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Research Article

Spatiotemporal Traffic Density Estimation Based on ADAS Probe Data

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This study aims to develop a spatiotemporal traffic density estimation method based on the advanced driver assistance system (ADAS) Probe data. This study uses the vehicle trajectory data collected from the ADAS equipped on the sample probe vehicles. Such vehicle trajectory data are used firstly to estimate the distance headway between the vehicles on a specific road section, and the postprocessed distance headway data are finally used to estimate the spatiotemporal traffic density. The innovation aspect of the proposed methodology in this study is that traffic density can be estimated in high accuracy only with a small size of data points in support of ADAS. On the other hand, existing density estimation method requires a large number of probe vehicles and its numerous data sets including either the global positioning system data or the dedicated short-range communication data. To verify the proposed methodology, a two-step evaluation is performed: the first step is a numerical evaluation that estimates the spatiotemporal traffic density based on the simulated vehicle trajectory data, and the second step is an empirical evaluation that estimates the density based on the real-road data in both peak and nonpeak periods. Beyond the methodology development, this study verified the estimation reliability of traffic density under various traffic conditions based on the sampling rate of ADAS-equipped vehicles. Consequently, the traffic density estimation error decreased as the sampling rate increased. Estimation accuracy of 90% or higher was observed in all scenarios when the sampling rate was 50% or higher. It indicates that fairly accurate traffic density estimation is feasible using probe vehicles that correspond to half of the vehicles driven on the road. Therefore, this practical approach is expected to mitigate the burden of density estimation, particularly in future road systems in which ADAS and autonomous vehicles are prevalent.

1. Introduction

Drivers on the freeway can be stressed under uncertain traffic conditions due to changes in speed, congestion, and risk of accidents [1]. They need to accurately perceive the traffic conditions of the road to maintain a smooth traffic flow and keep safety. Traffic density, which is a common indicator of traffic conditions on the roads, can be defined as accurately perceiving the traffic car at a specific time within a unit interval [2]. It is also considered the most important macro indicator because it is directly related to traffic demand on the road [3]. Traffic density is also used as a major measure of the effectiveness of a continuous traffic flow since it can adequately represent the characteristics of a traffic flow [2].

Since it is difficult to collect traffic density on the roads, photos or videos are typically used, or traffic volume, speed, and occupancy collected by detectors are commonly used for estimating traffic density [2]. Traffic information collected by detectors is largely distinguished into point-based detection and section-based detection according to the spatial range [4]. A point-based detection system generates traffic information by collecting information from the speed of vehicles passing through a specific point and their passing time at the point where a detector is installed. However, the point-based detection system requires high maintenance costs and is less accurate, which may result in a discrepancy in accuracy depending on travel time estimation methods. Moreover, the reliability of traffic density estimation during traffic congestion becomes low due to fixed point-based detection [5]. A section-based detection system calculates the time taken by a vehicle to pass through the starting and endpoints of a specific section. However, the equipment used in a section-based detection system is expensive and may occasionally omit data collection as information is collected intermittently [6]. Therefore, an effective and direct traffic density estimation methodology is needed to overcome the drawbacks of conventional detection systems and to be put into practical use in the field.

Advanced driver assistance systems (ADAS) data can collect traffic situation information during actual driving. In recent years, the importance has been emphasized due to an increased number of vehicles equipped with this system. According to recent reports on supply prediction of ADAS, the share of ADAS-equipped vehicles will reach 71% globally and the number of vehicles equipped with ADAS is expected to be around 83,905,000 in 2030 [7, 8]. The amount of collected data will sharply rise as with the rising number of ADAS-equipped vehicles, and the utilization of the ADAS data will gradually increase accordingly. This device assists drivers by recognizing and judging traffic situations during driving using advanced sensors such as LiDAR and radar, Global Positioning System (GPS), and communications intelligence video equipment. Such an advanced system can measure the distance between preceding vehicles in real-time and can estimate spatiotemporal traffic density based on the spacing measurement of the road. Therefore, the ADAS is utilized in this study in order to estimate traffic density with a high level of accuracy. By estimating traffic density using the ADAS data, the drawbacks of a conventional detection system such as high system maintenance cost, spatial constraints, and low reliability during congestions can be resolved.

This study aims to develop a spatiotemporal traffic density estimation method using the capability of ADAS data. This study uses a microscopic traffic simulation model to develop the traffic density estimation methodology and evaluate the performance under various traffic conditions situations. Furthermore, the proposed methodology is verified based on the distance headway collected from the ADAS-equipped vehicles under the simulation environment. Evaluation and validation of the ADAS distance headway-based traffic density estimation are performed using a hypothetical simulation road network and real road data. The distance headway data and trajectory data collected from probe vehicles equipped with ADAS are used to measure the total travel time of vehicles. Traffic density is estimated according to the changes in the sampling rate of ADAS-equipped vehicles, estimation time, and section size. The practical meaning of the sampling rate is the proportion of ADAS vehicles among all vehicles in the mixed traffic flow for which the traffic density is to be estimated. Finally, the accuracy of the estimated traffic density values is evaluated based on mean absolute percentage error (MAPE) and root mean square error (RMSE). Through this study is expected to estimate traffic density using a generalized definition calculated from the total travel time of vehicles during the unit time in a spatiotemporal diagram [9].

The rest of this paper is organized as follows. In Section 2, the distinction of this study is deduced based on the review of previous related studies. In Section 3, the spatiotemporal traffic density estimation method of a continuous flow using the data collected by the sample ADAS vehicle is explained. Section 4 deals with the application of the methodology through a numerical evaluation using a hypothetical network, as well as analysis results. Section 5 describes the verification of the methodology on real roads using an empirical evaluation. Lastly in Section 6, the study results are summarized, and the future direction is proposed for effective traffic density prediction methods.

2. Literature Review

Previous studies on traffic density estimation were generally performed using the traffic information collection devices installed on roads. Various density estimation methods have been proposed, including input-output analysis using traffic flow values and occupancy measurements [10]. Kim et al. proposed an in-out counting method in which the number of vehicles that remained between two points during the measurement time is detected by selecting the ramp section of a continuous flow as the estimation section. The results of such a method showed that estimation error tended to increase when the traffic volume or the measurement time interval increased [11]. Park et al. proposed a method using CCTV images. It is a method that directly counts the number of vehicles in the video by generating a panoramic image spanning over 1 km by coordinating eight CCTV images. This research examined the problems of conventional traffic density estimation methods using actual data and proposed an appropriate collection period [12]. However, the overlapping of images was not considered, and the collection period was proposed only for smooth traffic flows. Park et al. suggested an alternative to the conventional traffic density estimation method that employs CCTV images by estimating it using aerial photographs [13]. However, this method cannot collect data continuously and only provides analysis results at a specific time or section. Using aerial photographs or images and videos taken from high elevation areas for collecting data has its limitation in continuous measurements due to various constraints such as weather and expense. Kim et al. estimated Traffic density using the vehicle trajectory information from a radar detector and the point data from a Vehicle Detection System (VDS) installed 500 m before the radar detection. It was estimated using the time moved in the x-axis direction within the density estimation section of the vehicle trajectory data, length of the estimation section, and data collection time, and traffic density was calculated using the VDS data to compare the two methods. The results showed that the error is significant due to the difference in the space mean speed when density is 20 (veh/km/lane) or greater [14]. This study has significance in that it estimated traffic density based on the vehicle trajectory information but has a limitation in that it performed the estimation only at a specific point.

On the other hand, in recent years, most studies on traffic density estimation used data from a probe vehicle due to the limitations of existing collection equipment. Seo et al. obtained the sample data by operating a probe vehicle for an hour on a section of an urban expressway that circulates Tokyo spanning over 11 km, excluding the tunnel, and estimated the density. Map-matching was performed using the collected GPS data of each probe vehicle, and the road space was detected using the MonoEye camera. Approximately 28% error resulted when the error rate of estimate value was analyzed using the root mean square percentage error (RMSPE) [15]. This study proposed a method for calculating traffic density using the data of a probe vehicle, but the accuracy of estimation in various traffic conditions was unknown since the sample rate and the spatiotemporal area for traffic density estimation were fixed. Nam et al. estimated it based on the data from a radar sensor installed on a probe vehicle using NGSIM. The estimation error was analyzed according to different sampling rates at 1%, 5%, 10%, and 25% [16]. However, the limitation of this method is that the estimation period was set to 15 min. Herring et al. proposed a model for estimating a traffic flow using the data of a probe vehicle. The accuracy was improved by approximately 35% compared to the existing method when the accuracy of the model was verified using the GPS data collected from 500 taxis in San Francisco. The traffic flow was estimated using the mean travel speed [17]. On the other hand, the sampling rate of all the vehicles was not considered since a fixed number of probe vehicles were applied, and the estimation was limited to a specific time and section. Yang et al. proposed a method for estimating the traffic density based on the vehicle group information extracted through a tracking-based filtering algorithm, as well as the driving information and radar sensing data of a probe vehicle. The results provided an estimation accuracy that was 70% or higher in a continuous flow [18]. However, the limitation of actual application in large-scale sites remained. Qiu et al. proposed a method for estimating average density of a section on expressways using the loop detector data and the sample IntelliDrive information provided in real-time. When the proposed methodology was used to estimate the traffic density of Berkeley Highway using NGSIM, the estimation error was reduced compared to using the loop detector data [19]. However, the changes in the sampling rate were not considered, and the entire road was estimated rather than for a unit section.

Based on the literature review on traffic density estimation methodology, traffic density information, which is difficult to collect directly, has been estimated using the data collected by detectors. Existing detection systems, however, require high maintenance costs, have low reliability during congestions, and occasionally omit traffic information. Thus, various studies on estimation have been conducted in the past to overcome such drawbacks. Previous studies on traffic density estimation using traffic information collection equipment proposed the methods of using video information, photograph information, or radar detectors. These methods have limitations of being difficult to obtain continuous data or estimating traffic density of a specific point or section. For resolving the problems of these detection-system-data-based methods, a few studies employed the data obtained from probe vehicles. Previous studies that used probe vehicles analyzed the estimation accuracy only from specific sampling rates, thus failing to reflect various traffic conditions and actual driving trajectories of vehicles. Moreover, the spatiotemporal size of the estimation target is limited to a specific time and section. To overcome the limitation of previous studies and conventional estimation methods based on detection systems, this study estimates the spatiotemporal traffic density of a continuous flow using the distance headway data and vehicle trajectory data obtained from ADAS. Furthermore, estimation accuracy in diverse traffic conditions is proposed through an accuracy analysis of estimation according to the changes in the sampling rate and estimation space and time.

3. Methodology

3.1. Overall Methodology. The spatiotemporal traffic density of a continuous flow is estimated using the distance headway data of nearby vehicles and driving trajectory data collected from the sampled ADAS-equipped vehicles. The methodology processes by two steps: estimation of spatiotemporal traffic density using driving trajectory and distance headway data of ADAS-equipped vehicles collected through simulation, and traffic density error estimation based on unit space and time of traffic density estimation and sample rate of ADAS-equipped vehicles. First, the driving trajectory data of each vehicle is collected using PTV VISSIM 2020, which is microscopic traffic simulation software. Mobileye ADAS, which is currently commercially available, scans roads using camera sensors, records roadside properties such as road signs and lanes, and estimates mobility information such as traffic volume and distance headway [20]. Driving trajectory data and distance headway information could be collected from ADAS; thus, these data are extracted from the VISSIM simulation environment to be used for traffic density estimation. Sampled ADAS-equipped vehicles are extracted through random sampling without replacement, and the extracted driving trajectory data are processed to measure the distance headway data of nearby vehicles. The distance headway is divided into front-vehicle and side-vehicle headways, where in front-vehicle distance headway is the distance from the front end of the preceding vehicle in the same lane to the front end of the following vehicle. However, side-vehicle distance headway is the distance from the front center of the preceding vehicle to the front center of the following vehicle in a different lane. In the evaluation scenarios, front-vehicle distance headway information is used for the one-way one-lane case, whereas both front-vehicle and side-vehicle headway information is used for the one-way two-lane case. Second, the traffic density estimation methodology based on ADAS distance headway is evaluated through a numerical evaluation. Lastly, the applicability in real roads is verified through an empirical evaluation using the data of actual expressways.

3.2. Spatiotemporal Traffic Density Estimation. ADAS can collect distance headway data using various sensors, including cameras, radars, and LiDAR, but the performance varies depending on sensors and products. Herein, the measurement range of distance headway was set to 250 m based on the detection specifications of Mobileye ADAS, which is most commonly used in the global ADAS market with a market share of 70% [21]. The distance headway information was generated using the vehicle position and lane information based on the driving trajectory data of each vehicle through a simulation. (1) is for calculating the distance headway from the preceding vehicle in a simulation. The generalized definition method used for traffic density estimation in this study involves calculation through the total travel time that the vehicles consumed during the unit time in the time-space diagram [9]. This method has an advantage of a sample analysis since unit time and unit distance can be used instead of a specific point or section. Furthermore, traffic density can be estimated without spatial constraints since the estimation is based on driving trajectory data and distance headway data. The generalized definition and density estimation method are further explained in (3) and Figure 1.

$$H = \sqrt{\left(3.6 * \left(l_p - l_a\right)\right)^2 + \left(L_p - L_a\right)^2}. \quad (1)$$

H = headway

l_p = lane number of the preceding vehicle

l_a = lne number of the ADAS probe vehicle

L_p = location of the preceding vehicle

L_a = location of the ADAS probe vehicle

$$k = \frac{n}{L} = \frac{n\,dt}{L\,dt}. \quad (2)$$

k = density

n = number of vehicles

L = length of roadway

$$k = \frac{\sum \text{travel time}}{\sum \text{space region}} = \frac{\left(\sum_{i=1}^{n} t_i\right)}{(T \times D)} = k\left(\frac{\text{veh}}{m}\right). \quad (3)$$

k = generalized density

t_n = travel time in section of the nth vehicle

3.3. Error Estimation. For finding traffic density estimation error per sampling rate of the ADAS-equipped vehicles, probe vehicles were extracted through random sampling without replacement. This method has the advantages of generating various distance headway information and preventing duplicated extraction. As shown in Figure 2, the sampling rate is calculated based on the ratio of ADAS-equipped vehicles among the entire traffic volume, and, therefore, the sampling rate can affect traffic density estimation. The sampling rate was increased by 10% from 10% to 90% for each scenario. MAPE shows the error between the ground-truth value and the estimated value as a percentage, a comparison can be made in terms of relative error, and outliers can be corrected. MAPE was used for the estimated value of traffic density calculated per sampling rate since a residual comparison is possible by comparing the error rate between the ground-truth value and the estimated value per sampling rate. In addition, RMSE, which can represent the error between the ground-truth value and the estimated value as a numerical value, was used because MAPE cannot provide actual numerical values. For microscopic analysis of a traffic flow, error estimation was performed according to the changes in unit section and unit time of traffic density estimation. Traffic density estimation was performed by dividing the entire spatiotemporal domain into a certain interval. And the estimation error was suggested by comparing the ground-truth value and the estimated value of traffic density estimated according to the size of the divided spatiotemporal domain. Through this, the effects of the size of the unit section and unit time on traffic density estimation were identified.

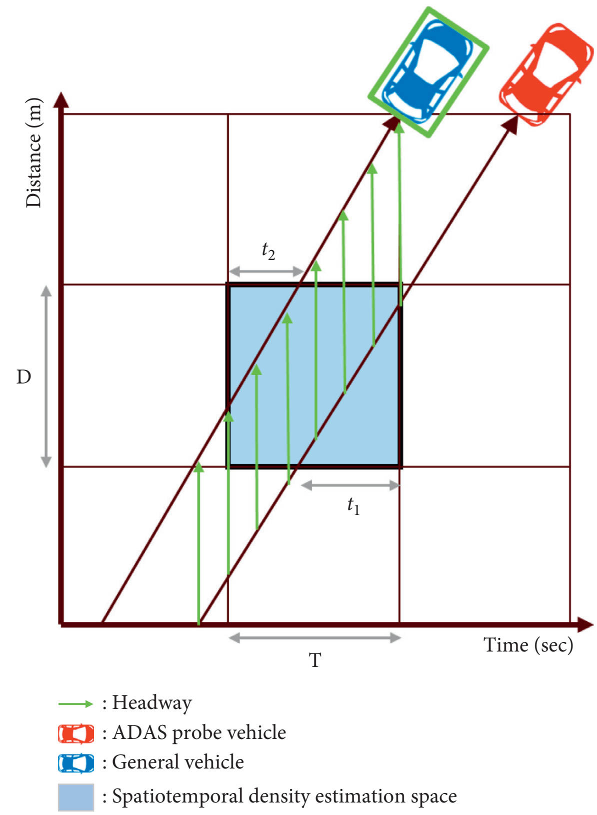
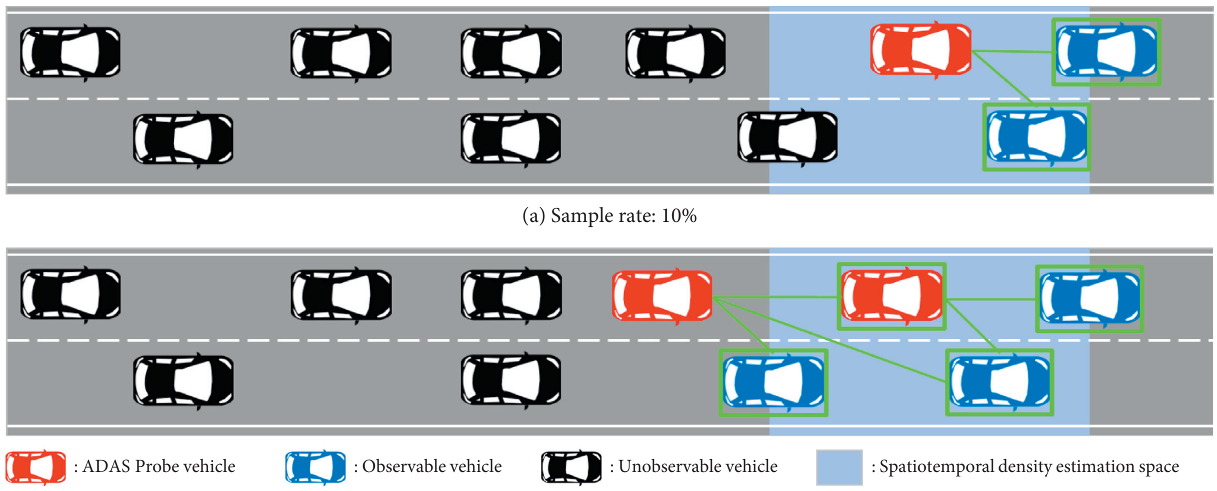


FIGURE 1: Spatiotemporal traffic density estimation using generalized definition.



(b) Sample rate: 20%

Figure 2: Example of sample rate. (a) Sample rate: 10%. (b) Sample rate: 20%.

Y_i = actual traffic density

$\hat{Y}_i$ = estimated traffic density

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right|,$$
$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}\frac{\left(Y_i - \hat{Y}_i\right)^2}{N}}. \quad (4)$$

4. Numerical Evaluation

In this study, an arbitrary road on a hypothetical network was set to apply and verify the traffic density estimation methodology through a numerical evaluation. For estimating traffic density in single-lane and multiple-lane situations, two scenarios were designed where scenario 1 used a one-way one-lane setting, while scenario 2 used one-way two-lane settings. The simulation was performed for 4,200 s for two scenarios in which the analysis was performed for 3,600 s excluding the first 600 s during which a traffic flow had not been formed in the network. The section length of a hypothetical network was 1 km; the ratio of a passenger vehicle to a Heavy Goods Vehicle (HGV) to the bus was set to 90 : 5 : 5 according to the status of vehicles traveling on expressways reported by Korea Expressway Corporation [22]. Design speed and traffic volume of scenario 1 and scenario 2 were set separately to assume that a relatively stable traffic flow without congestions is given Level of Service (LOS) D, while a traffic flow that is delayed for an extended period due to a light congestion factor of LOS E [23]. Detailed explanations on the design conditions are provided in Table 1.

Errors were predicted using MAPE and RMSE for the ground-truth values and estimated values of traffic density according to the sampling rate of the ADAS-equipped vehicles based on the simulation results for each scenario. The spatial unit of traffic density was set to 300 seconds, which is the standard for providing traffic information, and the temporal unit was estimated by dividing the entire section of 1km into 100 m units. When the comparison was made with the ground-truth value of traffic density, MAPE and RMSE were 64.23% and 11.39 (veh/km/lane) at 10% sampling rate of ADAS-equipped vehicles, respectively, which are significantly large. However, MAPE was less than 10%, and RMSE was below 2 (veh/km/lane) when the sampling rate was increased to 50%, thus showing fairly accurate traffic density estimation results. It can be inferred that the number of vehicles observable within the spatiotemporal traffic density estimation section increases as the sampling rate increases. In scenario 1 designed with one-way one lane, the traffic density estimate became similar to the ground-truth value as the sampling rate of ADAS increased. Figure 3 shows the spatiotemporal traffic density estimates at 10–30% sampling rate where the variation in the estimation accuracy and the ground-truth value of spatiotemporal traffic density was the greatest in scenario 1. The ground-truth value of traffic density had high density in space and time; the estimated traffic density according to the sampling rate was low at the lowest sampling rate of 10% but similar to the ground-truth value of traffic density as the sampling rate increased. MAPE and RMSE per sampling rate in scenario 1 are presented in Table 2.

In scenario 2 designed with two lanes in one way, the error from the ground-truth value decreased as the sampling rate increased as it did in scenario 1 when the traffic density estimate was compared to the ground-truth value according to the ADAS sampling rate using MAPE and RMSE. MAPE and RMSE were 38.5% and 7.26 (veh/km/lane) at a 10% sampling rate of ADAS vehicles, showing a significantly large error. However, MAPE decreased to 6.67% and RMSE decreased to 1.75 (veh/km/lane) at the sampling rate of 30%, which indicated that traffic density can be sufficiently estimated at a 30% sampling rate. Figure 4 shows the traffic density estimation value at 10–30% sampling rate and ground-truth traffic density value in scenario 2. Estimated and ground-truth values of traffic density become similar as the sampling rate increases. MAPE and RMSE per sampling rate in scenario 2 are presented in Table 3.

Table 1: Scenario descriptions of numerical evaluation.

Classification	Scenario 1	Scenario 2
Number of lanes	One-lane	Two-lane
Running time	4,200 s(burn-in-out: 600 s)	4,200 s (burn-in-out: 600 s)
Link length	1 km	1 km
Traffic volume	1,000 veh/h	2,000 veh/h
Vehicle ratio	Passenger car : HGV : Bus = 90 : 5 : 5	Passenger car : HGV : Bus = 90 : 5 : 5
Speed	50–80 km/h	50–70 km/h

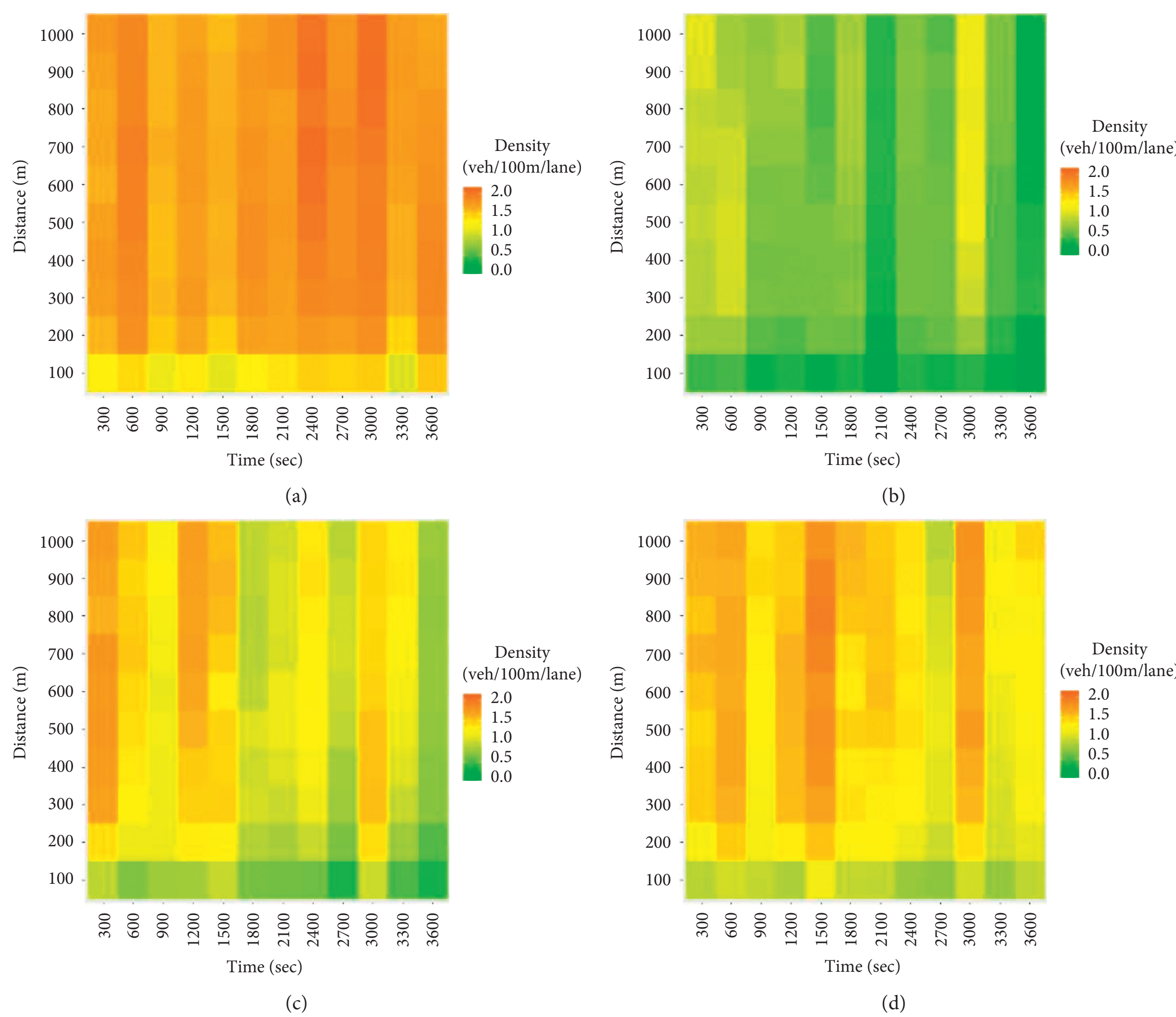


Figure 3: Estimated traffic density by sample rate of scenario 1(numerical evaluation) (a) Ground truth of traffic density (b) Estimated density at 10% sample rate (c) Estimated density at 20% sample rate (d) Estimated density at 30% sample rate.

Table 2: MAPE and RMSE comparison of scenario 1 (numerical evaluation).

Sample rate (%)	10	20	30	40	50	60	70	80	90
MAPE (%)	64.23	33.97	22.01	13.87	7.77	4.23	2.53	1.62	1.16
RMSE (veh/km/lane)	11.39	6.26	4.51	2.85	1.73	1.09	0.7	0.46	0.36

The numerical evaluation of the two scenarios showed that the error in traffic density estimation decreases as the sampling rate of ADAS increases. The difference in the estimation error of traffic density per scenario is shown in Figures 5 and 6. It shows the scatter plot of estimated values per sampling rate of scenarios 1 and 2 in which the x-axis represents the estimated traffic density while the y-axis represents the ground-truth value per sampling rate. Estimated and ground-truth values are similar, as the traffic density values in the scatter plots are closer to a diagonal

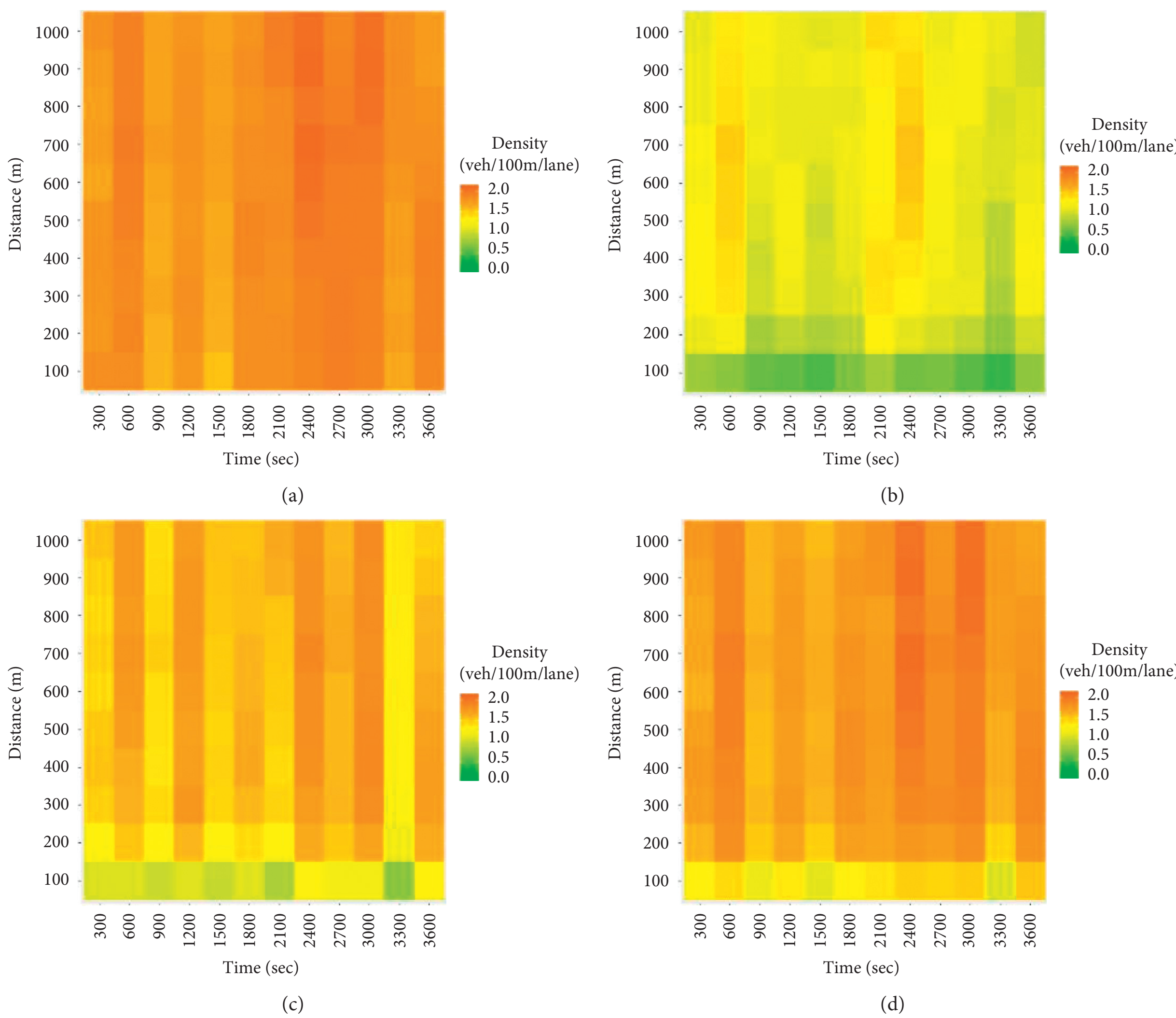


Figure 4: Estimated traffic density by sample rate of scenario 2 (numerical evaluation). (a) Ground truth of traffic density. (b) Estimated density at 10% sample rate. (c) Estimated density at 20% sample rate. (d) Estimated density at 30% sample rate.

Table 3: MAPE and RMSE comparison of scenario 2 (numerical evaluation).

Sample rate (%)	10	20	30	40	50	60	70	80	90
MAPE (%)	38.53	16.23	6.67	3.20	1.81	0.90	0.31	0.17	0.02
RMSE (veh/km/lane)	7.26	3.45	1.75	1.09	0.65	0.45	0.19	0.12	0.02

line. In general, as the sampling rate increases, the traffic density value approaches the diagonal, and the estimated density tends to approach the ground truth of density. However, it can be seen that estimated density is always formed lower than the ground truth of density. This is because the estimated density uses only the driving trajectories of vehicles that can collect data from the sample ADAS vehicle, so it appears lower than the ground truth of density using the driving trajectories of all vehicles. In each sampling rate, the distribution is more widespread in Figure 5 than in Figure 6. This means that overall, the estimation accuracy in Scenario 2 is higher than in Scenario 1. This is because, at the same sampling rate, it is possible to detect more vehicles in Scenario 2 with more traffic volume than Scenario 1.

The 1-km section was divided at the interval of 50, 100, 200, and 250 m for estimating spatiotemporal traffic density, while the entire period of 3,600 s was divided at the interval of 200, 300, and 600 s. Table 4 shows the MAPE of the estimated traffic density according to unit section and unit time in scenario 1, whereas Table 5 shows the MAPE of scenario 2. The two tables signify that the accuracy of traffic density estimation is affected by the set unit where the estimation error decreases as the section unit becomes greater. In this study, road spaces are detected based on the distance headway. The number of vehicles for which the ADAS can collect headway distance increases as the section unit becomes greater. There for, it can be seen that the estimation error decrease as unit section increases. However, a spatiotemporal unit that is too large may have low value in

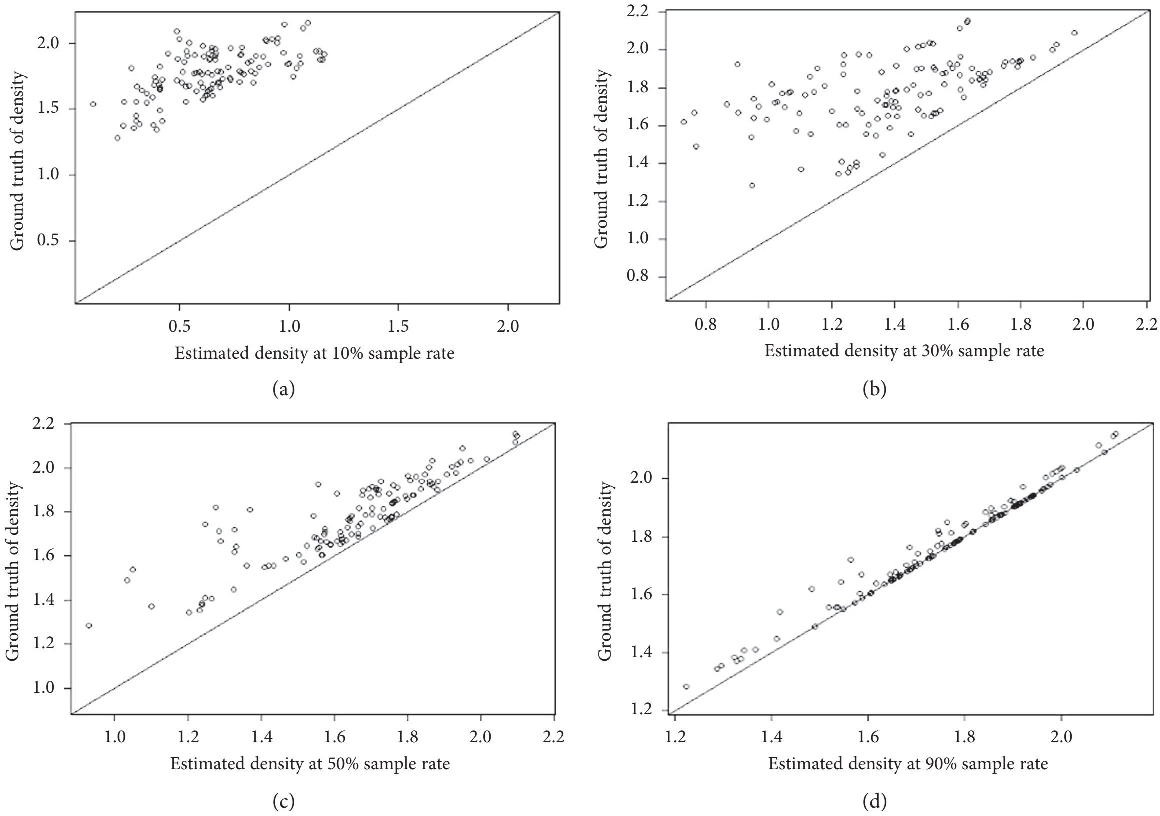


Figure 5: Scatter plot by sample rate of scenario 1 (numerical evaluation). (a) Scatter plot at 10% sample rate. (b) Scatter plot at 30% sample rate. (c) Scatter plot at 50% sample rate. (d) Scatter plot at 90% sample rate.

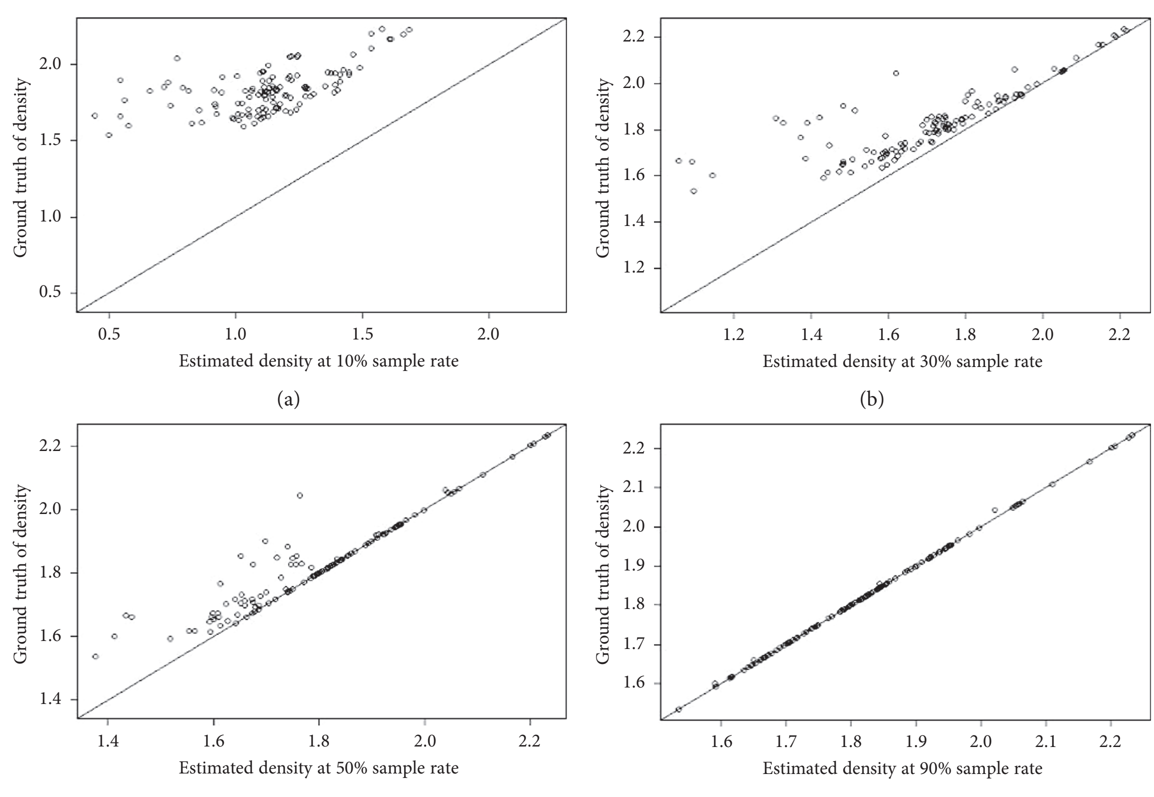


Figure 6: Scatter plot by sample rate of scenario 2 (numerical evaluation). (a) Scatter plot at 10% sample rate. (b) Scatter plot at 30% sample rate. (c) Scatter plot at 50% sample rate. (d) Scatter plot at 90% sample rate.

Table 4: MAPE by sample rate, unit section, and unit time of scenario 1 (numerical evaluation).

Sample rate (%)	$\triangle t$ (sec)\$\triangle d$ (m)	50	100	200	250
10%	200	65.00	64.19	62.88	61.07
	300	65.59	64.23	62.23	61.84
	600	65.61	64.82	63.43	61.22
20%	200	36.91	33.35	31.13	29.37
	300	37.06	33.97	31.55	29.66
	600	36.97	33.51	30.99	29.02
30%	200	23.38	22.23	20.14	18.37
	300	23.33	22.01	19.98	18.31
	600	23.58	22.31	20.09	18.63

Table 5: MAPE by sample rate, unit section, and unit time of scenario 2 (numerical evaluation).

Sample rate (%)	$\triangle t$ (sec)\$\triangle d$ (m)	50	100	200	250
10%	200	39.50	38.52	36.06	34.41
	300	40.04	38.53	35.99	34.35
	600	40.07	38.54	36.00	34.25
20%	200	17.46	16.21	13.68	12.55
	300	17.82	16.23	13.71	12.58
	600	17.65	16.03	13.46	12.26
30%	200	7.33	6.70	4.86	3.94
	300	8.06	6.67	4.76	4.00
	600	7.91	6.51	4.58	3.81

terms of providing traffic density information. Therefore, in this paper, 300 seconds, the standard for providing traffic information, was set as a unit time, and a total section of 1 km was divided into 100 m and set as a unit space.

5. Empirical Evaluation

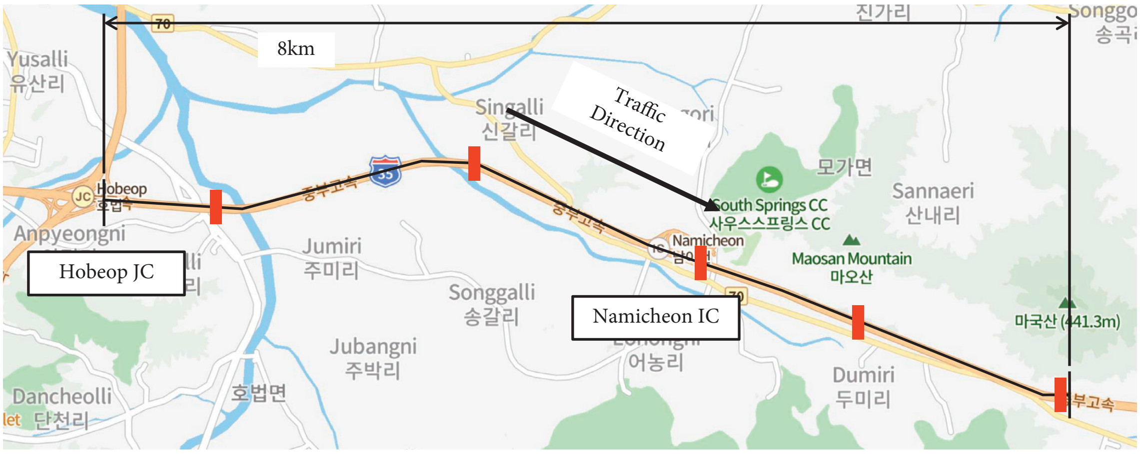
This study also includes an empirical evaluation for verifying the methodology using the data of real roads. The spatial range of the section on a real road selected for data collection is an 8-km section from Hobeop Junction to Iljuk Interchange on Jungbu Expressway which connects Hanam and Cheongju in Korea. This section consists of two lanes in one way, rest stop, and Icheon Interchange. This particular section was chosen since the road can be observed during both free flow and congestion. This section can be seen in Figure 7. The temporal range of the section on a real road was set to June 12, 2019, a Wednesday––when the influence of the day of the week is the least. Traffic density was estimated for two scenarios for peak hours (09 : 00–10 : 00) and nonpeak hours (15 : 00–16 : 00). The road section is 8 km long, and the ratio of a passenger vehicle to HGV was set to 83.6 : 16.4 based on the status of vehicles traveling on this specific section reported by Korea Expressway Corporation [22]. Detailed explanations on the scenario conditions are provided in Table 6.

For a car-following model, Wiedemann 99 model was used, which is suitable for implementing a continuous flow [24]. The model was calibrated by adjusting the parameters of the car-following model, traffic volume, and speed. For the verification, five-point detectors installed on the selected road section were reflected in the simulation, and it was verified whether the simulation accurately reflects the respective road section by comparing the traffic volume and speed collected by the detectors. The analysis results showed that the error rate of scenario 1 or the peak hours was 0.7% while that of scenario 2 or the non-peak hours was 6.7%, which indicated that the simulation implemented the actual road environment with high accuracy. Errors were estimated using MAPE and RMSE for the ground-truth value and the estimated value of traffic density according to the sampling rate of the ADAS vehicles. The range of comparative analysis of traffic density was set within a 500 m section at a 300 s interval. In scenario 1, which is during peak hours, the estimated value and ground-truth value became similar as the sampling rate increased. Figure 8 shows the estimation accuracy at a 10–30% sampling rate where the variation in the estimation accuracy was the greatest in scenario 1. The estimated value of traffic density according to the sampling rate has low traffic density at the lowest sampling rate of 10% but tends to be similar to the ground-truth value as the sampling rate increases. MAPE and RMSE were 37.84% and 6.7 (veh/km/lane), respectively, when the sampling rate of the ADAS vehicles was 10%. But, they decreased significantly to 5.19% and 1.04 (veh/km/lane), respectively, when the sampling rate was 30%. MAPE and RMSE per sampling rate in scenario 1 are presented in Table 7.

The error from the ground-truth value decreased as the sampling rate increased when the traffic density estimation error was analyzed according to the sampling rate for scenario 2, which is nonpeak hours. Figure 9 shows the spatiotemporal traffic density estimation values at the sampling rate of 10–30% in scenario 2. Traffic density values were below in all space and time due to being nonpeak hours, but the estimated traffic density tended to exhibit a similar pattern as the ground-truth value as the sampling rate increased. MAPE and RMSE were 50.92% and 4.92 (veh/km/lane) at a 10% sampling rate of the ADAS vehicles, which significantly reduced to 15.52% and 1.58 (veh/km/lane), respectively, when the sampling rate increased. MAPE and RMSE per sampling rate in scenario 2 are presented in Table 8.

The comparison of the two scenarios using an empirical evaluation showed that the traffic density estimation accuracy was substantially higher for scenario 1. Figures 10 and 11 show the scatter plot of estimated values per sampling rate of scenarios 1 and 2. When the two graphs are compared, the distribution is generally more widespread in Figure 11 than in Figure 10. The traffic density estimation accuracy is improved due to an increased number of sample ADAS vehicles in scenario 1, which is peak hours when compared to scenario 2, which is nonpeak hours.

Traffic density estimation error was analyzed according to the changes in unit section and unit time for the empirical evaluation. The entire unit section of 8 km was divided into 250, 500, 1,000, and 2,000 m, and the unit time of 3,600 s was divided into 60, 120, 300, and 600 s to estimate traffic density, which was compared with the ground-truth value using MAPE. Table 9 presents the MAPE of traffic density

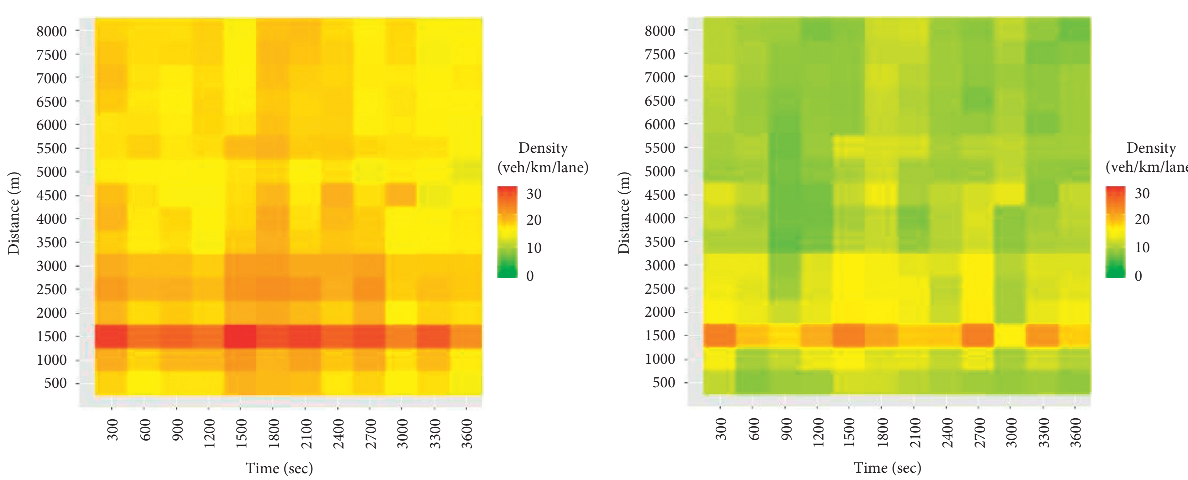


Vehicle Detection System

Figure 7: Spatial range of the section on a real road selected for data collection (empirical evaluation).

Table 6: Scenario descriptions of empirical evaluation.

Classification	Scenario 1	Scenario 2
Number of lanes	Two-lane	Two-lane
Running time	4,200 s (burn-in-out: 600 s)	4,200 s (burn-in-out: 600 s)
Link length	8 km	8 km
Traffic volume	2,696 veh/h	1,748 veh/h
Vehicle ratio	Passenger car : HGV = 83.6 : 16.4	Passenger car : HGV = 83.6 : 16.4
Speed	80–100 km/h	80–100 km/h



(a) (b)

Figure 8: Continued.

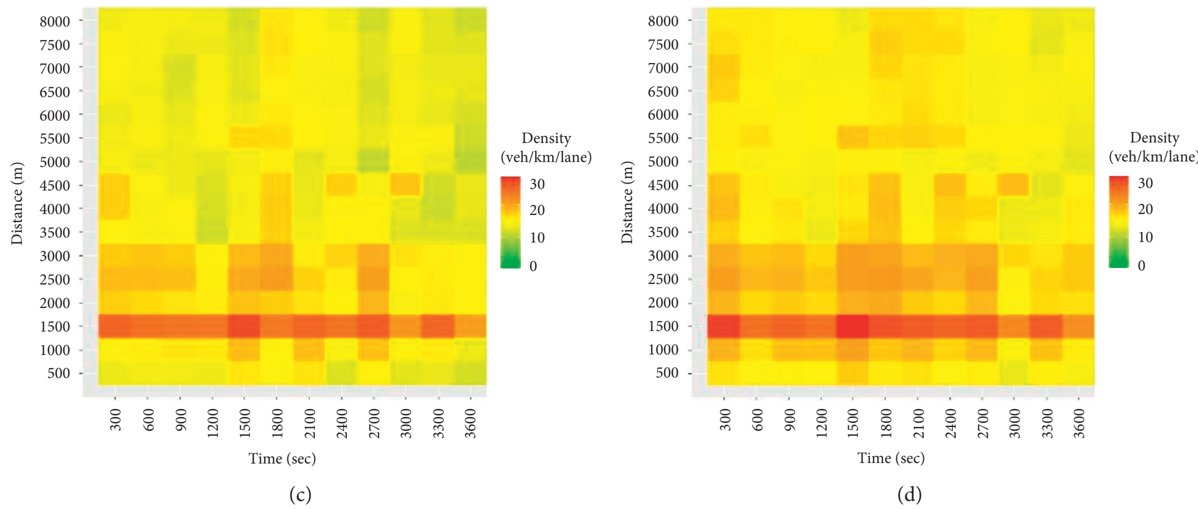


Figure 8: Estimated traffic density by sample rate of scenario 1 (empirical evaluation). (a) Ground truth of traffic density. (b) Estimated density at 10% sample rate. (c) Estimated density at 20% sample rate. (d) Estimated density at 30% sample rate.

Table 7: MAPE and RMSE comparison of scenario 1 (empirical evaluation).

Sample rate (%)	10	20	30	40	50	60	70	80	90
MAPE (%)	34.84	13.32	5.19	2.26	1.02	0.45	0.39	0.36	0.22
RMSE (veh/km/lane)	6.7	2.42	1.04	0.52	0.26	0.15	0.14	0.11	0.09

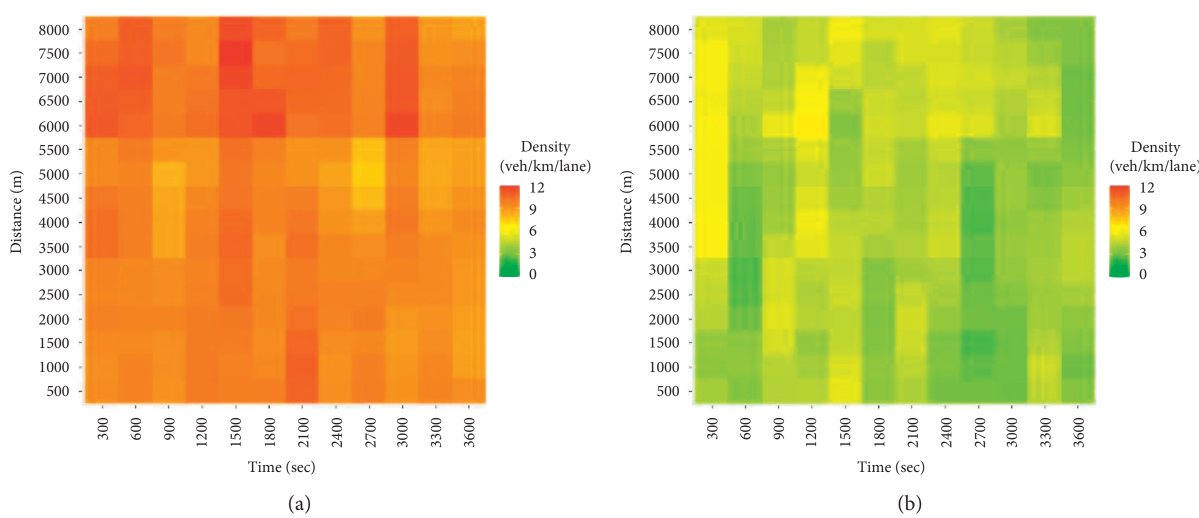
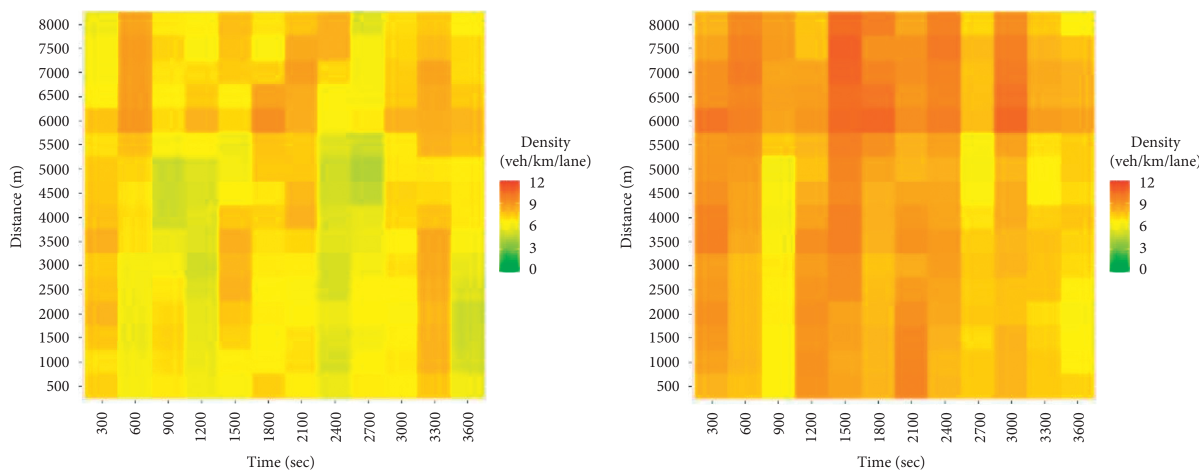


Figure 9: Continued.

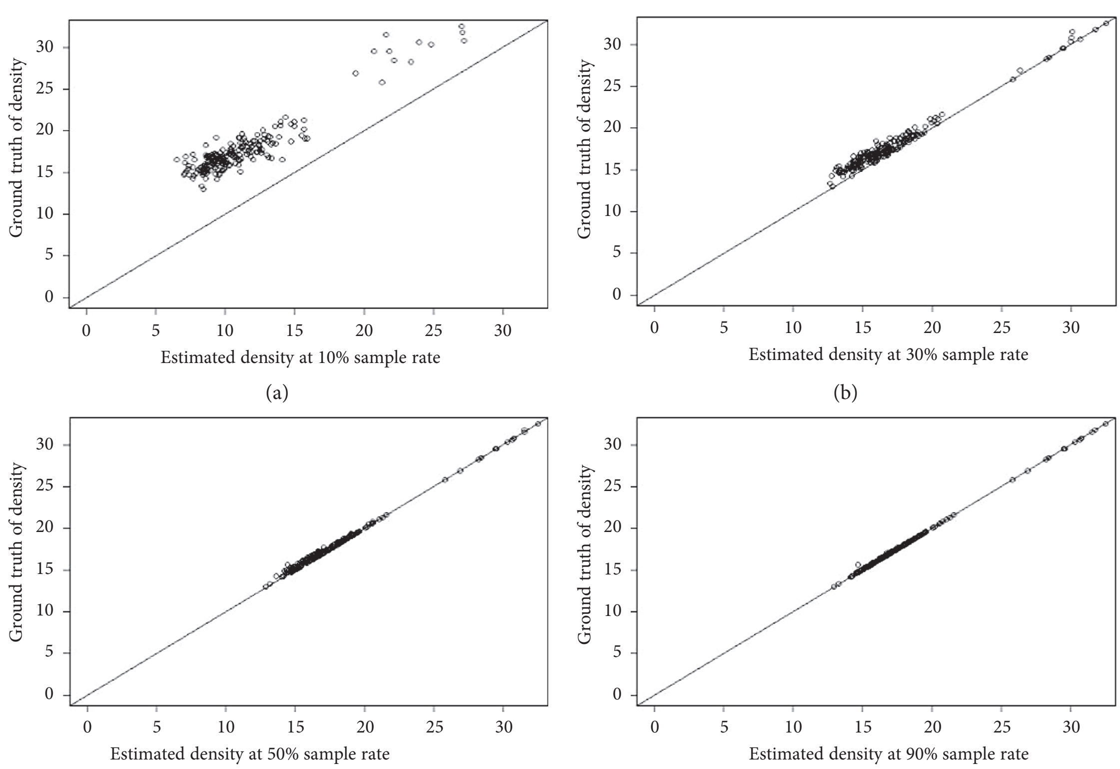


(c) (d)

Figure 9: Estimated traffic density by sample rate of scenario 2 (empirical evaluation). (a) Ground truth of traffic density. (b) Estimated density at 10% sample rate. (c) Estimated density at 20% sample rate. (d) Estimated density at 30% sample rate.

Table 8: MAPE and RMSE comparison of scenario 2 (empirical evaluation).

Sample rate (%)	10	20	30	40	50	60	70	80	90
MAPE (%)	50.92	32.94	15.52	8.82	8.02	6.35	4.01	3.08	2.26
RMSE (veh/km/lane)	4.91	3.2	1.58	0.91	0.89	0.64	0.41	0.32	0.24



(a) (b) (c) (d)

Figure 10: Scatter plot by sample rate of scenario 1 (empirical evaluation). (a) Scatter plot at 10% sample rate. (b) Scatter plot at 30% sample rate. (c) Scatter plot at 50% sample rate. (d) Scatter plot at 90% sample rate.

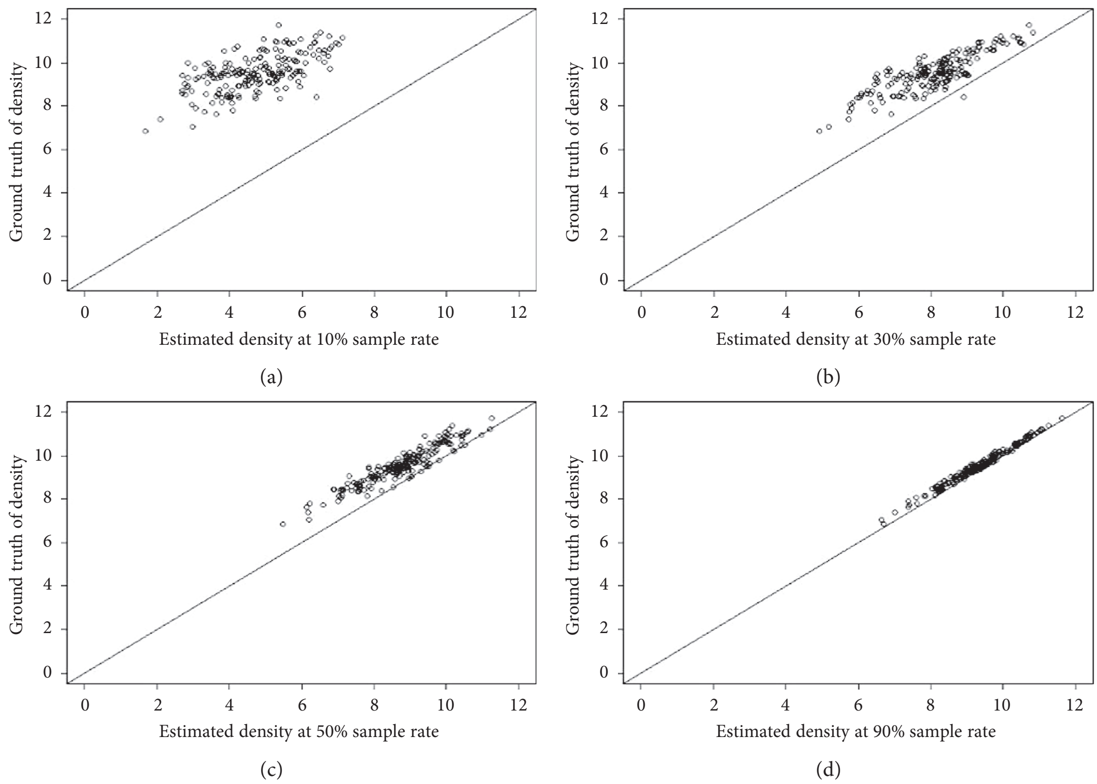


Figure 11: Scatter plot by sample rate of scenario 2 (empirical evaluation) (a) Scatter plot at 10% sample rate. (b) Scatter plot at 30% sample rate. (c) Scatter plot at 50% sample rate. (d) Scatter plot at 90% sample rate.

Table 9: MAPE by sample rate, unit section and unit time of scenario 1 (empirical evaluation).

Sample rate (%)	$\triangle t$ (sec)\$\triangle d$ (m)	250	500	1,000	2,000
10%	60	37.06	35.23	34.47	32.22
	120	36.43	34.49	32.21	30.01
	300	36.02	34.84	31.55	27.16
	600	35.89	33.49	30.87	25.56
20%	60	15.67	14.10	13.75	12.40
	120	15.12	13.80	12.35	10.91
	300	14.83	13.32	12.03	9.64
	600	14.72	13.54	11.55	8.62
30%	60	6.51	5.81	5.38	4.72
	120	6.23	5.40	4.56	3.90
	300	6.13	5.19	4.40	3.21
	600	6.06	5.07	4.15	2.60

Table 10: MAPE by sample rate, unit section, and unit time of scenario 2 (empirical evaluation).

Sample rate (%)	$\triangle t$ (sec)\$\triangle d$ (m)	250	500	1,000	2,000
10%	60	53.07	52.14	51.03	49.23
	120	52.51	51.48	50.08	47.84
	300	52.12	50.92	49.24	46.85
	600	51.88	50.66	48.70	45.56
20%	60	35.11	34.21	33.19	31.86
	120	34.57	33.62	32.27	30.37
	300	34.16	32.94	31.29	29.85
	600	33.95	32.77	30.80	28.82
30%	60	17.50	16.62	15.79	14.75
	120	17.05	16.12	15.03	13.49
	300	16.72	15.52	14.05	12.54
	600	16.51	15.43	13.86	11.58

estimation of scenario 1, while Table 10 presents the MAPE of scenario 2. The two tables showed that the size of the unit section influences the accuracy of traffic density estimation, and the error decreases as the unit section becomes greater.

6. Conclusion

This study proposed a spatiotemporal traffic density estimation method of a continuous flow using the driving trajectory and distance headway information collected and sampled from the ADAS-equipped vehicles. While the conventional traffic density estimation methods, including video recordings and loop detectors, are difficult to measure the density values or limited in terms of accuracy due to either significant effort on data collection or limited detection capabilities. However, the proposed methodology in this study achieved high accuracy on traffic density estimation using the driving trajectory data of the sampled ADAS-equipped vehicles and front-vehicle distance headway. Moreover, the reliability of the proposed methodology was validated by analyzing traffic density estimation errors according to sampling rate, unit section, and unit time under various traffic conditions.

To summarize the contributions of this study, first, this study proposed a method for estimating spatiotemporal traffic density using distance headway data and driving trajectory data of the sampled ADAS-equipped vehicles. And we confirmed its applicability as an alternative to conventional traffic density estimation methods in terms of the accuracy on traffic density estimation. Therefore, this study proved the utility of ADAS data in terms of traffic density estimation, since the sensors of ADAS are useful to detect the distance headway from preceding vehicles and the number of vehicles traveling on roads. Second, the methodology was verified through a numerical evaluation for which arbitrary road conditions were presumed, and the applicability in real roads was also verified through an empirical evaluation using the data of actual roads. Third, the errors in traffic density estimation were analyzed per sampling rate of the ADAS-equipped vehicles. Consequently, the error in traffic density estimation decreased as the sampling rate of the ADAS-equipped vehicles increased in each scenario, and the appropriate sampling rate that improves accuracy was determined. This implies that the proposed methodology becomes even more reliable as the share of ADAS-equipped vehicles increases in the future. Fourth, it turned out that accuracy improves as the unit section becomes larger by analyzing the error in traffic density estimation according to the changes in unit section and unit time. Driving trajectory data of a greater number of vehicles can be collected as the unit section becomes larger since the spatial characteristics of the road are detected based on the distance headway data of the ADAS-equipped vehicles. Such emphasis of this study implies that traffic density data can be efficiently collected from real roads, and preemptive traffic operation and management are feasible through an analysis of congestion sections and collected information. In addition, the proposed methodology can also be utilized in traffic density estimation and traffic flow analysis using the data collected from automated vehicles (AVs) once they are further commercialized and the share of AVs increases in the future. However, this study has a limitation in that verification through data of actual ADAS-equipped vehicles was not performed. In addition, the analysis section was limited to specific road sections and traffic conditions. Therefore, in future research, it is necessary to consider various road geometries and traffic conditions. And it is judged that it is necessary to verify the methodology using actual ADAS data.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

[1] V. Butakov and P. Ioannou, "Personalized driver/vehicle lane change models for ADAS," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 10, pp. 4422–4431, 2015.

[2] Transportation Research Board (TRB), *Highway Capacity Manual 2000*, Transportation Research Board, Washington, DC, USA, 2001.

[3] R. P. Roese, E. S. Prassas, and W. R. Mcshane, *Traffic Engineering*, Pearson Prentice Hall, Upper Saddle River, NJ, USA, 3rd edition, 2004.

[4] Ministry of Land, Infrastructure and Transport (MOLIT), *Research Report on Methods of Collecting and Providing Traffic Information on Urban Arterial Roads*, Ministry of Land, Infrastructure and Transport (MOLIT), Jeju, Korea, 2010.

[5] H. J. Kim and K. T. Jang, "Characteristics of travel time variability in congested traffic," in *Proceedings of the 23rd ITS World Congress*, Melbourne, Australia, October 2016.

[6] H. Kim, Y. Kim, and K. Jang, "Systematic relation of estimated travel speed and actual travel speed," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 10, pp. 2780–2789, 2017.

[7] Prescient & Strategic Intelligence, *ADAS Sensor Market Research Report: Industry Size, Trend, Growth and Demand Forecast to 2030*, Prescient & Strategic Intelligence, Noida, India, 2020.

[8] IRS Global, *Technology Development Trends and Business Prospects of Autonomous Things, a Strategic Technology in the Era of the 4th Industrial Revolution*, Information Research Services Global, Calabasas, CA, USA, 2019.

[9] L. C. Edie, *Discussion of Traffic Stream Measurements and Definitions*, Port of New York, New York, NY, USA, 1963.

[10] A. D. May, *Traffic Flow Fundamentals*, Prentice-Hall, Englewood Cliffs, NJ, USA, 1963.

[11] M. S. Kim, K. J. Eom, and C. W. Lee, "Density measurement for continuous flow segment using two point detectors," *The*

Journal of The Korea Intelligent Transportation Systems, vol. 8, no. 1, pp. 37–44, 2009.
[12] B. Park, C. G. Roh, C.-G. Roh, and J. Kim, "A case study of panoramic section image collection method for measuring density," *The Journal of The Korea Institute of Intelligent Transport Systems*, vol. 13, no. 4, pp. 20–29, 2014.
[13] B.-J. Park, T. Kim, I. Yang, J. Heo, and B. Son, "A method for measuring accurate traffic density by aerial photography," *Journal of Advanced Transportation*, vol. 49, no. 4, pp. 568–580, 2015.
[14] S.-G. Kim, E. Han, H.-P. Lee, H. Kim, and I. Yun, "Comparison of estimation methods for the density on expressways using vehicular trajectory data from a radar detector," *International Journal of Highway Engineering*, vol. 18, no. 5, pp. 117–125, 2016.
[15] T. Seo, T. Kusakabe, and Y. Asakura, "Estimation of flow and density using probe vehicles with spacing measurement equipment," *Transportation Research Part C: Emerging Technologies*, vol. 53, pp. 134–150, 2015.
[16] D. S. Nam, R. Lavanya, I. C. Yang, W. H. Jeon, and R. Jayakrishnan, "Traffic density estimation using radar sensor data from probe vehicles," in *Proceedings of the ITS World Congress Montreal*, Montréal, Canada, October 2017.
[17] R. Herring, P. Abbeel, A. Hofleitner, and A. Bayen, "Estimating arterial traffic conditions using sparse probe data," in *Proceedings of the 13th International IEEE Annual Conference on Intelligent Transportation systems Madeira Island*, 19-22 Sept. 2010.
[18] I. C. Yang, W. H. Jeon, H. M. Lee, and D. S. Nam, "A novel method to estimate traffic density using automotive radar sensors and deep learning algorithm," *Journal of Korean Society of Civil Engineers*, vol. 2018, no. 10, pp. 324-325, 2018.
[19] T. Z. Qiu, X. Y. Lu, A. H. F. Chow, and S. E. Shladover, "Estimation of freeway traffic density with loop detector and probe vehicle data," *Transportation Research Record: Journal of the transportation Research Board*, vol. 2178, pp. 20–29, 2010.
[20] D. Nimrod, *Mobileye: A New Approach to Transportation Management*, 2021.
[21] T. B. Lee, "Intel's mobileye has a plan to dominate self-driving-and it might work," 2021, https://arstechnica.com/cars/2020/01/intels-mobileye-has-a-plan-to-dominate-self-driving-and-it-might-work/.
[22] Korea Expressway Corporation, http://data.ex.co.kr/, 2020.
[23] S. H. Lee and J. C. Son, "Korea Highway Capacity Manual," *Ministry of Land Infrastructure and Transportation (MOLT)*, Sejong, India, 2013.
[24] PTV GROUP, *Ptv Vissim 2020 User Manual*, PTV Group, Karlsruhe, Germany, 2020.