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Paper title: Incident detection on freeways: a Bayesian network approach

Author(s) name(s): Kun Zhang and Michael A P Taylor

Organisation(s): Transport Systems Centre, University of South Australia

Contact details:

Postal address: GPO Box 2471, Adelaide SA 5001

Telephone: (08) 8302 1778

Facsimile: (08) 8302 1880

email: Kun.Zhang@postgrads.unisa.edu.au

Abstract (200 words):

This paper presents a novel approach to incident detection on freeway. The proposed incident detection algorithm is capable of detecting lane-blocking incident promptly as well as reporting incident location and duration. The algorithm consists of two major components: (1) data processing and (2) incident detection. Data processing is designed to deal with site specific traffic measurements. One standard traffic case, which contains states of selected traffic parameters, is generated using smoothed lane volume, occupancy and speed at each detection interval. Incident detection is performed by a dynamic Bayesian network through two-way reasoning using traffic cases. One step congestion and incident detection are fulfilled in the Bayesian network. The proposed algorithm is tested using simulated incidents. The results are very encouraging in terms of detection rate, false alarm rate, and mean time to detect. The Bayesian network based approach is considered promising.

Introduction

Modern life demands growing mobility. Dramatic increases in population mobility and commerce have often preceded the ability to manage subsequent increases in traffic volumes efficiently. In view of the limitations of capacity expansion as a structural solution and the complexities of travel demand management as a strategic solution to ever increasing congestion problems, assuring optimal use of the existing transportation infrastructure has become an increasingly important issue (Maas, Maggio, Shafie and Stough, 2001).

Intelligent transport systems (ITS) incorporate a smoothing or rationalizing process intended to help our existing supply of transportation infrastructure better meet current and future transportation demands. It opens up new ways of achieving sustainable mobility in our communications and information society. A major concern of advanced traffic management systems (ATMS - one of the major applications of ITS) is providing decision support to effectively detect, verify and develop response strategies for incidents that disrupt the flow of traffic. A key element in providing such support is an automated incident detection (AID) system (Ritchie 1990).

Automated incident detection system

An automated incident detection system consists of two main components: a traffic detection system and an incident detection algorithm. The traffic detection system provides the traffic information necessary for detecting an incident while the incident detection algorithm interprets that information and ascertains the presence or absence of incidents or non-recurring congestion. In Australia, inductive loop detectors are the primary traffic sensors used to measure traffic volume, speed and occupancy.

Freeway incident detection algorithms

Studies dealing specifically with AID started in the mid 1960s. Pattern matching algorithms based on decision trees with states for freeway incident detection were developed by Payne and Tignor (1978), and were later developed by others as the series of California algorithms. The McMaster algorithm (Gall and Hall, 1990, Hall, Shi and Atala, 1993, Persaud and Hall, 1989) was inspired by the application of catastrophe theory to the two dimensional analysis of traffic flow and lane occupancy data, by separating the areas corresponding to different states of traffic conditions. When specific changes of traffic states were observed over a period of time, an incident alarm was given. These two widely known algorithms are often used as the standard for measuring the performance of other algorithms.

Levin and Krause (1978) used a Bayesian approach to classify incident and non-incident data. It was based on the ratio of incident and incident-free conditional probability distributions of incidents, given traffic features and the probability of the occurrence of an incident at a particular location and time period. Algorithms were also developed based on statistical forecasting of traffic behaviour (Ahmed and Cook, 1982). These time series based methods provided a means of forecasting short term traffic behaviour. Significant deviations from observed and estimated values of traffic parameters lead to an incident alarm. Another set of statistical algorithms DELOS (Chassiakos and Stephanedes, 1993) model the stochastic traffic flow patterns obtained from the loop detector data. The algorithms employ smoothed detector occupancy measurements to signal an incident when significant temporal changes of

the smoothed occupancy occur. Three types of smoothers (average, statistical median, and exponential) are considered, leading to corresponding algorithms in the DELOS set.

In addition to the traditional detection rule-based algorithms cited above, artificial neural network (ANN) approaches have also been applied to freeway incident detection (Abdulhai and Ritchie, 1999, Dia and Rose, 1997, Ritchie and Cheu, 1993, 1995). Artificial neural networks are parallel distributed information processing architectures that are suitable for hardware implementation and real-time operation. Through intensive network training, the spatial and temporal patterns in traffic data can be recognized and classified by the neural network to detect incidents.

The performance issue for existing algorithms

The performance of an incident detection algorithm is measured by three criteria: detection rate (DR), false alarm rate (FAR) and mean time to detect (MTTD). The DR and FAR measure the effectiveness of an algorithm, and the MTTD reflects the efficiency of the algorithm.

The performance of existing incident detection algorithms shows that DR and FAR are positively correlated (Chung and Rosalion, 1999). In order to detect more incidents, the algorithm thresholds are relaxed which causes some incident-free intervals to be interpreted as incident intervals. Since false alarms are generally caused by random fluctuations of traffic flow, a persistence test is applied by raising an incident alarm when multiple incidents are detected in consecutive intervals. The trade off is that it increases the MTTD considerably. The most important issue concerning the existing AID algorithms would be how to reduce the FAR and maintain high DR without large increases in MTTD.

The traditional rule-based algorithms are executed in a serial fashion (e.g. decision tree with states). Each detection rule strictly follows the IF-THEN manner, and its thresholds work independently. Since the dependency between traffic parameters and events changes with knowledge of other traffic parameters and events, the incident detection is actually an evidential reasoning process under uncertainty. The basic knowledge when reasoning under uncertainty is whether or not information on some event influences the belief about other events (Jensen, 1996). Therefore, the rule-based algorithms could not fully capture the dependency between traffic parameters and events.

The advantage of ANN algorithms over rule-based algorithms is that no mathematical model of traffic operation is required, thus eliminating imperfection in model formulation. On the other hand, the application of ANN to incident detection can be constrained by non-availability of a large number of robust sets of training data, since the good performance of ANN algorithms largely depends on the successful network training. Meanwhile, the black-box nature of ANN makes it difficult to freely embed expert traffic knowledge into algorithms to cope with changing traffic conditions.

This paper reports our initial efforts to develop a new freeway incident detection algorithm. The proposed algorithm has a great potential to break the positive correlation between DR and FAR whilst maintaining a reasonable detection time.

Methodology

To deal with the performance issue concerning the existing AID algorithms, the proposed new algorithm must be capable of (1) effective storage and management of expert traffic knowledge, and (2) efficient and coherent evidential reasoning.

In this research, the Bayesian network (BN) technique is chosen to develop a new algorithm. BN is a causal probabilistic network. It can build an environment in which traffic parameters and events act, and it simulates the mechanism of the interaction among parameters and events. The ability to coordinate bi-directional inferences filled a void in expert systems technology of the early 1980s, and Bayesian networks have emerged as a general representation scheme for uncertain knowledge (Pearl, 1988).

Incidents generally refer to any problems on a freeway that require the attention of an operator or result in an operator formulating a response. The incident detection algorithm developed through this research is designed to detect lane-blocking incidents when their effects are manifested by certain patterns of deterioration in traffic conditions.

Bayesian Network (BN)

A Bayesian network consists of a set of variables and a set of directed edges between 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. A typical Bayesian network is shown in Figure 1. To each variable A with parents B_1, \dots, B_n is attached a conditional probability table $P(A | B_1, \dots, B_n)$ to quantify their causal relationships.

Let U be a universe of variables. Assume that we have easy access to $P(U)$, the joint probability table, then, the probability $P(A)$ for any variable A in U is easy to calculate through marginalization

$$P(A) = \sum_{U \setminus \{A\}} P(U) \quad (1)$$

A Bayesian network over U is a more compact representation of $P(U)$. Let BN be a Bayesian network over $U = \{A_1, \dots, A_n\}$. If the conditional independencies in the BN hold for U , then $P(U)$ is the product of all conditional probabilities specified in BN

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

where $p(A_i)$ is the parent set of A_i .

If new findings $e = \{f_1, \dots, f_m\}$ are provided, then the findings can be entered into the BN

$$P(U, e) = P(U) \cdot \underline{f_1} \cdots \underline{f_m} \quad (3)$$

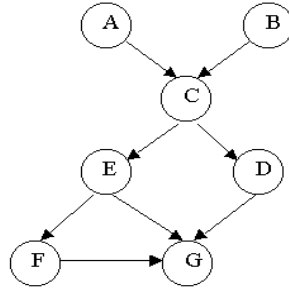


Figure 1 A Bayesian network (DAG)

and the probability updating in BN can be performed as follow

$$P(U | e) = \frac{P(U, e)}{P(e)} = \frac{P(U, e)}{\sum_U P(U, e)} \quad (4)$$

Through equations (1)-(4), all the probabilistic queries (i.e. finding the most likely explanation for the traffic information received) can be answered coherently using probability calculus.

Incident detection algorithm

The proposed incident detection algorithm consists of two major parts: (1) data processing and (2) incident detection. *Data processing* is designed to handle the site specific traffic measurements and normalize them into standard traffic cases. Each traffic case contains the states (instead of absolute values) of selected traffic parameters at each detection interval. *Incident detection* is a universal evidential reasoning process performed by a dynamic BN using newly received traffic case. This part of the algorithm focuses on expert traffic knowledge storage, updating and coherent reasoning.

Data processing

Detector configuration on freeways: A proposed traffic detector configuration is shown in Figure 2. Detector stations (DS1 ~ DS3) are evenly located (e.g. 500 metres apart)¹ along a section of a two-lane freeway. Lane traffic volume, occupancy and speed are collected over short time intervals (e.g. every 20 seconds) using loop detectors. The road section between DS2 and DS3 is the proposed detection zone.

Data processing: The first part of data processing consists of two basic functions: eliminating the random fluctuation from raw traffic measurements, and identifying a possible compression wave. A compression wave experienced on freeway is mainly due to the start-stop movement of vehicles, and is not considered as an incident.

Inspired by the good performance of DELOS algorithms, smoothed traffic data instead of raw traffic measurements are used to generate traffic cases. The raw traffic measurements are smoothed over a time window (n, k) , which incorporates the present $(t+k)$ and the past $(t-n)$.

¹ This situation is found, for instance, on Adelaide's Southern Expressway.

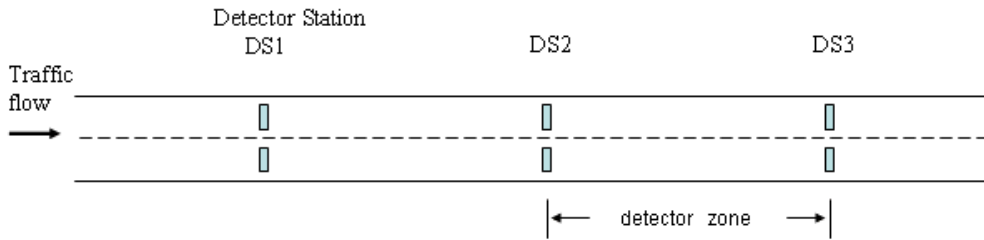


Figure 2 Detector configuration for freeway incident detection

In this research, moving average was chosen

$$S_i(t) = \frac{1}{L} \sum_{a=0}^{L-1} M_i(t-a) \quad (5)$$

where:

$S_i(t)$ is the smoothed traffic measurement at time t and detector station i ,

$M_i(t)$ is the traffic measurement at time t and detector station i , and

$L = k$ measurement value after t

$= n$ measurement value before t .

Since the smoothed measurements are not directly used by the incident detection process, only the previous two intervals ($n=2$) are used for smoothing.

A compression wave is better represented by high occupancy values experienced by the downstream detector station (Payne and Tignor, 1978). In the proposed algorithm, downstream occupancy measurements are compared against a threshold and a sequence of 1 / 0 is generated with 1 representing a possible compression wave. When a compression wave is detected at several consecutive detection intervals, incident detection on this section of the freeway will be suspended for certain time (e.g. five minutes) to allow the wave to pass through.

The second part of data processing can be treated as a traffic case generator. Smoothed traffic measurements (link average) are compared against predetermined thresholds to determine their states (e.g. traffic volume is High, Medium, or Low). The selected traffic parameters with their states at each detection interval form a traffic case. Traffic cases are used by incident detection process as evidence to detect incidents.

As shown in Figure 3, traffic case generation is based on smoothed traffic measurements at current detection interval (t) and controlled by the incident probability at pervious detection interval ($t-1$).

The idea of using a traffic case to detect incidents instead of absolute values of smoothed traffic measurements is that the knowledge base for incident detection can be used and managed independently from site specific features. Therefore, incident detection process can be performed in a universal way.

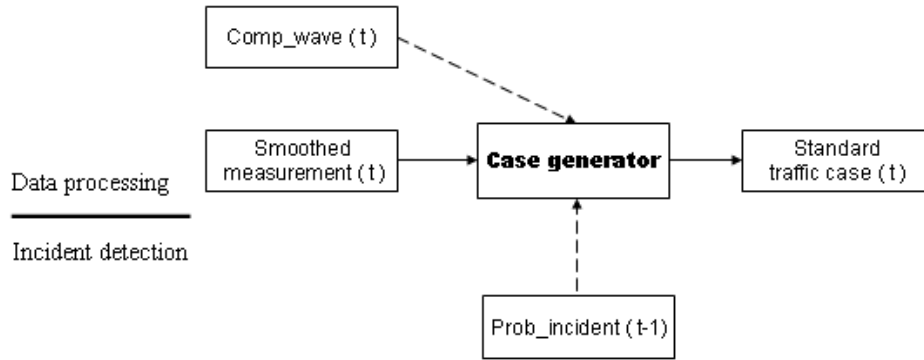


Figure 3 The process of traffic case generation

Incident detection

The new method for incident detection: The traditional rule-based algorithms detect incidents in two sequential steps: (1) identify traffic congestion, then, (2) find out the causes of the congestion (incident induced or not). In case the traffic volume is not high enough at the time of an incident, the first step of incident detection would take very long time. Meanwhile, the persistence test required by the algorithms would post extra delay on detection time. The efficiency of the algorithms is compromised. In the proposed algorithm, both congestion identification and incident pattern recognition are fulfilled through one step reasoning in the BN, and the states of all selected traffic parameters are considered in the mean time. The estimated congestion probability at current detection interval is taken into account as well.

Since the 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 reliable and relevant traffic information for incident detection under different traffic conditions. In our proposed algorithm, the traffic condition has two states: incident free (state 0) and suspect incident (state 1). Suppose the current state of the traffic is 0, all traffic parameters are used to identify the possible incident. When traffic condition shifts from state 0 to state 1 as the result of the incident detection at previous interval (t-1), only selected traffic parameters will be used. This new function is fulfilled by the dynamic control of case generation, which is shown in Figure 3. Further, the BN supports the reasoning using partially collected findings.

A Bayesian network for incident detection: The core part of incident detection algorithm is a dynamic Bayesian network which is shown in Figure 4 (b). It consists of two basic BNs (Figure 4 (a)).

The basic BN consists of two traffic events (incident: *Inc1_1*, congestion: *Con1_1*) and eight traffic parameters (traffic volumes: *Vol1_1* and *Vol2_1*, occupancies: *Occ1_1* and *Occ2_1*, speeds: *Spd1_1* and *Spd2_1*, occupancy difference between upstream and downstream: *D_occ1*, and lane volume difference at upstream *D_vol1*). The pointed link between traffic events and parameters represent their cause-effect relationship. This network is used to perform spatial comparison of traffic patterns to detect incidents and congestions.

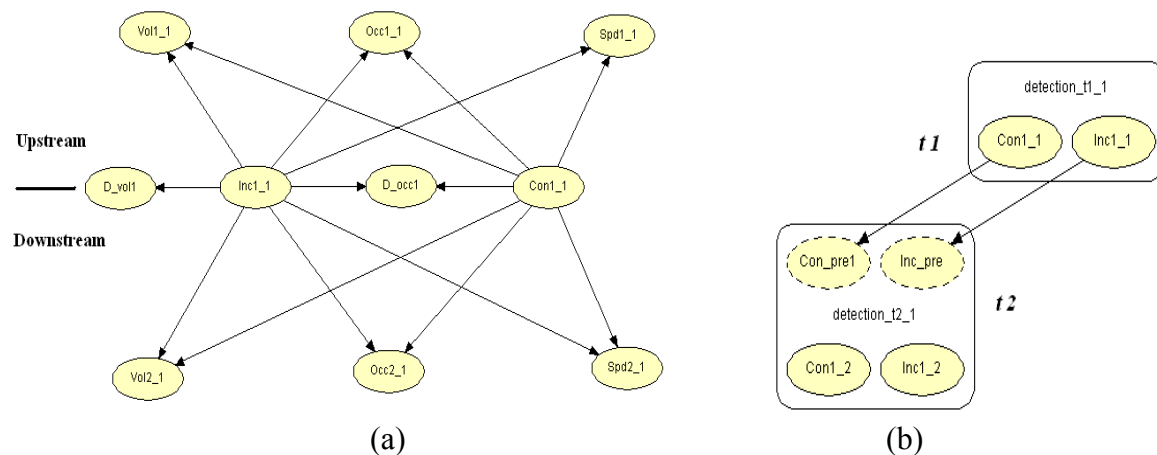


Figure 4 A dynamic BN for incident detection (b) and its building block (a)

D_occ1 is one of the primary indicators of an incident. This parameter is also used to compensate for the possible loss of the consistency during case generation, when the states of $Occ1_1$ and $Occ2_1$ are determined. Incident termination is mainly determined by D_occ1 , $Occ1_1$ and $Occ2_1$, and $Spd1_1$ is taken into account as well.

The accumulated value of D_vol1 at upstream is used to identify the location of the incident (the blocked lane). This function is evoked when an incident alarm is issued. From that point, the algorithm starts to search in two directions along the time coordinate for certain intervals to determine the incident location.

The proposed dynamic BN seeks to model the evolving traffic patterns at two consecutive intervals ($t1$ and $t2$). There are four temporal links between basic BNs. This temporal comparison of traffic patterns could be treated as a one step persistence test.

Evidential reasoning: As shown in Figure 4 (a), the connections between any parent node ($Inc1_1$ or $Con1_1$) and the rest of the nodes are diverging connections, and the states of those two parent nodes are unknown (determined by the states of traffic parameters). These two conditions indicate that all child nodes in the BN are *d-connected*, which means an evidence received at any child node can be propagated through the whole network. Therefore, each and every piece of traffic information can be made full use of to update the incident probability and to estimate the conditions of the traffic parameters with unknown states.

Evidential reasoning in BN, which is discussed in section 4, is made efficient enough for real time application by using Hugin propagation (Jensen 1996). Firstly, the BN is transformed into a junction tree. Then, Hugin propagation is performed. A node Rt in the junction tree is chosen as a root, and whenever the propagation takes place, CollectEvidence (Rt) is called followed by a call of DistributeEvidence (Rt). When the calls are finished, the tables are normalized so that they sum to one. The application program for incident detection is developed using Hugin Development Environment.

Conditional probability table (CPT): The initial conditional probability tables of the BN model are created using expert traffic knowledge. The first step of CPT creation is to partition the BN into small clusters of nodes containing parent-child pairs (i.e. $Inc1_1$, $Con1_1$ and $Vol1_1$). Then, each piece of knowledge concerning certain relationship between traffic

parameters and events (within certain cluster of nodes) is translated into subjective detection rules. Finally, these rules are quantified and converted into the entries of CPTs that are attached to the nodes of the cluster.

Since the CPTs are accessible, the certain entries of CPTs can be modified at any time during algorithm implementation to cope with the dynamic changing of traffic conditions, especially when the nature of the change could be well predicted by the traffic management personnel. This unique feature of the proposed algorithm could be viewed as subjective algorithm training.

To enhance the performance of the algorithm on the targeted freeway section, BN adaptation is carried out. BN adaptation is an objective algorithm training process, which is based on incident data collected on the targeted road section. By setting experience tables of each CPT, the extent of knowledge base modification is well controlled during each BN adaptation. In our initial tests, incidents used for adaptation are generated using micro-simulation traffic models (Paramics). Subsequent research is looking at real world data.

Algorithm evaluation

The performance of the proposed incident detection algorithm is tested using simulated incidents. The test site is Southern Expressway, Adelaide. The Southern Expressway is a novel one-way reversible direction expressway equipped with an ATMS. Under the prevailing tidal nature flow regime, the expressway is designed to operate northbound in the morning and southbound in the evening to relieve peak flow traffic on an alternative arterial route (Main South Road). To compare the congestion parameters and emissions of the two routes, and to investigate the impact of the ATMS implementation on the expressway, a micro-simulation model of the Southern Expressway has been constructed using Paramics (Quadstone,2000) at the Transport Systems Centre. Paramics is a suite of high performance software tools used to model the movement and behaviour of individual vehicle on urban and highway road network. The expressway model has been validated using field traffic data.

Taking advantage of the Southern Expressway microsimulation model, incidents at three different locations (upstream, middle block, downstream) between two selected detector stations are simulated. Two severity levels of incidents (1 lane and 2 lanes blocked) are considered at each location, and two different volume conditions (medium and heavy) are applied, which is based on morning peak period traffic. One incident is simulated during 45 minutes simulation run. Total number of the simulation runs is 36. Detection interval is 20 seconds.

The performance of the proposed incident detection algorithm is evaluated using three measures: DR, FAR, and MTTD. The incident probability threshold is set 85 per cent. The following results are obtained: the DR is 100 per cent during entire evaluation; the overall FAR is 0.07 per cent, this value is a little bit high for operational purpose; the MTTD is 113 seconds, it is reasonable for field application.

The most important findings from evaluation test are (1) both DR and FAR are not sensitive to the threshold of incident probability and are mainly controlled by the BN structure and its CPTs (knowledge base); and (2) reasonable low MTTD is maintained in the mean time. This unique feature of our proposed algorithm implies that the positive correlation between DR and FAR could be broken through subjective network training and adaptation without large

increases in MTTD. Caution must be exercised in interpreting these results. They are based on a simulation study using a model with limited validation. Current research is looking at real world incident data for the Southern Expressway and some other interstate freeways as more substantial tests of the proposed AID method.

Conclusions

In this research, new methods and techniques has been applied to develop a freeway incident detection algorithm. Using traffic case generator, the site specific features are filtered out from traffic measurement, and the universal incident detection is achieved. The feedback control of case generation makes incident termination report more reliable. These two advantages of the proposed algorithm are demonstrated by high DR and relatively low FAR during algorithm evaluation. Meanwhile, the one step congestion/incident detection using Bayesian network results in shorter MTTD.

Evaluation results also suggest that both DR and FAR are not sensitive to the threshold of incident probability and are controlled by the structure of the BN and its CPTs. This implies a potential for the proposed algorithm to break the positive correlation between DR and FAR through intensive subjective algorithm training and adaptation.

Besides that, the transparent casual structure of BN and its easily accessible CPTs could offer the traffic management personnel a great opportunity to fine tune the algorithm and achieve better performance for the specific site.

Current research is concerned with algorithm evaluation using field incidents.

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