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TRAFFIC INFORMATION ESTIMATION USING PERIODIC LOCATION UPDATE EVENTS

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Abstract. *In recent years considerable concerns have arisen over building intelligent transportation system (ITS) which focuses on efficiently managing the road network. Before this goal can be achieved, it is vital to obtain correct and real-time traffic information, so that traffic information services can be provided in a timely and effective manner. Using mobile stations (MS) as probes to track the vehicle movement is a low cost and immediate solution to obtain the real-time traffic information. In this paper, we propose an estimation method to analyze the relation between the amount of Periodic Location Update (PLU) events and traffic density. By numerical analysis and estimating real-time traffic information with level of service (LOS), the results show that the average accuracy of traffic density is 76.33% and the average traffic condition hit rate (TCHR) is 85%. Therefore, the proposed estimation method is feasible to estimate the traffic density and traffic congestion with lower cost and higher efficiency solution for ITS improvement.*

Keywords: Periodic location update, Intelligent transportation system, Cellular network, Traffic density estimation, Traffic condition estimation

1. **Introduction.** In recent years considerable concerns have arisen over building *intelligent transportation system* (ITS) which focuses on efficiently managing the road network. One of the important purposes of ITS is to improve the performance of transportation so as to extend the durability of vehicle which can be reduced the fuel consumption and travel time. Before this goal can be achieved, it is to obtain the correct and real-time traffic information which includes traffic density, traffic flow, vehicle speed, travel time, traffic conditions, and traffic accidents so that traffic information services can be provided in a timely and effective manner.

At present, the methods of collecting real-time traffic information can be classified into three categories as follows: (1) stationary traffic information detectors [16], (2) *global position system* (GPS)-based probe car reporting [8], and (3) tracking the location of mobile users through the cellular networks [2-4,6,9,13,15,18,19] (e.g., *Global System for*

Mobile Communications (GSM), *General Packet Radio Service* (GPRS), *Universal Mobile Telecommunications System* (UMTS), and *Long Term Evolution* (LTE)) [5,10].

By far the most intuitive way is to set up the stationary traffic information detectors on important road segments to gather the information, but this way needs excessive setup and maintenance costs [16]. In addition, several researches use GPS-equipped cars as probes. However, the sample size of GPS-equipped probe cars needs to be high enough to infer the traffic information accurately [8]. However, the additional costs are incurred when these GPS-equipped probe cars periodically report the traffic information through the air. To reduce the aforementioned building and maintenance costs, cost-effective and immediate alternatives need to be found. Therefore, the third collecting real-time traffic information method, tracking the location of mobile users through the cellular networks, is more and more popular. In recent years, everyone has his own *mobile stations* (MS), which would be used to as a probe to collect traffic information advisably [2-4,6,9,13,15,18,19].

Cellular networks have rigorous management processes to keep track of the movement of MSs. The control signal events are triggered through mobility management from cellular networks such as *Location Update* (LU). By grouping neighboring cells, *location areas* (LA) can be defined to describe high level locations information of MSs. When an MS moves from one LA to another LA, *a normal LU* (NLU) event is triggered to inform the cellular network about the MS's latest LA information through a specific cell. Besides, a *periodic LU* (PLU) event is triggered to update the MS's LA information through a specific cell periodically, even if the MS has been in idle mode in a period of time. Through the LU process, the network always knows the current cell and LA of an MS. However, previous studies focused on analyzing the amount of NLU events to estimate traffic flow [3,4]. The traffic density by analyzing the signal events from cellular networks has not been investigated. Therefore, the motivations of this paper are as follows.

(1) This study proposes a model to analyze the relation between the amount of PLU events and traffic density information.

(2) For traffic condition estimation, we combine the *semantic sensor web* (SSW) and *traffic information ontology* (TIO) [7,14] to estimate the traffic condition of each road segment by using the amount of PLU events and traffic density.

(3) The real-time estimation traffic information based on cheaper and effective solution (i.e., analyzing the signal events from cellular networks) can be referenced by road users and the ministry of transportation to improve the level of service and avoid traffic congestion for roadway.

The remainder of the paper is organized as follows. In Section 2 we provide background knowledge of collecting traffic information from cellular networks. In Section 3, we propose the analytical model and the derived formula. The numeric analysis is provided in Section 4. Section 5 illustrates the experimental results. Finally, conclusions and future work are given in Section 6.

2. Traffic Information Collection.

The amount of MSs and network signaling can be mapped to the traffic information in the last few years. Several methods are proposed to collect mobility/location data from the cellular networks. Mainly for the LU, *Routing Area Update* (RAU) and the handover (HO) to estimate the real-time traffic information. At present, the methods can be divided into the following three groups: (1) monitoring the amount of network signaling from control channels, (2) using mobile positioning algorithm to estimate the speed, and (3) using handover information to estimate the speed.

2.1. Monitoring control channel.

The MS will perform the LU/RAU after it is moving into the different LA/routing area (RA), even if it is in idle mode. When an MS performs a call, the *call arrival* (CA) event, HO events, and *call departure* (CD) event will be triggered. Some research used these network signalings (i.e., LU, RAU, CA, HO, and CD) from control channel to estimate the amount of MSs on the road segment covered in a specific cell and compare with previous data to find out whether there are abnormal conditions for the inference of abnormal traffic conditions [3,4]. In this part, there are two discussions: (1) the method of collecting and counting LU/RAU can estimate traffic flow and traffic accident; (2) the method of collecting and counting CA, HO, and CD can infer abnormal traffic.

2.2. **Mobile positioning algorithm.** The major of current location methods which are defined in *Location Service* (LCS) specification [1] by *3rd Generation Partnership Project* (3GPP) are the following.

(1) *Assisted GPS* (A-GPS): A-GPS navigation system is more efficient than the traditional GPS positioning. Through the network connection, the almanac data can be obtained from the assisted position server. A-GPS saves time to search the satellites and also lets the speed of location faster. In general A-GPS only needs thirty seconds to position.

(2) *Mobile scan report* (MSR)-based Location Methods: MSR-based location methods are using the MSR message (e.g., *received signal strength indication* (RSSI), *round-trip delay* (RTD), and *relative delay* (RD)) from MS to *base station* (BS) [6,13]. These location models can be classified into *angle of arrival* (AoA), *time of arrival* (ToA), and *time difference of arrival* (TDoA). However, this approach requires more computation power efficient.

(3) Database lookup methods: MS's location is determined through the static database query. When the network receives a location request, it identifies the cell ID of the BS serving the MS and looks up the geographic location of that BS in a database. However, in general the cell length is about 2 kilometers, and the large location error depends on the cell length.

2.3. **Handover estimation.** Nowadays, some research focus on collecting HO to estimate the real-time traffic information. For example, ITIS develops a complete traffic information system on *Cellular Floating Vehicle Data* (CFVD) [2,15]. Gundlegard et al. demonstrated good handover location accuracy for both GSM and UMTS, and the location accuracy in UMTS was better than in GSM [9]. Thiessenhusen et al. measured the traffic speed by *double handover* (DHO) event and compared the average speeds from cell phone probe data, floating car data, and loop detector data [18,19]. The DHO event can reflect the vehicle speed on a specific roadway to generate the estimation.

2.4. **Summary.** According to previous studies, while the analyses of the amount of NLU and RAU events can estimate traffic flow [3,4], they cannot provide the information of traffic desity and traffic congestion since the state of free flow is possible with high traffic flow. Though the positioning algorithms based on LCS and DHO can provide high speed estimation accuracy [2,6,9,13,15,18,19], these algorithms imply heavier network load. Therefore, we consider analyzing the relation between the amount of PLU events and traffic density information to provide the information of traffic density and traffic congestion with lower computation cost.

3. **A Traffic Information Estimation Model.** In our research, we track and analyze the location of mobile users signaling through interfaces of GSM, GPRS and UMTS networks. Firstly, we monitor the network interfaces (e.g., A and IuCS) and design

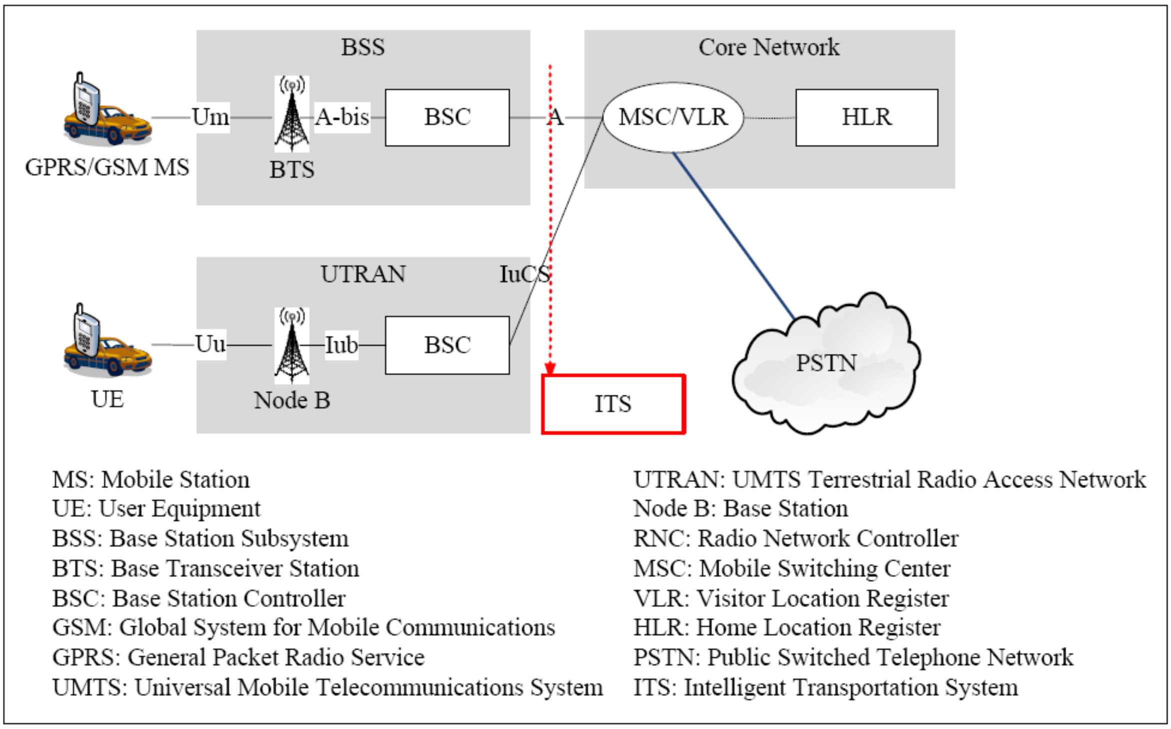

FIGURE 1. The architecture of intelligent transportation system

an ITS to retrieve the network signaling (e.g., PLU) and estimate the real-time traffic condition information as shown in Figure 1.

3.1. **Traffic density estimation.** When considering the probability of a PLU event in a specific cell, we have to take the following two scenarios: (1) there is no call between two consecutive PLU events and (2) there are several calls between two consecutive PLU events. Finally, we consider and sum up the two scenarios about the probability of PLU event in a specific cell for traffic density estimation.

3.1.1. *Scenario (1): No call between two consecutive PLU events.* The space diagram is illustrated in Figure 2 and the timing diagram is illustrated in Figure 3 for scenario (1). There is one car within an MS which moves along the road. The first PLU event is triggered at time t_0, and then the car enters the cell at time t_1. The second PLU event is triggered at time t_2, and then the car leaves the cell at time t_3.

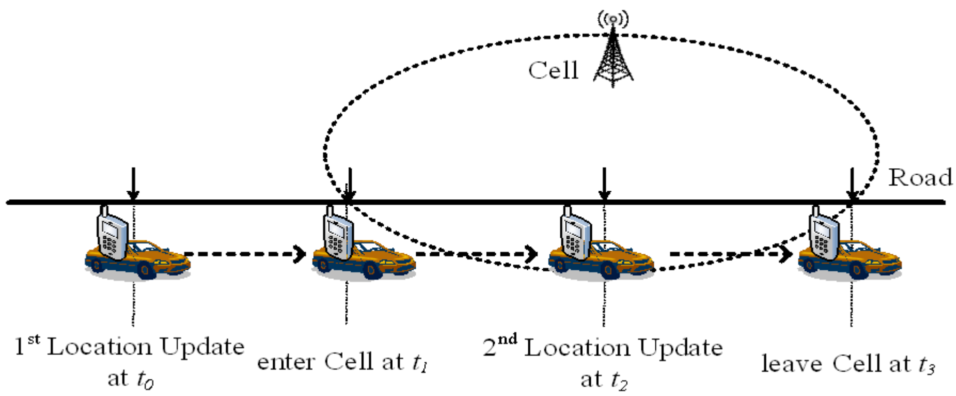

FIGURE 2. The scenario diagram for vehicle movement and PLU events on the road when there is no call between two consecutive PLU events

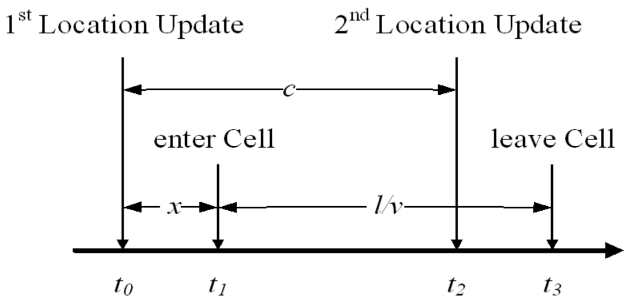

FIGURE 3. The timing diagram for vehicle movement and PLU events on the road when there is no call between two consecutive PLU events

The assumptions and parameters in the model are defined below.

- There is only one road residing in the cell.
- c (hr): The cycle time of the PLU.
- x (hr): The time difference between the first PLU event and entering the cell. We assume the time function $f(x)$ is a uniform distribution function as $f(x) = 1/c$.
- l (km): The length of road segment covered by a cell.
- v (km/hr): The average speed of a car crossing a cell.

In this scenario, the probability of PLU triggered in the cell is as Formula (1).

$$\begin{aligned}\Pr(\text{Scenario 1}) &= \Pr\left(x + \frac{l}{v} > c\right) \\ &= \int_{c-\frac{l}{v}}^{c} f(x)dx = \int_{c-\frac{l}{v}}^{c} \frac{1}{c}dx = \frac{l}{vc}\end{aligned} \tag{1}$$

3.1.2. *Scenario (2): Several calls between two consecutive PLU events.* The space diagram is illustrated in Figure 4 and the timing diagram is illustrated in Figure 5 for scenario (2). There is one car within an MS which moves along the road. The first PLU event is triggered at time t_0. There is a call arrived at time t_1, and then the car enters the cell at time t_2. The second PLU event is triggered at time t_3, and then the car leaves the cell at time t_4. After that, a second call arrives at time t_5.

The assumptions and parameters in the model are defined below.

- The call arrivals to/from one MS per one car along the road can be evaluated. The call arrival rate is λ (call/hr).

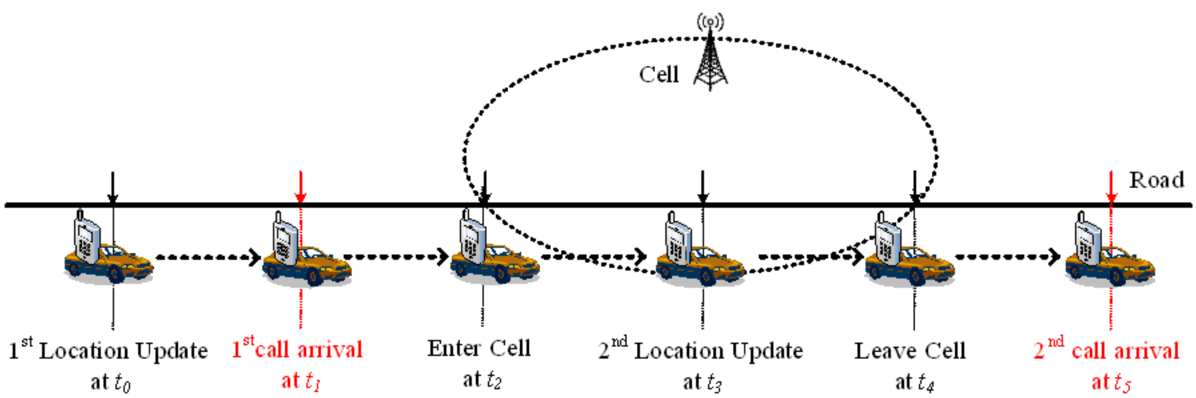

FIGURE 4. The scenario diagram for vehicle movement and PLU events on the road when there are several calls between two consecutive PLU events

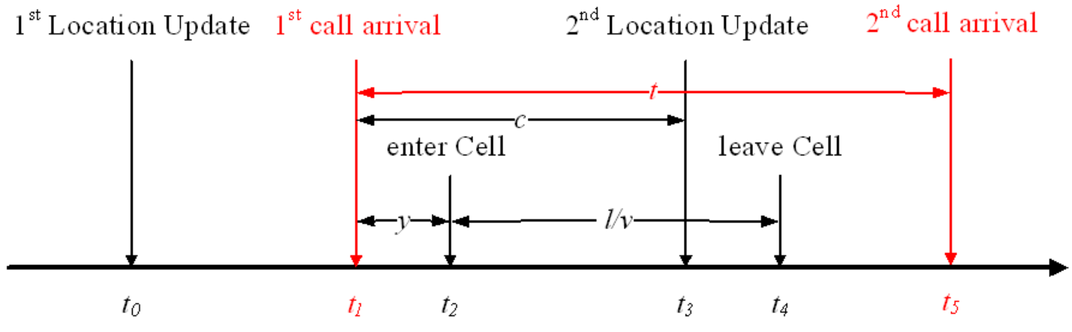

FIGURE 5. The time diagram for vehicle movement and PLU events on the road when there are several calls between two consecutive PLU events

- The call inter-arrival time t is exponentially distributed [12] with the mean $1/\lambda$.
- The call inter-arrival time function $g(t)$ is an exponential distribution function as $g(t) = \lambda e^{-\lambda t}$.
- y (hr): The time difference from first call arrival to entering cell.
- The time function $h(y)$ is a uniform distribution function so $h(y) = 1/(2c)$.

In this scenario, the probability of PLU triggered in the cell is as Formula (2).

$$\begin{aligned}\Pr(\text{Scenario 2}) &= \Pr\left(t > c \cap y + \frac{l}{v} > c\right) = \Pr\left(t > c\right) \times \Pr\left(y > c - \frac{l}{v}\right)\\ &= \int_c^\infty g(t)dt \times \int_{c-\frac{d}{v}}^{c} h(y)dy = \int_c^\infty \lambda e^{-\lambda t} dt \times \frac{l}{2vc} = e^{-\lambda c}\frac{l}{2vc}\end{aligned} \tag{2}$$

3.1.3. *Summary.* We use Formula (3) to consider and sum up the two scenarios about the probability of PLU events in a specific cell for traffic density estimation.

$$\begin{aligned}\Pr(\text{PLU}) &= \Pr\left(t > c\right) \times \Pr(\text{Senario 1}) + \Pr\left(t < c\right) \times \Pr(\text{Senario 2})\\ &= e^{-\lambda c} \times \frac{l}{vc} + \left(1 - e^{-\lambda c}\right) \times \left(e^{-\lambda c}\frac{l}{2vc}\right) = \left(3 - e^{-\lambda c}\right) \times \left(e^{-\lambda c}\frac{l}{2vc}\right)\end{aligned} \tag{3}$$

Formula (3) is the probability of PLU event triggered in a specific cell of one car. To find the probabilities of PLU events triggered in a specific cell of all cars, we have to multiply Formula (3) with the traffic flow f (car/hr). The amount of PLU events u (event/hr) on the road segment covered by a specific cell can be expressed as Formula (4) which shows the relation between the amount of PLU events and the actual traffic density D (car/hr). Therefore, we can use Formula (5) to infer the estimated traffic density d (car/hr).

$$\begin{aligned}u &= f \times \Pr(\text{PLU}) = f \times \left(3 - e^{-\lambda c}\right) \times \left(e^{-\lambda c}\frac{l}{2vc}\right)\\ &= D \times \left(3 - e^{-\lambda c}\right) \times \left(e^{-\lambda c}\frac{l}{2c}\right)\end{aligned} \tag{4}$$

$$d = \frac{u}{\left(3 - e^{-\lambda c}\right) \times \left(e^{-\lambda c}\frac{l}{2c}\right)} \tag{5}$$

3.2. **Traffic condition estimation.** For traffic condition estimation, we design the TIO to analyze the traffic information according to the *Highway Capacity Manual* (HCM) [11]. In this paper, we propose SSW to calculate the estimated density and classify the *level of service* (LOS). To set roadway capacity stands on "The roadways capacity in Taiwan report" [11] that defined free speed as 90 km/hr and maximum volume of traffic as 1,200 car/hr/lane to calculate LOS which is defined as class A-F by HCM shown in Table 1.

TABLE 1. The level of service in HCM

Level of Service	Traffic Density D (car/km)	Vehicle Speed v (km/hr)
A	$0 \leq D < 14$	$v \geq 90$
B	$14 \leq D < 18$	$v \geq 85$
C	$18 \leq D < 23$	$v \geq 80$
D	$23 \leq D < 29$	$v \geq 70$
E	$29 \leq D < 35$	$v \geq 60$
F	$D \geq 35$	$v < 60$

4. **Numeric Analysis.** In this section, we analyze the relation between the amount of PLU events and traffic density to evaluate the feasibility of our traffic information estimation model. For the purpose of demonstration, we adopt some parameters as the following to estimate the traffic density and the amount PLU events: $f = 5000$ car/hr, $\lambda = 1$ call/hr, $l = 1$ km and $c = 1$ hr. Figure 6 shows that the amount (u) of PLU events could reflect the trend of the actual traffic density (D) with different vehicle speeds. When the vehicle speed v gets higher, the amount (u) of PLU events and traffic density (D) will be reduced. When the vehicles are in high-speed state, the amount of PLU events that estimate the traffic density will be provided with high accuracy.

In low-speed and high traffic density state, the amount (u) of PLU events will be higher after the product process with $\frac{1}{\left(3-e^{-\lambda c}\right)\times\left(e^{-\lambda c\frac{l}{2c}}\right)}$ to correspond with the traffic density (D). Therefore, this model can be used to estimate traffic information for ITS to analyze the traffic information. Following the proposed method, we analyze the real highway traffic information and combine with TIO and SSW to estimate the traffic condition.

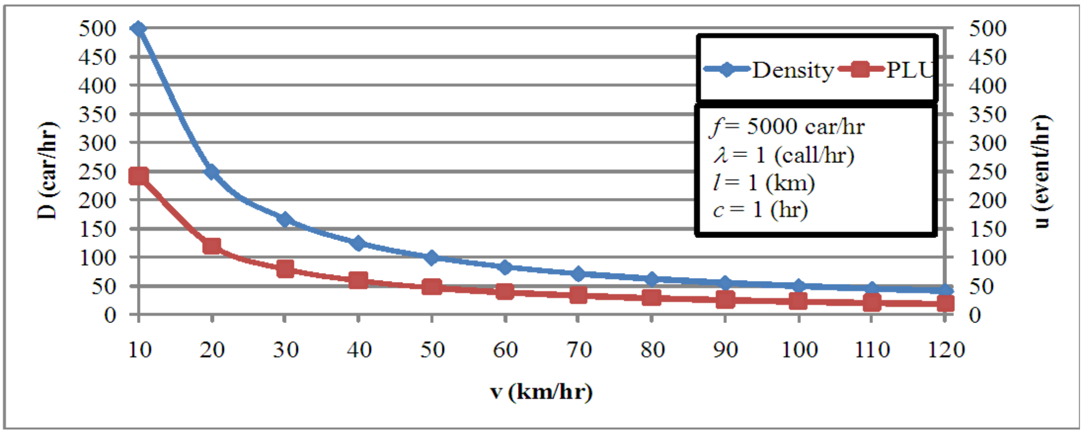

FIGURE 6. The relation between the amount of PLU events and traffic density with different vehicle speeds

5. **Simulation and Results.** In this section, we design trace-driven experiments to investigate the traffic information estimations from cellular network data. As shown in Figure 7, the approach consists of the vehicle movement trace generation, MS communication trace generation, and the combined trace generation of the two behaviors described below. The vehicle movement and MS communication trace files are obtained from the traffic simulator as well as real measurements of a highway in Taiwan. The inputs of trace generator include the road conditions (e.g., the length of the road, the number of lanes, the locations of handover points, and traffic flow), the vehicle movement behaviors (e.g.,

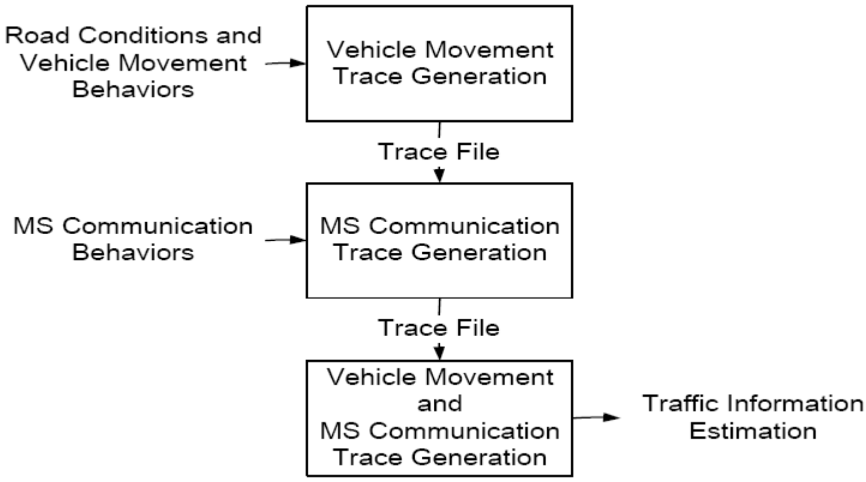

FIGURE 7. Trace-driven simulation for the traffic information estimations from cellular network data

the desired speeds, the car following model and lane-changing model) and MS communication behaviors (e.g., the call holding time and call inter-arrival time). We assume that for every car moving along the road is one MS. The output is a trace file which records the vehicle's ID, desired speed, its locations, its call arrival time, and its call departure time. The trace file is then used to drive the mobility management simulator to estimate the real-time traffic information, which includes speed, traffic density, and traffic flow.

5.1. **Traces generated from a traffic simulator.** The vehicle movement and MS communication traces are generated by a traffic simulation program VISSIM [17]. We consider the highway scenario characterized by the Wiedemann "psycho-physical" car-following model and lane changing model [17], where the length of a 3-lane highway is 10 km. There are 11 handover points and 12 cells distributed on the road from 0 km to 10 km, and the coverage of a cell is 1 km. Moreover, we assume that there are 10 *vehicle detectors* (VDs) which are built in the same locations with handover points. Those VDs can collect the real-time traffic information (e.g., vehicle speed, traffic density, and traffic flow). In experiments, the traffic flow, traffic density and vehicle speed were collected from specific VD during 24 hours on 31 July, 2008. For MS communication behaviors, we generate the random numbers of call holding time and call inter-arrival time for each MS in car. The call holding time is exponentially distributed with the mean $1/\mu$ and the call inter-arrival time is exponentially distributed with the mean $1/\lambda$ [12].

The assumptions used in the experiments are summarized below.

- The actual traffic density D_i car/km along the road can be obtained from the VD data on the road segment covered by Cell_i.
- The estimated traffic density d_i car/km along the road can be obtained from the CFVD data on the road segment covered by Cell_i.
- The expected value $(1/\mu)$ of call holding time is 1 min/call according to the statistical results from Chunghwa Telecom in Taiwan.
- The expected value $(1/\lambda)$ of call inter-arrival time is 1 hr/call according to the statistical results from Chunghwa Telecom in Taiwan.
- The accuracy of traffic density estimation is expressed as $1 - \frac{|D_i - d_i|}{D_i}$.

5.2. **Traffic density estimation accuracy.** In this section, the real amount u_i of call arrivals from the specific Cell_i is collected from cellular network data to generate the estimated traffic density d_i by Formulae (4) and (5). We compare the estimated traffic density d_i with the actual traffic density D_i and calculate the traffic density estimation accuracy. The actual traffic flow, traffic density and vehicle speed were collected from specific VD at 42 km milepost on National Highway No. 1 in Taiwan during 24 hours on 31 July, 2008. For example, the traffic information which includes vehicle speed, traffic density, and traffic flow on the road segment covered by Cell_1 is depicted in Figure 8.

We compare the estimated traffic information with the real traffic information from VD. By estimating simulation of Cell_1, the simulation results of actual and estimated traffic density are presented in Figure 9. There are fewer vehicles on the road and with high-speed during early morning hours (e.g., 2 a.m.-7 a.m.). Using Formula (5) to estimate the traffic density d which is consistent with the actual traffic density D, the results were corresponding with that the traffic density is low and that the amount of the PLU events are also less. Comparatively, the traffic density has two high peaks as an M-shape during rush hours (e.g., 8 a.m.-9 a.m. and 17 p.m.-18 p.m.).

The estimation method presents the trend of traffic density with the average accuracy of one day for each cell is 76.33% by using the accuracy estimation which is expressed as

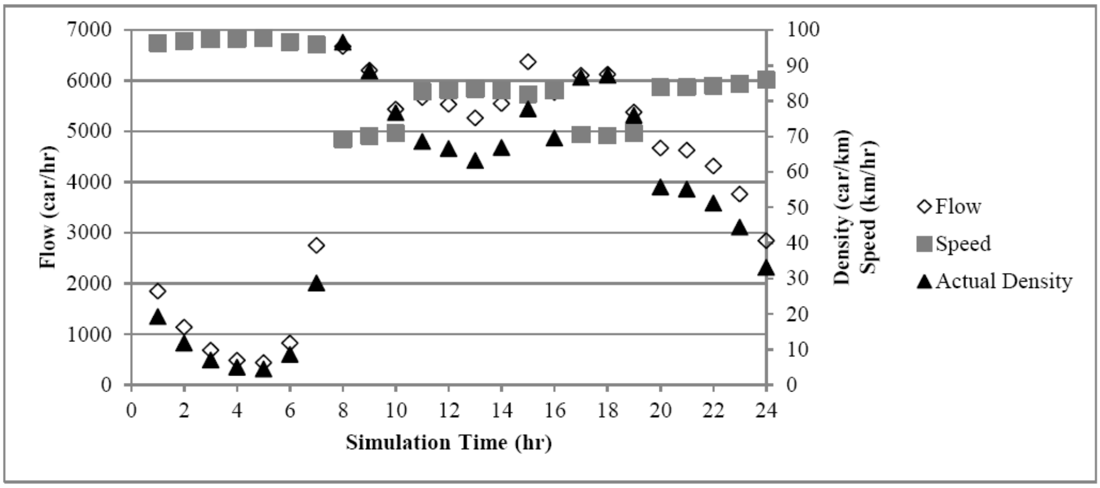

Figure 8. The real-time traffic information on the road segment covered by Cell_1

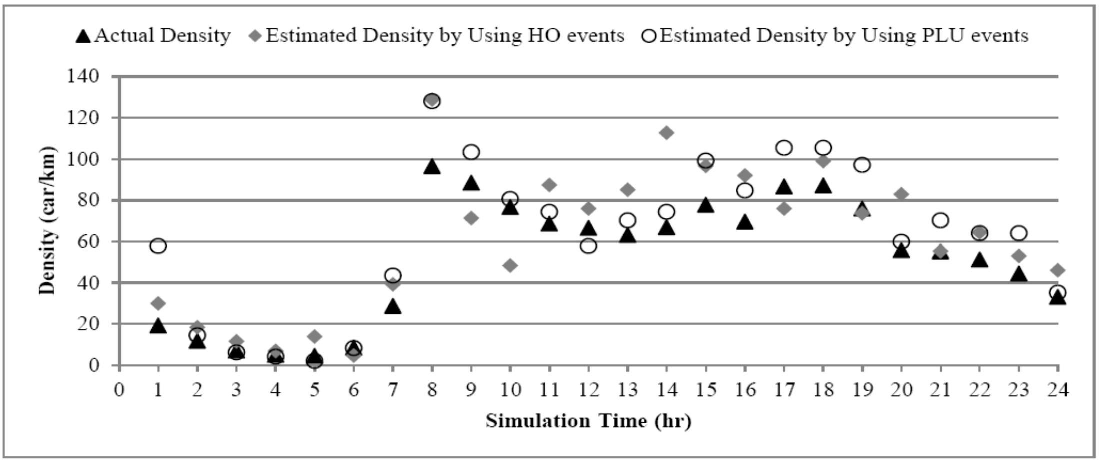

Figure 9. The comparison of actual and estimated traffic density on the road segment covered by Cell_1

$1 - \frac{|D_i - d_i|}{D_i}$. This study also collects and analyzes the handover events to estimate traffic density [12]. The average accuracy of one day for each cell which is 75.29% is lower than that of proposed method.

In experiments, we use Pearson correlation coefficient to measure the relationship between actual traffic density and estimated traffic density for different methods. Table 2 shows that the correlation coefficient of using PLU events is higher than that using HO events. This study also compares the computation cost of each method for reducing network load. The results indicate the computation cost of proposed method which is only 741 (event/cell/day) is lower than the amount of HO events. Therefore, the proposed estimation method based on analyzing the amount of PLU events can provide the lower cost and higher efficiency solution to estimate traffic density for ITS improvement.

TABLE 2. The comparison of different estimation methods

Estimation Method	Correlation	Computation Cost
Using PLU events	0.95	741 event/cell/day
Using HO events	0.91	1200 event/cell/day

5.3. **Traffic condition estimation accuracy.** We combined the TIO and SSW to describe the traffic condition according to the LOS function $L(d_t^i)$ with estimated traffic density d_t^i at time t shown in Table 1. We use Formula (6) to calculate the *traffic condition hit rate* (TCHR) to estimate the accuracy of traffic condition estimation.

$$TCHR = \frac{\sum_{t=1}^{k} h_t^i}{k}, \text{ where } h_t^i = \begin{cases} 1, & \text{if } L\left(d_t^i\right) = L\left(D_t^i\right) \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

For example, when the actual traffic density at 3 a.m. is 7.02 car/km, the $L(7.02)$ level is "A". If the estimated traffic density is 6.20 car/km, the $L(6.20)$ traffic condition which is level "A" is same with actual traffic condition and set $h_t^i = 1$. For this reason, the result shows that the average TCHR of proposed method is 85% and that of using HO events is 79.17%. Therefore, the proposed method is feasible to estimate traffic congestion for ITS improvement.

6. Conclusions and Future Work.

This paper studied an analytic model to analyze the speed report rate with considering communication behavior and traffic information for the feasibility evaluation of traffic information estimation from cellular data. With the amount of PLU events and traffic density, the proposed model can be used to estimate traffic information for ITS to analyze the traffic congestion, accidents, transportation delays, etc. The experiment results show that the average accuracy of traffic density is 76.33% and the average TCHR is 85%. As to computation cost, the cost of using HO events is 1.62 times of that of the proposed method. Therefore, the proposed estimation method is feasible to estimate the traffic density and traffic congestion with lower cost and higher efficiency solution for ITS improvement.

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