Research Article

Traffic Anomaly Detection on Chalerm Mahanakhon Expressway Using Web-Based Traffic State Data

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Abstract

Detection of traffic anomalies is useful in areas where traffic congestion is an issue of concern. This study aims at developing a system to detect traffic anomalies occurring on the Chalerm Mahanakhon expressway in Bangkok by using web-based traffic state data. In this study, artificial traffic sensors were placed along the expressway to analyze the traffic state data. A statistical model was developed to predict the traffic states on these artificial sensors based on Bayes's theorem. An algorithm to detect traffic anomalies was introduced. The degree of anomaly was defined by comparing the probability of the expected traffic state and the probability of the observed traffic state. The method can be applied to any area where sufficient historical data are available.

Keywords: Traffic state; Traffic anomaly detection; Expressway; Bayes' theorem; Traffic congestion

1. Introduction

During the last decades, the world population has been growing rapidly. More activities in the metropolitan areas have been created, resulting in the increasing number of motor vehicles every year. Traffic incidents cause traffic congestion, cut down the efficiency of the road network [1] and increase costs of road users [2]. A traffic incident is an event that happens unexpectedly. It disrupts traffic flow for a short period of time on a road segment [3]. Causes of traffic incidents could be traffic accidents, vehicle breakdown, road maintenance, inclement weather, special events (e.g. concerts, or special sale discounts) [4], etc. Traffic incidents are impossible to predict [5]; however, they can be detected. Since traffic incidents cause traffic congestion, when they are detected they should be cleared as soon as possible in order to minimize effects of the congestion. Many studies have been conducted to detect traffic incidents in real time. Numerous algorithms and technologies have been proposed and different kinds of data are applied in order to improve incident detection systems. There are generally two methods of incidents detection: non-automatic and automatic [6]. In non-automatic incident detection, incidents are reported to the authority by drivers or witnesses. In contrast, automatic incident detection uses algorithms to detect incidents. An example of automatic incident detection is the use of image processing on CCTVs or any other surveillance cameras, etc. [5]. Between these two methods, automatic incident detection provides more advantages when applied in an

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ATMS (Advance Traffic Management System) due to its faster detection rate.

Traffic congestion which is usually induced by exceeding of travel demand over capacity within a period of time (usually peak hour) is called recurrent congestion or spontaneous congestion [5, 7, 8]. Normally, this kind of congestion occurs frequently at the same time and locations within a day and it is noticed by regular road users or traffic operators [9]. This type of congestion can be predicted, however, it is difficult to resolve unless the congestion is released to the normal flow (demand is lower than capacity) [10]. On the other hand, traffic congestion which is caused by traffic incidents is called non-recurrent congestion or abnormal congestion. This type of congestion needs to be detected in real time in order to avoid heavy traffic congestion occurring after the incident [7]. Therefore, detecting non-recurrent congestion in real time is very crucial in ATMS.

The aim of this study is to develop a system to detect the traffic anomalies by using web-based traffic state data. In order to achieve this goal, first, a methodology of collecting traffic state data from online mapping services was developed. Then, image processing was conducted so as to get traffic intensity data which are used for analyzing traffic incidents. Next, the probability distribution of traffic states was calculated by using Bayes' theorem. The corresponding traffic state of the highest probability is defined as the expected traffic intensity (ETI). The method to define traffic anomaly is to compare the observed traffic intensity (OTI) to the ETI. If the OTI is different from the ETI, it is recorded as an abnormality. After that, the degree of traffic anomaly is measured by the ratio of the probability of ETI and probability of OTI.

This paper is organized as follows. In section 2, a review of literature is presented. Section 3 introduces a methodology of collecting traffic state data from online mapping services, image processing, and traffic incident detection method. Section 4 presents a case study of applying the method to Chalerm Mahanakhon expressway in Bangkok. Results of this study are discussed in section 5. Finally, we give the conclusion and discuss future work in section 6.

2. Literature Review

Traffic incidents produce a lot of negative effects such as worsening traffic safety, increasing travel time, creating air pollution, and consuming more energy [11]. The main purpose of the traffic incident management system (TIMS) is to reduce these negative effects. In recent years, many automatic incident detection methods have been explored; different techniques of data collection have been conducted; and different types of traffic data have been applied.

Since traffic incidents detected in real time are crucial for traffic management, many methods for automatic incident detection (AID) have been developed. Techniques such as pattern recognition, statistical methods, comparative methods, time series methods, smoothing or filtering methods, traffic modeling, artificial intelligence, and image processing have been applied in AID [12, 13]. The general concept of AID is basically to evaluate the change of traffic parameters (e.g. traffic volume, occupancy, speed) between upstream and downstream. In the study of [14], travel speeds were used to classify traffic conditions into 5 states: serious congestion, congestion, normal, smooth, and fast. Traffic congestion was detected by analyzing the travel speed collected from floating car data. Normally, vehicles move slowly in the congestion area, and should speed up to the limited speed of freeway. In the study of [15], acceleration and deceleration of vehicles was applied to the probe-UCB algorithm. An incident is alerted whenever speed and acceleration of a single vehicle exceed the threshold values. In another study [16], shockwave theory was applied in order to detect an incident. The concept was based on 3 consecutive vehicles of which one is assumed not to pass the incident, while the other two are assumed to pass. Speed of those two vehicles must be reduced at the time of passing the congested area. In a similar study by [3], a road was divided into segments and average speed of vehicles on each segment was calculated. By installing two adjacent detector stations, speed at upstream and downstream locations were collected. Mean and standard deviation of speed at a specific time interval were calculated over a period of study. Using mean and standard deviation, some studies proposed a short-term forecasting, to predict the normal traffic condition, or to find the expected traffic state in the next time interval [1, 6] . The expected value depends on the threshold value which is obtained from calibration of incident data. An incident is alerted when there are unusual and significant changes in traffic variables.

Traffic incidents also can be detected by comparing travel time [17, 18]. The comparison can be done between the observed travel time and the average travel time or the past travel time. Basically, the observed travel time increases, or travel speed reduces if an incident occurs. Based on these concepts, link-based algorithms were developed for traffic incident detection [16]. Travel times of two adjacent links were compared. The incident is detected whenever the upstream travel time is greater than the downstream travel time. Travel time difference ratio and flow rate difference ratio were calculated in order to compare with the threshold value.

Another general concept for traffic incident detection is to compare current traffic state (CTS) with the usual traffic state (UTS). The UTS is usually determined by historical data. In the study of [7], speed data collected from probe cars were used and converted into 3 states of traffic condition: good, moderate, and stop. The CTS was estimated from real time speed data and UTS was defined by archival data. The difference between CTS and UTS, divergence, was calculated in order to measure the degree of anomaly. A traffic incident is detected when high divergence is found. Another method to calculate the degree of traffic anomaly is to calculate the congestion rate. The threshold value is set to define the normal traffic condition. The observed traffic condition is said to be normal when the speed of vehicles is greater than or equal to the threshold value. In this case the degree of anomaly is equal to the negative value of the congestion rate [19].

Due to the recent improvement of information technology, the ways to collect real time traffic data are more convenient. Due to the pervasive uses of mobile devices, vehicle’s location and travel speed are now collected by using probe vehicles or smartphones as a probe device [7, 14, 16, 20-22]. Traffic information is generated in online mapping services such as Google Maps, Bing Maps, etc. Colors which overlay a road network in mapping services changes according to the number of road users on a particular road segment [23]. Thus, real time traffic information from online mapping services was used as the source of traffic state data in some previous studies [23-25]. The advantages of using web based data are its large area coverage and its cost-effectiveness. According to these reviews, most of the studies used traffic data such as speed, travel time, and occupancy from probe vehicles, loop detectors, or traffic sensors. The incident detection is based on the specific value of threshold which is defined by using incident data from simulation [12]. Different from the previous study, this study utilized a new kind traffic state data from online mapping for traffic anomaly detection. The expected traffic state was determined based on historical data, which corresponds to the highest probability calculated from Bayes’ theorem. The observed traffic state was compared with the expected traffic state to determine if traffic anomalies exist. Finally, the degree of traffic anomaly was based on the ratio of the probability of expected traffic state and observed traffic state.

3. Methodology

3.1 Traffic State Data Acquisition

In order to get traffic intensity data, scripts that automatically call web crawler and capture traffic state in the form of image were developed. Traffic state data in the form of images are collected in real time every 10 minutes. They were named by date and time and stored in the database. Image processing was conducted to get traffic states. Artificial traffic sensors (points) were placed at every 100 m. on the road to detect colors as shown in Fig. 1. Table 1 presents the assigned indices that correspond to each color of traffic state.

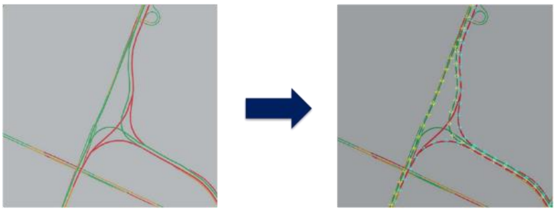

Figure 1. Assignment of artificial traffic sensors.

Table 1. Conversion of traffic state into traffic intensity by indexing [25].

Traffic state	Color	Indexing of traffic intensity
Free flow	Green	1
Moderate flow	Yellow	2
Congested flow	Red	3
Heavy congested flow	Dark red	4

3.2 Traffic Anomaly Detection

In this study, the traffic anomaly detection was done by comparing the observed traffic intensity (OTI) with the expected traffic intensity (ETI) which is calculated based on historical data. If the OTI is different from the ETI then the anomaly is detected. The degree of anomaly can be determined by comparing the probability of occurrences between the OTI and ETI.

The procedures of the traffic anomaly detection method are illustrated in Fig. 2 below:

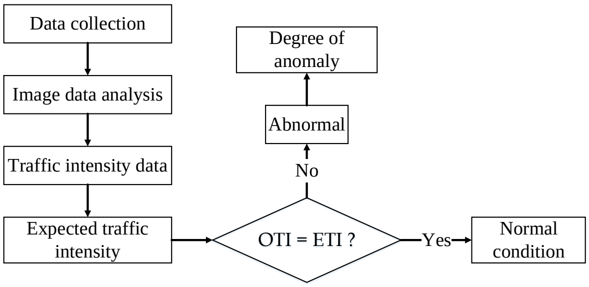

Figure 2. Precedures of traffic anomaly detection in this study.

3.2.1 Expected Traffic Intensity

This study proposed a method to find the expected value of traffic intensity. The expected value is defined by the highest probability of traffic state and it is a function of day of the week, date of the month, month of the year, special days (holidays), time, and space. Conditional probability based on Bayes' theorem is applied to compute the probability of the traffic intensity at each point in every time step. Bayes formula by giving four events is presented in equation (1) below:

$$P_{pt}(I_c / E_1E_2E_3E_4) = \frac{P_{pt}(E_1E_2E_3E_4 / I_c)P_{pt}(I_c)}{P_{pt}(E_1E_2E_3E_4 / I_c)P_{pt}(I_c) + P_{pt}(E_1E_2E_3E_4 / I'_c)P_{pt}(I'_c)} \quad (1)$$

Notations in this equation are described as follows:

P_{pt} $(I_c \mid E_1E_2E_3E_4)$: Probability of observed traffic state c at location p time t given *day of week*, *date of month*, *month of year*, and *holliday or non-holliday*.

p : Index of points along an expressway; every 100 m.

t : Index of time steps; 10 minutes intervals result in 144 time-steps per day.

I : Traffic state

c : Index of traffic state; green, yellow, red, and dark red.

E_1 : Day of week.

E_2 : Date of month

E_3 : Month of year

E_4 : Holiday or non-holiday

After evaluating the probability of each traffic state, the traffic state with the highest probability is taken as the expected traffic intensity (ETI).

3.2.2 Degree of Traffic Anomaly

In this study, the definition of traffic anomaly is a deviation from the expected (normal) traffic condition on the road network. In this context, a traffic anomaly may or may not cause traffic congestion. The degree of traffic anomaly is determined based on the ratio of the probability of OTI and ETI of each point. Positive sign of the degree of traffic anomaly indicates that the OTI is greater than the ETI (traffic is more congested than usual), and vice versa. The formula of the calculation follows equation (2) below:

$$DA_{pt} = \frac{OTI_{pt} - ETI_{pt}}{|OTI_{pt} - ETI_{pt}|} \times \left(1 - \frac{P(OTI)_{pt}}{P(ETI)_{pt}}\right) \quad (2)$$

Where,

p: Index of points (artificial traffic sensor) on the corridor

t: Index of time steps

DA_{pt}: Degree of traffic anomaly of point p at time t

ETI_{pt}: Expected traffic intensity of point p at time t

OTI_{pt}: Observed traffic intensity of point p at time t

$P(ETI)_{pt}$: Probability of expected traffic intensity of point p at time t

$P(OTI)_{pt}$: Probability of observed traffic intensity of point p at time t.

4. Data Collection and Case Study

In order to apply the method proposed above, Chalerm Mahanakhon expressway which is the first expressway in Bangkok city was selected as a case study. The length of this corridor is 26.7 km long. This expressway is divided into 2 directions:

- Din Daeng to Bang Na (15.1 km)
- Bang Mot to Khlong Toei (11.6 km)

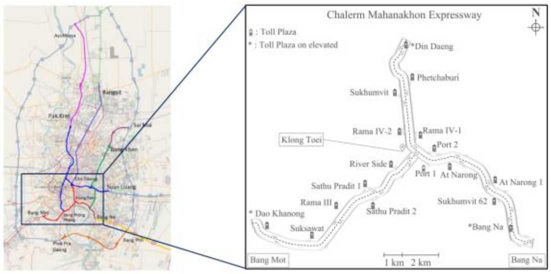

Figure 3. Chalerm Mahanakhon Expressway.

In total there are 17 toll plazas on both in-bound and out-bound corridors of the expressway. For the case study, the 15 km. section from Bangna to Din Daeng (in bound) was selected for the analysis.

Traffic state data was collected every 10 minutes (144 images per day) over one year from June 1, 2015 to May 31, 2016. However, only 333 days were usable due to missing data caused by the internet disconnections. Traffic state data were classified into groups based on day of the week, date of the month, month of the year, holidays, and non-holiday.

5. Results and Discussions

Results of observed traffic states, expected traffic states, and degree of traffic anomaly are presented in Fig. 4, Fig. 5, and Fig. 6, respectively.

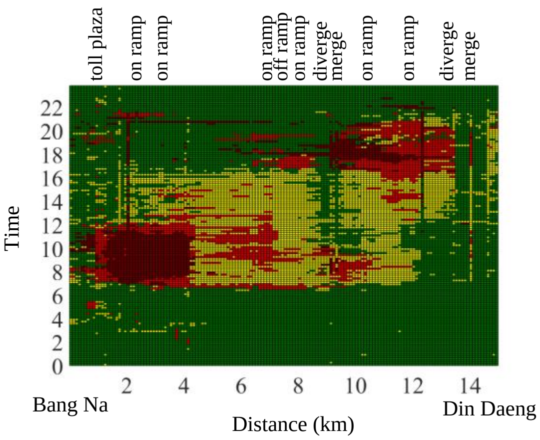

Figure 4. Expected traffic state on May 4, 2016.

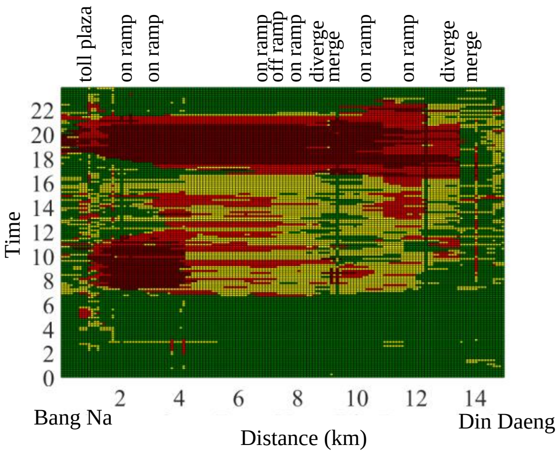

Figure 5. Actual traffic state on May 4, 2016.

May 4, 2016 was selected for an illustration purpose here. The selected date of analysis was one day before long holidays (May 5-9, 2016) in Thailand. Fig. 4 presents the expected traffic states on Chalerm Mahanakhon expressway from Bang Na to Din Daeng on May 4, 2016. Fig. 5 shows the actual traffic states observed on that day. Normally, the daily traffic conditions on the expressway change from time to time depending on travel demands of road users. It was observed that traffic patterns on the expressway were similar according to types of days. The result also revealed that there are some locations of traffic congestion that are different from the expected ones.

In this study, the difference of traffic state from the expected state was considered as an anomaly. Fig. 6 presents the result of degree of traffic anomaly detected. The degree of traffic anomaly ranges from -1 to 1. It is noted that when the observed traffic state is the same as expected traffic state the degree of anomaly is set to 0.

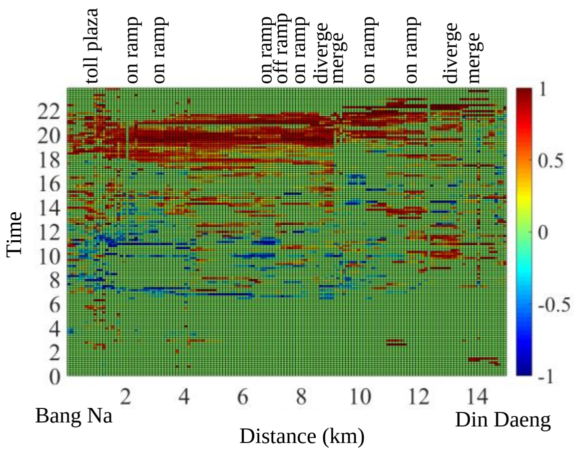

Figure 6. Traffic anomaly and degrees of anomallies detected on May 04, 2016.

The positive sign of the degree of anomaly indicates the higher traffic intensity compared to the normal condition (traffic is excessively congested than expected) and vice versa. The magnitude of the degree of traffic anomaly is related to the frequency of the event. If the event has small chance to happen and it occurs, then the degree of the anomaly is high. According to the results of traffic anomaly in Fig. 6, traffic anomalies occurred and were scattered along the expressway. Traffic anomalies which cause serious traffic congestion were observed in the evening around 6 pm to 9 pm. Anomalies took place mostly from Bang Na toll plaza to a merge (km.9).

Within a whole year of the study, the degree of severe traffic anomaly on each link of the expressway are summed together in order to see the frequency of locations where traffic anomaly occurred.

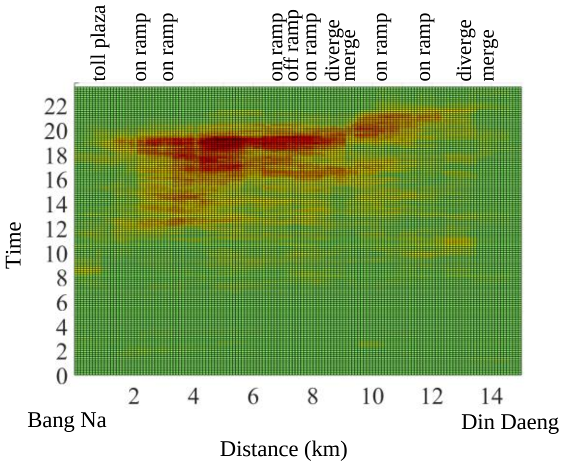

Figure 7. Positive traffic anomalies.

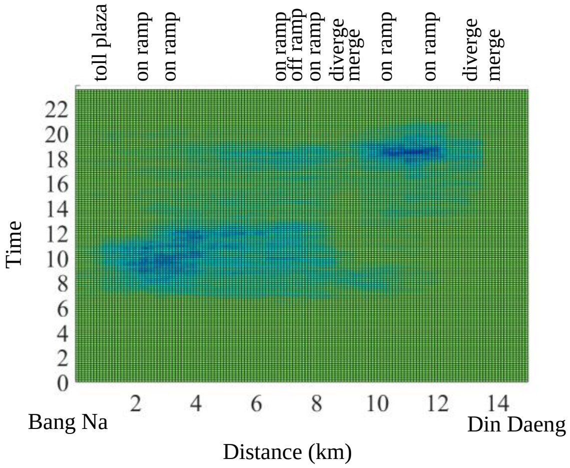

Figure 8. Negative traffic anomalies.

Results of frequent traffic anomalies that occurred are presented in Fig. 7 and Fig.8. Red color in Fig. 7 indicates the degree of traffic anomaly that occurred when the observed traffic intensity was higher than the expected condition. Green color shows areas and times where the observed traffic intensity was the same as expected traffic condition (no anomalies detected). In Fig. 8, blue color reveals the time-space that traffic anomaly took place when the observed traffic intensity was lower than the expected condition.

From the results of the aggregation of traffic anomalies above, in many instances traffic anomalies are observed in the evening. It was observed that, from Bang Na to Din Daeng, traffic anomalies cause traffic congestion between an on ramp at km.2.7 and a merge at km.9 around 8 pm

In this study, the number of traffic anomalies over a whole year was classified into 4 categories according to the degree of anomaly as shown in Table 4. Class 1 (0.0%) refers to correct predictions in which the expected traffic states are the same as observed traffic states. No anomalies were detected in this class. Class 2 (0.0 to 50%) refers to fluctuations of the traffic on the expressway. Class 3 (50% to 75%) is considered as abnormal traffic condition while class 4 (>75%) is considered as highly abnormal traffic conditions. The percentage of events detected are presented in Table 2 below. The results were summarized into two schemes, 24 hours and 15 hours from 6 am to 9 pm. (excluding nighttime when traffic is normally stable).

Table 2. Percentage of degree of traffic anomalies detected.

Class	Degree of anomalies (%)	Percentage of events detected	
		From 00:00 to 23:50	From 6:00 to 20:50
Class 1	0	86.36%	80.34%
Class 2	0.0 – 50	7.07%	10.39%
Class 3	50 – 75	3.99%	5.71%
Class 4	> 75	2.58%	3.55%

6. Conclusions

In this study, traffic state data were collected from online mapping services and used in order to develop a system to detect traffic anomalies on expressways in Bangkok. Image processing was applied to obtain traffic states from images. Bayes' theorem was applied to calculate the conditional probability of each traffic state. The traffic state that corresponds to the highest probability was taken as expected traffic intensity. A traffic anomaly is detected whenever observed traffic intensity and expected traffic intensity are different. The degree of traffic anomaly was also defined using the ratio of the probability of ETI and OTI. Degrees of traffic anomaly were summed up in order to see the locations and time that traffic anomalies usually occur. Chalerm Mahanakhon expressway in Bangkok was selected as a case study for an illustration purpose. The prediction method based on Bayes' theorem showed that the accuracy of the prediction within a period of study was acceptable. The proposed method can be used to apply to any area where there is sufficient historical traffic data. For the future work, the proposed method can be developed into real time traffic anomaly detection and more events such as the condition of the weather should be considered in the analysis.

7. Acknowledgment

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