

Effective arterial road incident detection: A Bayesian network based algorithm

Kun Zhang *, Michael A.P. Taylor ¹

Transport Systems Centre, University of South Australia, Adelaide, SA 5001, Australia

Received 14 December 2005; received in revised form 1 November 2006; accepted 2 November 2006

Abstract

Timely and accurate incident detection is an essential part of any successful advanced traffic management system. The complex nature of arterial road traffic makes automated incident detection a real challenge. Stable performance and strong transferability remain major issues concerning the existing incident detection algorithms. A new arterial road incident detection algorithm TSC_ar is presented in this paper. In this algorithm, Bayesian networks are used to quantitatively model the causal dependencies between traffic events (e.g. incident) and traffic parameters. Using real time traffic data as evidence, the Bayesian networks update the incident probability at each detection interval through two-way inference. An incident alarm is issued when the estimated incident probability exceeds the predefined decision threshold. The Bayesian networks allow us to subjectively build existing traffic knowledge into their conditional probability tables, which makes the knowledge base for incident detection robust and dynamic. Meanwhile, we incorporate intersection traffic signals into traffic data processing. A total of 40 different types of arterial road incidents are simulated to test the performance of the algorithm. The high detection rate of 88% is obtained while the false alarm rate of the algorithm is maintained as low as 0.62%. Most importantly, it is found that both the detection rate and false alarm rate are not sensitive to the incident decision thresholds. This is the unique feature of the TSC_ar algorithm, which suggests that the Bayesian network approach is advanced in enabling effective arterial road incident detection.

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Keywords: Arterial road incident detection; Bayesian networks

1. Introduction

Road incidents and incident induced traffic congestion provide real threats to the mobility and safety of our daily travel. Timely and accurate incident detection is an essential part of any successful advanced traffic management system. Automated incident detection (AID) systems, which employ an incident detection algorithm to detect incidents from traffic data, aim to improve the accuracy and efficiency of incident detection over a large road network. Urban arterial roads feature interrupted traffic flow, turning movements and a variety of

* Corresponding author. Tel.: +61 8 8302 1990; fax: +61 8 8302 1880.

E-mail addresses: Kun.Zhang@unisa.edu.au (K. Zhang), MAP.Taylor@unisa.edu.au (M.A.P. Taylor).

¹ Tel.: +61 8 8302 1861; fax: +61 8 8302 1880.

traffic controls, and therefore provide a more challenging environment for incident detection. Early arterial road AID algorithm development focused on simple comparison methods using raw traffic data (Bell and Thancanamootoo, 1988; Han and May, 1989; Stephanedes and Vassilakis, 1994). To enhance algorithm performance and to achieve real-time incident detection, advanced methods have been suggested, which include image processing (Hoose et al., 1992), vehicle positioning (Sermons and Koppelman, 1996), artificial neural networks (Khan and Ritchie, 1998; Thomas et al., 2001), support vector machines (Yuan and Cheu, 2003) and data fusion (Ivan, 1997; Thomas, 1998). Although these published new methods represent significant improvements, performance stability and transferability remain major issues concerning the existing arterial road AID algorithms.

To address these issues, the Bayesian network technique was applied to arterial road incident detection (Zhang and Taylor, 2004; Zhang and Taylor, 2005b). This new method attempted to incorporate the existing expert traffic knowledge into the AID algorithm to enhance its evidential reasoning capability. This paper introduces the original Bayesian network based TSC_ar algorithm and details major improvements recently been made to the algorithm. 'TSC' stands for Transport Systems Centre where the TSC_ar algorithm was developed. '_ar' refers to arterial roads as another Bayesian network based freeway AID algorithm TSC_fr (Zhang and Taylor, 2006) had also been developed in the TSC. The AID algorithms discussed in this paper aim to detect lane-blocking incidents when their effects are manifested by certain types of deterioration in traffic conditions. An incident that blocks the entire roadway between two signalized intersections (we call it link-blocking) is an extreme case of lane-blocking incidents.

This paper is organized into five sections. The first section considers arterial road incident detection problem as a decision making problem, and proposes a Bayesian network based method to tackle this problem. This method leads to the original TSC_ar algorithm, which is introduced in Section 2. In the third section, three major improvements of the algorithm are discussed. The performance of the modified TSC_ar algorithm is presented in Section 4. In the last section, conclusions are drawn and future research directions are indicated.

2. Methodology

Arterial road incident detection is a decision making process. Prior traffic knowledge and real time traffic information are essential to make an accurate decision. Experienced traffic operators can accurately detect incidents from data. In the human reasoning process, operators' general traffic knowledge is used to build a causal structure in which relations between traffic parameters (e.g. volume and occupancy, etc.) and traffic events (e.g. incident) are quantitatively described. The observed traffic data are used to determine the state of each traffic parameter, which is mainly based on their experience (site specific knowledge). Using traffic states as evidence, the likelihood of an incident can be sought from the causal structure. Clearly, the estimated incident probability given observed traffic data form the base of each decision making. To mimic such human reasoning, we use Bayesian networks (Jensen, 1996; Pearl, 1988) to store prior traffic knowledge and to perform evidence based inference in our proposed AID algorithm architecture. Bayesian networks are causal probabilistic networks, which are also called belief networks. The ability of Bayesian networks to coordinate bi-directional inferences filled a void in expert systems technology in early 1980s, and this method subsequently emerged as a general representation scheme for uncertain knowledge (Pearl, 1988).

Expert (prior) traffic knowledge about arterial road incidents can be either obtained from literatures and experienced traffic operators or learned from historical incident data. It is a challenge to try to collect high quality, very detailed incident data which represent a variety of arterial road incident scenarios and their associated intersection traffic signal controls. The strong site specific features embedded in each incident data set make it difficult to extract genuine incident patterns. Hence, we focus on the existing general traffic knowledge about incidents which can be obtained from both literatures and traffic operators, and seek a way to subjectively build them into the AID algorithm. Meanwhile, we are trying to describe real time traffic in a more general and concise manner using states instead of absolute values of each traffic parameter (e.g. volume is High, Medium or Low) in order to use the existing traffic knowledge more effectively. To overcome incident data scarcity during the AID algorithm development and testing, microscopic traffic simulation is conducted in this research to simulate arterial road incidents.

3. Arterial road AID algorithm TSC_ar

3.1. Algorithm architecture

Incorporating existing traffic knowledge into the AID algorithm is the central part of the original TSC_ar algorithm development. The AID algorithm architecture design focuses more on efficient traffic knowledge management which aims to improve performance stability and transferability of the algorithm. As shown in Fig. 1, our proposed AID algorithm architecture consists of two modules: data processing module (DP) and incident detection module (ID). This architecture has been successfully used to develop the freeway AID algorithm TSC_fr (Zhang and Taylor, 2006) in our earlier research.

The DP module can be treated as a traffic state generator. Real time traffic measurements on traffic parameters such as volume and occupancy, which are collected at each predetermined time interval, are processed in this module. The processed traffic measurement on each traffic parameter is then converted into its corresponding state (e.g. volume is High, Medium or Low) using a set of thresholds. Site specific traffic knowledge (operators' experience about the site) is used in the module to set up thresholds for each traffic parameter. The ID module works as an inference engine. The Bayesian networks form the core of this module, which quantitatively model the causal dependencies among traffic parameters and traffic events (e.g. incident or congestion). Using the traffic state as evidence, the Bayesian networks update the incident probability at each detection interval. If the incident probability exceeds the predefined decision threshold, an incident alarm will be issued. General traffic knowledge about incidents is used to create conditional probability tables of the Bayesian networks, which could be shared between different sites.

Two direct benefits gained from this design are (1) both the general knowledge base and the evidential reasoning process are independent of site specific data processing, which makes the ID module universal, and (2) traffic measurements to traffic state conversion only requires local traffic knowledge, which could substantially reduce the algorithm implementation requirements.

3.2. Data processing module (DP)

In the TSC_ar algorithm, we use the major traffic stream of the upstream intersection during each signal cycle as a probe to detect incidents downstream, especially when tidal flow occurs during peak periods. Traffic data processing is thus focused on extracting traffic information (i.e. volume and occupancy) corresponding to this major traffic stream and converting them into traffic states. Traffic signal incorporation plays an important role in the process.

Our proposed traffic detector configuration for incident detection is shown in Fig. 2. The detection zone (between detector station S11 and S21) covers the upstream intersection (Int. A) and the roadway between the two adjacent intersections. Under the SCATS (Hicks and Carter, 2000; Lowrie, 1982) signal control systems, which are dominant in major Australian cities, traffic detectors are located on the approach side of the signalized intersection just next to the stop line (i.e. S12 and S22 in Fig. 2). We propose the detectors (i.e. S11 and S21) for incident detection to be located 50 m away from the stop line further upstream. The rationale for such detector configuration is that the detector S11 can monitor the queue evolution during each signal cycle and it can indicate traffic demand better than stop-line detectors. In practice, one advanced video detector

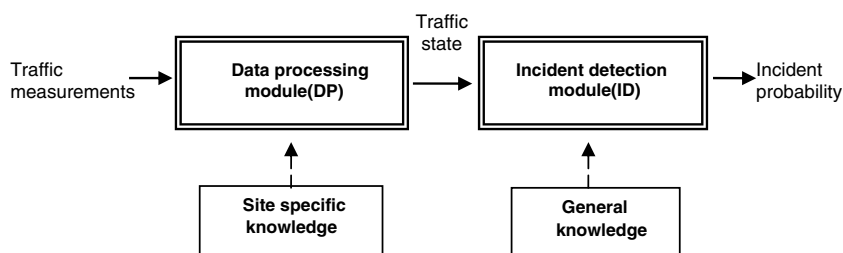


Fig. 1. AID algorithm architecture.

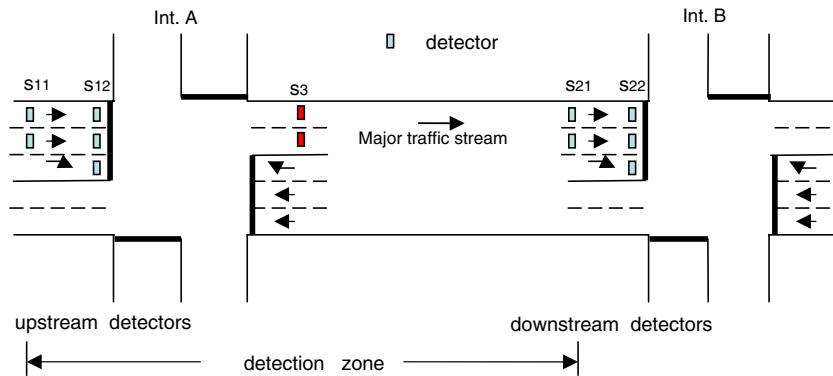


Fig. 2. Detector configuration for arterial road incident detection.

(Nelson, 2002) can provide such flexibility to monitor multiple traffic detector zones (e.g. cover both S11 and S12).

As mentioned before, we only use the major traffic stream of the upstream intersection as a probe to detect incidents downstream for each signal cycle. Traffic signal settings of both upstream and downstream intersections are incorporated into the DP module to perform traffic data extraction. The upstream volume that corresponds to the major traffic stream of each signal cycle is extracted from S12 data. Meanwhile, the upstream occupancy during the same major green phase is extracted from S11 data to provide the algorithm with concurrent queuing conditions. When processing S11 data, we use the extended data extraction period, which starts 5 s before each major green phase and terminates 10 s after the green. In this way, we try to capture the better travel demand at the approach side of the upstream intersection.

We only use S21 data to extract downstream volume and occupancy which corresponds to the same traffic stream from upstream intersection. Suppose that the traffic signals at the two intersections (Int. A and Int. B in Fig. 2) are coordinated. The offset value used by the downstream intersection can provide us with the starting time for S21 data extraction. If the two intersections are not coordinated, we use the empirical average travel time between the two intersections during the same periods to figure out the earliest green phase at the downstream intersection for traffic data extraction. The extracted phase-specific lane volumes and occupancies (both upstream and downstream) of each signal cycle are averaged over the number of lanes. The resultant lane average data are used to represent the entire signal cycle. By comparing the processed lane average data against the predefined thresholds, the state of each traffic parameter is determined. Incident detection interval for the TSC_ar algorithm depends on upstream traffic signal cycle time.

Our proposed detector configuration is different from the traditional one used in earlier works (e.g. Khan and Ritchie, 1998; Thomas et al., 2001; Yuan and Cheu, 2003), in which the incident detection zone was defined as the road section between S3 and S21 (see Fig. 2). Under the traditional detector configuration, traffic data processing is simpler, and incident detection can be performed at a fixed time step (like freeway AID) without considering the actual traffic signal plans for both upstream and downstream intersections. However, it is well known that traffic signals play an important role in traffic pattern formation (both incident and incident-free patterns). It is difficult to precisely describe incident patterns using S3 and S21 data without considering the specific traffic signal plans and their impacts on incident evolution, especially when adaptive traffic signal control (e.g. SCATS) is implemented at the intersections.

3.3. Incident detection module (ID)

3.3.1. Basic Bayesian network

The Bayesian networks form the core of the ID module. A Bayesian network consists of a set of nodes (the variables of interest) and a set of directed links between these nodes. Each variable has a finite set of mutually exclusive states. The directed links reflect cause–effect relations between the variables. Since these effects are normally not completely deterministic, the strength of an effect is modelled as a probability

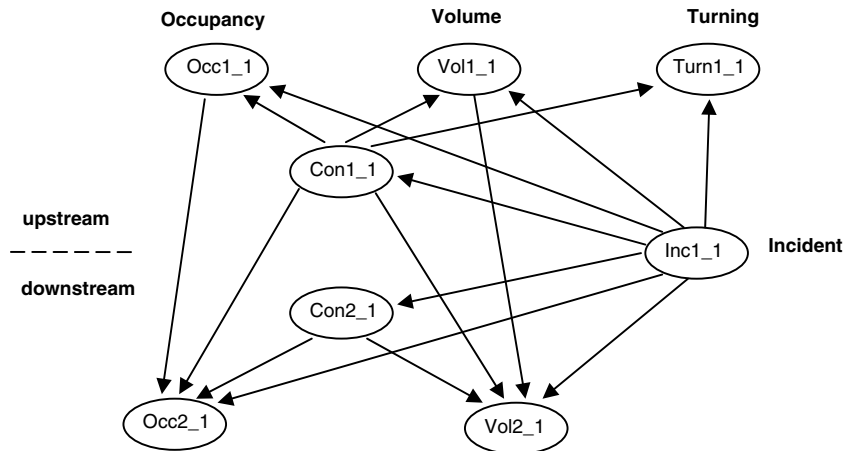


Fig. 3. Basic Bayesian network for arterial road incident detection.

(Jensen, 1996). The basic Bayesian network used in the ID module for arterial road incident detection is shown in Fig. 3. The network consists of three traffic events (incident: Inc1_1, congestion at both upstream and downstream intersections: Con1_1 and Con2_1) and five traffic parameters (turning count at the upstream intersection: Turn1_1, volumes of both intersections: Vol1_1 and Vol2_1 (representing the major traffic stream), and occupancies of both intersections: Occ1_1 and Occ2_1). Here, ‘_1’ stands for the 1st detection interval.

Note that arterial road traffic congestion is often characterized by queues surrounding certain intersections, the key points of an arterial road network (Taylor, 1992). To better represent this feature, the concept of *node congestion* instead of *link congestion* is used to construct the Bayesian network. As shown in Fig. 3, the nodes Con1_1 and Con2_1 are used to represent congestion at the upstream and downstream intersections, respectively. Through this treatment, the impact from incident to two individual intersection congestion situations can be modelled.

An arterial road incident does not always block upstream traffic and free downstream one as the typical freeway incident does. In case of a mid-block lane-blocking incident, a certain proportion of the platoon, which is released from the upstream intersection and is interrupted and delayed by the incident, may encounter a red signal at the downstream intersection (whereas normally it does not). Hence the incident induced long queue may appear downstream first. In addition to incidents themselves, the preceding traffic condition and the traffic signal control at both upstream and downstream intersections also influence incident pattern formation. To model these complicated arterial road incident scenarios, the causal link between each pair of upstream–downstream traffic parameters (e.g. Occ1_1 and Occ2_1) and the links from Con1_1 to both Occ2_1 and Vol2_1 are built up. Since, abnormal turning movements upstream are an important indicator of possible incidents, the node Turn1_1 is included into the basic Bayesian network, whose value is extracted from upstream stop-line detector (S12 in Fig. 2) data where possible. Note that the turning counts calculation is not based on each major green phase but on the entire signal cycle.

3.3.2. Conditional probability table (CPT)

Fig. 3 indicates that all nodes of the Bayesian network represent concepts that are well defined with respect to the domain under investigation. If a node in the Bayesian network does not have any parents (i.e. no links pointing towards it, such as Inc1_1), the node will contain a *marginal probability table*, a probability distribution over the states of the variable that it represents. If a node does have parents (i.e. one or more links pointing towards it, such as Occ1_1), the node contains a *conditional probability table* (CPT). Each cell in the CPT contains a conditional probability for the variable being in a specific state given a specific configuration of the states of its parents. The CPTs of the Bayesian network are used to quantify the causal relations described in the Bayesian network.

Prior traffic knowledge about incident detection is stored in each CPT of the Bayesian network. Table 1 shows the CPT of the variable Occ1_1, the upstream occupancy corresponding to the major traffic stream. The first entry of the table (0.9, upper left hand corner) means that given an incident happened in the detection zone which was followed by an incident induced congestion, it is almost certain that the upstream occupancy would be high. This example shows how we convert the existing traffic knowledge into each CPT.

From the above description of the Bayesian network and its CPTs, one can see that the Bayesian network is a transparent causal structure. It constitutes a model of general environment and simulates the mechanism that eight traffic variables act in the environment. That is why the knowledge base of the Bayesian network could be adapted to new traffic environment through simple modification of the existing CPTs using site specific knowledge (if needed). Currently, we assign two states (*Yes* or *No*) to each traffic event, and three states (*High*, *Medium*, and *Low*) to each traffic parameter. This arrangement aims to simplify CPT construction and make the ID module of the algorithm more general.

3.3.3. Probability updating

Fundamentally, a Bayesian network is used to update probability distributions of certain variables whenever information on the other variables of the network becomes available. The inference (probability updating) performed in the Bayesian network can be thought of as a message passing process. A message (e.g. the available state of a certain traffic parameter) can be passed along the link in both directions. The tool for inferring in the opposite direction (e.g. from Occ1_1 to Con1_1 in Fig. 3) is Bayes' theorem (Jensen, 1996):

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \quad (1)$$

where $P(B|A)$ is posterior probability distribution of B given that information on A is available, $P(A|B)$ is conditional probability distribution of A given B , which represents expert knowledge about the domain under investigation, and $P(B)$ and $P(A)$ are the prior probabilities of B and A , respectively. Bayes' theorem becomes the basis of Bayesian inference when B is the event of a specific hypothesis being true, and A as the event of observing specific data.

The message-passing process may be described mathematically as follows: Let U be the universe of variables in the Bayesian network, $U = \{A_1, \dots, A_n\}$, and let information e be the statement

“the joint configuration of A_1, \dots, A_n is (a_1, \dots, a_n) , which consists of information of several variables, and the information about each variable can be entered separately.”

The posterior probability distribution $P(X|e)$ for all variables X in U (X represent the variables of our primary interest, such as Inc1_1 in Fig. 3), which is updated beliefs on X given information e , is calculated in the following way:

1. Use the chain rule (2) (Jensen, 1996) to calculate $P(U)$, the joint probability table that provides the probabilities of all possible configurations of the universe U

$$P(U) = \prod_i P(A_i|p(A_i)) \quad (2)$$

where $p(A_i)$ is the parent set of the node A_i , and $P(A_i|p(A_i))$ is the conditional probability table of A_i .

Table 1
Conditional probability table of variable Occ1_1

Inc1_1	Yes		No	
	Yes	No	Yes	No
High	0.9	0.2	0.8	0.1
Medium	0.1	0.6	0.2	0.5
Low	0.0	0.2	0.0	0.4

2. Enter information e , $e = (a_1, \dots, a_n)$ into the Bayesian network to form $P(U, e)$, the part of $P(U)$ corresponding to the configuration (a_1, \dots, a_n) .

Information entering for single variable: Let A be a variable with m states, and the prior probability distribution of A over its states is $P(A) = (x_1, \dots, x_m)$. Assume that we get the information e that A can only be in states i and j . This statement says that all states except i and j are impossible, and we have the belief

$$P(A, e) = (0, \dots, 0, x_i, 0, \dots, 0, x_j, 0, \dots, 0) \quad (3)$$

The way that e is entered can be interpreted as a multiplication of $P(A)$ with an m -dimensional table $\underline{e} = (0, \dots, 0, 1, 0, \dots, 0, 1, 0, \dots, 0)$ resulting in $P(A, e)$ (Jensen, 1996).

In our case, e consists of several findings (a_1, \dots, a_n) , and each finding can be entered separately, then

$$P(U, e) = P(U) \cdot \underline{a}_1, \dots, \underline{a}_n \quad (4)$$

where \underline{a}_i is a m -dimensional table of zeros and ones corresponding to the information a_i on variable A_i , which has possible m states.

3. Marginalize $P(U, e)$ down to $P(X, e)$, for the variables X in U . For each state x of X , sum up all entries in $P(U, e)$ with X in state x

$$P(X, e) = \sum_{U \setminus \{X\}} P(U, e) \quad (5)$$

4. $P(X|e)$ is the result of normalizing $P(X, e)$ which is dividing $P(X, e)$ by the sum of all its entries. The Bayesian theorem (1) supports this calculation

$$P(X|e) = \frac{P(X, e)}{P(e)} = \frac{P(X, e)}{\sum_X P(X, e)} \quad (6)$$

The first algorithms proposed for probabilistic calculations in Bayesian networks used message-passing architecture and were limited to trees (Kim and Pearl, 1983). Techniques have since been developed to extend this tree-propagation method to general networks. A general method was presented by Lauritsen and Spiegelhalter (1988). The Hugin method proposed by Jensen et al. (1990), which is used in the ID module for probability updating, is a modification of the Lauritsen-Spiegelhalter method. Any node in the Bayesian network can receive information as the Bayesian network method does not distinguish between inference in or opposite to the direction of the links. Also, simultaneous input of information into several nodes will not affect the probability updating performed using Hugin method. These two features make the evidential reasoning process fast and coherent.

In an earlier AID research (Thomas, 1998), the Bayesian classifier was used to improve accuracy of traffic pattern classification in which the Bayes' rule (theorem) was used to minimize the conditional misclassification cost. The precision of pattern description using traffic parameters for each pattern class was crucial for such application. In contrast, the Bayesian network technique uses the Bayesian rule to perform evidence base reasoning which relies on the clearly defined and quantified knowledge base (CPTs of the Bayesian network). This technique enables us to subjectively build prior traffic knowledge into the Bayesian network and modify them at any stage of AID algorithm implementation to cope with traffic environment changes. Hence, the Bayesian network approach for incident detection is a more advanced use of the Bayesian rule to enhance evidential reasoning capability of the AID algorithm.

4. TSC_ar algorithm modification

The performance of an AID algorithm is normally assessed using three 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 the number of false alarms 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, while the MTTD measures the efficiency of the algorithm.

To enhance the performance of the original TSC_ar algorithm presented in the previous section, three major modifications are made to the ID module of the algorithm including (1) applying dynamic Bayesian network structure, (2) constructing scenario-specific Bayesian networks, and (3) using simplified Bayesian network topology for heavy traffic conditions. The first two modifications focus on the effectiveness of the algorithm, and the third one deals with algorithm efficiency.

4.1. Traffic simulation with Paramics

In our previous research (Zhang and Taylor, 2005a; Zhang and Taylor, 2006), the microscopic traffic simulation software package Paramics was successfully used to develop the Bayesian network based freeway AID algorithm TSC_fr. When a large number of field incident data sets were used to test the algorithm, its performance was very consistent with the one obtained from simulation studies. Given the scarcity of high quality field incident data and encouraged by the above result, simulated incident data are used to develop and test the TSC_ar algorithm in the current stage of algorithm development.

The original TSC_ar algorithm was developed on Cross Road, an urban arterial road in Adelaide, Australia. Cross Road is located in the Unley municipality which sits next to the Adelaide CBD. There are three major arterial roads (Goodwood Road, Unley Road and Fullarton Road) that run north-south through Unley and link this suburb to Adelaide CBD. The targeted arterial road (Cross Road) runs east-west and connects the above three arterial roads. The study area is the road section between Unley Road and Fullarton Road, which contains three signalized intersections (see Fig. 4).

The Cross Road traffic model used in this research is part of the validated Paramics micro-simulation model that covers the entire Unley road network (Woolley et al., 2001). This Paramics model was developed to evaluate the 40 km/h urban speed limit scheme applied to residential streets in that area. Our proposed traffic detector configuration (see Fig. 2) is applied to the Cross Road model to collect incident related traffic data. During traffic simulation, the morning peak period travel demand (from 7:00 a.m. to 9:00 a.m.) is used, but the traffic signal settings of the three selected intersections (Unley Road, Duthy Street and Fullarton Road) are adjusted. Generally, one incident is simulated during each 1-h simulation run. Incidents start 20 min after the beginning of each simulation run, and incident duration varies from 10 min to 35 min. Detection interval is based on the predefined signal cycle time (i.e. 60–90 s).

4.2. Dynamic Bayesian network

The general way to reduce the FAR of an AID algorithm is the persistence test, which raises an incident alarm after multiple incidents have been detected by the algorithm at several consecutive detection intervals.

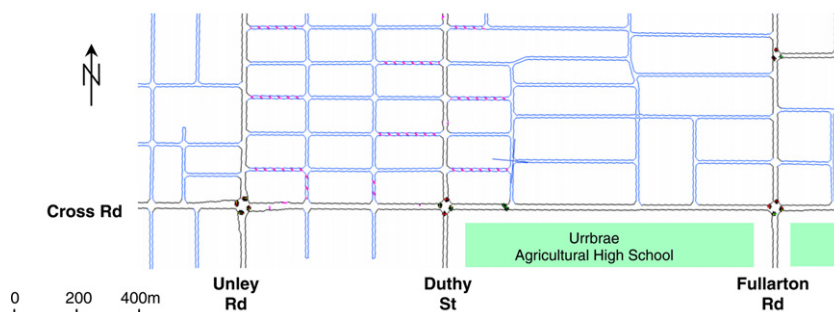


Fig. 4. Targeted arterial road section of Cross Road.

The detection interval used by the TSC_ar algorithm is based on traffic signal cycle time. The incident report could be delayed for several minutes if we simply adopt this approach to improve the FAR of the algorithm. Alternatively, the dynamic Bayesian network is used in the ID module to reduce the FAR of the algorithm. As shown in Fig. 5, the dynamic Bayesian network consists of two time slices. Each time slice represents one detection interval ($t - 1$ or t). The Bayesian network used in each time slice for incident probability updating is identical (see Fig. 3). To make the following discussion simpler, the details of the basic Bayesian network topology for each time slice are hidden. In Fig. 5, “_1” refers to the first time slice ($t - 1$) and “_2” refers to the second time slice (t).

The causal links between the nodes in two different time slices try to model the evolving traffic patterns caused by traffic events (i.e. incident and congestion) during two consecutive detection intervals. For time slice t , the incident probability updating is performed using both the states of traffic parameters at current interval t and the estimated incident and congestion probabilities at $t - 1$ (which are again based on the traffic states at $t - 1$). Taking that advantage of bi-directional reasoning capability of the Bayesian network, similar reasoning can be performed for time slice $t - 1$, which means the current states of both incident and congestion at detection interval t can be used to adjust the previous incident probability estimate and make it more reliable. This is how temporal information is used in the TSC_ar algorithm to perform joint reasoning for incident detection.

We simulate twelve lane-blocking incidents using the Cross Road model to test this new Bayesian network structure. Nine of them are simulated under heavy traffic conditions, which include three multiple incident scenarios. Each of these three special incidents contains two separate incidents that occurred simultaneously but at two different locations within the detection zone. The incident decision threshold is set to 70%, which means an incident alarm will be issued if the estimated incident probability exceeds this value. The performance of the dynamic Bayesian network and the basic Bayesian network is shown in Table 2.

The figures show that the dynamic Bayesian network improves the FAR of the algorithm by 0.37%, even though the FAR itself (1.85%) is still very high. Importantly, the MTTD of the algorithm is reduced by 47 s when the dynamic Bayesian network is used, which indicates that using the dynamic Bayesian network to improve the FAR does not compromise the efficiency of the algorithm but improves it. This is a major difference to the persistence test method used for the similar purpose.

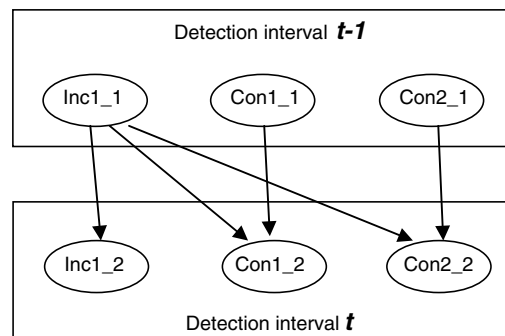


Fig. 5. Dynamic Bayesian network for arterial road incident detection.

Table 2

Performance of dynamic Bayesian network and basic Bayesian network on Cross Road data (12 incidents)

Detection method	Algorithm performance		
	Detection rate (%)	False alarm rate (%)	Mean time to detect (s)
Dynamic Bayesian network	100	1.85	80
Basic Bayesian network	100	2.22	127

4.3. Scenario-specific Bayesian networks

A link-blocking incident on arterial roads usually generates a distinct traffic pattern, which is similar to the severe freeway incident pattern. However, this pattern differs from a normal capacity-reducing lane-blocking incident pattern discussed in Section 3.3.1. To pick up both lane-blocking and link-blocking incidents and to reduce the FAR of the TSC_ar algorithm at the same time, we create two incident scenario specific Bayesian networks which work side by side in the ID module. The two scenario-specific Bayesian networks share the common network topology (see Fig. 3). However, each Bayesian network has its specific CPTs tailored for one of the two incident types.

Inside the ID module, the Bayesian network tailored for the link-blocking incident scenario works as the main inference engine. The updated incident and congestion probability in this network will automatically be used to produce the final estimate of incident probability for each detection interval. Meanwhile, the updated incident probability in the other Bayesian network (lane-blocking incident specific Bayesian network) is used as a switch. If its value is higher than the predefined threshold and the incident probability produced by the link-blocking specific Bayesian network is not high enough, then the two Bayesian networks will swap at the next detection interval. The incident report will then be based on the reasoning results from the lane-blocking specific Bayesian network. The reason for this design is that the link-blocking incident scenario can be more clearly described. In addition, we can apply a narrowed tolerance region to some entries of the CPTs for the link-blocking specific Bayesian network with little ambiguous interpretation, which could reduce the MTTD without a large increase in false alarms.

To test the scenario-specific Bayesian networks and the parallel structure of the ID module, another 12 incidents are simulated. Six out of the 12 incidents are link-blocking incidents, four of which are simulated under medium traffic conditions. Among the rest of the six lane-blocking incidents, four incidents are also obtained under medium traffic conditions. We keep the incident decision threshold as 70%. The performance of the scenario-specific Bayesian networks and the basic Bayesian network is shown in Table 3.

When we use the single basic Bayesian network to detect incidents, two link-blocking incidents are missed. For the rest of the four link-blocking incidents, the outputs of the algorithm experience a large fluctuation during the transit periods from incident-free to incident conditions and vice versa. Meanwhile, accurate incident termination reports are difficult to obtain. After we fine-tune the CPTs of the Bayesian network, the performance of the algorithm does not improve much as we have to use one of the two incident types (we chose the lane-blocking incident scenarios) as the base to perform such knowledge base adjustment. In contrast, the parallel scenario-specific Bayesian networks detect all 12 incidents with the low FAR of 0.5%. The only drawback of this design is that the MTTD of the algorithm increases by 29 s. These results suggest that the scenario-specific incident detection is a useful direction to pursue in order to achieve effective and stable arterial road incident detection.

4.4. Multiple Bayesian networks approach

Since the TSC_ar algorithm detects incidents on signal cycle basis, improving efficiency of the algorithm is always one of our primary objectives. For peak period operation, we propose a simplified version of the basic Bayesian network as we know that incident pattern formation and propagation are much quicker under heavy traffic conditions. As shown in Fig. 6, two original nodes Con1_1 and Con2_1 of the basic Bayesian network (see Fig. 3) are combined to form a single node Con1_1, and the causal link between incident Inc1_1 and

Table 3
Performance of scenario-specific Bayesian networks and basic Bayesian network on Cross Road data (12 incidents)

Detection method	Algorithm performance		
	Detection rate (%)	False alarm rate (%)	Mean time to detect (s)
Scenario-specific Bayesian networks	100	0.5	155
Basic Bayesian network	83	0.8	126

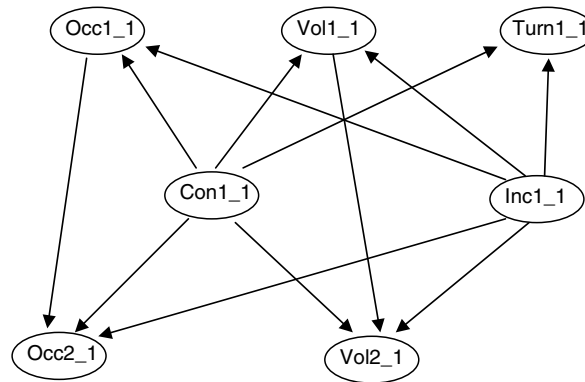


Fig. 6. Simplified Bayesian network for peak period operation.

congestion Con1_1 is severed. Now, the node Con1_1 represents the general congestion condition of the entire detection zone. In the simplified Bayesian network, the size of the CPT which is attached to each downstream node (i.e. Occ2_1 and Vol2_1) is greatly reduced, and traffic scenarios defined in the CPT are simplified. These modifications can speed up the entire decision making process for incident detection.

We use 18 lane-blocking incidents to test the performance of the simplified Bayesian network. These incidents are selected from the 24 simulated incidents which are used in the previous two algorithm tests. Eleven of them are simulated under heavy traffic conditions. The testing results are presented in Tables 4 and 5. Note that two different sets of thresholds are set up for traffic data processing under heavy and medium traffic conditions, respectively. Meanwhile, the incident decision threshold is set to 70%.

Table 4 shows that the simplified Bayesian network performs consistently with the basic Bayesian network in terms of the DR and FAR, and it does not compromise the DR of the algorithm. Meanwhile, the simplified Bayesian network improves the efficiency of the algorithm by 27 s under heavy traffic condition. To achieve fast incident detection during peak periods, the simplified Bayesian network is a better choice.

When the simplified Bayesian network is used under medium traffic conditions, a high FAR of 5.56% is produced. Even though the simplified Bayesian network reduces the MTTD by 93 s compared with the basic Bayesian network, the large increase of the FAR from 0.74% (produced by the basic Bayesian network) to 5.56% is unacceptable for field application. The basic lane-blocking specific Bayesian network is better for medium traffic conditions.

Table 4
Performance of simplified Bayesian network and basic Bayesian network on Cross Road data (11 incidents, heavy traffic)

Detection method	Algorithm performance		
	Detection rate (%)	False alarm rate (%)	Mean time to detect (s)
Simplified Bayesian network	100	1.85	73
Basic Bayesian network	100	1.48	100

Table 5
Performance of simplified Bayesian network and basic Bayesian network on Cross Road data (7 incidents, medium traffic)

Detection method	Algorithm performance		
	Detection rate (%)	False alarm rate (%)	Mean time to detect (s)
Simplified Bayesian network	100	5.56	147
Basic Bayesian network	100	0.74	240

5. TSC_ar algorithm performance

5.1. Algorithm performance

The modified TSC_ar algorithm is tested using 40 simulated incidents. Since link-blocking incidents are relatively easier to detect using scenario-specific Bayesian networks, sixteen new lane-blocking incidents (11 under medium traffic condition) are simulated using the Cross Road model for algorithm testing. Including the previous simulated incidents (24), the total number of incidents for the algorithm testing is 40. The characteristics of the simulated incidents are shown in Table 6. We intend to limit the scale (not the complexity) of the algorithm test, as our primary interest is to know how effective our new approach for arterial road AID would be at this initial stage of the algorithm development. The algorithm performance on these 40 incidents is presented in Table 7.

When the decision threshold is set to 70%, the DR of the algorithm is 88% and the FAR is 0.62%, which is very encouraging. The MTDD of the algorithm (178 s) is reasonable for field application.

Most excitingly, the DR of the TSC_ar algorithm reaches a stable region ($DR > 80\%$) when the incident decision threshold is set between 65% and 80%; meanwhile, the FAR of the algorithm is no longer sensitive to the decision threshold settings and improves slightly with the increase of the decision threshold. The above findings are very consistent with the performance of the TSC_fr algorithm (Zhang and Taylor, 2006), which demonstrates the capability of the Bayesian network approach in achieving the enhanced incident detection on arterial roads.

5.2. Algorithm performance comparison

To assess the competitiveness of the TSC_ar algorithm, the Bayesian network method is compared with several advanced incident detection methods which include the vehicle positioning method (Sermons and Koppelman, 1996), the neural networks method (Khan and Ritchie, 1998; Thomas et al., 2001), support vector machine (Yuan and Cheu, 2003), and the data fusion method (Ivan, 1997). The review of the above literature suggests that detector configuration used for incident detection varied from site to site. Meanwhile, different traffic signal controls made arterial road incident detection even more site specific when compared with freeway incident detection. It is very difficult to perform a stringent performance comparison between two algorithms on the same data set, especially when they have different theoretical foundations. Hence, the algorithm performance shown in Table 8 is obtained from research literature which represents the best results of those methods. These figures only provide a fairly general indication on the effectiveness of these mentioned arterial road AID algorithms. To test the vehicle positing based algorithm, the short-term lane closures were substituted for spontaneous incidents in the earlier research (Sermons and Koppelman, 1996).

Table 6
Simulated incidents for TSC_ar algorithm testing

Number of incidents	Incident characteristics						
	Heavy traffic		Medium traffic		Duration		
	Lane-blocking	Link-blocking	Lane-blocking	Link-blocking	10–15 min	20–25 min	35 min
40	16	2	18	4	12	13	15

Table 7
Performance of TSC_ar algorithm on Cross Road data (40 incidents)

Test site	Detection threshold (%)	Algorithm performance		
		Detection rate (%)	False alarm rate (%)	Mean time to detect (s)
Cross Road (40 incidents)	65	88	0.78	175
	70	88	0.62	178
	80	83	0.57	203

Table 8

Performance of the TSC_ar, MLF (basic and modular), PNN, SVM_P, vehicle positioning and data fusion algorithm

Algorithm	Source	Data set	Number of incidents	Decision threshold/ persistence test	Algorithm performance		
					DR (%)	FAR (%)	MTTD (s)
TSC_ar	Yuan and Cheu (2003)	Cross Road	40	70%	88	0.62	178
MLF		Ave west-Clementi	324	PT = 1	60.2	0.24	156
PNN				PT = 1	77.2	0.89	155
SVM_P				PT = 1	88.9	0.22	149
MLF (modular)	Thomas et al. (2001)	Coronation	13	PT = 2	85	0.64	114
MLF (basic)	Khan and Ritchie (1998)	Dr. Anaheim	108	PT = 0	76	1.16	1.63 cycle (126 s per cycle)
				PT = 1	60	0.23	2.63 cycle
Vehicle positioning	Sermons and Koppelman (1996)	Chicago	56	Incident prior <0.3	68	0	–
Data fusion	Ivan (1997)	Chicago	90 (training)		93	0	–

Except for this algorithm, the performances of the other algorithms shown in the table were obtained using simulation data.

The neural network based data fusion algorithm produced the best DR of 93% with a zero FAR (Ivan, 1997). Both fixed detector data and probe vehicle data were used for incident detection. The result implied a great potential of the data fusion method in tackling arterial road incident detection problems. Since this work focused on the algorithm output fusion network topology comparison, the algorithm performance shown in Table 8 was the best network training results rather than algorithm evaluation results. In addition to data fusion, the vehicle positioning based algorithm also produced the lowest FAR of zero. However, the relatively low DR of 68% was generated by the algorithm at the same time when the incident prior was set to 0.15 to minimize the number of false alarms (Sermons and Koppelman, 1996). It was also reported in the same literature that ‘it would not be appropriate to increase the incident priors to enhance the DR as this would generate a large number of false alarms in an application to new data’.

The basic MLF algorithm had also produced the low FAR of 0.23% by performing one-step persistence test (Khan and Ritchie, 1998). On the other hand, the resultant DR of the algorithm became low (60%) as well. This result was consistent with Yuan’s later work (Yuan and Cheu, 2003). To improve the DR of the algorithm and to maintain the low FAR, the modular neural networks was proposed by Khan and it was reported that the DR was improved to about 70% (based on Fig. 6 in that paper). This modular neural network architecture was used later in Thomas et al. (2001), in which both loop detector data and probe vehicle data were used to detect incidents, and the resultant DR was improved to 85%.

The TSC_ar algorithm produces a good DR of 88%, which is comparable with the SVM_P algorithm on fixed detector data and the modular MLF algorithm on multiple data sources. Meanwhile, the FAR is maintained at 0.62%. The distinct feature of the TSC_ar algorithm is that the DR of the algorithm reaches a stable region (DR > 80%) when the incident decision threshold was set between 65% and 80%. We think that this feature stems largely from the general knowledge base of the algorithm (CPTs of the Bayesian networks) and its strong reasoning capability. The transparent causal structure and fully accessible CPTs of the Bayesian networks can also facilitate the algorithm transfer from site to site, which is the other strength of our new approach to arterial incident detection and will be tested in our future research.

6. Conclusion and future work

In this research, we treat the incident detection problem as a decision making problem. The focus of the TSC_ar algorithm development is on effective traffic knowledge management and strong evidential reasoning capability. We develop a general incident detection module in which Bayesian networks are used to store general traffic knowledge and to work as an inference engine for decision making on incidents. Incident reporting is based on the updated incident probability estimated by the Bayesian networks at each detection interval. Meanwhile, we design another site specific data processing module to convert real time traffic measurements to traffic states. This module provides the Bayesian networks with concise traffic state information for evidential reasoning. To improve the performance of the algorithm, the multiple scenario-specific Bayesian networks approach is used in the incident detection module to deal with complicated arterial road incident detection problems.

The algorithm is tested using 40 different types of arterial incidents which are simulated using the validated Cross Road traffic model under different traffic conditions. The low FAR of 0.62% is achieved while the DR of the algorithm is maintained as high as 88%. Most importantly, when the incident decision threshold is set between 65% and 80%, the DR becomes stable and the FAR is no longer sensitive to the decision threshold. This unique feature of the algorithm demonstrates that the transparent causal structure and the fully accessible knowledge base of the Bayesian network is the key to the stable algorithm performance. The performance comparison between the TSC_ar algorithm and several other advanced arterial AID algorithms also shows the strong competitiveness of the algorithm.

As mentioned in the previous section, the TSC_ar algorithm testing is restricted to one section of Cross Road at current stage of algorithm development. We are looking at more simulation studies at different road sections with varying traffic signal settings to test the stability and transferability for which the TSC_ar algorithm is designed. Incident detection is a decision making process under uncertainty. “More information less

uncertainty” is also true for incident detection. The data fusion potential of the Bayesian network approach will be exploited further in our future research to enhance the performance of the TSC_{ar} algorithm further.

Acknowledgements

The authors would like to thank Jeremy Woolley and Branko Stazic for kind support with the Unley micro-simulation traffic models, and the MineLab Electronics Pty Ltd. for their financial support for the research project. The authors are grateful to three anonymous reviewers for their helpful comments on an earlier draft of this paper.

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