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TOWARDS TRANSFERABLE INCIDENT DETECTION ALGORITHMS

Kun ZHANG
PhD Candidate
Transport Systems Centre
University of South Australia
Adelaide, SA5001
Australia
Fax: +61-8-8302-1880
E-mail: kun.zhang@postgrads.unisa.edu.au

Michael A P TAYLOR
Professor
Transport Systems Centre
University of South Australia
Adelaide, SA5001
Australia
Fax: +61-8-8302-1880
E-mail: MAP.Taylor@unisa.edu.au

Abstract: This paper presents a new automated incident detection framework for both freeways and urban arterial roads. A common modular architecture that includes a special data processing module to handle site specialties is applied to the freeway algorithm (TSC_fr) and the arterial road algorithm (TSC_ar). Bayesian networks are constructed to store general expert traffic knowledge and perform universal incident detection. The TSC_fr algorithm is evaluated using a large number of field incident data sets, and the TSC_ar algorithm is tested using simulation data. The testing results are very encouraging. It is found that both detection rate (DR) and false alarm rate (FAR) are not sensitive to incident decision thresholds. When the decision threshold is above the certain level, both DR and FAR reaches a very stable region. This is the unique feature of the TSC algorithms. The results also demonstrate algorithm transferability is achievable under the new incident detection framework.

Keywords: automated incident detection, advanced traffic management systems, Bayesian networks, algorithm transferability, microscopic traffic simulation

1. INTRODUCTION

Ever-increasing volumes of traffic, coupled with limited new road construction, make it essential to maximize the efficiency and capacity of our existing road network facilities. The concept and the practice of intelligent transport system (ITS) open up new ways of solving wide spread congestion problems and achieving sustainable mobility in our communications and information society. Effective incident detection and management are well-recognized key components of any potentially successful advanced traffic management system (ATMS), which is one of the major applications of ITS.

Most of early studies dealing specifically with automated incident detection (AID) concentrated on freeway incident detection. The implementation of traditional rule-based freeway incident detection algorithms, such as the California algorithms (Payne and Tignor 1978), were hampered by limited performance reliability, substantial implementation needs, and strong data requirements (Chassiakos and Stephanedes 1993). More advanced algorithms were proposed using approaches such as neural networks (Abdulhai and Ritchie 1999; Dia and Rose 1997; Ritchie and Cheu 1995), filtering techniques (Chassiakos and Stephanedes 1993), and catastrophe theory (Hall et al. 1993). However, the algorithms still lack the universality in terms of the high performance and transferability, that comprehensive traffic management systems call for.

Urban arterial roads feature a variety of traffic controls, turning movements, relatively easy lane changing and rerouting of vehicles, therefore, a more complex and challenging environment for incident detection. It is difficult to transfer freeway incident detection techniques to arterial roads. Early AID research on arterial roads focused on simple comparison methods using raw traffic data (Bell and Thancanamootoo 1988; Stephanedes and Vassilakis 1994). To improve algorithm performance and to achieve real-time arterial road incident detection, various techniques were applied to arterial road incident detection including image processing technologies (Hoose et al. 1992), artificial neural networks (Khan and Ritchie 1994; Thomas et al. 2001), data fusion (Ivan 1997) and estimating lane-changing probabilities and queue length (Sheu and Ritchie 1998). Although these published arterial road incident detection methods represent significant improvements, they are all at the initial stage of development and testing. The strong positive correlation between detection rate and false alarm rate still dominates the arterial road incident detection. The stable performance remains a big issue concerning the existing algorithms.

This paper discusses the common issues concerning the existing AID algorithms for both freeways and arterial roads, and presents a universal incident detection framework using Bayesian network techniques. Two incident detection algorithms (TSC_fr for freeway and TSC_ar for arterial road), which are developed from the framework, have shown their capabilities of improving detection performance and algorithm transferability.

2. METHODOLOGY

This research is trying to address two major issues concerning AID algorithms: high performance and transferability.

2.1 Performance Issue: Coherent Reasoning under Uncertainty

Incident detection is a decision process using available traffic information. Since uncertainties are involved in the process (i.e. the dependency between traffic parameters and events changes with knowledge of other traffic parameters and events), the key factors of successful detection would be how to manage expert traffic knowledge to capture the causal dependency among traffic variables and events under incident and incident-free traffic conditions, and how to perform fast and coherent reasoning.

Experienced operators can detect incidents from data, and their specific traffic knowledge for incident detection is cumulative. To enhance the performance of incident detection, the knowledge should be built into incident detection algorithms. Continuously performing coherent reasoning under varying traffic conditions is a big challenge to every operator. Incident detection algorithms should take this role and make the reasoning more efficient.

A Bayesian network is a causal probabilistic network. Its ability to coordinate bi-directional inferences filled a void in expert systems technology of the early 1980s. Bayesian networks have emerged as a general representation scheme for uncertain knowledge (Pearl 1988). In this research, Bayesian network technique is the key technique used to develop incident detection algorithms. The proposed algorithms try to mimic how an experienced operator would use traffic data to detect incidents.

2.2 Transferability Issue: General Knowledge Base & Modular Architecture

Since each site has its own specific geometric features, travel demands and traffic control schemes, when an incident detection algorithm is applied to a large scale of road networks, algorithm transferability becomes a big issue. A transferable incident detection algorithm would not suffer large performance deterioration when it is transferred from site to site, and the algorithm retraining and calibration would not be difficult and time consuming.

Experienced operators can adapt themselves to a new site quickly. The successful transfer stems largely from the organization of their expert traffic knowledge that consists of a high level general knowledge base for reasoning and a low level interpretation system which can be adapted to new road environments.

To address algorithm transferability issue, the proposed incident detection algorithms have a common modular architecture, which includes a specific module to deal with the site specialties (low level interpretation system). The focus of algorithm transferability is then shifted to the general knowledge base construction and management for incident detection.

3. THE TSC ALGORITHMS ARCHITECTURE

The proposed incident detection algorithms (TSC_fr for freeway and TSC_ar for arterial road) have a common architecture that consists of two modules: data processing module and incident detection module.

3.1 Algorithm Architecture

Data processing module is designed to handle site specialties. Raw traffic measurements (lane volume, occupancy and speed) are processed and the link average of each traffic parameter is calculated at each detection interval. The link average is compared with thresholds that contain site heuristics, and the *state* of each traffic parameter (i.e. volume is MEDIUM) is determined. The selected traffic parameters with their states at each detection interval form a standard traffic case. The traffic case is the input of the incident detection module. The idea of using states of traffic parameters instead of their absolute values is that knowledge base of the incident detection module can be used and managed independently from site specific features. Therefore, incident detection can be performed in a universal way.

The incident detection module is developed to perform incident detection using newly received traffic case information at each detection interval. A Bayesian network is the core of this module, which stores expert traffic knowledge and performs coherent reasoning to estimate the incident probability. An incident alarm is issued when the estimated incident probability exceed a decision threshold.

There is a dynamic feedback link from the detection module to the data processing module. The estimated incident probability at previous detection interval is used to determine which traffic parameters would be chosen to form the current traffic case. This dynamic feedback control of traffic case generation is designed to improve the stability of incident detection and the accuracy of incident termination report.

3.2 Bayesian Networks

A Bayesian network consists of a set of variables and a set of directed edges between the variables. Each variable has a finite set of mutually exclusive states. The directed edge represents the cause-effect relationship between variables. The variables together with the directed edges form a directed acyclic graph. To each variable *A* with parents *B1, ... , Bn* (variables which represent the causes of the variable *A*) is attached a conditional probability table *P(A | B1, ..., Bn)* to quantify their causal relationships. A typical Bayesian network is shown in Figure 1 (Jensen 1996).

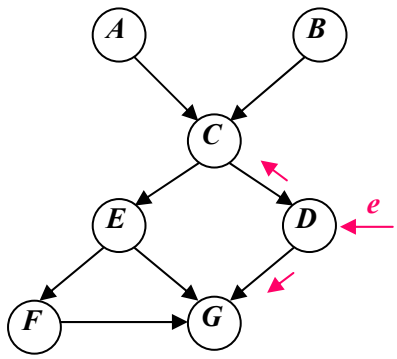

Figure 1. A Bayesian Network

The Bayesian network is used to estimate the probability distribution of those variables with unknown states using all the available information from the rest of the variables. The inference within the network can be thought as a message passing process among the variables. As shown in Figure 1, messages (***e*** the state of ***D***) can be passed along the links in both directions and the tool for inferring in the opposite direction (from ***D*** to ***C***) is Bayes's rule.

4. INCIDENT DETECTION ON FREEWAY – TSC_fr ALGORITHM

Incident detection on freeway is a classic detection problem. The proposed freeway incident detection algorithm (TSC_fr) attempts to address the following two issues concerning freeway incident detection: 1. fast incident detection, and 2. stable algorithm performance.

Figure 2 (from Zhang and Taylor 2004c) shows the Bayesian network for freeway incident detection between upstream and downstream detector stations. The variables of the Bayesian network include two traffic events (incident: ***Inc1_1***, congestion: ***Con1_1***) and seven traffic parameters (volumes: ***Vol1_1*** and ***Vol2_1***, occupancies: ***Occ1_1*** and ***Occ2_1***, speeds: ***Spd1_1*** and ***Spd2_1***, and the occupancy difference between upstream and downstream: ***D_occ1***). At each detection interval, a traffic case is loaded from the data processing module, and available states of the traffic parameters are propagated through the network. The updated probability distributions of both incident and congestion at current detection interval are used to estimate the current incident probability for incident report, and the estimated incident probability of the previous two detection intervals are taken into account at each interval.

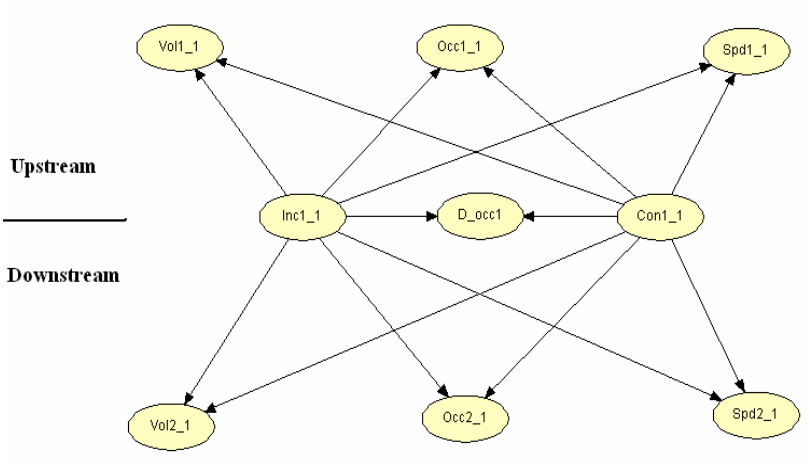

Figure 2. A Bayesian Network for Freeway Incident Detection

4.1 Fast Incident Detection

Fast incident detection depends on the way of reasoning. Figure 2 shows that both congestion identification and incident pattern recognition are accomplished through one step reasoning using all available traffic information. The updated congestion probability at current detection interval is taken into account when the incident probability is estimated. Hence, the incident declaration by the TSC_fr algorithm does not need to wait until the congestion actually appears given the estimated incident probability is above the decision threshold, which is a big contrast to traditional rule-based detection algorithms.

In general, a freeway incident always tends to block upstream traffic and frees downstream traffic. This common trend is quite obvious. To further improve the efficiency of the Bayesian network reasoning, all causal links between upstream and downstream traffic parameters are severed. Meanwhile, a new variable of ***D_occ1*** (which is generated during data processing) is inserted into the network.

4.2 Stable Algorithm Performance

Stable performance of incident detection algorithms relies on the type of knowledge content used and the traffic parameters chosen to detect incidents. The more general the knowledge base is, the more stable the detection performance will be. The conditional probability tables (CPTs) of the Bayesian network are used to store expert traffic knowledge about incident and incident-free traffic patterns. To achieve the generality, the construction of initial CPTs is performed in a subjective way that consists of extracting detection rule from operator's experience and from literature, and converting those rules into certain entries of CPTs. Objective Bayesian network training based on incident data is only performed when the incident data do represent the general incident features.

Since different traffic parameters (occupancy, volume and speed) operate in different ways during the transit period from incident free to incident traffic conditions or vice versa (Persaud and Hall 1989), it is crucial to select the most appropriate and reliable traffic parameters for incident detection under different traffic conditions. This function is fulfilled by the dynamic feedback link between data processing module and incident

detection module of the TSC_fr algorithm. If the estimated incident probability at the previous interval is high enough, which is a sign of possible incidents, certain traffic measurements (e.g. volumes at both upstream and downstream) are dropped off and rest of measurements are used to generate a traffic case. Because volumes at both upstream and downstream of incidents (not severe ones) is relatively consistent compared with occupancy and speed measurements. By dropping of volumes, the algorithm can pick up incident patterns quickly.

4.3 The TSC_fr Algorithm Evaluation Results

The performance of an AID algorithm is normally evaluated using three performance measures: detection rate (DR), false alarm rate (FAR) and mean time to detect (MTTD). The DR is defined as the ratio of the number of detected incidents to the recorded number of incidents in the test data set. The FAR is the ratio of incorrect detection intervals to the total number of intervals to which the algorithm is applied. The MTTD is the average time difference, between the time the incident is detected by the algorithm and the actual time the incident occurs. The DR and FAR measure the effectiveness of an algorithm, and the MTTD reflects the efficiency of the algorithm.

The original TSC_fr algorithm was developed on the Southern Expressway (SX) in Adelaide, Australia using microscope traffic simulation modelling tools (Zhang and Taylor 2004a). To evaluate the algorithm, a comprehensive and high quality field incident database is used. This database was used by Dr Hussein Dia to develop the best performing MLF (Multiple layer feed forward) incident detection algorithm (Dia and Rose 1997). The incident data were collected on the Tullamarine Freeway and the South Eastern Freeway (SEF) in Melbourne, Australia. Tullamarine data sets include 85 usable lane-blocking incidents, and the SEF data sets contain 15 incidents. To be consistent with the previous research the original study site and the associated data sets are kept the same. Both algorithm performance and its transferability capacity are tested.

1) *Performance test:* To adapt the original TSC_fr algorithm to the Tullamarine Freeway, ten incidents from Tullamarine data were chosen to re-train the algorithm. Five of the selected incidents were examined to set up the initial thresholds for traffic parameters which were used in the data processing module, the other five incidents were used to test the thresholds and fine-tune the data processing module. The original incident detection module of the algorithm was unchanged. The following results were obtained (Zhang and Taylor 2004c):

Table 1. TSC_fr algorithm evaluation results

Data set	Decision threshold (%)	Incident detection performance		
		Detection rate (%)	False alarm rate (%)	Mean time to detect (s)
100 incidents: Tullamarine (85) + SEF (15)	55	92	0.143	158
	60	92	0.103	165
	70	92	0.087	175

Detection rate: A very good DR of 92 per cent is achieved. The most important finding is that the DR is not sensitive to the decision thresholds. As mentioned in section 3.1,

decision threshold is a predefined threshold value of estimated incident probability. When the decision threshold is above 55 per cent, a very stable DR is obtained. It is consistent with the results from previous simulation study (Zhang and Taylor 2004a). This result implies that the TSC_fr algorithm has the potential to 'break' the positive correlation between DR and FAR, which is the big issue concerning the existing incident detection algorithms.

False alarm rate: The FAR is 0.103 per cent. This low FAR is slightly affected by the decision thresholds, decreasing with increasing values of decision thresholds.

Mean time to detect: The MTTD is less than 3 min. As noted in (Dia and Rose 1997), inspection of the log times corresponding to the evaluation data set revealed that the average time taken by the operators to detect the 38 out of 40 incidents was 6.9 min after their estimated occurrence times. The MTTD produced by the TSC_fr algorithm is 2.75 min. This suggests that the algorithm could provide more than 50 per cent improvement in efficiency compared to the average time taken by operators to detect incidents.

2) Transferability test: The TSC_fr algorithm was tested on three different freeway environments: the Southern Expressway in Adelaide, and the Tullamarine Freeway and the South Eastern Freeway in Melbourne. As discussed previously, the TSC_fr algorithm has a modular architecture. The incident detection module contains only general expert knowledge which could be shared by other freeways. To test this hypothesis, the Bayesian network and its CPTs of the original incident detection module were directly transferred to Tullamarine and SEF from SX without any further retraining. The testing results are shown in Table 2.

Table 2. TSC_fr algorithm transferability test

Test site	Number of incidents	Incident detection performance		
		Detection rate %	False alarm rate %	Mean time to detect (s)
SX	36	100	0.07	113
Tullamarine	85	90.6	0.11	181
SEF	15	100	0.02	95

The TSC_fr algorithm performs in a very consistent way in the three different freeway environments. Most excitingly, it performs even better on the South Eastern Freeway when it was transferred from Tullamarine Freeway without adjusting the thresholds of the data processing module. The testing results clearly demonstrate that algorithm transferability is achievable under the new TSC algorithm framework.

5. INCIDENT DETECTION ON ARTERIAL ROAD – TSC_ar ALGORITHM

Incident detection on urban arterial roads is a complex detection problem. The interrupted traffic flow coupled with easy lane changing under low speed driving condition make incident detection on arterial roads a real challenge. How to improve the effectiveness of incident detection, especially how to reduce the false alarm rate, becomes a major issue that the proposed TSC_ar algorithm has to address. Three methods are proposed and combined into the TSC_ar algorithm, which include 1. new detector configuration and

traffic signal incorporation, 2. modified causal structure of the Bayesian network for TSC_fr, and 3. joint reasoning using multiple scenario specific Bayesian networks.

5.1 Traffic Detector Configuration

On urban arterial roads, traffic signals play an important role in traffic pattern formation under both incident and incident-free traffic conditions. It is indispensable to incorporate traffic signal plans into the TSC_ar algorithm. A new detector configuration on arterial roads for incident detection was proposed (Zhang and Taylor 2004b). As shown in Figure 3, Intersection *A* and *B* are coordinated intersections. The detector pairs (***a1, b1***) are used to collect lane traffic volumes and occupancies for incident detection. Traffic data are collected at 5s interval. The detector pairs (***a2, b2***) are mainly used to collect data for intersection traffic control, and treated as supplementary data source. Under this configuration, the demand flow of traffic and the intervention from the traffic signal to the platoon at upstream intersection *A* are captured. To efficiently detect incidents, the focus is given to the major phase of each signal cycle, and the major stream of the through traffic is used as a probe to detect incidents.

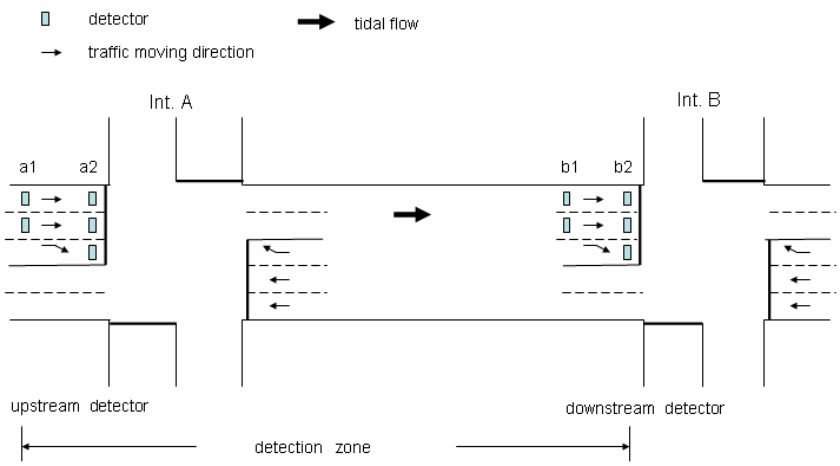

Figure 3. Detector configuration for arterial roads

5.2 Causal Dependency between Upstream and Downstream Traffic Parameters

The Bayesian network for arterial road incident detection is show in Figure 4. The network consists of three traffic events (incident: ***Inc1_1***, congestions: ***Con1_1*** and ***Con2_1***) and five traffic parameters (turning count: ***Turning_1***, volumes: ***Vol1_1*** and ***Vol2_1***, and occupancies: ***Occ1_1*** and ***Occ2_1***). In contrast to freeway incident detection, arterial road incident detection is predicated on the traffic signal cycle basis, and the causal dependencies between upstream and downstream traffic parameters are very strong at each signal cycle. Therefore, the causal links between upstream and downstream volumes and occupancies are built up respectively. In addition, an abnormal turning movement at upstream intersection is a good indicator of a possible incident downstream. An extra variable of ***Turning_1*** is included in the network.

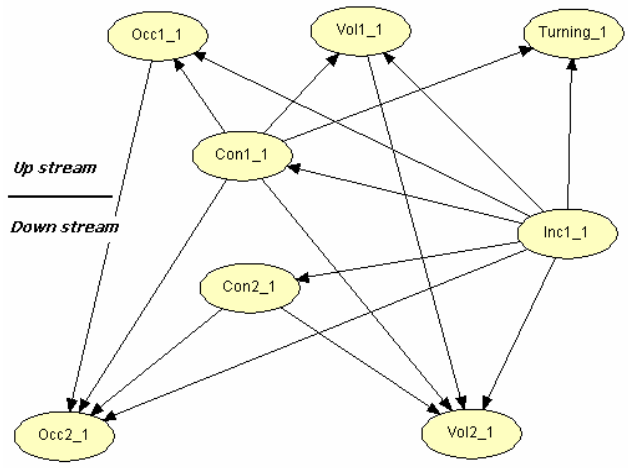

Figure 4. A Bayesian network for arterial road incident detection

5.3 Multiple Bayesian Networks Approach

It was found in the previous research (Zhang and Taylor 2004b) that the FAR was very high, and accurate incident termination reports were sometimes difficult to obtain when incident induced congestion occurred under heavy traffic conditions. To tackle those problems, the scenario based incident detection is proposed: several scenario specific Bayesian networks are working together to detect any possible incident, and different Bayesian networks are used at different time period. Firstly, two different sets of CPTs (knowledge base) of the same Bayesian network are constructed for lane blocking incidents and link blocking incidents respectively. The resultant two new Bayesian networks with different CPTs work together in parallel. The incident probability for each detection interval is estimated by fusing the updated probability distributions of both incident and congestion from those two networks. Secondly, incident detection during peak-period (under heavy traffic condition) is performed using the simplified version of the Bayesian network. In the simplified network, the original variables ***Con1_1*** and ***Con2-1*** (in Figure 4) are combined to form a new single variable. The resultant new network can pick up the distinct incident patterns much faster than the original Bayesian network and maintains low FAR at the same time.

5.4 TSC_ar Evaluation Results

Encouraged by the successful development of the TSC_fr algorithm using microscopic traffic simulation modelling method, the general arterial road environment with typical traffic signal settings is build up using the same micro-simulation package Paramics (Quadstone 2000) to reduce the TSC_ar algorithm development cycle. As is well known, high quality, detailed real incident data on arterial roads are not only very sparse but also very difficult to obtain. The desired types of incidents under different traffic conditions are firstly generated using pseudo micro-simulation models which are not developed based on the real arterial roads. Since the microscopic traffic simulation is only used for testing the initial knowledge contents of the proposed Bayesian network rather than new knowledge acquisition, the accuracy of the simulation is not a critical issue.

The TSC_ar algorithm is tested using simulated incident data. In contrast to the algorithm development using pseudo micro-simulation models, existing Adelaide CBD and Unley City micro-simulation traffic models are used to simulate incidents on a major arterial road (Cross Road). The micro-simulation models were developed by Transport Systems Centre, University of South Australia using the Paramics software, and calibrated using updated field traffic data. Each type of incidents is simulated using a single OD matrix (morning peak period) combined with different seed values and feedback times for different simulation runs. The seed value affects the vehicle release pattern, while the feedback time controls driver's response to the dynamic changes of traffic conditions. Different traffic scenarios are tested. Lane traffic data (volume and occupancy) associated with each simulated incident are collected at 5s intervals.

Incidents at three different locations (upstream, middle block, downstream) between selected two coordinated intersections are simulated under two different volume conditions (medium and heavy). Two severity levels (lane blockage and link blockage) are considered at each location. Incidents start at 20 minute from the beginning of the simulation, and last from 10 to 30 minutes. One incident is simulated during each simulation run. Total number of the simulation runs is 45 (one hour each). Detection interval is 1 minute. The following evaluation results are obtained based on the decision threshold of 70 per cent:

Detection rate: 100 per cent DR is achieved during the entire evaluation. The most important finding from the evaluation is that both DR and FAR are not sensitive to the thresholds of incident probability (once the decision threshold is above 60 per cent, a very stable DR of 100 per cent is obtained), which is consistent with the performance produced by the TSC_fr algorithm.

False alarm rate: FAR is improved to 0.93 per cent from 1.50 per cent of the previous study (Zhang and Taylor 2004b). This result demonstrates the suitability of using multiple scenario specific Bayesian networks to perform joint evidential reasoning to detect incidents.

Mean time to detect: MTTD is 153 seconds. This detection time is longer than the one obtained from the previous research (113s). It is still reasonable for field application. In order to test the robustness of the TSC_ar algorithm, the proportion of the middle block incidents under medium traffic flow condition (the most difficult scenario for the algorithm to work out) is increased during the evaluation. This is thought to be the major contributor to the longer MTTD. The MTTD is also affected by the length of the detection zone, because the spatial comparison of traffic patterns is based on the major stream of through traffic flow.

6. CONCLUSION

This paper presents a universal incident detection framework for both freeway and urban arterial road. Bayesian network techniques are successfully used to develop the TSC_fr and TSC_ar algorithms. Evaluation of the algorithms reveals that both DR and FAR are not sensitive to incident decision thresholds, and the stable DR is achievable without making compromise on FAR. This unique feature implies a potential for the algorithms to 'break' the positive correlation between DR and FAR, which is the big issue concerning the existing incident detection algorithms.

The modular architecture of the TSC algorithms facilitates algorithm transferability. Meanwhile, it makes the algorithms easy to train in a subjective way without the need to employ a large number of field incident data sets. An experienced operator's knowledge about the specific road environment is good enough to adapt the algorithms to the site. Those capabilities of the TSC algorithms are clearly demonstrated in algorithm performance test and transferability test.

It needs to be emphasized that a Bayesian network does not require each of its variables to have a renewed state at every detection interval, and the evidential reasoning can be performed by the Bayesian network using partially available traffic information. This flexibility of the Bayesian network approach offers an opportunity for other information sources (e.g. probe travel time data), which cannot supply continuous report at every detection interval, to be used by the TSC algorithms to enhance their performance. Our future research will focus on TSC_ar algorithm evaluation using field incident data, TSC_fr algorithm on-line testing, and incorporating other traffic information (e.g. travel time) into the TSC algorithms to enhance their performance.

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