Research Article

Potentialities of Autonomous Vehicles for Online Monitoring of Motorway Traffic Volume

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The fact that real-time autonomous vehicle (AV) traffic volume can be collected without a field detector by virtue of advanced global positioning system (GPS) and wireless communication technologies can render a promising solution to online monitoring of traffic volume in the upcoming AV era. To demonstrate this opportunity, this paper proposes a new method to monitor real-time motorway traffic volumes for road locations where no detector is installed using AV traffic volume. The modeling concept is based on the obvious fact that AV traffic volume is a direct portion of total traffic volume. The capabilities of the method are demonstrated through an experimental study using real-world GPS-enabled smartphone vehicle navigation data. The results show that online motorway traffic volume can be effectively monitored throughout the day with 5.69% average error at the 14.91% penetration rate of AVs during the daytime. Therefore, it is expected that AVs can at least be used as complementary means for the role of vehicle detectors in the near future due to the fact that the detection range of AVs is not spatially constrained.

1. Introduction

Real-time traffic volume is essential for traffic control and management in intelligent transportation systems (ITS). Since the introduction of ITS, various vehicle detectors that are based on in-roadway and over-roadway sensor technologies have been utilized to monitor traffic flow variables (i.e., volume, speed, and density). Typically, the spatially consecutive and dense deployment of vehicle detectors is utilized for the instant and accurate monitoring of the variables due to the fact that the spatial coverage of current detectors ranging from conventional inductive loop to radar sensing is constrained to fixed point or fixed short length. This surveillance strategy requires extensive budgets and resources in order to guarantee the reliability of monitored information. In addition, vehicle detectors are operated without the change of their locations in many cases after they are installed in the field.

To address these obstacles from the perspective of ITS infrastructure management and the constrained spatial coverage of vehicle detectors, several investigations to produce the three traffic variables for unmeasured points or road sections using advanced data have been introduced in our literature review. The existing studies have been focused on travel speed or density, showing remarkable and distinguished estimation accuracy according to the data used. Despite the importance of traffic volume, however, any method for dynamic traffic volume still has not been reported even under the condition of advanced data. As such, dynamic traffic volume estimation for unmeasured locations is a new research topic for solving the spatially constrained and fixed coverage of vehicle detectors and then for reducing the budgets and resources for surveillance infrastructure in modern and near future ITS.

Fortunately, it is expected that AVs play a key role as a new moving probe source by virtue of an advanced global positioning system (GPS) and communication technologies for their driving. To mine this promising opportunity, the aim of this study is to initiatively demonstrate the potential of autonomous vehicles (AVs) for producing dynamic traffic volumes for an unmeasured location by using a novel method. The proposed method in this paper is to develop
a new concept that contracts and then expands AV traffic volumes into overall traffic volumes. In addition, based on the analysis results, some findings and research directions for the online monitoring of traffic volume in the present and near future era are discussed.

2. Literature Review

Despite advanced vehicle detection technologies in modern ITS, it seems that the measurements are insufficient due to constrained space coverage (i.e., fixed point or short-length detection area) and the high costs of installation and maintenance. To address these hindrances, academic investigations to dynamically estimate three traffic flow variables (i.e., volume, speed, and density) have been conducted using advanced (probe) data. Note that the literature review of this paper is focused on academic research in which real-world advanced data was employed to produce the three variables.

For the dynamic measurement of travel speed or time, four types of probes have been employed: automatic vehicle identification (AVI) [1], vehicle-based GPS mobile sensor [2, 3], cellular phone (CP) [4–6], and GPS-enabled CP [7, 8].

Probe data that is collected from AVI or vehicle-based GPS mobile sensor systems was employed as a direct portion of vehicle travels in [1–3]. AVI probe data from the San Antonio TransGuide system was employed for estimating average link travel time in [1]. The study demonstrated that a low sampling rate, less than 1%, can represent average link travel time effectively. Travel speed was estimated using GPS-based taxi probe data in [2, 3]. The two studies indicated that imperfect probe data can be used for monitoring traffic status in practice. The results of the two studies in [1, 2] are similar to [9, 10] in terms of a minimum sampling rate of 1–3%.

CP probe data based on tracking CP footprints in a cellular communication network was used to measure travel speed and time between freeway locations in [4–6]. The potentialities of a CP-based system for monitoring traffic status were demonstrated. Despite the reliable measurement accuracy of the CP probe, research indicated in [4] that the noise of the CP probe should be addressed successfully. The noise problem occurs when travel speed is low. Thus, CP-based monitoring systems are suitable for a high-speed roadway such as a motorway [5]. The measurement accuracy was highly improved through an advanced tracking algorithm in [6]. The CP-based system only measures traffic status between two fixed cells (i.e., antennas), as the system totally relies on the geographical configuration of cells. Therefore, the CP-based system is not suitable for measuring traffic status in an urban road network.

Noticeably, two studies demonstrated that the spatiotemporal dotted trajectory of an individual GPS-enabled smartphone can be employed as an effective traffic probe to measure accurate traffic status in [7, 8]. The two studies proved that a 2–3% penetration of GPS probes in the driver population is sufficient to measure accurate traffic speed [7]. The uncertainty of speed measurements caused by the noise of a GPS signal was effectively addressed in [8]. The study showed that the behaviors of speed measured by smartphone trajectory are statistically the same as those of actual speed. The strength of the trajectory probe is suitable for various measurements of traffic status without spatial constraints.

A few studies for estimating traffic density [11] and hourly traffic volume [12, 13] have been reported. A combination method of a kinematic wave model and a probability model for dynamically estimating traffic density was developed based on reconstructing individual vehicle trajectory using heterogeneous data (loop detector, AVI probe, and GPS probe data) in [11]. An innovative methodology for estimating hourly traffic volumes using cellular-phone call count and its probability crossing intercell boundaries was proposed in [12, 13]. The two studies demonstrated that cellular-phone call data can be employed for inferring hourly traffic volumes, where the resulting estimation error was 20%. Despite the initiative efforts, it can be seen that more accuracy should be achieved with more short time length such as a level of five-minute data aggregation for the applications of ITS.

Based on the literature review on the dynamic estimation of the traffic variables using advanced probe data, several studies for traffic speed and density have reached an acceptable level in terms of estimation accuracy. However, more investigations of traffic volume need to be performed at a level of acceptable accuracy. In a strict sense, research for estimating dynamic traffic volumes has not been reported or highly correlated using advanced probe data that is a direct portion of traffic volume. In addition, the dynamic evolution of traffic volume behaves like a chaotic system [14, 15]. That is, a time-series of traffic volume data naturally reveals intensive and wide fluctuations in ergodic and nonperiodic manners. This fact makes it difficult to directly estimate reliable traffic volumes by using either direct low probe data from a GPS-enabled vehicle or indirect probe data from a GPS-enabled mobile phone. More importantly, a new approach should be developed, which is capable of adaptively recognizing the temporal evolution of traffic volumes even in the case when the penetration rate of probe data available to traffic volume is low. In this context, the direct monitoring of dynamic traffic volume using the trajectory probe data of AV is one of new research directions in modern ITS.

3. Methodology

3.1. Approach Concept. The operation of AVs should be supported with advanced GPS and communication technologies. That is, AVs that are on a driving service can be considered a moving GPS probe in a road network. It is also surely expected that detailed point-to-point operation trajectory data can be stocked by virtue of the GPS technology, and then the trajectory data can be transferred to an advanced data centre through the communication technology online. This develops the assumption that AV probe volume is a direct portion of total traffic volume or at least is very highly related to that in some way. If this assumption is reasonable, then traffic volume at a target road location can be produced using a suitable relationship between probe volumes and traffic volumes that are collected from the nearby locations of the target road location. Moreover, the AV trajectory data is not spatially constrained unlike existing vehicle detectors, and thus, the probe volume can be accurately monitored at any
road location. This implies in turn that traffic volume at any road location (used by AVs) can be effectively monitored using the probe volume. Therefore, it is expected that AVs render golden opportunities against the traffic surveillance system of modern and future ITS.

To demonstrate the potential of AVs for the real-time monitoring of traffic volume, a new method to produce dynamic traffic volume at any road location using AV probe volume data is proposed in this study. The method is developed on the basic concept that probe volume data provide key information to solve the uncertainty problem in the direct monitoring of traffic volume. This modeling approach is also supported by the fact that probe volume is at least a direct portion of traffic volume. The method consists of two modeling concepts: contraction and expansion of probe volume. In the contraction method, time-series probe volume data are adjusted into suitable data by eliminating its unnecessary random noise. The method also adaptively interpolates zero probe volume values into useful values, because zero probe volume values inevitably occurs when either traffic volume and/or the penetration rate of AV is low. In the expansion method, an adjusted probe volume at a road location where a traffic volume estimation is desired is converted into a traffic volume value by using a relationship between adjusted probe volumes and traffic volumes. As such, the combination of the two methods can solve the problem of direct monitoring traffic volume efficaciously by diminishing the number of uncertainties that inevitably occurs in solving this problem.

3.2. Contraction Method. It is natural that the temporal evolution of AV probe volume reveals more wide relative variations than that of overall traffic volume under the condition that the penetration rate (0.0–1.0) of AV to traffic volume is less than 1.0. This is because the probe volume is a sort of random sample with a given penetration rate. In this case, undesirable estimation results (i.e., over- and under-estimation problems) are unavoidable when a time series of probe volume data that includes the random-sampling variation in itself is directly used for the monitoring of traffic volume without any filtering process. This problem becomes more serious when the sampling variability of collected temporal probe volumes increases under the condition of low AV penetration rates and/or low traffic volumes. Zero probe volumes can also occur frequently, even when traffic volumes are low and AV penetration rates are not low.

To address this problem effectively and to ensure the reliability of traffic volume monitoring, two processes that adjust raw probe volumes into suitable probe volumes are essentially required as follows: unnecessary random variations that intrinsically exist in raw probe volumes should be filtered; and zero probe volume values should also be interpolated with useful values. The two processes are concurrently conducted by a contraction method proposed in this study.

The contraction method is devised based on the assumption that the temporal variation of actual traffic volumes is highly related to that of raw probe volumes. This assumption could be reasonable if the raw probe volume that includes random-sampling variation is a part of the traffic volume.

Thus, the unnecessary variation of raw probe volumes can be removed by using the distribution of relative variation (RV) of raw temporal probe volumes and that of RV of temporal traffic volumes. To measure time-series RV values, time-series values and moving-average values for traffic volume and probe volume are defined as follows. Let \( s = \{tg, up, dn\} \) be the target location (tg) and the upstream and downstream of tg, respectively. Let \( x = [q, p] \) be a set of traffic volume (\( q \), vehicles per length of time interval) and probe volume (\( p \), vehicles per length of time interval). Let \( X = \{Q, P\} \) be time-series sets of \( x \). Note that a form of time series (i.e., a series of time intervals) at the present time interval \( t \) toward the past is defined as \( T = [(t), (t - 1), \ldots, (t - d)] \), where \( d \) is the embedding size of time series. Let \( X_s = [x_s(t), x_s(t - 1), \ldots, x_s(t - d)] \) be a time series of \( x \) for \( s \). Let \( X_s^b = [x_s^b(t), x_s^b(t - 1), \ldots, x_s^b(t - d)] \) be a time series of moving-average values for \( X_s \) and \( s \), where each element of \( X_s^b \) (i.e., \( x_s^b(t) \)) is calculated as \( \frac{\sum_{k=0}^{m} x_s(t - k)}{m + 1} \) with \( m \geq 1 \), \( (\forall x, s, \text{ and } i \in T) \). Let \( R_s^T = \{r_s^T(t), r_s^T(t - 1), \ldots, r_s^T(t - d)\} \) be a time series of RV values for \( X_s \) and \( s \). Thus, each element of \( R_s^X \) is computed using each element of \( X_s \) and that of \( X_s^b \) (where if \( s = tg \), then \( X \neq Q \)), as follows:

\[
r_s^i(i) = \frac{x_s(i) - x_s^b(i)}{x_s^b(i)}, \quad \forall s, x, i, \ i \in T
\]  

(1)

Figure 1 shows the RV distributions of traffic and probe volumes (i.e., \( R_s^Q \) and \( R_s^P \)), where the variance of probe volume is greater than that of traffic volume. The RV distribution of probe volume can be adjusted similar to that of traffic volume using the standard deviation. This statistical principle is employed to modify a variation of temporal probe volumes. Let \( \sigma_s^X \) be the standard deviation of \( R_s^X \) (where if \( s = tg \), then \( X \neq Q \)). Let \( P_s^T = [p_s^T(t), p_s^T(t - 1), \ldots, p_s^T(t - d)] \) be a time series of adjusted probe volumes for \( s \). Finally, each element of \( P_s^T \) is estimated based on each component of \( p_s^T \) and the rate of \( \sigma_s^Q \) to \( \sigma_s^P \) as

![Figure 1: Distributions of relative variation.](image)
Thus, each probe volume \( p_i(t) \) is contracted into \( p^s_i(t) \) by removing unnecessary random-sampling variation. Additionally, \( p^s_i(t) \) is effectively generated in the case of a low value of \( p_i(t) \), and \( p_i(t) \) is also interpolated with a useful value even when \( p_i(t)=0.0 \), if \( p^s_i(t) > 0.0, \sigma^s_i > 0.0, \) and \( \sigma_i > 0.0 \).

Due to the fact that no traffic volume is collected at the target location, it is impossible to directly compute the adjusting factor (i.e., the rate of \( \sigma_i \)). To prevent these undesirable results, a power curve (i.e., \( \sigma_i \)) for temporal nonstationarity can be expressed as

\[
\sigma_i = \frac{(p^b_i(t) - p^s_i(t))^2}{\sum_i c_i^{-1}},
\]

\[
\sum_i c_i^{-1}
\]

\( s \neq t \), \( t \in T \)

As such, \( p_{tg}(t) \) is modified into \( p^s_{tg}(t) \) by using the two adjusting-factor values (i.e., \( \sigma^Q_i / \sigma^s_i \)) and the inverse of \( c_i \) (i.e., \( c_i^{-1} \)). Furthermore, \( p^s_{tg}(t) \) is robustly estimated when a value of \( p_{tg}(t) \) is very low, and \( p_{tg}(t) \) is also interpolated with a useful value even when \( p_{tg}(t)=0.0, \) if \( p^b_{tg}(t) > 0.0, \) and \( \sigma_i > 0.0 \).

### 3.3. Expansion Method

To expand the contracted probe volume (i.e., \( p^s_{tg}(t) \)) to a traffic volume (i.e., \( \tilde{q}_{tg}(t) \)) for the target location \( (tg) \) at time interval \( (t) \), a weighted power curve is employed to determine a relationship between contracted probe volumes (i.e., \( p^s_i(t), s \neq t, i \in T \)) and traffic volumes (i.e., \( p_i(t), s \neq t, i \in T \)) in this study. The expansion method is stated according to two parts: a weighting function and the determination of an optimal fitting curve. From the perspective of temporal development of traffic flow, it is self-evident that the temporal evolution of traffic flow nearer to \( (t) \) is more related to traffic flow at \( (t) \) [14–16]. This is considered with the bisquare weighting function that was introduced to explain nonstationary relationships between spatial elements in [17]. Let \( W_t = [w_i(t), w_i(t-1), \ldots, w_i(t-d)] \) be a series of weight values (0.0–1.0) for \( T \). The variation of weight value according to the proximity of time is illustrated in Figure 2(a), which can be efficaciously used in the case that the penetration rate of AV varies according to the time periods of day (e.g., peak and off-peak time). The bisquare function for temporal nonstationarity can be expressed as

\[
w_i = \left[ 1 - \left( \frac{i}{d} \right)^2 \right]^2, i = 0, 1, \ldots, d
\]

In order to find an optimal power curve, traffic volume data and contracted probe volume data for upstream and downstream locations are used as a dependent variable and an independent variable, respectively. The dependent and independent variables are defined as follows. Let \( Q = [Q_{tg}, Q_{dn}], \) and \( P = [P^a, P_{dn}] \) be sets of traffic volumes and adjusted probe volumes for the upstream and downstream locations, respectively. In addition, let \( W = [W_{up}, W_{dn}] \) be a set of weight values for the two locations. For the convenience of the description of the expansion method, these definitions are redefined with the number of observations \( (N=2\times(d+1)) \). Let \( Q = [q_1, q_2, \ldots, q_N] \) and \( P = [p_1, p_2, \ldots, p_N] \) be dependent and independent variables, and let \( W = [w_1, w_2, \ldots, w_N] \) be a set of weight values.

The temporal evolution of traffic volume states reveals intensive variation in ergodic and nonperiodic manners [14, 15]. Hence, it is natural that the temporal variation of probe volumes varies more steeply and widely than that of traffic volumes, even though the probe is a direct part of traffic volume. Thus, if a linear regression model is employed, then unacceptable results (e.g., repetitive overestimations and underestimations, and even negative estimations) can occur by failing the directionality of relationship between \( P \) and \( Q \). To prevent these undesirable results, a power curve with versatility in curve fitting (ranging from logarithmic, linear, to positively exponential types) is used to understand the relationship between the two variables as shown in Figure 2(b). The power curve for the members of \([P, Q]\) (i.e., \([p_i, q_i], i \in N\)) is defined as

\[
q_i = \alpha \cdot p_i^\beta + \gamma
\]

where \( \alpha (>0.0) \) and \( \beta (>0.0) \) are the coefficient and exponent of \( p_i \), respectively; \( \gamma (0.0 \leq \gamma \leq \gamma_{max}) \) is a constant term; \( \gamma_{max} = \min(Q_i) \); and \( Q_i \) is an average of elements of \( Q_i \), where \( s = \ldots \)
\{up, dn\}. To prevent negative estimations, $\alpha$ is greater than 0.0 and $\gamma$ is greater than or equal to 0.0. $\beta$ is greater than 0.0 and $\gamma$ is less than or equal to $\gamma_{\text{max}}$, since traffic volumes do not decrease according to the increase of probe volumes. For an optimal curve that minimizes total estimation error, a local error for each observation can be expressed as

$$
e_i = q_i - (\hat{\alpha} \cdot p_i^{\hat{\beta}} + \hat{\gamma})$$

where $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ are optimal $\alpha$, $\beta$, and $\gamma$ values, respectively, and $e_i$ is the estimation error for observation $i$, $i \in N$.

As mentioned, temporal traffic volumes fluctuate widely, and then the quantity of traffic volume varies from low to high levels. Thus, a family of the residual sum of squares that are widely employed as an objective function for determining an optimal fitting can have a ‘bias and variation problem’ in the case of low traffic volumes [18]. That is, the low traffic volume can be over- or underestimated, due to its low contributions in decision-making of an optimal curve fitting.

To handle this problem effectively, the sum of a weighted absolute relative error is used as an objective function of a minimization problem to determine an optimal power curve. The absolute relative error also provides an unbiased basis [18], and thus, it is widely used as a performance measure in the area of time-series estimation and prediction. Here, a minimization problem for determining an optimal expansion curve is defined as

$$\text{Min.} \quad \frac{\sum_{i=1}^{N} w_i \times |q_i - (\hat{\alpha} \cdot p_i^{\hat{\beta}} + \hat{\gamma})| / q_i}{\sum_{i=1}^{N} w_i}$$

S.T. \quad 0.0 < \hat{\alpha},

\quad \quad \quad 0.0 < \hat{\beta},

\quad \quad \quad 0.0 \leq \hat{\gamma} \leq \gamma_{\text{max}} \quad (8)

Once, the estimated values of $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ for an optimal curve are identified through solving the minimization problem, a traffic volume for $tg$ at $(t)$ is directly produced as

$$\hat{q}_{tg}(t) = \hat{\alpha} \cdot p_{tg}^{\hat{\beta}} + \hat{\gamma}$$

where $\hat{q}_{tg}(t)$ and $p_{tg}^{\hat{\beta}}(t)$ is the estimated traffic volume and the adjusted probe volume for $tg$ at $(t)$, respectively.

4. Results and Potentialities

4.1. Study Design. In order to demonstrate the potential of GPS probe data collected by autonomous vehicles, a case study was conducted using two types of data: GPS probe volume data and traffic volume data. The GPS probe data that was collected by a smartphone vehicle navigation system is most similar to the probe data of autonomous vehicles under the present conditions, due to the fact that the vehicle-probe volume is a direct portion of traffic volume. In this context, it seems at least that the used probe data contains the characteristics of probe data that are collected through autonomous vehicles, even though the features of mixed traffic flow with general vehicles and autonomous vehicles have not been investigated with real-world data so far. The used motorway data is shown in Figure 3. The test bed is a part of the Seoul External Circulation Motorway 100, one of the main motorways in South Korea. The target road location consists of four lanes, and the upstream road section includes one interchange and one junction and the distance is 11.6 km. The downstream road section contains two interchanges and four junctions and the distance is 25.6 km. It can be seen that the test-bed conditions are unfavorably severe for the experimental condition, whereas the test-bed conditions are desirable to demonstrate the potential of the
proposed method in this paper. One-week individual point-to-point trajectory data was collected on December 24-30, 2016. The individual data was aggregated with a 5-minute interval. In addition, traffic volume data with a 5-minute aggregation was collected by an electronic toll collection system.

The temporal evolution of the two types of data are shown in Figure 4. The traffic volume varies from 27 to 442, and its temporal development reveals intensive variation in terms of relative percentage difference (RPD) (%), \(\frac{x(t + 1) - x(t)}{x(t)} \times 100\). RDP values range widely from -21.10 to 39.27. Regarding the probe volume ranges from 0 to 82, the RDP values vary from -100.0 to 800.0 except for a zero probe volume. As such, it is obvious that the temporal evolution of probe volumes exhibits more intensive and steep variation than that of traffic volumes by means of RDP. Despite these intensive variations, the statistical correlation between the two types of data is up to 0.933. This fact directly indicates that the probe volume is a direct portion of traffic volume and can reflect the features of traffic volume in some way.

Figure 5 shows the penetration rate (PR) of probe volume to traffic volume, where PR = \(\frac{\text{probe volume}}{\text{traffic volume}}\). PR widely varies spanning from 0.06 to 0.25 with an average of 0.149. It seems that the evolution behavior of PR according to traffic volume is near to a mixed state but also has a closed boundary condition. The width of variation becomes narrower when traffic volumes increase, due to the fact that the sampling variability decreases when either the sample size (i.e., probe volume) increases or the variance of population (i.e., traffic volume) decreases. Moreover, a trend curve of PR shows logarithmic growth and increases when traffic volumes increase. This is because drivers have a tendency to use more vehicle navigation systems when their travel distance increases and because traffic congestion usually occurs at daytime.

To measure the performance of the propose method in this paper, the following four performance measures were carefully selected. Absolute percentage error (APE, %) and relative percentage error (RPE, %) provide a useful basis for comparison when traffic volume varies widely \([15, 16]\). APE and RPE have a weakness in the case of low traffic volume, as the relative temporal variation of low traffic volume is high. In this vein, straight error for lane (SEL, vehicles per lane), which can be useful in practice, is introduced in this study. The hit rate, one of crucial performance measures for real-life applications, was also utilized with RPE and SEL. In addition, the mean of APEs was employed to analyze and identify the optimal parameter values (i.e., \(d\) and \(m\) values)
of the presented method. APE, RPE, and SEL are expressed as

\[
\text{APE} = \frac{\hat{y}_i - y_i}{y_i} \times 100, \quad y_i > 0.0 \quad (10)
\]

\[
\text{RPE} = \frac{\hat{y}_i - y_i}{y_i} \times 100, \quad y_i > 0.0 \quad (11)
\]

\[
\text{SEL (veh)} = \frac{\hat{y}_i - y_i}{l} \quad (12)
\]

where \(y_i\) and \(\hat{y}_i\) is the observed value and the estimated value of sample \(i\), respectively, and \(l\) is the number of lanes.

4.2. Results and Findings. The proposed model was developed based on the combination of the contraction and conversion method (C2C). Hence, the performances of the C2C method are highly dependent on the \(m\) and \(d\) values in terms of estimation accuracy. The \(m\) and \(d\) values contribute key roles to contract the temporal variation of probe volumes, and the \(d\) value highly influences the determination of optimal curve fitting. The effects of the combination of the two parameter values on estimation accuracy are shown with estimation error rates in Figure 6. As for the \(m\) value, the estimation error curve steeply decreases \((m=3 \rightarrow 9)\) and then stays \((m=9 \rightarrow 11)\) at the optimal error space and then increases \((m=11 \rightarrow 18)\) when the \(d\) values are greater than 9. This indicates that a locality of temporal evolution of probe or traffic volumes exists in terms of moving average, even though the temporal development of probe and traffic volumes reveals intensive and steep variations. Regarding the \(d\) value, the estimation error exponentially decreases to the optimal error space and then gradually increases when the \(d\) value increases with little variation. This indirectly implies that a locality of temporal evolution of probe or traffic volumes exists in terms of determination of optimal relationship between probe and traffic volumes, whether the boundary condition is obvious or not. The optimal error space is very stable within a minimal error +0.5%, which indicates that suitable parameter values can be analyzed and determined within the margin of error on a daily or monthly basis in advance.

In addition, the optimal \(m\) and \(d\) values of 10 and 14, respectively, were selected for more analysis.

Two relationships between \(\alpha\) and \(\beta\) values according to \(\gamma\) values are shown in Figures 7(a)-7(b), where the explanatory power of probe volume data is divided into two regimes with an obvious boundary condition. As for \(\gamma=0.0\), the \(\beta\) value exponentially decreases when the \(\alpha\) value increases, showing a high relationship with the \(R^2\) value of 0.93. The cases of \(\beta < 1.0\) reach to 83.02%. This means that the relationships between probe and traffic volumes are logarithmic in many cases. This fact also indicates that negative estimations inevitably arise in the case of very low probe volume if a linear relationship is used, which is directly connected to the prediction failure. Regarding the case of \(\gamma > 0.0\), the \(\beta\) value steeply decreases according to the increment of the \(\alpha\) value, and the two parameters are more highly connected than the upper relationship by means of \(R^2\). The cases of \(\beta > 1.0\) are up to 91.90%. This indicates that the relationships between probe and traffic volumes are upward in many cases. This fact also implies that the underestimation problem unavoidably occurs when probe volume is very low if a single linear relationship is employed. Therefore, it can be seen in our case that if a linear model is used, estimation failure inevitably occurs in the case of low traffic volume except for a few cases of \(\gamma > 0.0\).

Figure 8 demonstrates the time-series variations of raw probe volumes and contracted probe volumes. Extreme variations, which can cause undesirable estimation results, are adjusted within the range of temporal variations of traffic volumes. The standard deviation of the RDP (SDRDP) of raw probe volume is 76.94%, whereas that of filtered probe volume is 7.73%. Similarly, adjustment gain is up to 89.95% \([=(76.94-7.73)/76.94 \times 100]\). The SDRDP value of adjusted probe volume is also similar to that of traffic volume (7.45%). This suggests that extreme estimations can be effectively prevented through the contraction of temporal variation of probe volumes.

The relationships between probe volumes and traffic volumes for the before and after cases are shown in Figure 9. The contraction method effectively improves the relationship of the two variables in terms of \(R^2\), where the \(R^2\) value increases from 0.84 to 0.95. It can be seen at least that this result is acceptable, even considering that the natural attribute of \(R^2\) increases when the number of observations increases. Specifically, the effect of variation contraction is distinguished in the case when traffic volumes are less than 100. This is because temporal traffic volumes exhibit less variation than that of probe volumes as shown in Figure 4. In the same context, the explanatory power of probe volumes is remarkably improved when traffic volumes are greater than 300.

The analysis results are summarized with three traffic volume regimes in Table 1, showing noticeable performances.
For all regimes, it can be seen that the accuracy performance of the C2C method is at least comparable to those of modern vehicle detectors in terms of the mean of APE (MAPE, %), 5.69%. Note that the accuracy performances of traffic counting for inductive loop, laser scanner, weight-in-motion (WIM) piezoelectric, and WIM quartz detectors in the case of 5-minute data aggregation were reported as 10.6, 24.1, 7.4, and 17.6% by means of MAPE, respectively [19]. The worst performances for APE and RPE measures are shown in the low-volume regime, excluding SEL as shown in Figures 10 and 11. The APEs are greater than 20% for several cases, which is undesirable from the standpoint of forecasting. Note that the tolerable detection error in the case of vehicle detectors should not vary from actual volumes by more than 20.0% [12]. Despite these undesirable performances, forecasting for the low regime can be also acceptable with the maximal SEL of 4.73, which is almost equal to one vehicle per one minute in practice. The hit rate within RPE±10% does not reach 90.0% for all regimes, whereas the hit rate within SEL±10 vehicles are up to 98.86%. On the contrary, in the cases of middle and heavy volume regimes, the APE values are less than 10.0% in most cases as shown in Figure 10, where the temporal variation of estimations concurs with that of the observations. The hit rate within RPE±10% is also up to 91.27%. In addition, the hit rate within RPE±20.0% for the middle and heavy regimes reaches 99.61% (Figure 11(a)). Moreover, the worst cases that span to -32.32% or +32.60% occur in the late-night hours, even though they are acceptable in terms of SEL within ±3.0 vehicles (Figure 11(b)). Note that the accuracy performances of the proposed method for the case of low traffic volume are comparable to those of pattern selection-based single-interval forecasting [15, 16] in terms of MAPE. Therefore, traffic volumes estimated from AV probe volumes can also be regarded as a promising option for traffic volume detection.

4.3. Present and Future Potentialities. For more real-world applications in the present and near future, more analysis for the potential of the C2C method was conducted through both the data-aggregation level and the penetration rate of AVs. Figure 12 shows the performances of the hit rate within RPE±10% according to data-aggregation levels. Note that accuracy performances (MAPE) for inductive loop, video image, laser scanner, WIM piezoelectric, and WIM quartz detectors in the case of 15-minute data aggregation were reported as 9.4, 34.1, 19.8, 5.7, and 12.3, respectively [19]. As for the 10-minute aggregation level, the hit rate reached 88.39% with the MAPE of 4.85% for all regimes and was up to 94.65% with the MAPE of 3.77% when traffic volume (vehicles/10 min) is greater than 200. In regard to the 15-minute and 30-minute aggregation levels, it can be seen that the performance of the C2C method is obviously comparable to the required detection accuracy for modern vehicle detectors. Accordingly, it is expected that the C2C method for directly monitoring traffic volumes can at least be feasible...
Table 1: Summary of the results.

| Performance Measures | All regimes Cases (volume) | Low regime (cases <100) | Middle regime (cases 100–300) | Heavy regime (cases ≥300) |
|-----------------------|---------------------------|-------------------------|-------------------------------|---------------------------|
| APE (%)               | Mean: 5.69               | 9.93                    | 6.08                          | 3.45                      |
|                       | Max: 32.60               | 32.60                   | 21.62                         | 15.74                     |
|                       | Median: 3.98             | 8.41                    | 5.04                          | 2.73                      |
| RPE (%)               | Mean: 0.17               | 0.47                    | 0.22                          | -0.01                     |
|                       | Max: 32.60               | 32.60                   | 21.62                         | 15.74                     |
|                       | Min: -32.32              | -32.32                  | -12.53                        | -12.53                    |
|                       | SD: 7.91                 | 12.51                   | 7.67                          | 4.42                      |
|                       | HR±10%: 83.28            | 57.80                   | 80.45                         | 97.01                     |
|                       | HR±20%: 96.83            | 87.94                   | 98.87                         | 100.00                    |
| SEL (veh)             | Mean: -0.01              | 0.02                    | 0.12                          | -0.10                     |
|                       | Max: 14.00               | 4.73                    | 12.87                         | 14.00                     |
|                       | Min: -12.07              | -6.02                   | -12.07                        | -11.89                    |
|                       | SD: 3.45                 | 1.49                    | 3.74                          | 3.92                      |
|                       | HR±5 veh: 85.07          | 99.79                   | 82.52                         | 79.36                     |
|                       | HR±10 veh: 98.86         | 100.00                  | 98.87                         | 98.31                     |

Note: SD stands for standard deviation.

Figure 9: Efficacy of the contraction method.

as complementary means for the role of vehicle detectors if vehicle trajectory data is available with the penetration rate of 0.15%. Moreover, the levels of estimation reliability can be flexibly considered and employed according to the various tactics of traffic operation and control.

In order to demonstrate the potentialities of AV probe volume according to the penetration rate of AVs in the near future, we conducted a random simulation to generate temporal probe volume data. The penetration rate of the probe data used in our case study was employed for the basis of the probability of random selection (rather than a simple random sampling) to consider actual sampling rate. In addition, it is not easy for a random-sampling method to realistically mimic the temporal evolution of probe volumes while considering that of traffic volumes, due to the chaotic behaviors of traffic flow as mentioned before. The probability of selection was computed as

\[ p_{sel} = \frac{PR_d}{PR_r} \]

where \( p_{sel} (0.0-1.0) \) is the probability of selection, \( PR_r (0.0-1.0) \) is the real-world penetration rate of probe volume to
traffic volume, and $RP_d (0.0 \leq PR_d \leq PR_r)$ is a desired penetration rate. Thus, a random sample value for each time interval ($t$) was generated by using $p_{sel}$ and a probe volume at ($t$). 14 scenarios of $p_{sel}$ from 0.01 to 0.14 were repeated twenty times for each probe volume data for the day time (06:00-24:00).

Figure 13 shows the performances of the C2C method according to each scenario with the median of 20 MAPE values. The estimation errors exponentially decrease when the penetration rate increases. The span of errors also decreases from 1.80% to 0.16% as the penetration rate increases. Based on the results, it can be seen that the monitoring accuracy of 93.77% can be accomplished within the maximum average error of 6.63% at the penetration rate of 0.05. In addition, it seems that the penetration rate of 0.10 can yield the monitoring accuracy of 94.78%. These analysis results suggest that the direct monitoring of real-time traffic volumes can be realized since the introduction of AVs to real roadways. There are also obvious possibilities that the monitoring accuracy can be improved dramatically according to the results of this study, where the error curve does not converge within a minimum error space. Furthermore, the probe volume of autonomous vehicles can be combined with that of a smartphone car navigation system (or a vehicle-GPS system) to guarantee the monitoring accuracy of real-time traffic volume until the market occupancy of AVs reaches a suitable level.

5. Conclusion Remarks

It is expected that autonomous vehicles can render new solutions to fundamental hindrances and unsolved academic issues in modern ITS. One of the fundamental hindrances is vehicle detectors that are essential for real-time traffic surveillance, which requires extensive budgets and resources in order to guarantee the reliability of monitored information. In addition, their spatial coverage of detection is constrained to fixed point or fixed short length.
To realize this opportunity, a new concept for direct real-time monitoring was initiatively introduced in this paper. Using real-world probe volume data collected from a smartphone car navigation system, the potentialities of autonomous vehicles for direct monitoring of traffic volumes for road locations where real-time traffic volumes are desired were demonstrated with a novel and practical approach. The results were noticeable in terms of explanation of temporal variation of real-life traffic volumes. It turned out that the monitoring accuracy of the developed method is at least comparable to the actual detection accuracy of modern vehicle detectors, and it can reliably meet the required detection accuracy of vehicle detectors. Therefore, it can be seen that the direct monitoring of traffic volume is one of promising approaches to solve the current hindrance of traffic volume surveillance. In addition, the developed method is instantly feasible when probe volume data is available at least with the penetration rate of 0.05.

This study contributes a first step in proposing a promising solution to the direct monitoring of real-time traffic volumes. Despite the meaningful results of this research, there are other opportunities in direct real-time monitoring of traffic flow for unobserved road locations with advanced methodologies. We are still conducting investigations to improve the performance of the method and are searching for new potentialities in modern ITS.
Data Availability

The smartphone vehicle navigation data used to support the findings of this study were provided only for academic research by SK Telecom.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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