Chapter 6
Intelligent Transportation Systems in Future Smart Cities

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Introduction

Overview

Intelligent transportation systems (ITS) are state-of-the-art applications to improve the transportation safety and mobility, as well as move towards an environmentally friendly system. ITS plays a pivotal role in future smart cities in terms of providing the users with more informed, safer, more secured, and cost-effective transportation system. To this end, ITS takes advantage of modern technologies including communication infrastructure to enable efficient data transfer among smart agents, advanced computational methods to deal with large-scale optimization problems, autonomous vehicles, electrified vehicles, connected vehicles, and intelligent traffic signals. In this chapter, we provide a comprehensive overview of some ITS technologies. Some of the recent methods to enable these technologies are introduced to pave the road for future researchers working in this area. To provide readers with case examples of ITS, two connected vehicle applications are elaborated in this chapter: queue warning and automatic incident detection. Queue warning systems are designed to inform the drivers about the back-of-queue (BOQ) location so that

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they brake safely and in a timely manner. An automatic incident detection (AID) system aims to detect incident occurrence automatically utilizing traffic data such as speed, volume, and occupancy.

Forecasting the driving patterns and the data provided by advanced traveler information systems that affects the traffic in transportation network flow is important in modernizing the transportation networks and enabling intelligent transportation systems (ITS). Sharing the predicted traffic conditions, they are able to make more optimal decisions while traveling. This will lead to traffic congestion reduction as well as increased efficiency of transportation by enhancing the utilization of the current assets [1]. In [2], authors proposed an algorithm that takes into account several effective parameters (e.g., waiting time, density of vehicles, and volume of traffic) to control the traffic in a real-time fashion based on the wirelessly collected data. Their method estimates the green light sequence as well as the duration of each green light. In [3] a route optimization method is proposed for electrified vehicles which considers variables from both power systems and transportation networks. In this approach, traffic conditions, electricity price for charging the battery, and behavioral preferences of drivers are considered while determining the optimal route from the given origin to the expected destination. A comprehensive introduction to the theoretical approaches for ITS applications is provided in [4]. These methods are not only for intelligent transportation networks, but also applicable to other smart infrastructure. Transportation networks are among crucial sustainable interdependent networks [5]. First, there is an increasing evolution towards modernizing these networks by deploying more electric vehicles [6]; second, they are considered as key players of future smart cities [7]; third, they involve several other networks such as power systems and communication networks. The interdependent aspects of power and transportation networks have been extensively studied in [2]. Further, the effect of electrified vehicle charging demand on the operation of power systems is investigated in [6].

More information about the performance measures, detection rate (DR), false alarm rate (FAR), and mean time to detect (MTTD), is provided in [8, 9].

Automatic Incident Detection

An automatic incident detection (AID) system aims to detect incident occurrence automatically utilizing traffic data such as speed, volume, and occupancy. An AID system has two components: a data collection system and an incident detection algorithm. The data collection system provides real-time traffic data such as speed, occupancy, and flow using data collection devices (e.g., point detectors, CCTV cameras, tag readers, Bluetooth). The collected data is analyzed through incident detection algorithms to declare the incident occurrence. The performance of incident detection algorithms is normally evaluated using three commonly used performance measures: detection rate (DR), false alarm rate (FAR),and mean time to detect

(MTTD) [8, 9]. DR is the ratio of number of correct detections by total number of actual incidents occurring in a time period and is shown in Eq. (6.1):

$$\mathrm{DR} = \frac{\text{Number of correct detections}}{\text{Total number of incidents}} \times 100\% \tag{6.1}$$

Different researchers have defined different FARs for different purposes. $\mathrm{FAR}_{\text{online}}$ and $\mathrm{FAR}_{\text{off-line}}$ are the two main detentions found in the literature. $\mathrm{FAR}_{\text{online}}$ is the percentage of the number of incorrect decisions by the total number of algorithm decisions (all the declared alarms) while $\mathrm{FAR}_{\text{off-line}}$ is the ratio of algorithm incorrect decisions by the number of algorithm applications [10]:

$$\mathrm{FAR}_{\text{online}} = \frac{\text{Number of incorrect detections}}{\text{Total number of algorithem decisions}} \times 100\% \tag{6.2}$$

$$\mathrm{FAR}_{\text{off}-\text{line}} = \frac{\text{Number of incorrect detections}}{\text{Total number of algorithem decisions}} \times 100\% \tag{6.3}$$

MTTD is the difference between estimated incident time by the algorithm and the observed incident time which is shown in Eq. (6.4).

$$\mathrm{MTTD} = \text{Estimated incident time} - \text{Observed incident time} \tag{6.4}$$

Generally, automatic incident detection methods are categorized into two main groups: point detector-based and probe-based algorithms. Most of the traditional automatic incident detection algorithms use point detector data to detect incidents. However, there are some disadvantages in using point detector data. The main drawback of the point detector-based methods is that they cannot detect the incident until the queue caused by the incident reaches the upstream detector [11], which may take a long time and even may never happen if the queues due to incidents are short or do not exist. These algorithms were also found to produce large numbers of false alarms [12–14]. Furthermore, these sensors cannot be deployed all over the network as they are expensive and they cannot cover the entire network. It is also difficult to realize the true traffic conditions, as sensors collect spot traffic data. Incidents may be detected more efficiently using travel time measurements collected by probes (e.g., Bluetooth, Wi-Fi, electronic toll tag readers, and GPS) as they have a wider roadway coverage. Further, spectrum allocation of wireless networks is important to ensure the energy-efficient communication [15]. Mohammadi et al. proposed a highly efficient approach to reduce the power consumption of communication networks using fuzzy logics [15]. Their approach has several advantages compared with the existing communication platforms and can be deployed for different applications such as intelligent transportation networks. A summary of the point detector-based and probe-based algorithm performance reviewed above and other algorithms are shown in Table 6.1.

Table 6.1 Summary of point detector-based and probe vehicle-based algorithm performances

Point detector-based algorithms [16]					
Algorithm name	*DR (%)*	*MTTD (min)*	*FAR (%)*	*Location*	
California	82	0.85	1.73	California, Chicago, Texas	
McMaster	68	2.2	0.0018	Minnesota	
Neural Networks	89	0.96	0.012	Modeling, Simulation, and Analysis (MSA)	
Low-Pass Filter [17]	80	4	0.3	Modeling	
DES (Double-Exponential Smoothing) [18]	92	0.7	1.87	Toronto	
Bayesian [19]	100	4	0	Modeling	
Probe-based algorithms					
Algorithm name	*Probe technology*	*Penetration rate*	*Environment type*	*Data requirement*	*MTTD*
MIT [20]	AVI/ETC	50%	MITSIM-based simulation	Travel time and headway by lane, lane switches, volume by lane	0.8 min
TTI [21]	Cellular probe system	5-min headway	Field in Houston, TX	Travel time	15 min
TRANSMIT [22]	AVI/ETC	1-min headway	Field in metropolitan NYC	Travel time	15 min
Waterloo [23]	AVI/ETC	10%	INTEGRATION-based simulation	Travel time	0.3 min
MOSES [11]	Mobile Sensor	5–50%	Paramics microsimulation	Travel time	12–4 min
DSRC-based method [24]	DSRC	30%	CORSIM microsimulation	Travel time	−2 to 4 min, reader spacing 2 miles −2.5 to 14 min reader, spacing 10
Bluetooth-based method [25]	Bluetooth	6%	Field in Oregon	Travel time and volume	Not reported
GPS-based method [26]	GPS	1%	AIMSUN microsimulation	Travel time	14.8 min

Methodology

This study tests two freeway incident detection methods based on connected vehicle data. The methods are based on the vehicle's acceleration estimated based on connected vehicle data. Due to the fact that the vehicle's acceleration after slowing at and then passing the incident location is always positive, the acceleration after the incident location was selected to identify the incident signature for the proposed methods.

The methods were tested using the VISSIM microscopic simulation tool. VISSIM was used to emulate incident occurring in a mixed connected vehicle and not connected vehicles in a traffic stream. The vehicle's trajectories produced by VISSIM were fed to the Trajectory Conversion Algorithm (TCA) tool, produced by the Federal Highway Administration (FHWA) (25) to emulate BSM messages generating from the simulation. Then, the generated BSM messages were input to the incident detection methods to investigate their performances. More description of the TCA tool is presented in the case study section. The subsection below provides more details about the tested methods.

Method I: The Average Acceleration Distribution Method

This method aims to detect the abnormality in the traffic conditions using a predefined threshold based on the acceptable probability of false alarms. In this method, the network is decomposed to m segments. Using historical data of connected vehicle measurements, the acceleration distribution is derived for each segment for no-incident conditions. Four different hypothesis testing resolutions of 30, 60, and 90 ft. were conducted and the results were compared. In this study, the distributions are derived using multiple VISSIM runs under no-incident condition. According to central limit theorem, the average of large number of iterates of a random variable, regardless of the underlying distribution, is approximately normally distributed. So, the average acceleration in each segment is normally distributed. This distribution changes when the traffic demand changes. Thus, different distributions need to be derived for different periods. In practice, the lengths of the periods can be done using clustering analysis or other statistical techniques. The focus of this chapter is incident detection during medium and high traffic demand (high and medium congestion) for the simple test networks. Thus, for each segment two distributions were developed based on VISSIM runs with no incident and considered to be adequate for the purpose of this study. The 95th percentile of the average acceleration rate in each segment m for the two congestion levels was selected as the threshold for incident detection Method I. This means that the probability of the false alarms was set at 5%. The process of calculating the thresholds was done off-line. To detect the incident in real time, in each time interval, the whole network was scanned. If a segment average acceleration was higher than the threshold, the segment was detected as an incident location.

Method II: The LRT-Based Method

As with Method I, the incident detection problem is converted to a hypothesis testing problem with the null hypothesis being no incident presence and the alternative hypothesis being incident presence. The purpose of the hypothesis testing is to decide whether an incident happened or not in a specific time and location in the network based on an observed set of measurements $\{x[0], x[1], \ldots, x[N-1]\}$, with each of these measurements representing the individual measurements ahead of the tested segment for potential incident occurrence. Based on our observation of acceleration rate measurements in VISSIM, the influence area of the incident is 150 ft. after the incident location. This 150 ft. is decomposed to n_{sig} sub-segments and for each sub-segment the distribution under the incident and no-incident conditions is derived. Each of the N measurements within this 150 ft. belongs to any of n_{sig} distributions. The length of each sub-segment was selected to be 15 ft. However the resolution for deriving the distributions (15 ft.) can be different from the hypothesis test segment resolution. The hypothesis test segment resolution was selected to be 30 ft. However, the hypothesis test segment resolution can be longer in the expense of losing the accuracy of identification of the exact incident location. To clarify, if the hypothesis test segment resolution is 150 ft. and one segment is detected to have incident in it, the exact location of the incident within this 150 ft. cannot be determined. It should be realized that in most applications, locating the incidents to within 150 ft. is sufficient.

Hypothesis testing is conducted by looking at the N measurements within the 150 ft. after the segment and utilizing the pre-stored distributions of the measurements with and without incidents for the n_{sig} segments. The threshold in the hypothesis testing is not fixed as in Method I and is updated for each segment at each time interval. Since the measurements are not uniformly distributed at all locations in all time step, the number of measurements for each hypothesis testing is not known beforehand. Furthermore, the relative distance of the measurements to the respective location of the hypothesis testing is also unknown beforehand. Therefore the utilized incident detection algorithm is an adaptive detector that changes its form (test statistic) according to the number of available measurements and the relative distance of them to the respective hypothesis location. Detector form means the way to process the data and come up with a test statistic to compare it with a threshold. To clarify the methodology, suppose we are testing the ith segment of the network at time interval t. Measurements within 150 ft. after segment ith during time t are processed (using Eq. (6.7)) and compared with a threshold which is calculated using Eq. (6.8). According to Neyman-Pearson Theorem [27], in order to maximize the probability of detection (P_D) for a given probability of false alarm:

$(P_{FA}) = \alpha$, we accept H_1 if

$$L(X) = \frac{P\,(X;\,H_1)}{P\,(X;\,H_0)} > \gamma \tag{6.5}$$

where

X is the measurement vector.

$L(X)$ is the likelihood ratio that determines the likelihood of each X belonging to H_1 versus the likelihood of X belonging to H_0, and γ is the threshold which is obtained from Eq. (6.6):

$$P_{FA} = \int_{\{x:L(x)>\gamma\}} p\,(x;\,H_0)\,dx = \alpha \tag{6.6}$$

The test statistic and the threshold were calculated by simplification of Eqs. (6.5) and (6.6), respectively, and are shown in Eqs. (6.7) and (6.8):

$$T_{mk}(X) = \sum_{i=1}^{N-1} \frac{x_i\left(s_i' - s_i\right)}{\sigma^2} \tag{6.7}$$

$$\gamma_{lk}' = \frac{Q^{-1}\,(P_{FA}) * \mathrm{var}\left(T_{mk}\left(X\right)\right)}{\left(E\left(T_{mk}(X)\right)\right)} \tag{6.8}$$

where

x_i is the ith measurement for testing the hypothesis at segment m and time step k.

s_i' is the expected value of ith measurement under the incident case.

s_i is the expected value of ith measurement under the no-incident case.

$T_{mk}(X)$ is the test statistic to be compared with γ_{mk}'. If $T_{mk}(X) > \gamma_{mk}'$ we accept H_1 and conclude that there is an incident in Milepost m and time step k.

Results

The incident detection results for different scenarios are shown in Tables 6.2 and 6.3. Table 6.2 shows the results for Method I with different test segment resolutions. As shown in Table 6.2, this method was unable to detect the incidents when the network was congested when the incident detection threshold was set to 95% and 99% of the average normal acceleration distribution. When the threshold was changed to 99%, the PFA and DR decreased as expected but the method could not detect incidents after the merge even under no-breakdown conditions The reason appears to be the

Table 6.2 Method I incident detection results

				Incident before merge			Incident after merge		
H.R[a]	T[b]	Congestion level	MP (%)	DR %	PFA%	MTTD	DR %	PFA%	MTTD
30 ft.	95%	With breakdown	3	Unable to detect			Unable to detect		
			20						
		Without breakdown	3	100%	4.5%	1 min	100%	2.43%	1 min
			20	100%	3.65%	1 min	100%	1.57%	1 min
	99%	With breakdown	3	Unable to detect			Unable to detect		
			20						
		Without breakdown	3	85%	0.48%	2 min	Unable to detect		
			20	85%	0.32%	2 min			
60 ft.	95%	With breakdown	3	Unable to detect			Unable to detect		
			20						
		Without breakdown	3	100%	2.81%	1 min	100%	1.16%	1 min
			20	100%	2.57%	1 min	100%	1.08%	1 min
	99%	With breakdown	3	Unable to detect			Unable to detect		
			20						
		Without breakdown	3	70%	0	2 min	Unable to detect		
			20	75%	0	2 min			
90 ft.	95%	With breakdown	3	Unable to detect			Unable to detect		
			20						
		Without breakdown	3	100%	2.67%	1 min	100%	0.79%	1 min
			20	100%	2.48%	1 min	100%	0.42%	1 min
	99%	With breakdown	3	Unable to detect			Unable to detect		
			20						
		Without breakdown	3	Unable to detect			Unable to detect		
			20	70%	0	2 min			

[a]Hypothesis testing resolution
[b]Threshold

Table 6.3 Method II incident detection results

		Incident before merge			Incident after merge		
Congestion level	MP (%)	DR %	PFA%	MTTD	DR %	PFA%	MTTD
With breakdown	3	100	0	1 min	100	0.02	1 min
	20	100	0	1 min	100	0	1 min
Without breakdown	3	100	0.2	1 min	100	0.46	1 min
	20	100	0.06	1 min	100	0.3	1 min

overlap between the average acceleration distribution beyond the incident location and the average acceleration distribution beyond the on-ramp merge location, which make the differentiation between these two conditions difficult. As can be seen from Table 6.3, 90 ft. testing segment resolution produced the best incident detection performance, but it was still not able to detect incidents at the merge area during traffic breakdown. Table 6.3 shows that Method II (the LTR method) performed significantly better than Method I, particularly for breakdown conditions, in terms of the ability to detect the incidents and false alarm rates. The probability of false alarm was set to 10^{-4} (threshold: 9999th percentile) and with this probability of false alarm it was possible to obtain the best performance of incident detection among the methods and parameters tested, as shown in Table 6.3. Compare to the other probe-based methods reviewed in the literature, Method II demonstrated promising performance with the average DR of 100%, FAR of 0.13%, and MTTD of 1 min.

Queue Warning

In the previous section, the incident detection method based on CV data, as utilized in this study, was explained. Once the incident is detected, the back-of-queue estimation algorithm and queue warning are activated in the simulation model. To identify the back of queue, the segments are sorted based on their position, compared to the incident location. If a segment average speed is below a threshold, the segment is considered queued. The algorithm continues to test if the next upstream segment is queued and the first unqueued segment upstream of the incident is declared as the back of queue. The BOQ estimation algorithm is shown in Fig. 6.1. Lastly, the performance of the connected vehicle-based BOQ detection is compared with the ground truth queue based on VISSIM results and with the queue estimated based on point detection in the simulation. The point detector-based BOQ algorithm is taken from the Pesti et al. [28] study, which estimates the location of queue using the following equation:

$$X = X_{\mathrm{DET}}(i) + \frac{1}{2}\Delta X_{\mathrm{DET}} \tag{6.9}$$

where

X = back-of-queue location.

$X_{\mathrm{DET}}(i)$ = distance from the incident location to the speed detector i.

ΔX_{DET} = detector spacing.

The queue warning system is activated when the incident (or recurrent bottleneck) is detected and the queue starts growing. In this study, the queue warning impact is modeled by changing a certain percentage of a vehicle's speed upstream of the queue using the VISSIM COM interface. It is assumed that the back of queue is detected by the connected vehicle data and the queue warning message is shown dynamically at a specific location upstream of the back of queue using a DMS or connected vehicle onboard units (OBUs). The proportions of vehicles changing speeds in response to OBU messages reflect the number of connected vehicles equipped with OBU and driver acceptance of the message advisory. In the future, with the introduction of connected automated vehicles, the response to queue warning messages will be set automatically by the vehicle, and the driver acceptance will become less of a factor.

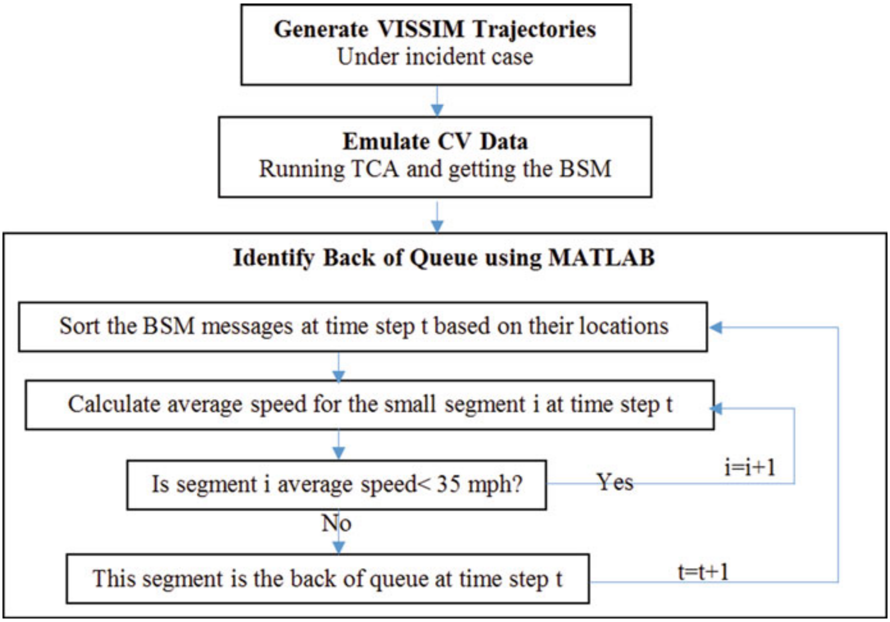

Fig. 6.1 Back-of-queue (BOQ) estimation algorithm

The vehicle's trajectories produced by VISSIM are fed to the TCA tool to emulate BSM messages generating from the simulated vehicles. The generated BSM messages are input to the incident and BOQ detection algorithms utilized in this study to investigate their performances. The results of this part can be found in Reference [29].

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