Automatic Incident Detection for Urban Roads in Hong Kong

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Abstract: In this paper, two models are proposed for automatic incident detection on urban roads in Hong Kong. The first model is the threshold-based incident detection model, adopting the ratio of predicted speed over estimated speed as the detection criterion. The second model is established on a basis of the discriminant analysis. These two models are evaluated, in terms of detection rate, false alarm rate and mean time to detect, under different pre-incident traffic conditions (represented as level of service), using the traffic data from a real-time travel information system in Hong Kong. Also, the impacts of level of service on the model detection performance are specified and quantified in this study. The empirical results indicate that the pre-incident traffic conditions (congested or non-congested) may significantly affect the detection performance of models.

Key Words: automatic incident detection, urban roads, level of service

1. INTRODUCTION

A road incident is an unexpected event which temporarily adversely affects the traffic flow on roadway (Sethi et al., 1995). Car crashes, spilled debris on the road, or simply vehicle breakdown are common examples of road incidents (Luk et al., 2001). When an incident occurs on a road, travel time would increase due to the reduction in the capacity of the roadway. Moreover, the incident would result in excessive travel delay and increase the chance in secondary accidents and pollutant emission (Luathep et al., 2010; Luk et al., 2001; Sethi et al., 1995). Thus, rapid detection and clearance of incidents become more and more vital in traffic management.
In recent years, many studies have been focused on the development of automatic incident detection (AID) algorithms. Among these studies, however, most of the literatures have focused on AID on freeways (Cheu and Ritchie, 1995; Stephanedes and Chassiakos, 1993). In their studies, inductive loop detectors (ILDs) were installed at regular intervals along a freeway to collect traffic data, such as occupancy and traffic flows for incident detection. With the emergence of automatic vehicle identification (AVI) technology, some studies about AID on freeways using this technology have been carried out (Balke et al., 1996; Hellinga and Knapp, 2000; Sermons and Koppelman, 1996).

While AID on freeways has reached a mature stage of development, the detection of incidents for urban roads has gained relatively less attention (Luk et al., 2001). In fact, some studies did try to develop methods to detect the incidents for urban roads on the basis of ILDs. Thancanamootoo and Bell (1988) developed an occupancy-based model for incident detection for urban roads. Both of the occupancies at upstream and downstream were calculated and compared with two predetermined thresholds to detect incidents. Luk et al. (2001) have tried to analyze the characteristics of incidents on an urban road and proposed an approach to detect incidents on urban roads.

However, few studies have applied AVI technology to detect incidents on urban roads. This is mainly due to the limitation of AVI-based systems such as the electronic road pricing system. Also, collection of reliable and useful AVI data on urban roads is quite difficult because of special characteristics of urban road networks. For example, the main difference between AVI data collection on freeways and arterial roads is the conservation of flows. On freeways, traffic entering them must equal to traffic leaving them in the absence of on- or off-ramps (Luk et al., 2001). So the tagged vehicles recorded by AVI tag reader at upstream must be recorded again at downstream of the freeways. However, in urban road networks, traffic can turn into or enter from various side-streets. Therefore, some of the tag records at upstream cannot be matched at downstream. This will largely reduce the number of useful tag records for incident detection.

Although with little studies on automatic incident detection for urban roads, an effective detection model is still strongly required. Due to large traffic demands on urban roads, congestion caused by incidents may be more severe than that on freeways. Moreover, area of influence by incidents on urban roads may be larger than that caused by incidents on freeways. On freeways, congestion caused by an incident likely occurs at the upstream of the incident location only. However, on urban roads, congestion occurs not only at the upstream of incident location but also at the adjacent road segments of incident location. This phenomenon exists because of the increasing traffic flow transferring from the incident location to the nearby road segments. Thus, rapid detection and clearance of incidents on the urban roads are very important and can help to reduce this non-recurrent congestion effectively.

In Hong Kong, an AVI-based electronic road pricing system for eleven tunnels/links has been established by Autotoll Limited. On the basis of the AVI data provided by this road pricing
system, a Real-time Travel Information System (RTIS) has been established. Tam and Lam (2008) presented that the real-time estimated travel times and speeds on major roads in Hong Kong are provided by the RTIS every 5 minutes. These travel times and speeds are generated using real-time AVI data and off-line estimates. Furthermore, a modified k-NN method was proposed for short-term travel time forecasting by using the historical travel time estimates and their temporal variance-covariance relationships (Lam et al., 2008). Using these estimated and predicted travel times/speeds, a threshold-based algorithm was proposed to detect incidents on a selected path in Hong Kong urban area (Lam et al., 2008).

However, in the study of Lam et al. (2008), only one selected path was studied and one incident was chosen to evaluate the performance of the detection algorithm. It did not consider various types of incidents and different traffic conditions, which may reduce the transferability of the detection method to others paths. In other words, the calibrated threshold based on one incident on one path may not be suitable and effective for detecting others types of incidents on others paths. In order to overcome this limitation, several paths under various traffic conditions and different types of incidents are recommended to be considered when calibrating the detection threshold.

Moreover, the pre-incident traffic conditions (represented as level of service (LOS)) of roads on which incidents occur have not been considered in previous related studies. However, traffic volumes would affect the performance of the incident detection model. This is because with lower traffic demands at the high LOS road conditions, the non-recurrent congestion caused by an incident is not as severe as that at the road with low LOS. Therefore, the impact of the incident on the travel times or speeds tends to be lower at the road with high LOS. In addition, fewer AVI data are available for travel time estimation in RTIS under low traffic condition (i.e. at high LOS). With limited AVI data, the estimated travel times and speeds may be less accurate for reflecting the real traffic condition. If so, the likelihood of detecting an incident at the road with high LOS may not as great as that at low LOS. It is thus meaningful and necessary to consider the effects of the LOS of road when evaluating the incident detection models.

The remainder of this paper is organized as below. Firstly, two proposed incident detection methods, namely threshold-based model and discriminant analysis, are introduced in Section 2. Section 3 presents the evaluation results of the proposed methods. Finally, conclusions are given in Section 4, together with recommendations for further studies.

2. METHODOLOGY

2.1 Threshold-based Model
In the literature, it is well known that there is strong relationship between traffic condition and incidents. For example, when an incident occurs on a major urban road, the travel times (or speeds) would increase (or decrease) sharply due to the reduction in road capacity at the incident location. Based on this phenomenon, several threshold-based incident detection
models have been developed (Balke et al., 1996; Lam et al., 2008; Sethi et al., 1995). The
detection logic of these models is that an incident alarm is issued when significant deviation
between the current and the historical travel time/speed caused by incidents is identified.

As aforementioned, on the basis of the RTIS database, the average travel times on major roads
in Hong Kong are estimated and predicted at the current and next 5-minute intervals,
respectively. The estimated travel times and speeds are generated using real-time AVI data and
off-line estimates. With the use of real-time AVI data, the estimated travel times and speeds
can reflect the real-time traffic condition. However, the predicted travel times and speeds are
calculated mainly using the historical travel time estimates and their temporal
variance-covariance relationships. Thus, the predicted travel times and speeds cannot reflect
real-time traffic condition immediately, in particular when incidents or unexpected events
occur.

Using this detection logic, Lam et al. (2008) proposed that an incident alarm is sounded if the
difference between the predicted and the estimated travel time (or speed) is larger than a fixed
threshold. However, using the travel time/speed difference as a detection criterion may reduce
the transferability of the detection model. For example, there are two roads, A and B, with
different road types and free flow speeds. Table 1 shows the predicted and estimated speeds
for road A and road B at a certain time interval. It is assumed that an incident alarm is
sounded if the estimated speed were less than half of the predicted speed. Thus, the detection
thresholds for these two roads are both 2 if taking the ratio of predicted speed over estimated
speed as detection criterion. However, if taking the difference between the predicted and
estimated speed as detection criterion, the detection thresholds for these two roads are
different, 20km/h for road A and 35km/h for road B.

<table>
<thead>
<tr>
<th>Road</th>
<th>Predicted speed</th>
<th>Estimated speed</th>
<th>Detection threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>40km/h</td>
<td>20km/h</td>
<td>2</td>
</tr>
<tr>
<td>B</td>
<td>70km/h</td>
<td>35km/h</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 1 Comparison of different detection criteria for different roads

Detection criterion: Difference between the predicted and estimated travel speed

<table>
<thead>
<tr>
<th>Road</th>
<th>Predicted speed</th>
<th>Estimated speed</th>
<th>Detection threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>40km/h</td>
<td>20km/h</td>
<td>20km/h</td>
</tr>
<tr>
<td>B</td>
<td>70km/h</td>
<td>35km/h</td>
<td>35km/h</td>
</tr>
</tbody>
</table>

With a different value, the threshold calibrated for road A is not suitable for road B if using
the difference between the predicted and estimated travel speed as a detection criterion. For
the detection criterion of ratio of predicted speed over estimated speed, the thresholds for two
roads are the same, with a value of 2. In other words, the detection threshold calibrated for
road A is suitable for road B if using the ratio of predicted speed over estimated speed as a
detection criterion. Thus, adopting ratio of predicted speed over estimated speed as the
detection criterion can increase the transferability of the detection model. Moreover, the
previous studies (such as Sethi et al., 1995) showed that models using the ratio of predicted
speed over estimated speed had a better performance than those using the difference between estimated and predicted speeds. In view of this, the ratio of predicted speed over estimated speed is adopted as the detection criterion in the proposed threshold-based model.

As aforementioned, the estimated travel times and speeds can reflect the real-time traffic conditions with the use of real-time AVI data. When an incident occurs on a major urban road, the estimated travel speeds decrease at the incident location. Thus, the ratio of predicted speed over estimated speed would be larger than 1 under incident circumstances. In this study, it is proposed that an incident alarm will be issued if the ratio of predicted speed over estimated speed is larger than a calibrated threshold more than one time interval after the occurrence of the incident. The equation is shown as below:

\[
\frac{S_p(t)}{S_e(t)} > T_s
\]

where,

- \( S_p(t) \) is the predicted speed at time interval \( t \);
- \( S_e(t) \) is the estimated speed at time interval \( t \);
- \( T_s \) is threshold to be calibrated.

### 2.2 Models Based on Discriminant Analysis

With the use of the estimated and predicted travel times and speeds, another detection model based on discriminant analysis is proposed. Discriminant analysis is a statistical technique which studies the differences between two or more groups of objects with respect to several variables simultaneously (Klecka, 1980). The proposed incident detection model is established using discriminant analysis in which several variables describing traffic conditions (such as estimated and predicted travel time and speed) are considered. Using the proposed model, real-time traffic conditions can be classified into two mutually exclusive categories, with incident and without incident.

Classification in the detection model based on discriminant analysis is dependent on a discriminant score, which is determined by certain variables describing traffic conditions and the prior probability of an incident (Sethi et al., 1995). The prior probability reflects the probability of an incident occurs during certain observation (time interval). In the real traffic conditions, incidents occur during only a small percentage of time intervals. Thus, an incident prior probability of 0.01 is adopted in this study for representing the low probability of occurrence of incidents in practice. In the study of Sethi et al. (1995), the prior probability was also adopted as 0.01.

In this study, four variables reflecting the traffic conditions are considered and selected as the predictor variables for the discriminant models. They are (1) the difference between estimated...
and predicted travel time, (2) the ratio of the predicted travel time over the estimated travel time, (3) the difference between estimated and predicted speed, and (4) the ratio of the predicted speed over the estimated speed.

3. EVALUATION OF THE PROPOSED MODELS

3.1 Data

In Hong Kong, there is a road traffic accident database, namely Hong Kong Traffic Accident Database System (TRADS). This database is updated by the Hong Kong Police and the Transport Department. The TRADS consists of information on the attributes of each traffic accident, such as the severity of accident (fatal, serious injury and slight injury), the date and time of accident, the precise location of accident, the number of vehicles involved and the number of casualties involved, etc.

In this study, only serious and fatal accidents are considered for evaluating the proposed incident models. This is because that serious or fatal accident has more significant adverse impact on the traffic conditions than slight accident. Three selected two-way paths, toll plaza of Lion Rock Tunnel to toll plaza of Cross Harbour Tunnel (LRT-CHT), toll plaza of Tseung Kwan O Tunnel to toll plaza of toll plaza of Eastern Harbour Crossing (TKOT-EHC) and toll plaza of Aberdeen Tunnel to toll plaza of Cross Harbour Tunnel (ABT-CHT) are chosen for this study. The locations of these three selected paths are shown in Figure 1. The tunnels of LRT, CHT and ABT are shown by dotted lines. Two Central Business Districts (CBDs) located in Tsim Sha Tsui and Central and the Hong Kong International Airport in Hong Kong are also shown in Figure 1.

The lengths of these selected paths, LRT-CHT, TKOT-EHC and ABT-CHT, are 6.78km, 2.93km and 8.01km, respectively. According to the historical travel time data from RTIS, it was found that the average free-flow speeds of the paths of LRT-CHT, TKOT-EHC and ABT-CHT are 55km/h, 60km/h and 70km/h, respectively. Also, these three paths are connecting five tunnels, namely LRT, CHT, ABT, EHC and TKOT. Table 2 shows the characteristics of these five tunnels which are obtained from Annual Traffic Census 2008 (Transport Department, 2009). From Table 2, it is observed that three tunnels have the same speed limit (50km/h), while the EHC and TKOT have a speed limit of 70km/h. It is also seen that the tunnel of CHT has the largest annual average daily traffic (AADT) and peak hour flows among the five tunnels. CHT is the major tunnel crossing harbor between Kowloon and Hong Kong Island in Hong Kong.
Table 2 Features of the tunnels of LRT, CHT, ABT, EHC and TKOT

<table>
<thead>
<tr>
<th>Tunnel</th>
<th>Speed limit (km/h)</th>
<th>Annual Average Daily Traffic (AADT) (veh/day)</th>
<th>AM peak hour flows (veh/h)</th>
<th>PM peak hour flows (veh/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LRT</td>
<td>50</td>
<td>85710</td>
<td>4780</td>
<td>5400</td>
</tr>
<tr>
<td>CHT</td>
<td>50</td>
<td>122790</td>
<td>5970</td>
<td>6190</td>
</tr>
<tr>
<td>ABT</td>
<td>50</td>
<td>61970</td>
<td>3780</td>
<td>3450</td>
</tr>
<tr>
<td>EHC</td>
<td>70</td>
<td>63330</td>
<td>4980</td>
<td>5070</td>
</tr>
<tr>
<td>TKOT</td>
<td>70</td>
<td>72730</td>
<td>4750</td>
<td>4570</td>
</tr>
</tbody>
</table>

From the TRADS, there are 25 serious and fatal accidents occurred in 2008 on the three selected paths. Table 3 summarizes the number of road accidents on the three selected paths by LOS. It is observed from Table 3 that 12 accidents are on the path of LRT-CHT, 8 accidents are on the path of TKOT-EHC and 5 accidents are on the path of ABT-CHT. Furthermore, according to the Highway Capacity Manual 2000 (Transportation Research
Board, 2000), the LOS can be divided into six levels from A to F. However, due to the limited number of accidents on the selected paths in 2008, only two classifications of LOS are considered in this study. We classify levels A to C as high LOS and levels D to F as low LOS. In the incident dataset being considered, 13 accidents happened at the road conditions with high LOS and 12 accidents occurred under the traffic conditions with low LOS.

<table>
<thead>
<tr>
<th>LOS</th>
<th>Selected studied paths</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LRT-CHT</td>
<td>TKOT-EHC</td>
</tr>
<tr>
<td>LOS A-C</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>LOS D-F</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>12</td>
<td>8</td>
</tr>
</tbody>
</table>

### 3.2 Measures of Effectiveness

The performance of the incident detection models is evaluated by three measures of effectiveness, namely, detection rate (DR), false alarm rate (FAR) and the mean time to detect (MTTD).

Detection rate is defined as the ratio of the number of detected incidents over the actual number of incidents being considered in the data set. The detection rate can be calculated by the following equation (Wang et al., 2008).

\[
DR = \frac{\text{number of incidents detected}}{\text{total number of incidents}}
\]

A studied non-incident which is incorrectly classified as an incident is considered as a false alarm. The false alarm rate can be gained by dividing the number of false alarms by the total number of non-incidents (Wang et al., 2008).

\[
FAR = \frac{\text{number of false alarms}}{\text{total number of non-incidents}}
\]

The mean time to detect (MTTD) is usually used to represent the efficiency of a detection model. It is calculated by taking average of the times to detect for all incidents. The time to detect represents the elapsed time from the incident occurrence time to the time detected by a detection model (Wang et al., 2008).

\[
MTTD = \frac{\sum_{i=1}^{n} TTD_i}{n}
\]

where,
- \(TTD_i\) is the time to detect for accident \(i\);
- \(n\) is the number of accidents.
3.3 Evaluation Results
In this study, the time series data of estimated and predicted travel times and speeds during the
time period between half an hour before and after the occurrence of studied incidents are
extracted to establish a database which is used to detect incidents. Also, the estimated and
predicted travel times and speeds at 1000 time intervals (5*1000=5000 minutes) without the
occurrence of incidents are added to the database to conduct the sensitivity analysis and
calculate the FARs. For the threshold-based model, a sensitivity analysis is conducted with
setting the threshold \(T_s\) from 0.6 to 1.5 (shown in Figure 2). The DR and FAR for each
threshold value is calculated by Equations (2) and (3) with the use the database established.
While, for the models based on discriminant analysis, four variables reflecting the traffic
conditions are selected as the predictor variables. Furthermore, we calibrate the thresholds and
evaluate the performance (DR, FAR and MTTD) of the proposed models under three
scenarios: (1) LOS A-C scenario (high LOS scenario); (2) LOS D-F scenario (low LOS
scenario); and (3) Overall scenario. It was found that the detection performances of the
models are quite different under varied scenarios. The details of these evaluation results for
these two models are discussed as follows.

3.3.1 Evaluation Results of Threshold-based Model
Figure 2 presents the performance of the threshold-based model in terms of detection rate and
false alarm rate under three scenarios, high LOS scenario, low LOS scenario and overall
scenario. The threshold value is set from 0.6 to 1.5. All of these three figures indicate that
both of detection rate and false alarm rate decrease as the threshold increases. It is because, at
a large threshold value, the detection criterion (ratio of predicted speed over estimated speed)
must be much higher for an incident alarm to be issued compared to small threshold values. In
other words, the incident must have a serious impact on the traffic conditions to be detected at
a large threshold value. Therefore, under this circumstance those incidents causing less
serious effects cannot be detected, which finally results in a small detection rate.

On the other hand, at a higher threshold value, there are lower chances that an alarm is
sounded when no incident occurs. It is because the estimated speed may decrease due to some
fluctuations even when there is no incident occurring at times. These unexpected decreases in
estimated speed would result in some false alarms if the model adopting a low threshold value.
However, for those models with higher threshold values, these errors can be largely
eliminated. Thus, the false alarm rate decreases as the threshold value increases. Similar
findings have been concluded in the previous study of Balke et al. (1996).
In order to calibrate the preferred thresholds for the models under different scenarios, a decision scheme is proposed. In this proposed scheme, a decision criterion \( Y \) in the Equation (5) is proposed to be determined by the detection rate and false alarm rate. The objective function and constraints are shown in the Equations (5-9). In the objective function, it is tried to minimize the \( Y \) value by finding the optimal solutions for detection rate (as large as possible) and false alarm rate (as small as possible) subject to three constraints.

Minimize  
\[
Y = \alpha_{DR} \frac{1}{DR_{T_s}} + \alpha_{FAR} FAR_{T_s}
\]  

Subject to:  
\[
0 \leq \alpha_{DR} \leq 1
\]  
\[
0 \leq \alpha_{FAR} \leq 1
\]  
\[
\alpha_{DR} + \alpha_{FAR} = 1
\]  
\[
0.6 \leq T_s \leq 1.5
\]

where,  
\( Y \) is the decision criterion;

Data:
1. 25 accidents.
2. Time series data of estimated and predicted travel times and speeds between half an hour before and after studied incidents.
3. Estimated and predicted travel times and speeds at 1000 time intervals without the occurrence of incidents.

Figure 2 Performance of threshold-based model under (a) LOS A-C (b) LOS D-F (c) Overall scenarios during the study period
\textit{DR}_{T_s} \text{ is the detection rate when setting the threshold as } T_s \text{ value;}

\textit{FAR}_{T_s} \text{ is the false alarm rate when setting the threshold as } T_s \text{ value;}

\alpha_{DR}, \alpha_{FAR} \text{ are the weighted factors.}

From the Equations (6-7), it was seen that the weighted factors of \alpha_{DR} \text{ and } \alpha_{FAR} \text{ are ranging from zero to one. The values of these factors indicate how we value the importance of these two effectiveness measures (DR and FAR). Usually, we will assign a greater weighted factor to the FAR than DR. It is because one unit (such as, 1\%) increase of FAR would cause much more adverse impacts on the overall detection performance than one unit decrease of DR. For instance, if an incident detection system detects incidents using the data updated every five minutes, then this system performs incident detection 288 times on one day at one path \left(60/5 \times 24 = 288\right). Therefore, the number of false alarms would increase by about 3 (2.88) when the FAR increases by 1\%. For detection rate, it is assumed that there are 5 incidents on one day at one path. Thus, the number of successful detections would decrease by 0.05 when the DR decreases by 1\%. In this study, therefore, it is proposed to set \alpha_{DR} as 0.1 while to set \alpha_{FAR} as 0.9. For different transport operators, different combinations of values of these two factors can be set depending on the importance of DR and FAR to them.

After solving the objective function by increasing the threshold value \(T_s\) from 0.6 to 1.5 at one increment of 0.1, the preferred thresholds for threshold-based models under different scenarios are calibrated (shown in Table 4). Also, the detection rates and false alarm rates under different scenarios are presented in Table 4.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>LOS A-C (High LOS)</th>
<th>LOS D-F (Low LOS)</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibrated threshold</td>
<td>1.1</td>
<td>1.3</td>
<td>1.2</td>
</tr>
<tr>
<td>Detection rate</td>
<td>38.5%</td>
<td>66.7%</td>
<td>48.0%</td>
</tr>
<tr>
<td>False alarm rate</td>
<td>8.6%</td>
<td>0.3%</td>
<td>3.2%</td>
</tr>
</tbody>
</table>

The detection rate is about 67\% under low LOS scenario when the threshold value is set as 1.3. In addition, the false alarm rate under this scenario is about 0.3\%, which is quite acceptable in operational level. Additionally, it is seen from Table 4 that the detection rate drops to 38.5\% when the threshold value is 1.1 under high LOS scenario. In other words,
under this scenario most of the ratios of predicted speed over estimated speed are lower than 1.1 even if there are incidents occurring at the path. Under such non-congested traffic conditions with higher LOS, the adverse impacts caused by incidents might not be significant enough to be detected and may vanish quickly after handling the incidents. Therefore, it is more difficult to detect incidents under non-congested traffic conditions than those under approaching congested or congested traffic conditions. The false alarm rate under high LOS scenario is much larger than the one under low LOS scenario due to the lower value of threshold.

Besides the detection rate and false alarm rate, the mean time to detect for detection models has been calculated to evaluate their performance. Similarly, this effectiveness measure is discussed under different LOS scenarios. Table 5 shows the mean detection times for the threshold-based models under three scenarios. From this table, it was found that it was much faster to detect those incidents under congested traffic conditions than the ones under non-congested traffic conditions (11.4 minutes compared to 16.8 minutes). It is because incidents happened under non-congested conditions would cause less effects on the traffic flow at the beginning and thus it may take longer to accumulate these effects to be large enough to be detected. Also, as mentioned in the previous paragraphs, the estimated speeds are provided by RTIS every five minutes. Therefore, the overall time to detect is a little bit longer than the previous studies due to restriction of this system.

Table 5 Mean time to detect of threshold-based model under different scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>LOS A-C (High LOS)</th>
<th>LOS D-F (Low LOS)</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean time to detect (min)</td>
<td>16.8</td>
<td>11.4</td>
<td>14.4</td>
</tr>
</tbody>
</table>

3.3.2 Evaluation Results of Models Based on Discriminant Analysis

Table 6 shows four detection models based on discriminant analysis which consider different variables under three scenarios, along with their detection rates, false alarm rates and mean times to detect. From Table 6, it was found that travel speed (speed difference, speed ratio) is more preferable than travel time (travel time difference, travel time ratio) for reflecting the effect of an incident on a road so as to detect an incident. It is observed that the detection rates of all of the speed models are not smaller than those of travel time models. Moreover, the efficiencies of speed models in terms of mean time to detect are also better than those of travel time models. In addition, for each of incident and non-incident cases, the travel time ratio and speed ratio are the same. Thus, the detection rates and false alarm rates of Model 2 and Model 4 are the same as shown in Table 6.

Additionally, it is observed that the performances of the detection models by discriminant analysis are quite different under different scenarios. For low LOS scenario with congested traffic condition, the detection rates of Model 2, Model 3 and Model 4 are high (66.7%) and their false alarm rates are acceptably low (0.3% and 0.4%). On the other hand, under high LOS scenario, the detection rates of all models are very low (ranging from 7.7% to 15.4%). It
is mainly due to the low traffic volume under non-congested traffic conditions. Under such traffic condition, an incident may have little or even no adverse effect on the travel speed on the road. Therefore, the incidents occurred under less congested conditions with higher LOS cannot be detected. Regarding the mean time to detect, similar findings with threshold-based model can be obtained. It was much faster to detect those incidents under congested traffic condition than the ones under non-congested traffic condition. Moreover, compared to Model 4, Model 3 has higher detection rates for high LOS scenario and overall scenario but has worse performance of the false alarm rate. These results are slightly different from the previous study (Sethi et al., 1995) that speed ratio model has a better detection performance than speed difference model. However, the differences of performance between these two models are not significant. In practical application, which speed model is adopted depends on which criterion (DR or FAR) is more important to the transport operators.

Table 6 Performance of the detection models based on discriminant analysis under different scenarios

<table>
<thead>
<tr>
<th>Variable</th>
<th>Travel time models</th>
<th>Speed models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Travel time difference</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Travel time ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed difference</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOS A-C (High LOS)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detection rate</td>
<td>0%</td>
<td>7.7%</td>
</tr>
<tr>
<td>False alarm rate</td>
<td>0%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Mean time to detect (min)</td>
<td>20</td>
<td>19.5</td>
</tr>
<tr>
<td>LOS D-F (Low LOS)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detection rate</td>
<td>8.3%</td>
<td>66.7%</td>
</tr>
<tr>
<td>False alarm rate</td>
<td>0%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Mean time to detect (min)</td>
<td>19.2</td>
<td>11.4</td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detection rate</td>
<td>0%</td>
<td>36.0%</td>
</tr>
<tr>
<td>False alarm rate</td>
<td>0%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Mean time to detect (min)</td>
<td>20</td>
<td>15.6</td>
</tr>
</tbody>
</table>

Besides the above four models, some analyses on the combination of different variables have also been conducted. However, it was found that combination of different variables cannot improve the detection performance. Thus, for simplicity, the detection models with only one variable listed as Table 6 are proposed and evaluated.

4. CONCLUSIONS

This paper presented two incident detection models for urban roads in Hong Kong. These two models were proposed with use of the estimated and predicted travel time and speed data.
from Real-time Travel Information System (RTIS) available in Hong Kong. The threshold-based model was developed by adopting the ratio of predicted speed over estimated speed as a detection criterion. Another detection model was established based on the discriminant analysis in which several traffic variables, such as ratio of predicted speed over estimated speed, were considered. Both of these two models have been evaluated under three different levels of service (LOS) scenarios, by comparing their detection rates, false alarm rates and mean times to detect.

The overall detection performances in term of three measures of effectiveness of two proposed detection models have been compared and summarized in Table 7. From this table, it was found that incidents are easier to be detected if they occurred on urban roads under congested conditions with lower LOS (comparatively high detection rate and short mean time to detect). It is because under congested conditions incidents may cause serious adverse effects on the traffic condition and these effects could be quickly accumulated to be detected. On the contrary, incidents happened under non-congested conditions may result in less adverse effects and these effects would evanish quickly after the clearance of incidents. Therefore, it would be harder to detect these incidents. Regarding the measure of false alarm rate, the performances of models are quite similar under different scenarios.

Table 7 Comparison table of detection performance under different scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Measures of effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection rate</td>
<td>False alarm rate</td>
</tr>
<tr>
<td>LOS A-C (High LOS)</td>
<td>Low</td>
</tr>
<tr>
<td>LOS D-F (Low LOS)</td>
<td>High</td>
</tr>
<tr>
<td>Overall</td>
<td>Medium</td>
</tr>
</tbody>
</table>

Two other significant insights can be found in the evaluation results. Firstly, both detection rates and false alarm rates decrease as the threshold increases in the threshold-based model. Secondly, among the models based on discriminant analysis, it was observed that using speed models to detect an incident is more favorable.

The thresholds of the proposed threshold-based detection model will be further calibrated and validated empirically with more accident data. Moreover, further studies will be conducted on improving the proposed models’ performance of detecting incidents under less congested conditions with higher LOS scenario. Other traffic data such as traffic flow and spot speed collected by traffic detectors will be considered for enhancement of model performance. With the use of these traffic data, a link-based detection model instead of path-based model described in this paper is being developed. The link-based detection model is expected to be able to identify the incident locations more precisely.

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