Incident Detection Methods Using Probe Vehicles with On-board GPS Equipment

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Abstract

Mobile communication instruments have made detecting traffic incidents possible by using floating traffic data. This paper studies the properties of traffic flow dynamics during incidents and proposes incident detection methods using floating data collected by probe vehicles equipped with on-board global positioning system (GPS) equipment. The proposed algorithms predict the time and location of traffic congestion caused by an incident. The detection rate and false rate of the models are examined using a traffic flow simulator, and the performance measures of the proposed methods are compared with those of previous methods.

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1. Introduction

Effective management of limited resources is essential in our modern society; time, in particular is one of the most valuable and coveted resources. Managing travel time has increased the need for more accurate and reliable travel services for road traffic. Estimating the time and location of recurring traffic congestion has been made possible by advanced statistical methods and a large scale database of traffic flows. The accuracy of travel information provisions continues to improve for ordinary traffic conditions.

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A traffic incident is defined as a sudden event in traffic flow that is accompanied by an extraordinary drop in capacity and increased congestion. Traffic accidents are impossible to predict before they actually occur; such unpredictability can cause transport systems to fail, which greatly inconveniences our modern lifestyle. Prompt and accurate detection of traffic incidents is one of the most important actions for achieving reliable travel services.

Roadside traffic detectors have been installed to monitor traffic flows. Flow rate, spot speed, and time occupancy at a certain location are automatically observed for a given period of time. Observed traffic flow data has been used to study a wide variety of incident detection methods over the years. Dudek et al. (1974) developed the standard normal deviation (SND) algorithm. Dudek used past accumulated traffic data to estimate probability distributions; the probability of current, observed traffic volumes was examined to detect the occurrence of an incident. Payne (1976) developed the California algorithm, in which the space-time variation of time occupancy was compared to a threshold value estimated using past accumulated data. Lin and Daganzo (1997) proposed the University of California, Berkeley (UCB) algorithm. In this method, statistical fluctuations of time occupancy are recognized as random walks, and values that are out of range, are indicative of traffic incidents. Recently, Jeong et al. (2011) proposed a wavelet-based, freeway incident detection algorithm that combines the multi-resolution property of wavelet transforms with varying threshold values. Jeong et al. also introduced a new feature selection technique to select features that discriminate between normal and incident traffic conditions.

Performance of incident detection methods, based on traffic detectors, depends on the position of roadside equipment. If densely allocated traffic detectors are available, and data collection intervals are short enough, incident detection methods with fixed point observations are very effective. Ideal environments, such as this is, are limited, however; one example is urban expressways in Japan with supersonic traffic detectors installed every 200-300 meters. On the other hand, sparsely located detectors and longer data collection intervals may result in a failure or delay in identifying incidents.

The SND, California, and UCB algorithms are all examples of algorithms that are used by fixed observation systems. Nowadays, in addition to the traditional fixed point observation systems, mobile communication instruments have become available for road traffic monitoring. Vehicle trajectories can be observed by probe vehicles equipped with on-board GPS equipment and communication devices. Traffic incidents are detected using these floating traffic data. A small number of studies have been conducted to compare fixed-detector-based incident detection methods to traffic incident detection using probe vehicles.

Sermos and Koppleman (1996) proposed a dynamic measurement algorithm based on the ADVANCE project, in which both travel time and spatial location data are used. Petty et al. (1997) proposed the Probe-UCB algorithm, which utilizes the acceleration and deceleration of an individual vehicle. After a probe vehicle passes through a congested area of traffic, its speed will increase until it reaches the free flow speed. An incident is detected when the acceleration and speed of the probe exceeds threshold values. Only a single probe vehicle is necessary to detect the occurrence of an incident; detection time is also minimized. Determining whether traffic congestion was caused by a traffic incident or not is difficult; thus, detection rates may be relatively low.

Chue et al. (2002) developed a mobile sensor and sample-based algorithm (MOSES) to detect incidents on freeways. MOSES is based on the statistical difference in the mean section travel time from two sets of probe vehicle samples before and during an incident. Algorithm performance depends on the percentage of probe vehicles; more than 50% of vehicles should be sampled as probes.

Li and McDonald (2005) developed a bivariate analysis model (BEAM) using two variables: the average travel times of probe vehicles and the travel time differences between adjacent time intervals. The magnitudes of increases in link travel time were compared for incident and non-incident conditions. An incident is identified by an increase in magnitude of travel time. This method uses the aggregated link travel times observed by several probe vehicles in a time interval.

Zhu et al. (2009) applied an outlier mining method to incident detection, which is based on probe vehicle data on urban arterial roads. Zhu et al. used changes of vehicle speed in space time dimensions. The speed differences between adjacent sections and adjacent time intervals were selected as feature vectors. Distance-based outlier detection was applied to distinguish incidents from non-incidents.

Recently, Kinoshita et al. (2014) have focused their attention on an anomaly detection method of traffic incidents by discovering abnormal car movements, and distinguished such movements from those occurring in spontaneous
congestion. They compare the actual travel time of a probe vehicle to past travel times. These methods, however, cannot successfully distinguish a bottleneck caused by a traffic incident from recurring bottlenecks.

This paper studies the properties of traffic flow dynamics during incidents and proposes incident detection methods using floating data of probe vehicles equipped with on-board GPS equipment. The time and location of bottlenecks caused by traffic incidents are identified using the proposed algorithms. The detection rate and false rate of the models are examined using a traffic flow simulator, and the performance measures of the proposed methods are compared with those of previous methods.

2. Properties of Traffic Flow during an Incident

2.1. Probe vehicle data and actual vehicle trajectories

Commercial vehicles with data collection equipment were used as probe vehicles. The purpose of the probe data was to obtain operation records of commercial vehicles. The movements of 25,000 vehicles with on-board devices were monitored, and their location and travel speed were recorded at one second intervals. Data from September and October 2013 was used in this study. Vehicles used the outbound direction of Shibuya Line; a corridor of the Tokyo Metropolitan Expressway (MEX) was extracted for analysis. Figure 1 shows the study section consisting of two off-ramps, four on-ramps, and one junction. The length of the section was 11.8 km length and consisted of two lanes carrying 3,000 to 4,000 vehicles per hour. There was a sag between the Ikejiri on-ramp and Sangenchaya off-ramp. According to a MEX report, in this particular section, 440 incidents occurred between 2010 and 2012.

On weekdays, 2,500 probe vehicles were used, while 1,000 vehicles were used on weekends. Compared to all traffic, the penetration rates of the probe vehicles were 0.5% during weekdays and 0.2% during weekends, respectively. The average headway between two consecutive probes was approximately five minutes on weekdays.

Figure 2 shows an example of a probe vehicle trajectory on 9 September, 2013. The colour bar indicates the speed of the probe vehicle; blue, for example, represents a slow speed, which is indicative of traffic congestion. A bottleneck (BN) can be found at the sag. As shown in the figure, traffic congestion continued throughout the day; specifically, an incident occurred near the end of the corridor before noon on September 9. A sudden decrease in vehicle speed in the upstream section can be clearly identified.

The MEX network was also observed by supersonic traffic detectors, which are installed at 250 to 300 meter intervals. Traffic volume, speed, and time occupancy were obtained every one minute. Figure 3 depicts the within-day speed diagram of the study section during the same time of day as Fig. 2. The same tendency of vehicle speed can be observed in both figures. The probe vehicle trajectories are consistent with the speed diagram observed by traffic detectors.

In addition to slow moving traffic, a traffic incident may also cause lane closures. When the state variables of traffic flow are compared in space and time dimensions, finding the properties of traffic flow during an incident becomes possible. Traffic density and time occupancy in the upstream section of a BN increases until it surpasses that of the downstream section. The traffic flow rate in the downstream section of a BN suddenly decreases. These tendencies were confirmed by the actual probe vehicle trajectories observed in the MEX corridor.

Fig. 1. Study section of the Tokyo Metropolitan Highway (numbers indicate traffic detectors)
2.2. Traffic Flow Simulation during an Incident

This study applies a traffic simulation to evaluate the proposed incident detection algorithms. The traffic simulator was expected to optimally describe traffic flow dynamics during an incident. Nguyen et al. (2013) examined the performance of AIMSUN 7.0 when it was used to analyse the effects of congestion propagation caused by traffic incidents.

Model parameters were calibrated to fit the simulated traffic volumes at detector stations to the actual volumes. The simulated speeds at detector stations were then matched to real measurements. Furthermore, the queue was taken into consideration to understand the characteristics of congestion propagation. Parameters of the queue length were set so that simulation lengths were as close to observed lengths as possible.

To evaluate the goodness-of-fit of the calibration results, estimated results were compared to field data. Statistical measures were used to calculate the error values. The root-mean-square percent (RMSP) error was used to measure the relative differences between estimated and field values.

Simulation data (i.e., traffic volumes and speeds recorded by the eight detector stations shown in Fig. 1) was used to evaluate the accuracy of the calibration process. Statistical measures on the goodness-of-fit indicated that calibration results and actual measures matched considerably. The RMSPs were 10% and 32% for traffic volume and traffic speed, respectively. These values significantly improved compared to those obtained during the first estimation using default parameters.
Fig. 4. Comparison of speed propagation on Shibuya Line

a) Actual data   b) Simulation data
Figure 4 compares the simulated propagation of speed change to that observed by data detectors. Jammed speeds, due to the sag section near station 24, propagate to the upstream sections, especially from 9:00 to 22:00. Shockwaves of speed, due to incidents at station 43, propagate toward upstream sections from 14:00 and on. When these shockwaves meet the upstream sag section, the jammed speeds at these sections decrease. After the shockwaves have passed, speeds generally return to the previous jammed speed.

Vehicles speeds fluctuate considerably in Sections 24 and 26 when shockwaves of speed occur. This is because these sections are located near on/off-ramps; thus, speeds are likely affected by car platoons entering from on-ramps or exiting at off-ramps. This phenomenon was adequately reproduced in the simulation by adjusting the parameter of lane changing cooperation. In summary, AIMSUM simulated results are consistent with the observed data.

3. Incident Detection Methods

3.1. Algorithm I

Two different methods are proposed to identify traffic incidents using probe vehicles. In the first method (Algorithm I), a target corridor is divided into multiple sub-sections (links) with the same unit distance. Suppose the travel times of a probe vehicle travelling at two consecutive links are compared. If a bottleneck exists in the upstream link, the travel time of the link is greater than that of the downstream link. Both absolute and relative differences of link travel times of the probe vehicle are used to identify the bottleneck. The candidate link, however, may be a recurring bottleneck without an incident. The number of probe vehicles passing through a bottleneck in a time interval can affect the flow rate. If the number of probes is sufficiently small, the bottleneck is likely to have been generated by an incident.

Notations in Algorithm I are summarized as follows: Figure 5 shows the variables in a time-space diagram. Here, \( l \) indicates a link and \( l-1 \) is the upstream link of link \( l \). The present time step is denoted by \( t \). The time step is used to aggregate the number of probe vehicles in a time interval. \( TT_i(l) \) denotes the travel time of link \( l \) observed by the \( i \)th probe. \( N(l, t) \) denotes the number of probe vehicles passing through link \( l \) during time step \( t \). C1, C2, and C3 are the common assumed threshold values for all links and time intervals. Algorithm I consists of the following three steps.

![Fig. 5. Variables of Algorithm I in a time-space diagram](image-url)
STEP 1: Calculate the travel time difference of the $i$th vehicle between two adjacent links: $TT_i(l-1)-TT_i(l)$.

If $TT_i(l-1)-TT_i(l) > C1$, go to STEP 2.

STEP 2: Calculate the travel time difference ratio of the $i$th vehicle between two adjacent links:

$\{TT_i(l-1)-TT_i(l)\}/TT_i(l)$. If $TT_i(l-1)-TT_i(l)/TT_i(l) > C2$, go to STEP 3.

STEP 3: Calculate the flow rate difference ratio between two time steps: $\{N(l,t-1)-N(l,t)\}/N(l,t)$. If $\{N(l,t-1)-N(l,t)\}/N(l,t) > C3$, an incident is detected in link $l-1$ at time step $t-1$.

If a link includes a bottleneck caused by an incident, the link travel time becomes larger than the travel time of the downstream link. The absolute and relative differences of the travel times between two adjacent links determine if an incident has occurred in the upstream link. STEP 1 and STEP 2 locate a candidate link with a large travel time differences. A candidate link is identified by a probe vehicle.

In addition to the travel time differences of a probe vehicle, the reduction of the flow rate is used to confirm a bottleneck link. The number of passing probe vehicles corresponds to the flow rate; STEP 3 determines if the flow rate has decreased sufficiently at the downstream of the bottleneck link. This algorithm requires three threshold values, $C1$, $C2$, and $C3$, to compare travel times and flow rates. These values can be empirically determined from the time step length and link length. These values depend on the penetration rate of probe vehicles.

3.2. Algorithm II

The second proposed method (Algorithm II) applies shockwave theory. Figure 6 provides a graphical representation of Algorithm II. In this method, three consecutive probe vehicles ($i-1$, $i$, $i+1$) are necessary. The first vehicle $i-1$ is assumed to not experience an incident, while the following two vehicles, $i$ and $i+1$, are assumed to pass the bottleneck caused by an incident. These two vehicles must reduce their speed at the end of the congested area; in other words, these two vehicles meet the backward wave caused by the incident. If the times and locations of this speed reduction are identified, the speed of the backward wave can be calculated by $u_{bw}=(x_{i+1}-x_i)/(t_{i+1}-t_i)$, where $x_i$ and $t_i$ denote the location and time, respectively, where the $i$th probe vehicle meets the backward wave. Variables $x_{i+1}$ and $t_{i+1}$ correspond to the location and time of the $(i+1)$st probe vehicle. The intersection $c(T, X)$ of the backward wave and the trajectory of the proceeding vehicle indicate the location, $X$, and occurrence time, $T$, of the traffic incident.

Fig. 6. Concept Algorithm II in a time-space diagram
Moreover, the headway ratio of the two probe vehicles is used to check for a reduction in the flow rate at the bottleneck. The flow rate $q$ of the two probes is proportional to the inverse of the headway $h$. Variables $h_1$ and $h_2$ denote the headways of vehicles $i-1$ and $i+1$ at the upstream and downstream of the bottleneck, respectively. When the ratio of the headways $h_2/h_1$ is large enough, the flow rate drops sufficiently at the bottleneck. Algorithm II consists of the following four steps:

**STEP 1:** Calculate the speed drop for each probe vehicle in current time. If the speed reduction of a probe vehicle exceeds threshold $V_d$, vehicle ($i+1$) meets the tail of the congestion at the current time; that is, the point $(x_{i+1}, t_{i+1})$ is identified. If the vehicle ahead ($i$) also meets the congestion tail at the previous time, the point $(x_i, t_i)$ is identified. If the preceding vehicle ($i-1$) did not reduce its speed, these three vehicles satisfy the above conditions, so go to STEP 2.

**STEP 2:** Calculate the speed of the backward wave $u_{sw}$ using the two points found in STEP 1:

$$u_{sw} = \frac{(x_{i+1} - x_i)}{(t_{i+1} - t_i)}.$$  

The upper and lower constraints for the shockwave speed, $U_{sw}^U \leq u_{sw} \leq U_{sw}^L$, are considered in order to exclude unrealistic waves.

**STEP 3:** Estimate the intersection $e(T, X)$ of the backward wave and the vehicle trajectory of the preceding vehicle ($i-1$).

**STEP 4:** Examine the flow rate drop using the ratio of the headway. If $h_2/h_1 > R_h$, an incident has occurred at time $T$ and location $X$, estimated in STEP 3.

Since Algorithm II uses only three consecutive probe vehicles, delay time can be saved for incident detection. However, detecting the tail of congestion using speed drop may not always be accurate because of the fluctuation of speed. This, in turn, can cause inaccurate estimation of the backward wave. Using many probe vehicles may increase the precision of the backward wave estimate, however, it will increase the delay time for detection when the density of probe vehicles is low.

### 4. Performance Tests using Traffic Simulation

#### 4.1. Input Conditions and Performance Measures

The performance of Algorithms I and II is examined using traffic flow data in the outbound direction of Shibuya Line in MEX. Details of the study section can be found in Chapter 2. AIMSUN 7.0 was employed to simulate traffic flows for 90 days (1 July to 28 September, 2012). During this time, 42 traffic incidents were reported by MEX. The location, time of occurrence, and duration of lane closure were taken from incident reports and used as input to AIMSUN. We also assumed that traffic was closed for 200 meters on the outside lane. Hypothetical probe vehicles were generated in the simulation, and the location data of each hypothetical probe were observed. The number of probes was used as the control parameter to examine the effects of the vehicle probe penetration rate on total traffic.

The performance of the incident detection algorithms was evaluated using three measures: detection rate (DR), false alarm rate (FAR), and mean time to detect (MTTD). These quantities are given by

$$\text{DR} = \frac{\text{number of precise detections}}{\text{number of actual incidents}} \times 100\%$$  \hspace{1cm} (1)$$

$$\text{FAR} = \frac{\text{number of false alarms}}{\text{number of detections}} \times 100\%$$  \hspace{1cm} (2)$$

$$\text{MTTD} = \frac{\sum (t_i^{\text{ext}} - t_i^{\text{obs}})}{N}$$  \hspace{1cm} (3)$$

DR denotes the percentage of precisely detected incidents. When DR is close to 100%, the algorithm works well to detect incidents. However, higher DR values may indicate that the algorithm is sensitive, which may result in more false alarms. The FAR value indicates the accuracy of the algorithm. The FAR denominator is the number of detections during a given period. For example, when traffic conditions are scanned once every five minutes (12
times per hour) and two of them are false alarms, the FAR is 16.7%. MTTD is the average delay time for precisely detected incidents, where \( N \) is the number of precisely detected incidents.

### 4.2. Numerical Experiments

For given network conditions, Algorithm I was numerically examined for different combinations of threshold values \( C_1, C_2, \) and \( C_3 \). The penetration rate of probe vehicles was fixed at 1%. Figure 7 shows the relationship between the DR and FAR for each combination of threshold values. Clearly, improved values of DR may cause worse FAR values. When large FAR values are allowed, DR reaches its upper limit of improvement near 70%. The combination of threshold values that minimize FAR when DR is greater than 50.0% was \( \{C_1, C_2, C_3\} = \{40, 0.3, 0.3\} \). DR, FAR, and MTTD were 55.0%, 0.041% and 14.8 minutes, respectively. A FAR value of 0.041% corresponds to 6.9 false alarms per day. It was difficult to detect small incidents with shorter lane closure times; in this case, DR values were not as high. When small incidents, causing less than 10 minutes of lane closure, were excluded, the DR value improved to 83%.

Table 1 compares the performance of Algorithm I for different penetration rates of probe vehicles. For higher percentages of probes, the performance of DR and MTTD improve. When more than 0.5% of total traffic volume is used as probe vehicles, the performance of Algorithm I is satisfactory. As mentioned above, small incidents may not be detected, and DR may not improve if a higher penetration of probes is available. Algorithm I requires the aggregation of probes for a time interval, and MTTD does not improve. When the number of probe vehicles becomes large, the frequency of false alarms is unavoidable, and FAR values do not differ much across cases.

Algorithm II was also examined in the same manner for Algorithm I. When the penetration rate of probe vehicles was 5%, the best combination of threshold values was \( \{V_d, U_{wr}, R_u\} = \{60, -1.0, 5.0 \times 10^{-3}\} \). DR, FAR, and MTTD were 50.0%, 2.2 \times 10^{-4} and 6.4 minutes, respectively. When the penetration rate was 1%, DR was only 19%.

![Fig. 7. DR and FAR values for Algorithm I](image-url)

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<th>FAR (%)</th>
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4.3. Comparison of Algorithms

Table 2 summarizes the performance of Algorithm I and Algorithm II compared to the previously proposed Probe-UCB algorithm. The penetration rate in these probe based algorithms was assumed to be 1%, which corresponds to an average headway of 2.5 minutes. In addition to the probe based algorithms, the performance of the California algorithm is shown as a reference for fixed detector based algorithm. The performance of Algorithm I is better than that of the Probe-UCB algorithm in terms of DR and FAR values. Although the MTTD of Algorithm I is not as comparable, DR and FAR values of Algorithm I are almost equivalent to those of the California algorithm. Algorithm II shows better FAR and MTTD values than other probe based algorithms. Since this algorithm uses only three probe vehicles, it is capable of reduce detection time. However, DR of Algorithm II is not sufficient.

In this paper, traffic incident detection methods using probe vehicles were developed. The performance of the proposed algorithms was examined through traffic simulations. Numerical tests indicated that the proposed methods were capable of achieving accurate and prompt detection. Probe based incident detection methods are applicable to any road section without densely installed roadside traffic detectors. However, the accuracy and detection speeds of the algorithms depend on the penetration rate of probe vehicles. In the near future, more vehicles will be able to provide location and speed data through advanced driving assist systems. The information obtained from such advanced probe vehicles will be fully utilized for incident detection.

5. Conclusion

In this paper, traffic incident detection methods using probe vehicles were developed. The performance of the proposed algorithms was examined through traffic simulations. Numerical tests indicated that the proposed methods were capable of achieving accurate and prompt detection. Probe based incident detection methods are applicable to any road section without densely installed roadside traffic detectors. However, the accuracy and detection speeds of the algorithms depend on the penetration rate of probe vehicles. In the near future, more vehicles will be able to provide location and speed data through advanced driving assist systems. The information obtained from such advanced probe vehicles will be fully utilized for incident detection.

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