Incident Detection Method using Longitudinal Occupancy Time-Series Data

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Abstract: Incidents frequently occur in the expressway. A fast and precise detection of incidents is required to mitigate negative impacts caused by delay of traffic managements. This study proposes an incident detection method using a non-parametric model. In the proposed method, traffic incidents are detected by developing a conditional probability function of traffic state using the long term data which is observed by traffic detectors (longitudinal occupancy time-series data). The proposed method was verified empirically using actual field data, then compared with existing incident detection methods. Analysis results show that the proposed method has high applicability due to no need of complex parameter calibrations.

Key Words: incident detection; longitudinal time-series data; traffic detector; non-parametric model

1. INTRODUCTION

1.1 Background

Traffic incidents cause traffic congestion and result in severe traffic delays. In order to mitigate negative impacts of traffic incidents, besides using traffic control and management measures, the development of a method of traffic incident detection is necessary. For example, Funaoka *et al.* (2009) found that a fast and precise incident detection can greatly improve quality of travel time prediction (e.g. average prediction error was reduced to 5min from 25min).

Several previous studies proposed incident detection methods using roadside traffic detector data. These methods could be classified into time series methods and rule based methods. For time series methods, Ahmed and Cook (1980) introduced autoregressive integrated moving average model. UCB algorithm developed by Lin and Daganzo (1997) utilized random walk theory on changes of occupancy to detect incidents. In rule based method, california algorithm (Payne *et al.* 1978) detects incidents by considering changes of occupancy. MEX algorithm (Funaoka *et al.* 2009) is another method that aims to reduce false alarms by considering various traffic factors including occupancy. All of above methodologies applied parametric stochastic models or deterministic models based on traffic flow theory. In general, to represent traffic flow using parametric model, an adequate model and its initial parameters should be selected to give better results. However, it is not technically easy to calibrate its parameters in consideration of the entire road network.

Nowadays, the database technologies and high quality/quantity monitoring systems enable us to develop the incident detection method more relying on the longitudinal large traffic flow data. Using such data, a non-parametric approach which depends on the observed data instead of the strong assumptions of the traffic flow models becomes possible. For non-parametric models, a few assumptions could simplify the calculation progress and reduce costs of the implementation of actual road administrations.

1.2 Objective

This study aims to develop an incident detection method based on a non-parametric approach and validate the proposed method using traffic detector data.

The method in this study is designed to detect traffic incidents by calculating occurrence probability of observed traffic state, which is estimated by a non-parametric approach without strong assumptions on probability distribution function. The non-parametric model simply aggregates a large amount of the historical data of traffic detectors (longitudinal occupancy time-series data). The obtained frequency distribution of traffic state is applied to find un-ordinary events which have lower probability. The proposed incident detection method may have higher applicability in practical field, as it does not require complex procedure of calibrating parameters in comparison to existing incident detection methods.

In the validation procedure, the proposed method was validated by using actual observed data at Tokyo Metropolitan Expressway and compared with two existing incident detection methods: UCB algorithm (Lin and Daganzo 1997) and MEX algorithm (Funaoka *et al.* 2009).

2. METHODOLOGY

2.1 Concept of non-parametric model

This study developed a non-parametric model which detects a "singular" traffic state which describes the occurrence of a traffic incident. The proposed model distinguishes whether traffic states are singular or not by using a probability functions that are derived from the historical traffic flow data collected by traffic detectors. In order to represent the singularity, this study employed a conditional probability function of traffic state that describes the state of the adjacent time step at each road section. The current traffic state is assumed to depend on the state observed in the adjacent time step. If the low-probability state is estimated, it means that a traffic incident occurs.

The features of the proposed method are introduced as followings. First, the proposed method uses the less number of parameters due to a large amount of observed occupancy data used to represent traffic flow's characteristics. Second, it is not required to conduct a parameter calibration per each road sections because the collected traffic detector data reflects each road sections' characteristics. Third, the proposed method relies on the large amount of data, thus the well-equipped traffic detectors' system and stored data are necessary.

2.2 Incident detection model based on conditional probability function of traffic state

As mentioned in section 2.1, traffic incidents can be detected by using conditional probability function of traffic states. This subsection will define the probability function and describes the method to detect the incident using the probability function.

The conditional probability function of traffic state depending on traffic state of the adjacent time step can be described as Equation (1)

$$p_{\mathrm{i}}(\boldsymbol{y}_t|\boldsymbol{x}_{t-1}) \tag{1}$$

where

i: an index of position in road section
t: an index of time
$\boldsymbol{x}_{t-1}$: a traffic state vector at time $t-1$
$\boldsymbol{y}_t$: a traffic state vector at time t

$p_{\mathrm{i}}(\boldsymbol{y}_t|\boldsymbol{x}_{t-1})$ represents the probability of traffic state $\boldsymbol{y}_t$ occurring in time t when the traffic state $\boldsymbol{x}_{t-1}$ is observed at time $t-1$ in position i. When p is less than a certain threshold value $\boldsymbol{p}_c$, the traffic state $\boldsymbol{y}_t$ can be regarded as a singular state or an incident state as follows:

$$\begin{cases} incident & \text{if } p_i(\boldsymbol{y}_t|\boldsymbol{x}_{t-1}) < p_c \\ normal\ state & \text{if } p_i(\boldsymbol{y}_t|\boldsymbol{x}_{t-1}) \geq p_c \end{cases} \tag{2}$$

Occupancy data observed by traffic detectors is employed as variables of traffic state. Traffic state $\boldsymbol{y}_t$, it is replaced by (o_t^i) to consider the location i of the traffic detector. Spatial characteristic of traffic flow, $\boldsymbol{x}_{t-1}$ consists of three traffic states $(o_{t-1}^{i-1}, o_{t-1}^{i}, o_{t-1}^{i+1})$: o_{t-1}^{i} represents the occupancy data at time $t-1$ observed by the traffic detector i, o_{t-1}^{i+1} expresses the effect of extension of queue from downstream section $i+1$ (i.e. backward wave), o_{t-1}^{i-1} denotes the effect of change of demand of upstream section $i-1$ (i.e. forward wave).

2.3 Method for estimating conditional probability function

To estimate the probability function $p_{\mathrm{i}}(\boldsymbol{y}_t|\boldsymbol{x}_{t-1})$ without using any specific form of functions and parameters, we employed the histogram method (Pearson, 1895) that utilizes k-means clustering (MacQueen, 1967). Histogram method represents the probability as a frequency distribution of the normalized number of observations that fall into each interval of values that is called as cluster. In the k-means clustering method, centroid vectors of each cluster are estimated from the stored data which is assigned to their nearest clusters. Hence, the distributions of $\boldsymbol{y}_t$ and $\boldsymbol{x}_t$ are classified into certain number of the clusters derived by the k-means clustering method. Then, the conditional probability $p_{\mathrm{i}}(\boldsymbol{y}_t|\boldsymbol{x}_{t-1})$ is calculated by the historical data belonging to the cluster. For details, historical data $\boldsymbol{x}_{\tau-1}$ and $\boldsymbol{y}_\tau$ ($\tau = 1, \ldots, T$; where T represent the number of data for estimation) are assigned to cluster $z_x(\boldsymbol{x}_{\tau-1})$ and $z_y(\boldsymbol{y}_\tau)$ using k-means clustering method. Two cluster numbers of $z_x(\boldsymbol{x}_{\tau-1})$ and $z_y(\boldsymbol{y}_\tau)$ are similar and given by parameter K. When $\boldsymbol{x}_{t-1}$ and $\boldsymbol{y}_t$ are observed and assigned to $z_x(\boldsymbol{x}_{t-1})$ and $z_y(\boldsymbol{y}_t)$, Equation (1) is estimated as Equation (3):.

$$p(\boldsymbol{y}_t|\boldsymbol{x}_{t-1}) = \frac{\sum_{\tau=1}^{T} \delta_{z_x(x_{t-1}),z_x(x_{\tau-1})} \delta_{z_y(y_t),z_y(y_\tau)}}{\sum_{\tau=1}^{T} \delta_{z_x(x_{t-1}),z_x(x_{\tau-1})}} \tag{3}$$

where

$\delta_{n,m}$: Kronecker delta ($\delta_{n,m} = 1$ if $n = m$; $\delta_{n,m} = 0$ otherwise)

The denominator of Equation (3) represents the number of the historical data in the same cluster of $z_x(\boldsymbol{x}_{\tau-1})$. The numerator expresses the number of the historical data belonging to both the same cluster of $z_y(\boldsymbol{y}_\tau)$ and the same cluster of $z_x(\boldsymbol{x}_{\tau-1})$ at the same time.

2.4 Summary of the proposed incident detection method

The flowchart of the proposed method is shown as Figure 1. In the estimation process of the conditional probability function, the inputs are required as follows:

- Longitudinal traffic detector data (occupancy data)
- Number of data T for conditional probability function estimation (derived from D that denotes the number of the days for data collection in the empirical analysis in Section 3.)
- Number of clusters K

By using the estimated conditional probability function Equation (1), the incidents are detected using the following;

- Detector data $\boldsymbol{x}_{t-1}, \boldsymbol{y}_t$ (data to be judged whether incident occurs or not)
- Threshold value p_c

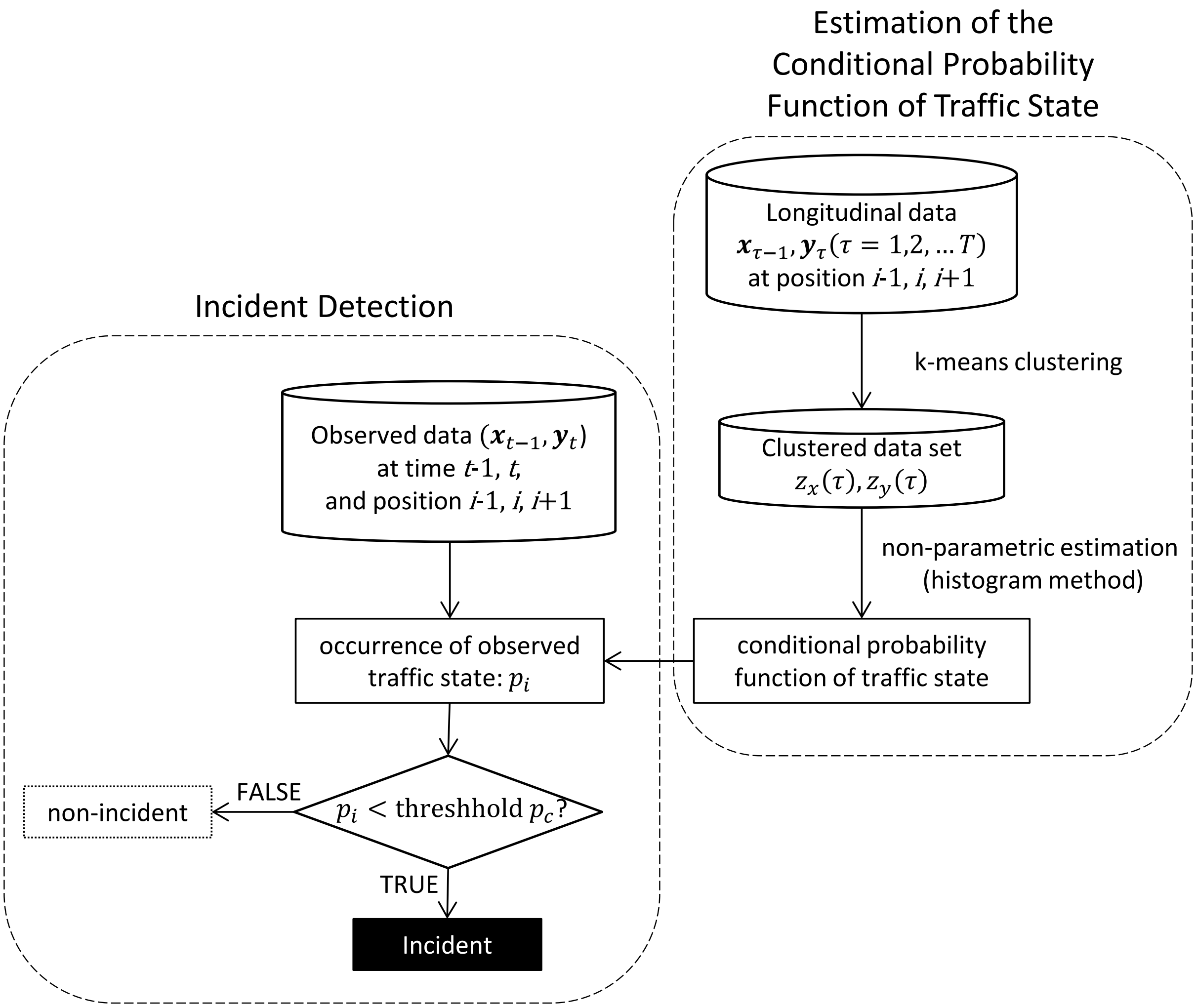

Figure 1. Flowchart of incident detection method

3. EMPIRICAL ANALYSIS

In this section, characteristics of the proposed method are analysed and verified using actual traffic detector data. First, relation between performance of the proposed method and input parameters (the number of days of longitudinal traffic detector data *D*, the number of clusters *K* and the threshold value p_c) and their practical combinations are empirically examined. Second, the precision of the proposed method is compared with that of other existing incident detection methods, namely UCB algorithm and MEX algorithm.

3.1 Definitions of precision

The precision of a method, is represented by the results of detection shown in Table 1. The detection result is called as "Correct Detection" when the model detects incident correctly; "False Alarms" when the model detects the state as incident though incident is not actually occurring; "Miss-Detection" when the model can't detect the incident; and "True Nagative" when incident does not occur and the model does not detect incident.

Table 1. Confusion Matrix

		Actual Incident	
		True	False
Detection result by the method	Incident	Correct Detection	False Alarm
	Normal	Miss-detection	True Negative

These detection results can be evaluated by indices of precision evaluation described as follows:

1. Recall Rate:

$$\mathrm{RR} = 1 - \frac{\text{"Miss}-\text{detection"}}{\text{"total number of incidents"}} \tag{4}$$

2. Precision Rate:

$$\mathrm{PR} = \frac{\text{"Correct detection"}}{\text{"Correct detection"+"False Alarm"}} \tag{5}$$

RR represents the rate of detection among the actual incident. If RR is very small, it means that the model cannot detect incidents. PR represents the correct rate of detection among all the detection. If PR is small, many incidents are false alarm.

In this study, data of incidents were reported by the local road administrator. However, the reported time of incident happening is not always correct because these reports were hand-made. The influences by incidents on the traffic flow sometimes appear a few minutes before or after the reported time. Therefore, this study assumes that the incidents happen during ±15 minutes of the reported time.

3.2 Conditions of verification

The road section for examination of the proposed model is the one in the outbound direction from Tokyo on the Metropolitan Expressway Route 3 (Shibuya Line) whose length is about 12 km. Traffic detectors are installed in Shibuya Line at a distance interval of around 300 m, and used for collecting empirical data in an observation time interval of 5 min is. The expressway was divided into 16 sections (as shown in Table 2) for evaluating RR and PR. Data for verification was collected for 90 days from 10th December 2010. The number of incident during this period is 194 in total. Data for estimating the conditional probability of traffic state are stored during 7 days, 30 days, 60 days or 100 days from 1st September 2010. The thresholds of probability p_c to detect incidents are given by 1.0×10^{-2}, 1.0×10^{-3}, 1.0×10^{-4} or 1.0×10^{-5}. The number of clusters K in the k-means method is assumed to range between 5 and 15.

Table 2. Location of the sections

section No.	3	4	5	6	7	8	9	10	11	12	13	14	15	16
from[km]	0.3	1.1	1.8	2.5	3.2	4.1	5.2	5.7	6.5	7.4	8.4	9.3	10.2	10.8
to [km]	1.1	1.8	2.5	3.2	4.1	4.9	5.6	6.5	7.4	8.4	9.3	10.2	10.8	11.5

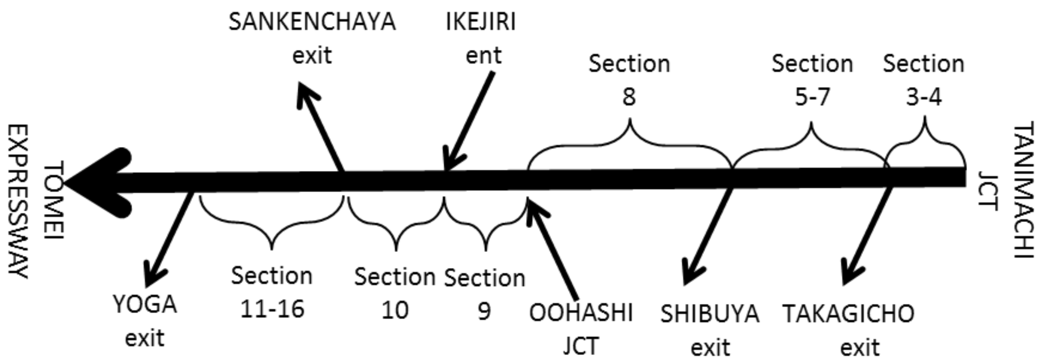

Figure 2. Schematic of Shibuya line

MEX algorithm (Funaoka *et al.* 2009, see appendix for detail) and UCB algorithm (Lin and Daganzo 1997) are used for comparison. Parameters used in these algorithms are selected as recommended values in their original papers.

3.3 Results

Spatial-temporal changes in the occupancy at Metropolitan Expressway Route 3 on 10th December 2010 is shown by the colour contour map in Figure 3. The area drawn by a black colour represents the incidents detected by the proposed method with the parameter (D=30, K=15, p_c=1.0 $\times 10^{-3}$; where D represent the days for collecting data). According to road reports, only one traffic incident occurs at 8 km point and one of the two lanes closed from 21:00 to next day of 3:00. Hence, the proposed model exactly detected the actual traffic incident. However, there are some false alarms because the model sometimes detects the state of end of congestion as an incident. The state of end of congestion is merely observed in the historical data. It is expected to observe several times a day at most in the most of the sections. Thus a proper cluster which includes such a state is not existed. This might be one of the reasons for the low value of PR. This problem can be partially mitigated by increasing the number of clusters. MEX algorithm and UCB algorithm do not detect these states of the end of congestion as those of incident because these two detection methods are focused on the increasing of occupancies.

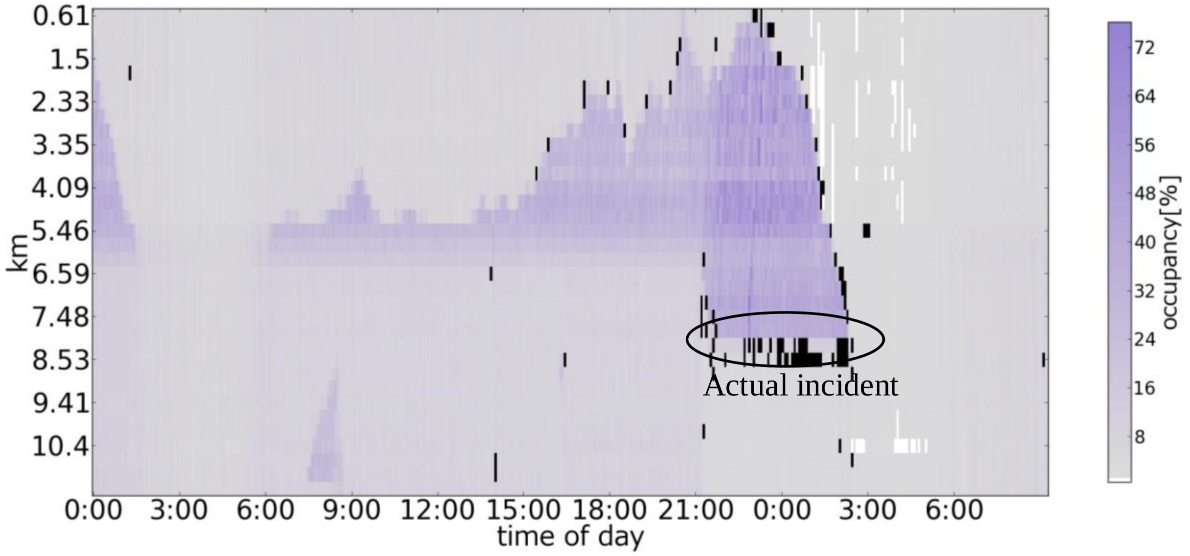

Figure 3. Contour map of occupancy and detected incidents

Figure 4 to 11 show the PR and RR of the proposed method, UCB algorithm and MEX algorithm in terms of road sections. Figure 4 and 5 represent RR and PR at each section with different values of p_c (*K* and *D* is fixed). Figure 6, 7 and 8 represent these precision indices at each section for different values of *K* ($p_c$and *D* is fixed). Figure 9, 10 and 11 represent the indices at each section for different values of *D* (*K* and p_c is fixed).

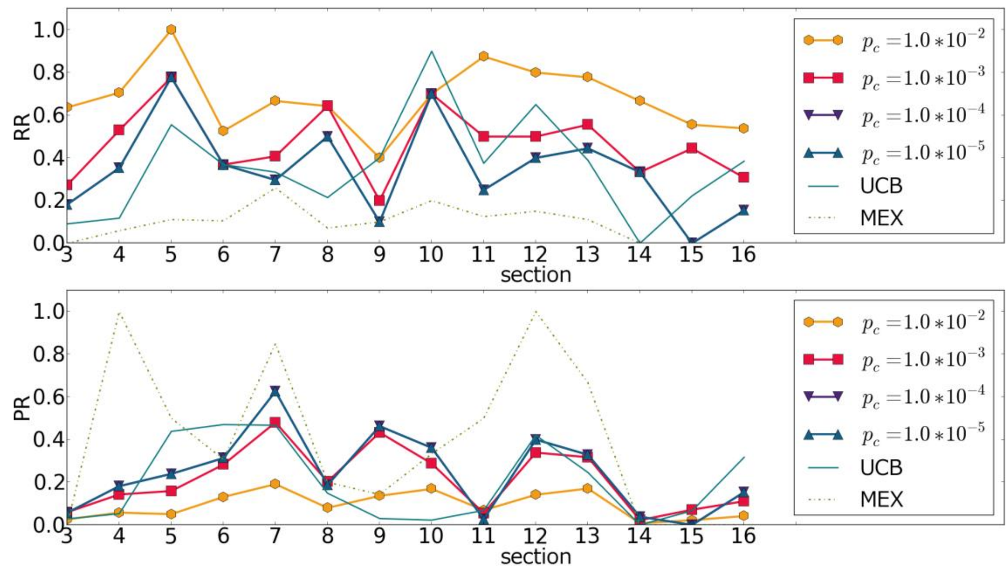

Figure 4. The result of verification on p_c (*K*=10, *D*=60)

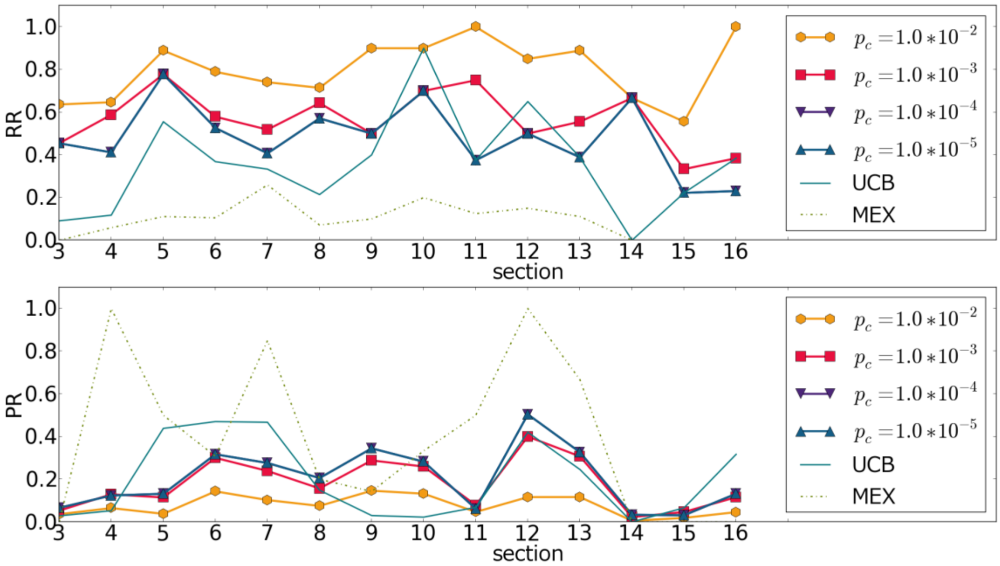

Figure 5. Results of verification on p_c (K=15, D=60)

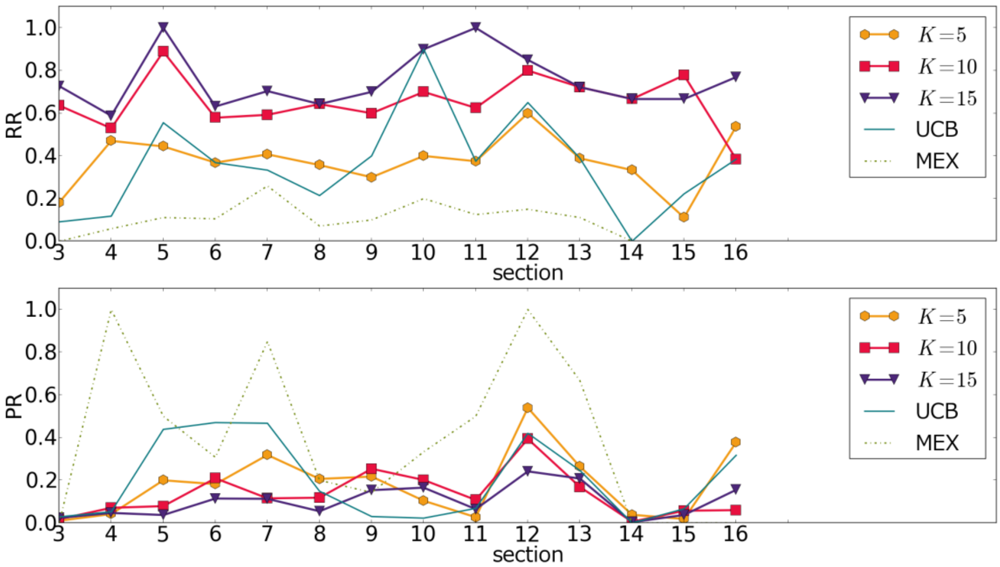

Figure 6. Results of verification on K (D=7, p_c=1.0×10^{-3})

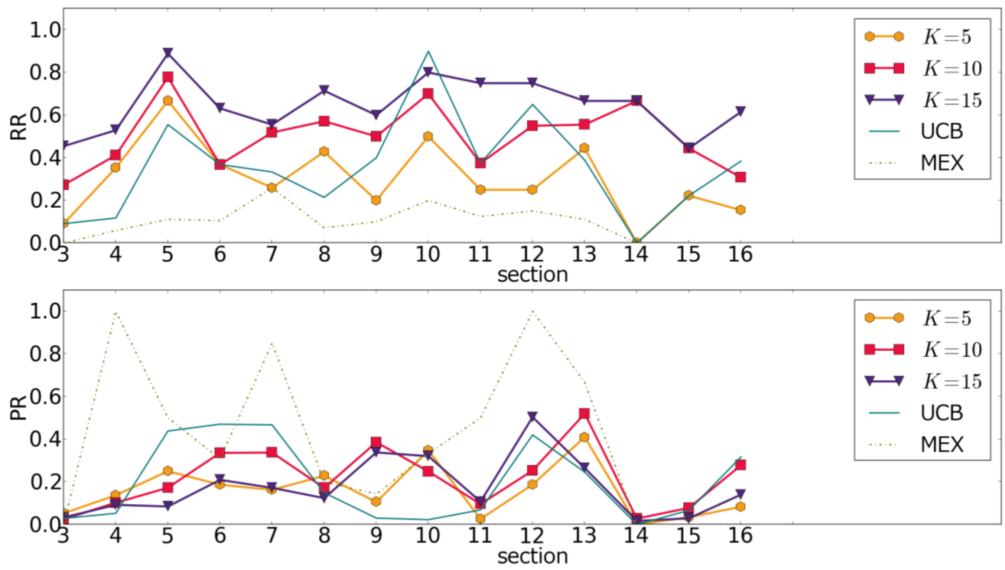

Figure 7. Results of verification on K (D=30, p_c=1.0 × 10^{-3})

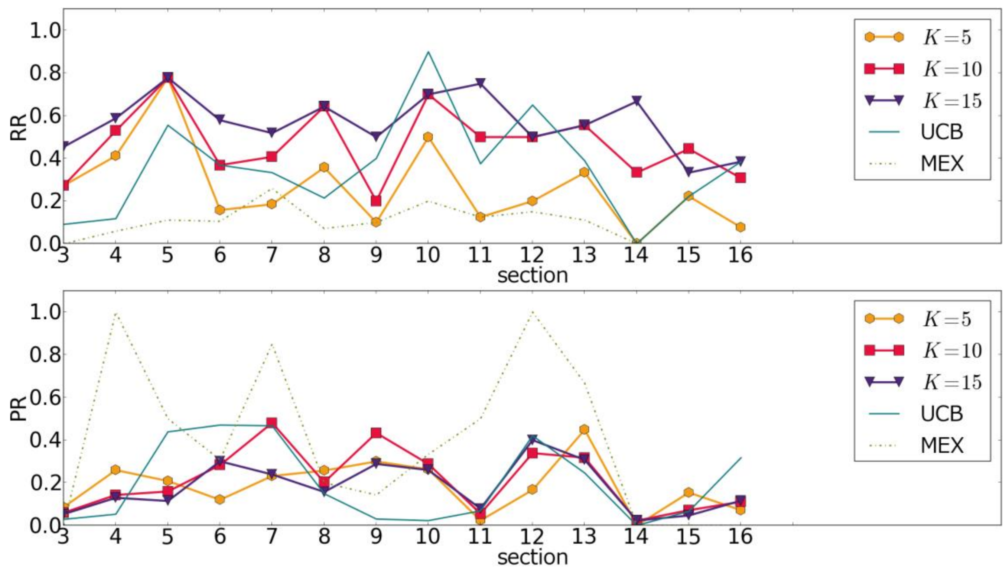

Figure 8. Results of verification on K (D=60, p_c=1.0 × 10^{-3})

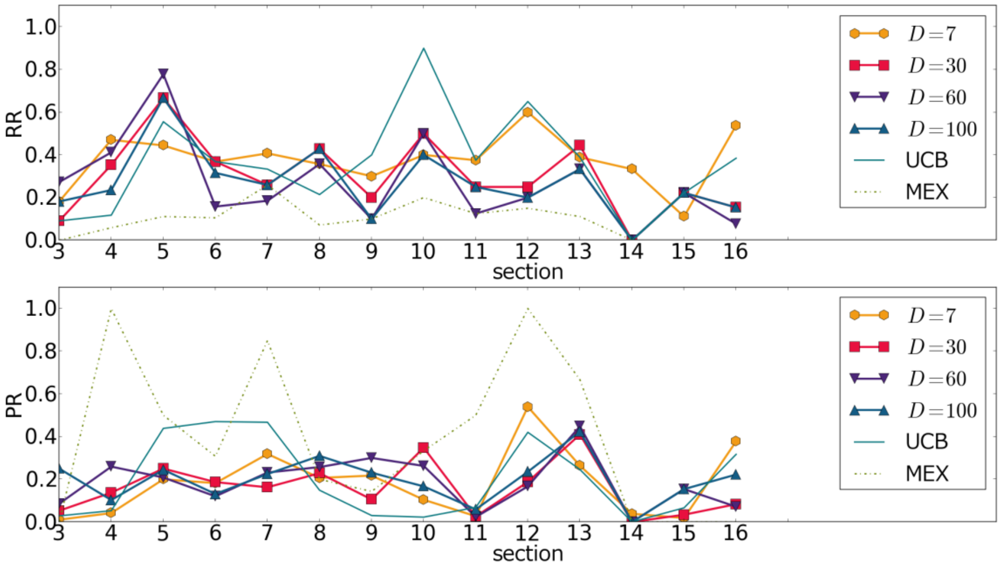

Figure 9. Results of verification on D (K=5, p_c=1.0 × 10^{-3})

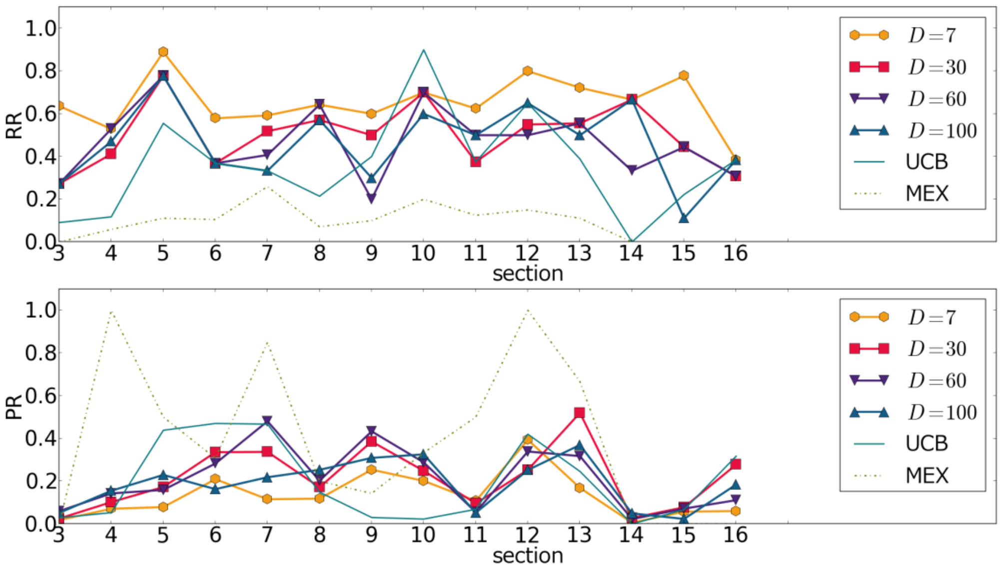

Figure 10. Results of verification on D (K=10, p_c=1.0 × 10^{-3})

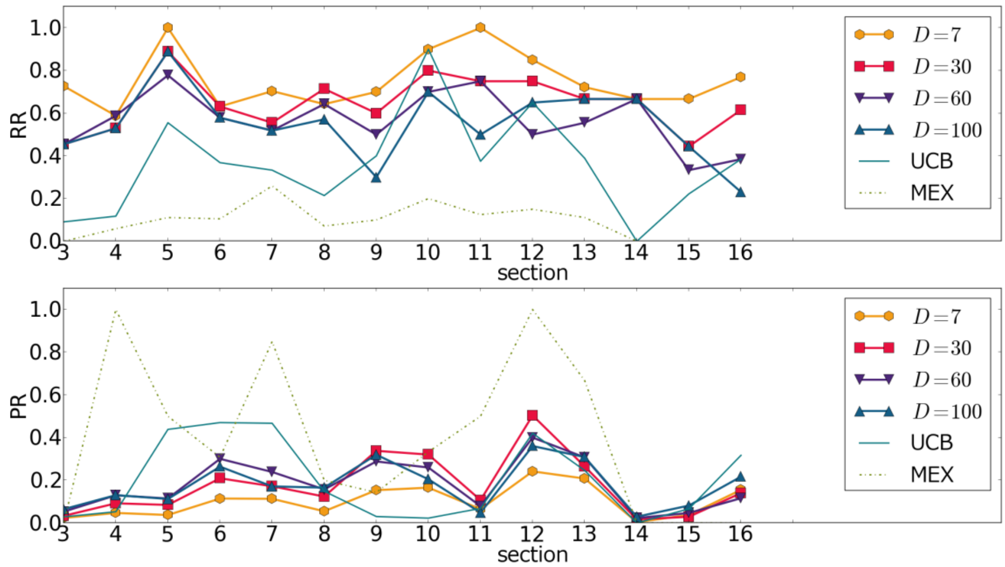

Figure 11. Results of verification on D (K=15, p_c=1.0 × 10^{-3})

As shown in Figure 4 and 5, RR is increasing and PR is decreasing as the threshold p_c becomes larger. This is because normal conditions are detected as incidents when p_c is small. However, when p_c is equal to 1.0 ×10^{-4} and 1.0 ×10^{-5}, the results are not different. The reason is because probability distribution of histogram method is discrete. Figure 6, 7 and 8 show the effects of changes of K. These figures show that RR is decreasing as K becomes smaller. Figure 9, 10 and 11 show the effects of changes of D. As D is larger, PR tends to increase and RR decreases. This may be related to varieties of traffic states that included in data for estimating the prediction distribution.

Figure 12 shows performances of these detection methods. The horizontal axis represents RR and the vertical axis represents PR for all the sections. The proposed models show the best RR case, the best PR case and the best RR×PR case. The parameters (D, K, p_c) are (7, 15, 1.0 × 10^{-2}) for the best PR case, (100, 11, 1.0 × 10^{-4}) for the best RR case and (100, 15, 1.0 × 10^{-5}) for the best PR×RR case. PR and RR of UCB and MEX algorithms are also shown in the figure for comparison.

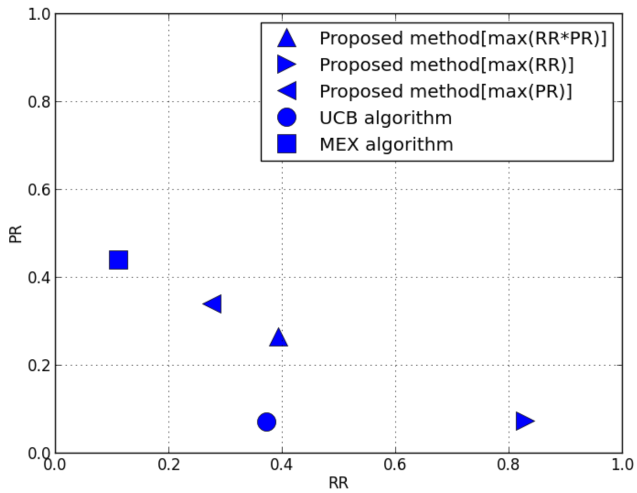

Figure 12. Performance of each detection method

The proposed method showed good precisions without complex adjustments of parameters, compared with UCB algorithm. Moreover, PR of the proposed model is better than UCB algorithm at section 8, 9 and 10 near junctions, on-ramps and off-ramps where characteristics of traffic flow have turbulence and hence it is hard to be described by parametric models. This is an advantage of the proposed non-parametric model. However, PR of the proposed method is lower than MEX algorithm. This may be due to MEX algorithm which is designed to reduce false alarm (i.e. increase PR) at the cost of RR.

4. CONCLUSIONS

This study proposed an incident detection method using the longitudinal observed traffic flow data. The proposed method relies on the calculation of the conditional probability of traffic state that depends on the state of the adjacent time step. If the probability of observed change in traffic state is low, the state is found as an incident. The conditional probability function can be estimated by a non-parametric model using longitudinal occupancy data. By using this approach, the proposed method can detect incidents based on historical data without using strong assumptions for parametric models. It can be said that the proposed method has a high applicability in practical field because it does not require complex parameter calibrations over many road sections.

The proposed method was verified using actual traffic detector data in the Metropolitan Expressway in Japan. In the empirical analysis, the precisions of the proposed method ware compared with existing incident detection methods (UCB and MEX algorithms). As a result, the proposed method is better than existing methods in the most situations.

To improve accuracy of the proposed method, it is needed to reduce false alarms at end of congestion. The state of the end of congestion is hard to be predicted because the state is rarely occurring and observed. Such false alarms can be reduced by using some rule-based methods like MEX algorithm.

ACKNOWLEDGMENTS

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APPENDIX

AREVIEW OF MEX ALGORITHM

MEX algorithm (Funaoka *et al.* 2009) is an incident detection method using decision trees. Since this algorithm may not have introduced in English, it is explained in this appendix.

This method aims to minimize false alarms in order to reflect opinions of road administrators. Two logics for finding incidents at a bottleneck are used in this method. One is used for the free flow state (Figure 13) and the other is used for the congested flow state (Figure 14). Let v_t^i denotes speed observed by traffic detector *i* at time *t* and q_t^i represent the volume of traffic observed by traffic detector i at time t. $\mathrm{V_c}[km/h]$ expresses critical velocity. $\mathrm{Q_u}[Veh/5min]$, $\mathrm{K_u}[Veh/km]$, $\mathrm{Q_c}[Veh/5min]$ denotes minimum traffic capacity, maximum traffic density, traffic capacity under traffic congestion, respectively.

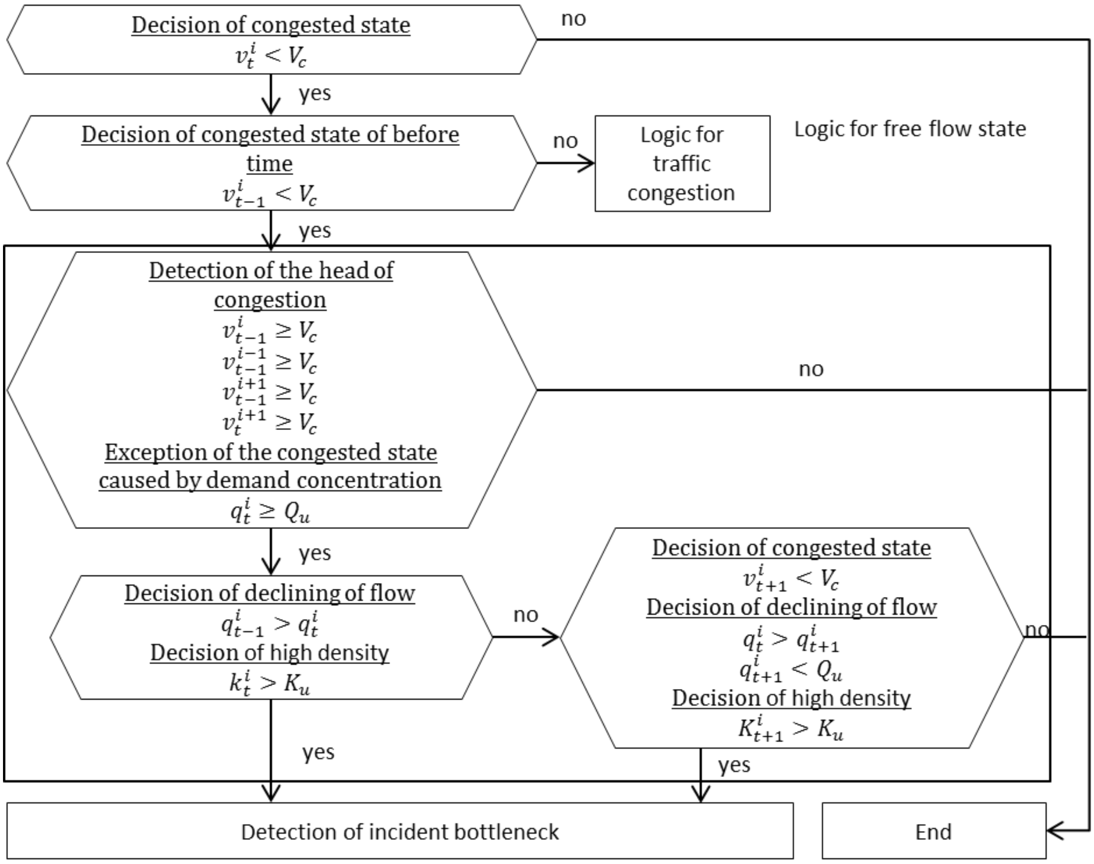

Figure 13. MEX algorithm for free flow state

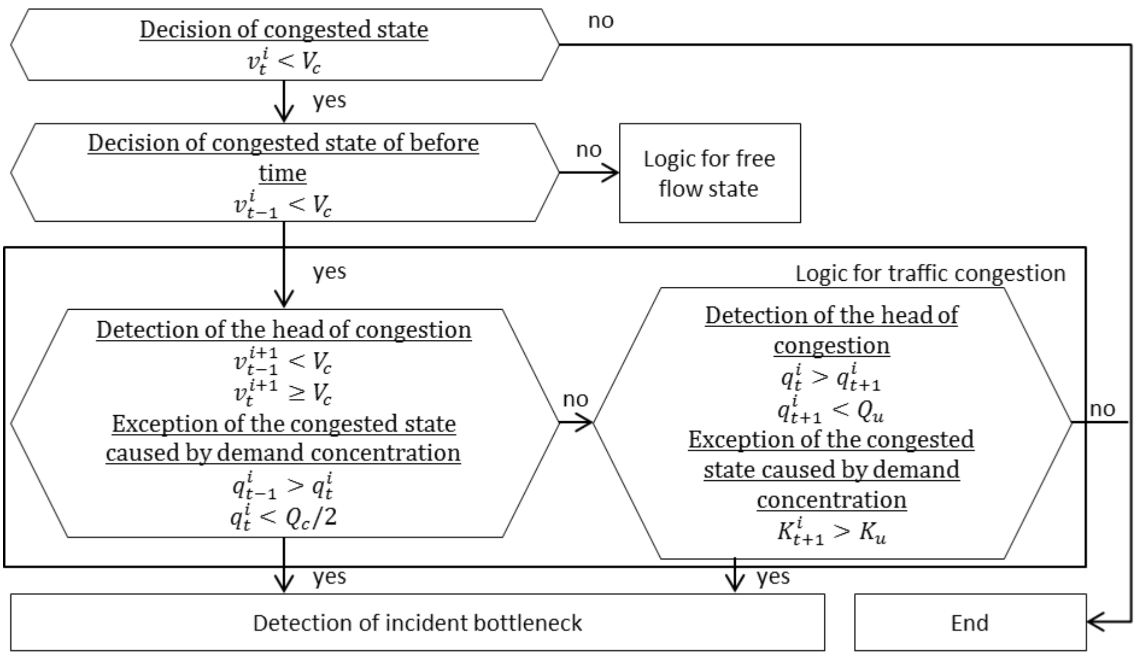

Figure 14. MEX algorithm for traffic congestion

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