Traffic Anomaly Detection Using Mobile Sensors

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Abstract

This paper presents an algorithm for traffic anomaly detection based on information from offline probe vehicles, traffic anomalies in this paper refers to anomalous traffic patterns associated with traffic incidents. Currently,fixed sensorshavebeen used for detecting abnormal traffic,such as loop detectors and traffic cameras,but they have problems with installation, maintenance,and the distribution of fixed sensors. The basic idea in the traffic anomaly detection using mobile sensors is that by observing the speed of the probe vehicles, probe vehicles should be in a slow-movingspeed at the incident.When probe vehicles pass the incident,they will move at a normal speed.In this study, we use the incident data from a traffic simulation based onGippssafe-distance car-following model. The methodology ofincident detection process consistsof two parts: 1) detecting abnormal traffic patterns and behavior of each probe vehicle; 2) calculating the probability of abnormal incident occurrences from several probe vehicles in the same time period, then comparing the probability of an abnormal incident withtheprevious period.The preliminary experiment result shows the evaluation of the performance of the incident detection in terms of Detection Rate (DR) and False Alarm Rate (FAR). This algorithm can detect abnormal traffic incident and estimate theposition of an abnormal incident and abnormal levels of incident.

Keywords: Traffic anomaly detection, Probe vehicles, Mobile sensors

1. Introduction

Traffic congestion isa problem in many areas. There aremany ways that trafficcongestion affectthe qualityof life. Traffic congestion occurs when a volume of traffic or modal split generates demand for space greater than the available road capacity.In addition, the problem of traffic congestion is caused by an abnormal incident, any type of incident,such as accidents or vehicle breakdowns.

Fromthetrafficcongestioncaused by abnormal incidents,there are several methods used to detect an abnormal traffic incident.Today, fixedsensors are used to detect abnormal traffic incident, such as loop detectorsandtraffic cameras.However, in the long highway, such a

method may have difficulty in sufficientdistributions of fixed sensors. An anomaly may not be detected, or a long congestion delay may occurbefore the anomaly can beidentified.In addition,fixed sensorscanbe costly due to installation and maintenance.

2. Literature review

In the past, there have been many algorithms for traffic anomaly detection based on probe vehicles. The basic idea in the traffic anomaly detection using mobile sensors is derived from the model of the Incident Detection with Probe Vehicles [1], which present an incident detection algorithm based on information received in real-time from probe vehicles and a model which allows us to estimate the upper bound detection rate for a given density of probe vehicles. The principle of this model is stated that by observing the speed of probe vehicles, an algorithm can determine when it has passed an incident, as follows. At the upstream positionof an incident, vehicles should be in a slow-moving speed and when they pass the incident location, they should speed up to free flow speed (See Fig. 1)

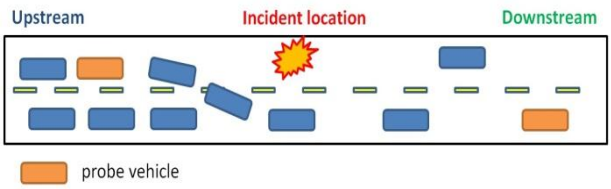

Fig. 1 Example of abnormal incidents

By looking for this change in speed of the probe vehicles (See Fig. 2), when a probe vehicle moves through an abnormal traffic incident,the speed from each probe vehicle. After that,we compare an average speed and current window speed during which a probe vehicle moves through road segments. At anytime, total average speed (V_{total}) of a sample probe vehicle is calculated as

$$V_{total_t} = \frac{1}{t}\sum_{i=1}^{t} v_i \qquad (1)$$

And window speed (V_{w_t}) for time t and $t \geq \frac{w}{2}$ is calculated as

speed will increase rapidly until it returns to the normal movement.

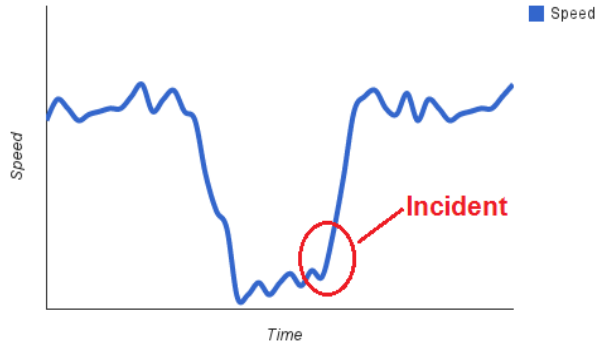

Fig. 2 Speed Vs. Time for incident detection based on the probe vehicle speed

Another work in the field of incident detection using probe vehicles is using A MultilevelTraffic Incidents Detection Approach [2]. This paper presents a multilevel approach for detecting traffic incidents causing congestion on major roads based on probe vehicle data. That method can detect abnormal traffic incidents with high efficiency in detection rate and false alarm rate, but that algorithm is a complex work and requires many probe vehicles forcalculation.

3. Methodology

3.1 Analyzing traffic pattern from each probe

In the firstpart of this algorithm, we presentdetecting abnormal traffic patternsand behaviorof each probe vehicle. Data inthis study include timestamp, vehicle id, current position and current speed collected every five seconds.

As a first step, we identify the current

$$V_{w_t} = \frac{1}{w}\sum_{i=t-\frac{w}{2}}^{t+\frac{w}{2}} v_i \qquad (2)$$

Then, thedifferent average speed (V_{diff_t}) between total average speed (V_{total_t}) and current window speed (V_{w_t}) at time t as follows

$$V_{diff_t} = V_{total_t} - V_{w_t} \qquad (3)$$

Where: v_i is a current speed at time i
w is a window size with even number

Following equation (3), inthe case of normal traffic, that total average speed and current window speed of probe vehicle are stable.As a result, then difference average speed (V_{diff}) is low (See Fig. 3).

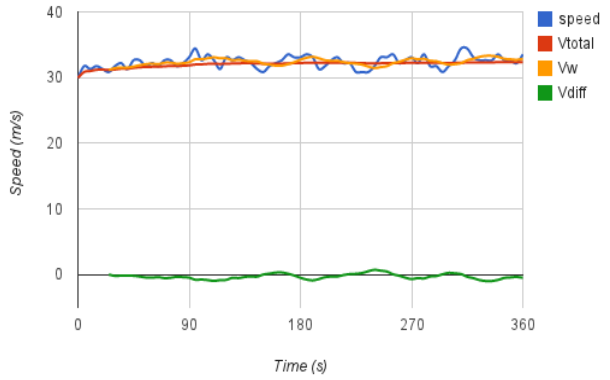

Fig. 3 Different average speed of normal traffic

Butwhenan unusual traffic condition occurs, upstream traffic of an incident should slow moving, As a result, the current window speed of probe vehiclechanges quickly, while little has changed fortotal average speed. Then,the difference average speed (V_{diff}) is higher at the time of incident (See Fig. 4).

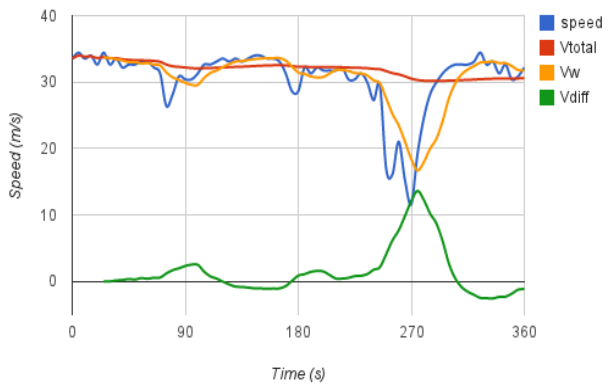

Fig. 4 Different average speed of abnormal traffic

Next, we calculate cumulative distribution function (CDF) of abnormal incidents in freeway from different average speed (V_{diff}) at time *t*. For a generic normal distribution from different average speed collection of normal and abnormal events with mean μand deviation σ, the cumulative distribution function (CDF) is

$$F(x) = \Phi\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right] \quad (4)$$

The CDF of abnormal incidents at any time for eachprobe vehicle willbeused to detect abnormal traffic conditionsat any position on freeway in the next section.

3.2 Calculating probability of abnormal incidents from several vehicles in the same time period

In this part,the road is divided into smaller subsections, such thatit is easier to locate the incident that occurred. The road is divided into groups of 10 meters long and each time interval. At any time, subsections will start at s1 to s1000 (See Fig. 5), for example, when the probe vehicle is at 755meters from the starting point, that the probe vehicle will be in S75.The CDFof abnormal incident in thefirst part are analyzed in the followingsteps to identify the position and time if an incident may have occurred.

Time							
t-2	S_1	S_2	S_3	…	S_{998}	S_{999}	S_{1000}
t-1	S_1	S_2	S_3	…	S_{998}	S_{999}	S_{1000}
t	S_1	S_2	S_3	…	S_{998}	S_{999}	S_{1000}

Road subsections

Fig. 5 The road is divided into subsections

As a first step,we identify the CDF and the position of abnormal incidents at that time, and then determinetheCDF in the road subsections that are in the same time and position for the probe vehicle.

Next, if CDF of the probe vehicle at any subsections is more than 0.9,then mark this subsection and compare the subsection that containing the value of CDF more than 0.9 with neighboring subsections. If neighboring subsections containing theCDF less than 0.9, this algorithm will alert an abnormal traffic incident and return the position ofsubsection in the time that the incident occurred.

The second part of this algorithm at time *t*, current subsection is S_n and CDF in subsection S_n is CDF_n , canbe summarized in the following flowchart as Fig 6

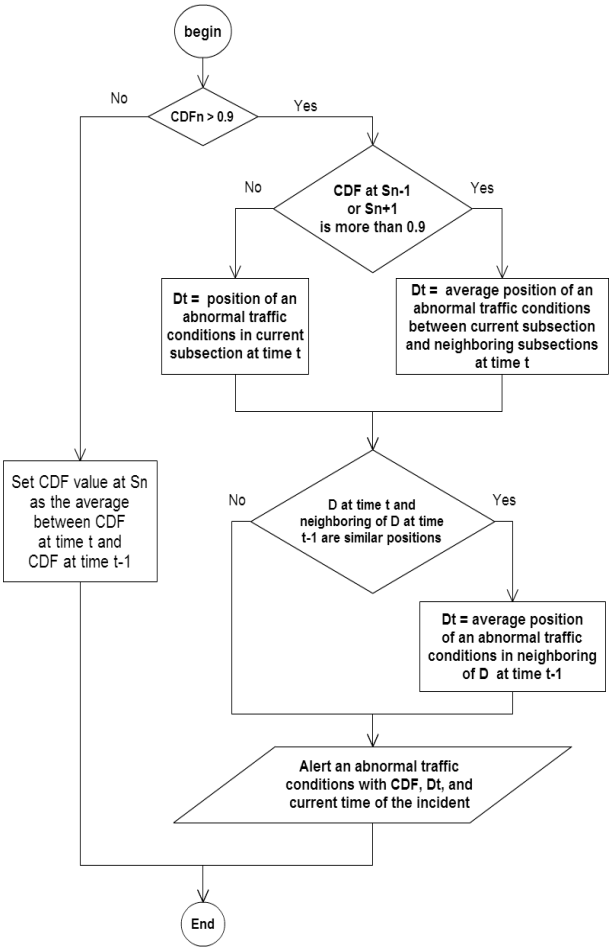

Fig. 6 Calculating the probability of abnormal incidentsfrom several probe vehicles

However, in case of the probe vehicle not moving through each subsection for a long period of time, to solvethis error, if don't have a probe vehicle moving through the subsection within 10 minutes, then the CDF of that subsection is reduced by half.

4. Experimentation and results

4.1 Data used

We use the trafficincidentdata fromthe traffic simulation [3],that implemented Gipps safe-distance car-following model into the microscopic traffic simulation environmentGroovenet [4]. On the two-lane freeway segment, each simulated vehicle recorded itstimestamp,speed and the current position. In General, there were betweenfour and ten probe vehicles on the freeway at any one time, speed of the probevehicles in normal traffic conditions with average speed at 110 km/h.

4.2 Results

In this study, we ran this algorithm with data set on four weeks and total of 56 incidents.The abnormal incidentwas modeled to occur at different time and different position.

As aresult, when this algorithm detects abnormal traffic incidents, it shows the position and the timethat causes of an abnormal trafficincident (See Fig. 7).Finally, this algorithm can estimate abnormallevels of theincident by value of the CDF.If the high levels of an abnormal incident occur, the CDF of the probe vehicles that through the incident at that time is higher.

```
Incident #8
Time = 5004     Subsection = 671
Time = 5005     Subsection = 671
Time = 5006     Subsection = 671
Time = 5007     Subsection = 671
Time = 5008     Subsection = 671
Time = 5009     Subsection = 671
Time = 5010     Subsection = 671
Time = 5011     Subsection = 671
Time = 5012     Subsection = 671
Time = 5013     Subsection = 671
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Fig. 7 An example for a notification of incident

In addition, we analyzea sample of the incident that occurs at adistance of 5,800 meters from the starting point and theincident that occurred in10 minutes from traffic events in an hour. By lookingfor this change in speed of the each probe vehicle (See Fig. 8. (a)) and theCDF(See Fig. 8. (b))ofthe sample incident,The CDF will be as high as possible when the probe vehicle is moving through thearea withan incident occurred.

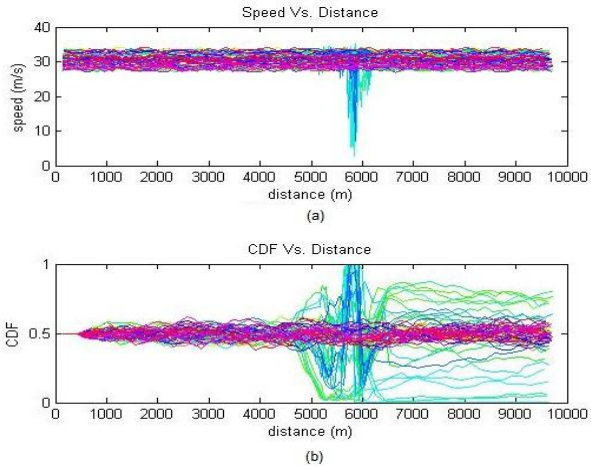

Fig. 8 Analysis of a sample incident for (a) Speed Vs. Distance,(b)CDFVs. Distance

4.3 Performance evaluation

This section evaluates the performance of the incident detection in terms of Detection Rate (DR) and False Alarm Rate (FAR) of this algorithm

The results for the incident detection in this algorithm as shown on Table 1, that table shows the effect of the CDF threshold on Detection Rate (DR) and False Alarm Rate (FAR).

Detection Rate (DR) is detected incidents divided by actual incidents and False Alarm Rate (FAR) is number of incident free interval with false incidents alarms divided by the total number of incident free intervals

Table 1 Effect of CDF on DR and FAR

CDF (greater-than)	Detected incidents	actual incidents	DR (%)	FAR (%)
0.80	75	56	100	33.93
0.82	65	56	100	16.07
0.84	60	56	100	7.14
0.86	59	56	100	5.36
0.88	55	56	98.21	0.00
0.90	55	56	98.21	0.00
0.92	52	56	92.86	0.00
0.94	50	56	89.29	0.00
0.96	46	56	82.14	0.00
0.98	46	56	82.14	0.00

It can be seen in Table 1, if we use the CDF is less than 0.88, as result in the detection rate have a high efficiency, but false alarm rate is high as well. Next, when we use the CDF is greater than or equal to 0.88, detection rate will be reduced slightly and false alarm rate havegreatly reduced.In this study,we use the CDF more than or equal to 0.8for the calculation.

Next, The Table 2 shows Detection Rate (DR) and False Alarm Rate (FAR) with different number of the probe vehicle during the same time

Table 2 DR with different number of the probe

Number of probe vehicle	Detected incidents	actual incidents	DR (%)	FAR (%)
1 - 3	1	14	7.14	0.00
4 - 6	11	14	78.57	0.00
7 - 9	14	14	100.00	0.00
9 - 12	14	14	100.00	0.00

It can be seen in Table 2 that detection rate are highly effective, when the number of probe vehicle on the road during that time more than 7 vehicles.In this study, the length of road is 10 km, which can be summarized as follows. Detection rate of abnormal traffic will be highly effective whenthe minimum time headway of the probe vehicle is less than 1 minute, when time headway is the time gap between consecutive probe vehicles.

5.Conclusion

This paperproposed analgorithm for traffic anomaly detection based on information from offlineprobe vehicles. By using the informationfrommobilesensorsfor incident detection, we hope itcancomplement the use of fixed sensors in incident detection.

The preliminary results presented in section 4.3 (Performance evaluations), shows the factors that effect of Detection Rate (DR) and False Alarm Rate (FAR).In thisstudy with the traffic incident data fromtrafficsimulation based on Gipps safe-distance car-following model, this method is highly effective in detecting anabnormal incident.Butif this method has been applied to the real-world data, there may actually be a slight error in detecting abnormalities. To resolve that error, there may need to be some adjustments, such as the CDF values for separation of an abnormal incident ormodification of the window size.

Forthe nextstage of this research, we will apply this algorithm to the highway in Thailand.One of the foreseeable problems is that, there is not enoughhighway traffic probe information in Thailand.For the resolution, we may use the traffic information from the simulation based on the actual highway in Thailand.Moreover, traffic information may be obtained from real-time probe vehicles, which passed the road test during that time. Then, this algorithmwill process the real-time traffic information and alert to the road users if an incident may have occurred. Notification of abnormal traffic detection canhelp road users to find a better alternate route while driving.

6.Acknowledgment

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