



Traffic speed estimation based on normal location updates and call arrivals from cellular networks

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ABSTRACT

Information and communication technologies have improved the quality of Intelligent Transportation Systems (ITS). By estimating from Cellular Floating Vehicle Data (CFVD) is more cost-effective, and easier to acquire than traditional ways. In this paper, this study proposes a novel approach to evaluate the relation of normal location update, call arrivals, traffic flow, and traffic density. Moreover, the traffic speed is estimated by the proposed approach according to CFVD. In the simulation, this study compares the real traffic information with the estimated traffic information by Vehicle Detector (VD). The experiment results show that the accuracy of traffic speed estimation is 92.92%. Therefore, the proposed approach can be used to estimate traffic speed from CFVD for ITS.

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1. Introduction

In recent years, the rise of economic growth and technology advance has led to demand the *Intelligent Transportation System* (ITS) for traffic service. How to construct real-time traffic information systems of ITS is more and more important. Real-time traffic information, such as average traffic speed, travel time, traffic flow, and traffic congestion can be referenced by road users and the ministry of transportation to improve the level of service for roadways. Therefore, many existing research articles have been done to improve traffic information service.

The recent research articles indicate that the methods of collecting real-time traffic information can be divided into three ways: *Vehicle Detector* (VD), *Global Position System* (GPS)-based probe cars reporting, and *Cellular Floating Vehicle Data* (CFVD). Traffic information has traditionally been gathered by public agencies (Departments of Transportation) via stationary VDs installed in the roadways. Traditionally the VDs are deployed on major roadways to detect the average vehicle speed and traffic flow. However, it is quite costly to install and maintain such devices. Alternatively, traffic information can be collected from traveling vehicles equipped with GPS receivers and wireless communication capability as probes on the road network. However, the penetration rate of GPS-based probe cars needs to be high enough to infer more accurate real-time traffic information. The third kind of methods, CFVD, which collects and detects the real-time traffic information by tracking the location of *Mobile Stations* (MSs) through cellular network signaling (e.g., *Normal Location Update* (NLU) and *Call Arrival* (CA)) is more and more popular for ITS. For example, ITIS Holdings, which is a leading European traffic information company, applied the patented CFVD technology for measuring and forecasting real-time traffic information based on anonymously sampling

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the positions of MSs [8]. Therefore, CFVD is cost-effective, immediate, and easy to maintain. As the number of people owning cell phones has increased, using MS as a probe for obtaining traffic information is feasible.

To maintain the quality of service, 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 grouped cells, *Location Areas* (LAs) can be defined to describe high level locations information of MSs. When a MS moves from one LA to another, a NLU event is triggered to inform cellular network the MS's latest LA information through a specific cell. The message content consists of MS ID (i.e., *International Mobile Subscriber Identity* (IMSI)), *LA identifier* (LAI), *Cell Identity* (CI), timestamp and the update reason. For instance, Caceres et al. use location update events as a “virtual traffic counter” to monitor the passage through two LAs for phones so as to measuring traffic flow [1,2].

Moreover, some studies analyzed the relation between the amount of cellular calls and traffic density. A study developed by INRETS detected the change of call volume and related it to the occurrence of incidents [13]. Ratti et al. reported that the amount of phone calls is closely linked to vehicular density by analyzing the real data they collected [12]. However, the exact estimation of traffic density and from cell phone probe data has not been investigated.

For traffic speed estimation, Lin et al. proposed a fingerprint positioning algorithm to analyze the location and traffic speed of MS with measurement reports [7,3,4]. Gundlegard and Karlsson analyzed the traffic speed estimation accuracies according to handover locations [5]. While these approaches provide higher location determination accuracy, each measurement reports should be analyzed with higher power consumption.

In this paper, this study proposes a novel approach to *evaluate* the relation between *NLUs*, *CAs*, traffic flow, and traffic density to estimate traffic speed. This paper examines the proposed approach by simulation and the experimental results show that the proposed model is feasible.

The remainder of the paper is organized as follows. In Section 2, this study proposes the traffic speed information estimation model from *CFVD*. This study also provides a numerical analysis of the proposed model and illustrates the experiment results and analyses in Section 3. Finally, this study concludes the paper in Section 4.

2. Traffic information estimation

In this paper, this study employs *CFVD* to estimate traffic speed and traffic density. The proposed approach indicates the relation between *NLUs*, *CAs*, traffic flow, and traffic density. Afterword, the traffic speed estimation can be calculated by *NLUs* and *CAs*.

2.1. Traffic flow estimation

This study considers the amount of *NLUs* (q_i) to estimate traffic flow (Q_i) on the road segment covered by Cell_{*i*}. Fig. 1 illustrates the space diagram for vehicle movement and NLU on the road. Here this study supposes that there is a road

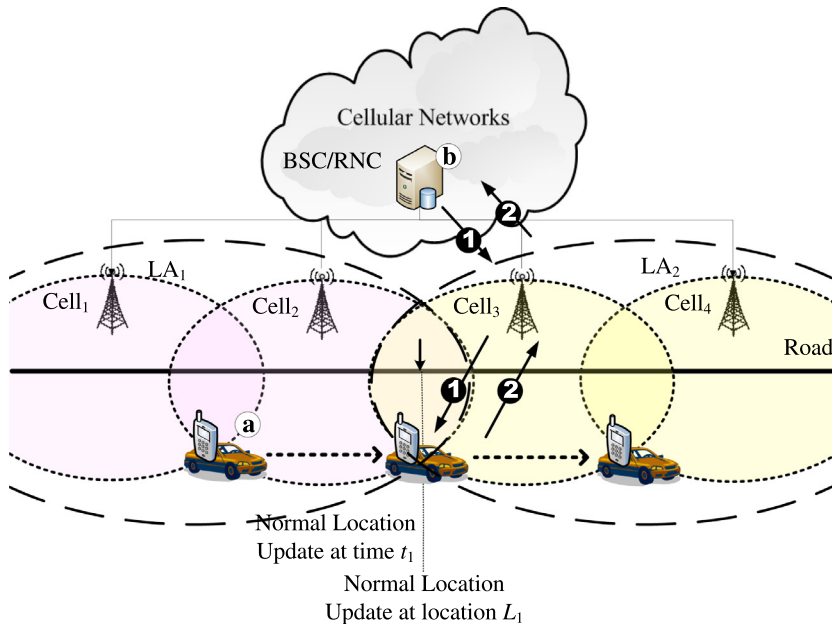


Fig. 1. The space diagram for vehicle movement and NLU on the road.

covered by two LAs which are divided into a set of cells and a communicating MS (Fig. 1a) in car on the road. The detail steps are as follow.

Step 1. The MS received continuously LAI from Base Station Controller (BSC) and Radio Network Controller (RNC) (Fig. 1b) in Global System for Mobile Communications (GSM) and Universal Mobile Telecommunications System (UMTS) for assisting the network in a potential location update decision, respectively.

Step 2. When the car moves from LA₁ to LA₂, the NLU procedure is executed. The MS sends the command message to BSC or RNC. Simultaneously, this study records the message which contains the location of NLU L_1 and NLU time t_1 .

In Taiwan, the Ministry of Transportation & Communications (MOTC) reported that the average number of persons per car in highway was 3.3 in 2011; moreover, the Chunghwa Telecom had a market share of 33% [10]. Therefore, this study assumes that the each vehicle carries in average a MS per operator. When one car is passing through the location of NLU, the NLU event is always triggered. Therefore, this study can get that the amount of NLUs (q_i) is equal to traffic flow (Q_i).

2.2. Traffic density estimation

For traffic density estimation, Fig. 2 depicts the timing diagram for vehicle movement and CA on the road. When a MS in the car moving along the road performs the first call set-up (at time t_0) and enters Cell_{*i*} coverage (at time t_1). Moreover, the MS performs the second call set-up at time t_2 before leaving Cell_{*i*} coverage (at time t_3).

This study proposes a novel model to evaluate the relation of the amount of CAs (r_i) and traffic density (k_i). This approach takes communication behavior, traffic condition, and the distance of the specific cell coverage into consideration when estimating the traffic density.

The assumptions adopted in the model are summarized below.

- The call arrivals to/from one MS per car along the road can be evaluated. The call arrival rate to a cell is λ which can be measured by the mobile operator.
- The call inter-arrival time τ is exponentially distributed with the mean $1/\lambda$ [6].
- The real traffic flow Q_i , real vehicle speed U_i , and real traffic density K_i along the road can be collected from the VD data on the road segment covered by Cell_{*i*}. The traffic density can be estimated as $K_i = Q_i/U_i$ [9].
- The mileage x is the time difference traveled from the first call arrival location to entering Cell_{*i*}.
- The mileage l_i is the distance of road segment covered by Cell_{*i*}.

The output measure is r_i which is the amount of CA on the road segment covered by Cell_{*i*}.

This approach considers the time of CA, entering the cell, and leaving the cell of an MS to estimate the amount of CAs (r_i). The amount of CAs on the road segment can be expressed as Formula (1). This study assumes that the estimated traffic flow (q_i) is equal to the real traffic flow (Q_i). Therefore, the estimated traffic density (k_i) can be estimated by using Formula (2).

$$\begin{aligned}
 r_i &= Q_i \times \Pr[t_1 < t_2 < t_3] \\
 &= Q_i \times \int_{x=0}^{\infty} \Pr\left[x < \tau < x + \frac{l_i}{U_i}\right] dx \\
 &= Q_i \times \int_{x=0}^{\infty} \int_{\tau=x}^{x+\frac{l_i}{U_i}} \lambda e^{-\lambda\tau} d\tau dx \\
 &= Q_i \times \frac{1 - e^{-\frac{\lambda l_i}{U_i}}}{\lambda} \\
 \Rightarrow 1 - \frac{\lambda r_i}{Q_i} &= e^{-\frac{\lambda l_i}{U_i}}
 \end{aligned}$$

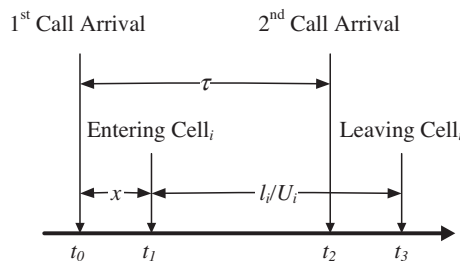


Fig. 2. The timing diagram for vehicle movement and CA on the road.

$$\begin{aligned}
&\Rightarrow \left(1 - \frac{\lambda r_i}{Q_i}\right)^{\frac{1}{\lambda_i}} = e^{-\frac{1}{U_i}} \\
&\Rightarrow 1 - \left(1 - \frac{\lambda r_i}{Q_i}\right)^{\frac{1}{\lambda_i}} = 1 - e^{-\frac{1}{U_i}} \\
&\Rightarrow 1 - \left(1 - \frac{\lambda r_i}{Q_i}\right)^{\frac{1}{\lambda_i}} \approx \frac{1}{U_i}, \quad \text{where } \lim_{U_i \rightarrow \infty} 1 - e^{-\frac{1}{U_i}} = \frac{1}{U_i} \\
&\Rightarrow Q_i \left[1 - \left(1 - \frac{\lambda r_i}{Q_i}\right)^{\frac{1}{\lambda_i}}\right] \approx \frac{Q_i}{U_i} = K_i, \quad \text{where } \lim_{U_i \rightarrow \infty} 1 - e^{-\frac{1}{U_i}} = \frac{1}{U_i}
\end{aligned} \tag{1}$$

$$k_i = q_i \left[1 - \left(1 - \frac{\lambda r_i}{q_i}\right)^{\frac{1}{\lambda_i}}\right] \approx \frac{Q_i}{U_i} = K_i, \quad \text{where } \lim_{U_i \rightarrow \infty} 1 - e^{-\frac{1}{U_i}} = \frac{1}{U_i} \tag{2}$$

2.3. Traffic speed estimation

In this paper, the traffic speed is estimated by estimated traffic flow (q_i) and estimated traffic density (k_i) from the amount of NLUs and CAs. Based on Section 2.1 and Formula (2), the estimated traffic speed (u_i) can be expressed as Formula (3).

$$u_i = \frac{q_i}{k_i} = \left[1 - \left(1 - \frac{\lambda r_i}{q_i}\right)^{\frac{1}{\lambda_i}}\right]^{-1} \tag{3}$$

3. Experiment results

This study provides a numerical analysis of the proposed model to discuss the effect on real traffic speed and traffic speed estimation accuracy in Section 3.1. Moreover, the trace-driven experiments are designed to simulate the traffic and communications environments for traffic information estimations in Section 3.2.

3.1. Numerical analysis

In this section, this study first applies the real speed data obtained from the specific VD on a highway in Taiwan to Formula (1) and derive the estimated amount of calls. This study uses the amount of calls to compare the estimated traffic density with real traffic density to show the correlation between them. Then this study compares the estimated traffic speed with real traffic speed. Finally, this study discusses the proposed model by using different values for call arrival rate λ .

3.1.1. Estimated traffic speed derived by real data from VD

Fig. 3 shows the real traffic information, which includes traffic density and vehicle speed from specific VD at 42 km mile-post on highway in Taiwan during February, 2008. For the amount of call arrivals, this study adopts the following parameters: $l_i = 1.0$ km and $\lambda = 1$ call/h according to the statistical results collected by Chunghwa Telecom in Taiwan. Fig. 4 shows the estimated traffic density derived from Formulas (1) and (2) using the real traffic data from VD logs as inputs. The results show that the average absolute difference between the real traffic density and estimated traffic density is 0.63%. This study observes that the real traffic density and estimated traffic density are quite similar. That is, this study can retrieve the estimated traffic density (k_i) on the road segment covered by the specific cell (Cell_{*i*} in Fig. 2) from cellular networks to estimate the real-time traffic density of the road segment.

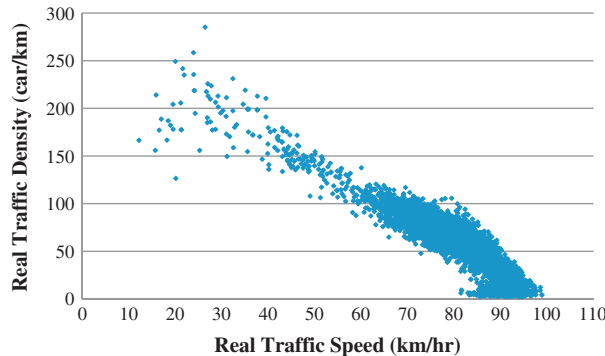


Fig. 3. The real traffic information (traffic speed and traffic density) from VD.

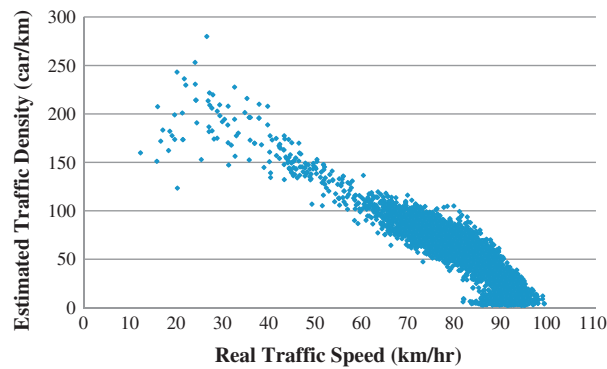


Fig. 4. The estimated traffic density in the specific cell by using VD logs.

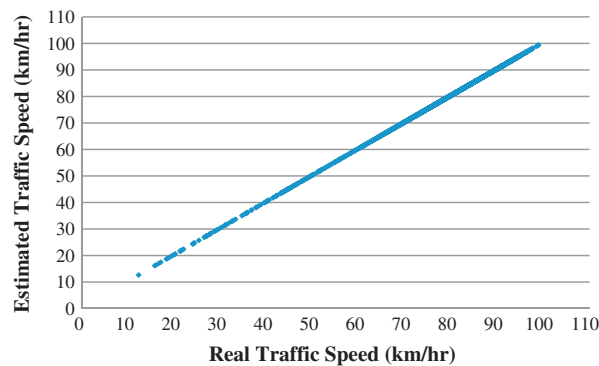


Fig. 5. The estimated traffic speed in the specific cell by using VD logs.

For traffic speed estimation, this study adopts the estimated traffic flow and estimated traffic density from the results in Fig. 4. Then this study uses Formula (3) to estimate traffic speed by using VD logs. The results show the average absolute difference between the real traffic speed and estimated traffic speed is 0.63% in Fig. 5.

3.1.2. Effect on real traffic speed and traffic speed estimation accuracy

In this section, this study considers the real traffic speed (U_i) and estimated traffic speed (u_i) to calculate the traffic speed estimation accuracy which is defined as $1 - \frac{|U_i - u_i|}{U_i}$. In this paper, this study uses $\lambda = 1$ call/h according to the actual statistical results collected by Chunghwa Telecom in Taiwan. To show the correlation between traffic speed estimation accuracy and real traffic speed (U_i), this study adopts the following parameters: $Q_i = 3600$ car/h, $l_i = 1.0$ km, and call arrival rate $\lambda = 1$ call/h. Fig. 6 depicts that the accuracies of speed estimation are higher than 94.92% when real traffic speed (U_i) ranges from 10 to 110.

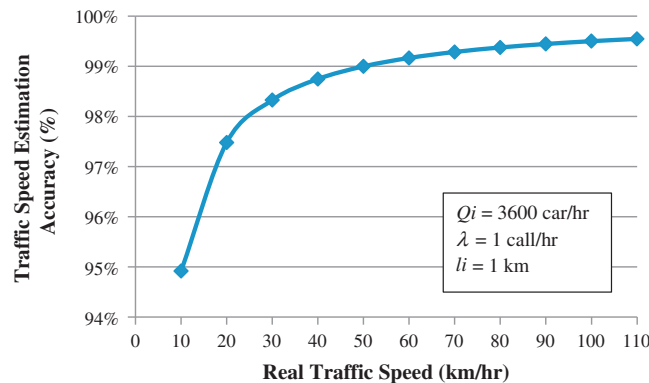


Fig. 6. The correlation of real traffic speed and traffic speed estimation accuracy.

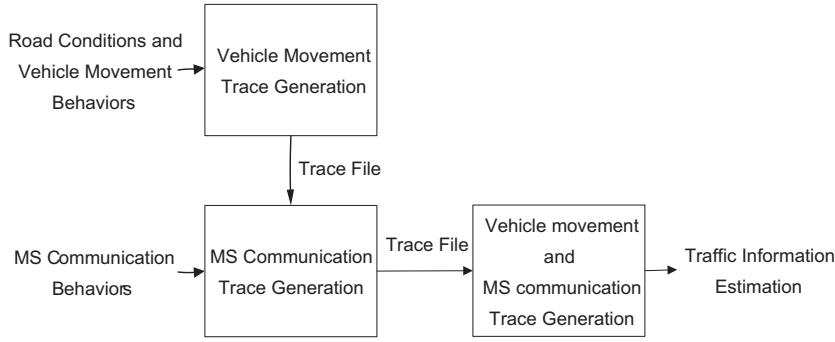


Fig. 7. Trace-driven simulation for the traffic information estimations from cellular-network-based data.

3.2. Simulation results

In this section, this study designs trace-driven experiments to investigate the traffic information estimations from CFVD. Fig. 7 illustrates this approach that consists of the vehicle movement trace generation, MS communication trace generation, and the combined trace generation of the two behaviors. 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., the desired speeds, the car following model and lane-changing model), and MS communication behaviors (e.g., normal location update and call inter-arrival time). 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. These trace files are obtained from the traffic simulators as well as real measurements of a highway in Taiwan. In addition they are used to drive the mobility management simulator to estimate the real-time traffic information which includes speed and traffic density.

3.2.1. Traces generated from a traffic simulator

The vehicle movement and MS communication traces are generated by a traffic simulation program VISSIM [11]. The highway scenario which is characterized by the Wiedemann "psycho-physical" car-following model and lane changing model, where the vehicle speeds range from 85 km/h to 120 km/h and the length of a 3-lane highway is 10 km. Fig. 8 shows 10 handover points and 10 cells distributed in four location areas on the road from 0 km to 10 km, and the coverage of a cell is 1 km. Moreover, this study assumes that there are 10 VDs which are built in the same locations with handover points. Those VDs can collect the real-time traffic information, including vehicle speed and traffic density. In each simulation run, up to 3600 vehicles are injected in the road during 1 simulated hour, where the desired speed of a vehicle is uniformly randomly selected between 85 and 120 km/h. For MS communication behaviors, this study generates 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 $1/\lambda$ [6].

The assumptions used in the experiments are summarized below.

- The real traffic speed U_i km/h, real traffic density K_i car/km, and real traffic flow Q_i car/h along the road can be obtained from the VD data on the road segment covered by Cell_{*i*}.
- The estimated vehicle speed u_i km/h, estimated traffic density k_i car/km, and estimated traffic flow q_i car/h along the road can be obtained from the CFVD data on the road segment covered by Cell_{*i*}.
- The expected value $(1/\lambda)$ of call inter-arrival time is 1 h/call.
- The accuracies of traffic density estimation and traffic speed estimation are expressed as $1 - \frac{|K_i - k_i|}{K_i}$ and $1 - \frac{|U_i - u_i|}{U_i}$.

3.2.2. Traffic density estimation accuracy

In the proposed approach, the real amount of call arrivals from Cell_{*i*} is collected from CFVD to generate the estimated traffic density (k_i). Because NLU is only performed with MS entering new LA, the estimated traffic flows are consistence in the

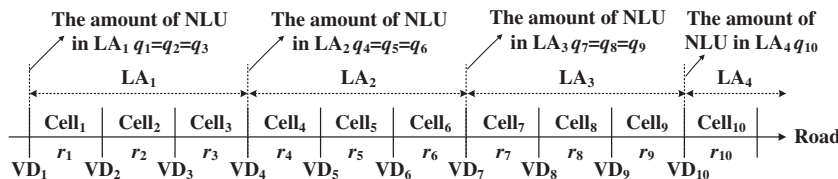


Fig. 8. The distribution of cells, location areas, and VDs in simulation experiment.

Table 1

The comparisons of traffic density estimation accuracy.

LA	Cell	Q_i	U_i	K_i	q_i	k_i	Traffic density estimation accuracy (%)
1	1	3547	94.40	38.17	3547	38	99.56
1	2	3520	94.02	37.58	3547	37	98.47
1	3	3489	93.66	37.44	3547	31	82.80
2	4	3449	93.42	37.25	3449	35	93.95
2	5	3395	93.50	36.92	3449	37	99.78
2	6	3353	93.37	36.31	3449	38	95.34
3	7	3311	93.30	35.91	3311	33	91.90
3	8	3269	93.19	35.49	3311	30	84.54
3	9	3225	93.22	35.08	3311	33	94.07
4	10	3196	94.52	34.59	3196	35	98.83
Average							93.92

Table 2

The comparisons of traffic speed estimation accuracy.

LA	Cell	q_i	k_i	u_i	U_i	Traffic speed estimation accuracy (%)
1	1	3547	38	93.34	94.40	98.88
1	2	3547	37	95.86	94.02	98.04
1	3	3547	31	114.42	93.66	77.84
2	4	3449	35	98.54	93.42	94.52
2	5	3449	37	93.22	93.50	99.70
2	6	3449	38	90.76	93.37	97.21
3	7	3311	33	100.33	93.30	92.46
3	8	3311	30	110.37	93.19	81.57
3	9	3311	33	100.33	93.22	92.37
4	10	3196	35	91.31	94.52	96.61
Average						92.92

Table 3*t*-Test for real traffic speed and estimated traffic speed.

	u_i	U_i
Mean	98.85	93.66
Variances	63.63	0.23
<i>t</i> -Value	2.00	
Critical value	2.26	
<i>P</i> -value	7.63%	

95% Confidence interval for difference.

same LA in the proposed approach. For example, all of the estimated traffic flows q_1 , q_2 , and q_3 in LA₁ are 3547 NLU events. Moreover, there are 38 calls (i.e., the estimated traffic density k_1) which are generated by MS according the MS communication behaviors (e.g., the expected value ($1/\lambda$) of call inter-arrival time is 1 h/call) on the road segment covered by Cell₁ in LA₁ in experiments. This study compares the estimated traffic density k_1 with the real traffic density K_1 which is calculated as Q_1/U_1 from VD No. 1. As shown in Table 1, the results of the traffic density comparisons with VD and CFVD indicate that the average traffic density accuracy is 93.92% by CFVD.

3.2.3. Traffic speed estimation accuracy

For traffic speed estimation, this study can use the estimated traffic flow q_i and estimated traffic density k_i to estimate the traffic speed u_i by Formula (3). The estimated traffic speed u_1 can be calculated as q_1/k_1 . For example, the estimated traffic speed u_1 is 93.34 km/h when the estimated traffic flow q_1 is 3547 car/h and estimated traffic density k_1 is 38 car/km. Then this study compares the estimated traffic speed with the real traffic speed U_1 from VD No. 1 in experiments. As shown in Table 2, the average speed accuracy is 92.92% by CFVD.

This study also used two-tailed *t*-test to determine significance of the difference between real traffic speed U_i and estimated traffic speed u_i . Table 3 shows the *t*-test for the population means of two independent samples and α is set to

0.05. Comparing the population means, the test results show that P -value is 7.63% and there is not significantly difference. Therefore, the null hypothesis ($H_0: \bar{u}_i = \bar{U}_i$) is accepted.

4. Conclusions and future work

Several studies have reviewed and analyzed how to obtain the traffic information from CFVD. In this paper, this study proposes a novel model to evaluate the relation between the amounts of NLUs and CAs to estimate the traffic speed by using CFVD and the proposed model. In experiments, this study compares the estimated traffic information with the real traffic information from VD. The results show that the accuracy of traffic speed estimation is 92.92%. As demand for real-time traffic information increases, the next goal is to estimate and analyze the traffic congestion and transportation delays for ITS with the proposed model.

Acknowledgement

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