02:20	0:22:20	7:54:25	0:14:25
110	20030120	401DW0030DWE	10:17:00	11:56:00	1:39:00	10:30:25	0:13:25

Video/Data Set 1 Statistics (Cont'd)

Incident No.	Date	Incident Location Upstream Station	*Corrected Start Time	*Corrected End Time	Duration	Operator Logged Start Time	Operator Logged End Time
111	20030120	401DW0090DEC	10:45:00	11:15:00	0:30:00	11:05:56	0:20:56
112	20030120	401DE0140DEC	11:44:00	13:11:40	1:27:40	11:45:24	0:01:24
113	20030120	401DE0290DWC	12:52:00	13:09:20	0:17:20	12:58:07	0:06:07
114	20030120	401DW0180DWC	14:40:00	18:45:00	4:05:00	14:42:44	0:02:44
115	20030120	401DE0120DEC	15:15:00	15:35:00	0:20:00	15:23:25	0:08:25
116	20030120	401DW0060DEC	-	-	-	16:28:00	16:28:00
117	20030121	401DE0280DWC	0:33:20	1:06:40	0:33:20	0:43:45	0:10:25
118	20030121	401DW0110DEE	6:46:00	7:26:00	0:40:00	7:18:28	0:32:28
119	20030121	401DW0040DWE	7:55:00	9:24:40	1:29:40	8:07:12	0:12:12
120	20030102	401DW0040DWS	14:22:00	15:29:40	1:07:40	14:33:28	0:11:28
121	20030102	401DE0250DEC	17:23:00	18:08:40	0:45:40	17:12:26	0:10:34
122	20030102	401DW0010DWE	-	-	-	18:06:26	18:06:26
123	20030103	401DW0130DWC	-	-	-	7:01:04	7:01:04
124	20030103	401DE0370DEC	13:43:40	15:32:20	1:48:40	15:12:21	1:28:41
125	20030104	401DE0200DEE	8:54:40	9:22:40	0:28:00	8:53:48	0:00:52
126	20030104	401DW0070DWE	8:55:20	9:08:40	0:13:20	8:58:23	0:10:17
127	20030105	401DW0030DWE	13:59:00	15:22:20	1:23:20	14:43:00	0:39:20
128	20030104	401DE0120DEE	10:15:20	11:16:40	1:01:20	10:33:02	0:17:42
129	20030104	401DW0030DWS	18:37:00	19:19:00	0:42:00	18:49:25	0:12:25
130	20030104	401DW0070DEC	16:03:40	18:02:20	1:58:40	16:05:54	0:02:14
131	20030104	401DW0020DWE	-	-	-	16:13:00	16:13:00
132	20030105	401DW0020DWS	-	-	-	18:13:29	18:13:29
133	20030106	401DW0010DWE	-	-	-	7:54:10	7:54:10
134	20030103	401DE0370DEC	13:43:40	15:32:20	1:48:40	15:12:21	1:28:41
135	20030104	401DE0200DEE	8:54:40	9:22:40	0:28:00	8:53:48	0:00:52

Video/Data Set 2

Incident No.	Date	Incident Location Upstream Station	*Start Time	*End Time	Duration
1	20040209	401DE0090DEC	11:45:00	12:15:00	0:30:00
2	20040211	401DE0140DEC	14:44:00	15:11:40	1:27:40
3	20040216	401DE0290DWC	08:52:00	9:09:20	0:17:20
4	20040218	401DW0180DWC	14:40:00	15:45:00	1:05:00
5	20040224	401DE0120DEC	15:15:00	15:35:00	0:20:00
6	20040225	401DW0060DEC	07:34:00	08:01:00	0:27:00
7	20040304	401DE0280DWC	0:33:20	1:06:40	0:33:20

*Note: Start-time is estimated via visual inspection of the data and end-time is confirmed via video recordings

Video/Data Set 3

Incident No.	Date	Incident Location Upstream Station	*Start Time	*End Time	Duration
1	20040615	401DE0270DEC	14:33:00	14:57:00	0:24:00
2	20040616	401DE0160DEC	16:22:00	17:45:00	1:23:00
3	20040622	401DE0060DEE	13:03:00	13:40:00	0:37:00
4	20040621	401DE0310DWC	6:57:00	8:06:00	1:09:00
5	20040621	401DE0040DEE	17:34:00	19:40:00	2:06:00
6	20040622	401DE0500DEE	8:21:00	8:59:00	0:38:00
7	20040623	401DE0160DEC	8:54:00	9:46:00	0:52:00
8	20040623	401DE0240DWC	16:46:00	17:01:00	0:15:00
9	20040624	401DW0090DWC	7:50:00	8:07:00	0:17:00
10	20040624	401DE0260DWE	15:28:00	16:32:00	1:04:00
11	20040624	401DW0170DWC	17:30:00	17:50:00	0:20:00
12	20040629	401DE0240DWC	19:20:00	19:56:00	0:36:00
13	20040624	401DW0050DES	18:16:00	18:56:00	0:40:00
14	20040628	401DE0260DEC	17:11:00	17:51:09	0:40:09
15	20040629	401DE0190DWC	14:20:00	14:56:00	0:36:00
16	20040629	401DE0270DEC	16:21:00	17:08:00	0:47:00
17	20040702	401DW0070DEC	15:35:00	16:28:00	0:53:00
18	20040713	401DE0330DEC	17:31:00	18:07:00	0:36:00
19	20040715	401DE0200DEC	7:46:00	8:37:00	0:51:00
20	20040716	401DW0250DEE	17:01:00	17:39:00	0:38:00

*Note: Start-time is estimated via visual inspection of the data and end-time is confirmed via video recordings with the exception of incidents 2 and 12 where the incident start-time was confirmed via the video recordings.

APPENDIX D – INCIDENT TEST RESULTS

Overall Test Results

Incident No.	California 8					McMaster					GAID (75%)				
	Detection Rate		TTD (min.)	Nuisance	False Normal	Detection Rate		TTD (min.)	Nuisance	False Normal	Detection Rate		TTD (min.)	Nuisance	False Normal
	Event	PCC				Event	PCC				Event	PCC			
1	1	78%	3.7	3	4	1	77%	3.7	2	2	1	72%	19.7	0	1
2	Incident Not Detected					Incident Not Detected					1	39%	12	3	3
3	1	84%	1	1	2	1	80%	0.7	3	4	1	85%	0.3	1	1
4	1	96%	2	0	1	1	95%	2.3	2	3	1	92%	4	0	1
5	1	59%	5.3	0	0	1	59%	5.3	0	0	1	72%	3.7	0	1
6	Incident Not Detected					1	31%	11.3	0	1	1	22%	14	0	1
7	1	76%	5	3	3	1	57%	5	0	1	1	70%	5.7	1	1
8	1	47%	N/A	2	3	Incident Not Detected					1	81%	N/A	1	1
9	1	16%	1.7	1	1	1	14%	2.3	0	1	1	15%	1	1	1
10	1	4%	1	0	1	Incident Not Detected					Incident Not Detected				
11	1	95%	2.3	0	1	1	93%	3	0	0	1	92%	4	0	1
12	1	97%	1	0	0	1	97%	1	0	0	1	91%	3.3	0	0
13	1	100%	0	0	0	1	72%	6.7	3	3	1	61%	18.7	0	1
14	1	83%	4	3	4	1	11%	12	0	1	1	54%	1.7	1	1
15	1	84%	6	0	0	1	79%	4.3	2	2	1	88%	4.3	1	1
16	1	87%	6.7	0	0	1	84%	7	3	3	1	88%	5.3	1	1
17	1	81%	1.3	0	0	1	75%	3.3	0	0	1	84%	3.33	1	1
18	1	92%	5.7	5	5	1	83%	2.3	0	1	1	96%	2	1	1
19	1	75%	2	2	3	1	60%	5.7	0	1	1	83%	6	1	1
20	1	93%	2	1	2	1	89%	3.3	3	3	1	91%	4.7	0	1
FAR - Event	0.35%					0.07%					0.03%				
PCC - Normal	69%					71%					89%				

Incident No.	Citilog-VisioPAD				
	Detection Rate		TTD (min.)	Nuisance	False Normal
	Event	PCC			
1	1	68%	12.3	3	4
2	1	97%	1.0	1	1
3	1	44%	15.0	3	4
4	1	67%	20.3	5	6
5	1	78%	10.7	2	3
6	1	66%	9.7	2	3
7	1	44%	8.7	2	3
8	1	49%	7.0	1	2
9	1	30%	10.7	1	2
10	1	22%	5.0	1	2
11	1	65%	10.7	2	3
12	1	98%	1.0	1	1
13	1	61%	10.3	2	3
14	1	54%	7.7	1	2
15	1	88%	9.7	2	3
16	1	87%	14.7	5	6
17	1	95%	5.3	2	2
18	1	87%	9.3	2	3
19	1	44%	13.7	5	6
20	1	40%	9.7	3	4
FAR - Event	0.00%				
PCC - Normal	100%				

*Note: DR, $PCC_{Incident}$, TTD, NR and FN are determined using Video/Data Set 3 and FAR and PCC_{Normal} are determined using Video/Data Set 2

APPENDIX E – SAMPLE AID CAAT REPORTS

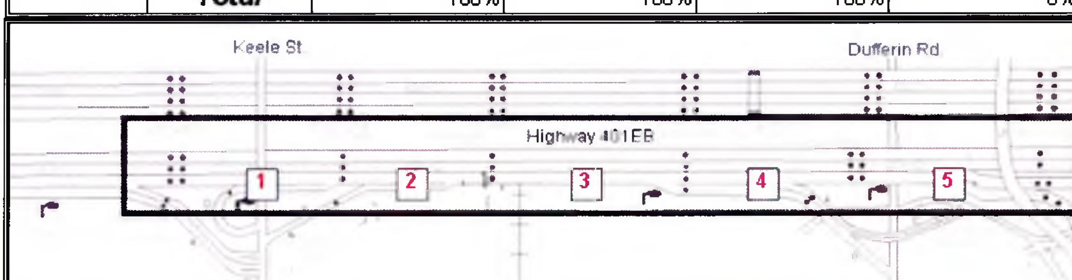
The AID CAAT can be used to generate user-defined reports for any given test conducted. The following are actual example reports made based on the comparative analysis conducted.

The following table depicts when the majority of false alarms are occurring. The AID CAAT reported that the majority of false alarms were occurring primarily during the morning and afternoon peak periods.

	AID CAAT REPORT		
Period Number	*Period Begin*	*Period End*	*Percent of False Incident Detections Occuring* (Combined for All AID Systems)
1	0:00:00	6:30:00	0%
2	6:30:00	10:00:00	25%
3	10:00:00	16:00:00	20%
4	16:00:00	19:00:00	50%
5	19:00:00	0:00:00	5%
	Total		100%

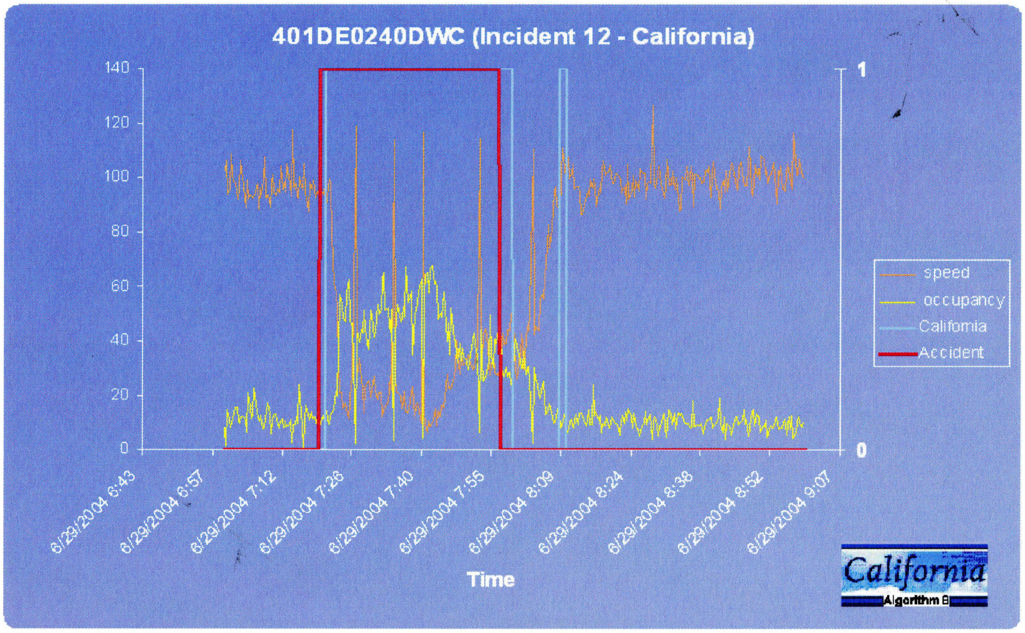
The following table depicts the percentage breakdown of false alarms for each location and for each AID systems exhibited. The AID CAAT reported that most algorithms to have most difficulty in distinguishing incident from normal between locations 3 and 5.

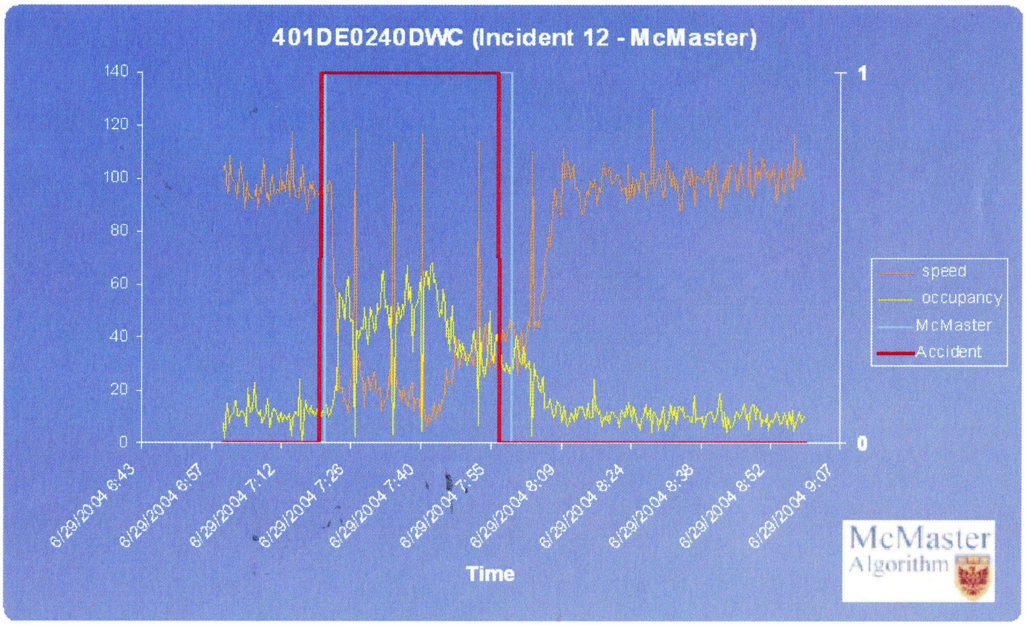
	AID CAAT REPORT				
StationPair Number	StationPair	*False Alarm Location - Percentage Breakdown*			
		California 8	McMaster	GAID	Citilog-VisioPAD
1	10DEC-20DEC	7%	9%	18%	0%
2	20DEC-30DEC	8%	8%	18%	0%
3	30DEC-40DEC	12%	12%	22%	0%
4	40DEC-50DEC	5%	6%	19%	0%
5	50DEC-60DEC	68%	65%	23%	0%
	Total	100%	100%	100%	0%



Sample AID CAAT Reports (Cont'd)
Graphs from Incident #12

*Note: The red line represents the actual incident as confirmed via video and visual inspection of the data. The blue line represents the AID systems output given the data. The speed and occupancy plot is taken from the station upstream of the actual incident.





Sample AID CAAT Reports - Graphs from Incident #12 (Cont'd)