Deriving the Vehicle Speeds from a Mobile Telecommunications Network

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***Abstract*—Vehicle speeds are often measured by *intelligent transportation systems* (ITSs) by utilizing sensors or software solutions. Our previous work proposed the *Lin–Chang–Huangfu* (LCH) scheme to compute the cell residence times by the standard counter values in mobile telecommunications switches. In this paper, we use mathematical and statistical developments to investigate the accuracy of the LCH scheme by deriving the bias of the cell residence times computed in this scheme. Then, we extend the LCH scheme with some filtering and compensation techniques for vehicle speed estimation and validate our approach with vehicle detector (VD) measurements at National Highway 3, Longtan Township, Taoyuan County, Taiwan. Our study indicates that the LCH scheme is an effective approach to vehicle speed estimation.**

***Index Terms*—Lin–Chang–Huangfu (LCH) scheme, mobile switching center (MSC), telecommunication, vehicle speed.**

I. Introduction

MOST *intelligent transportation systems* (ITSs) measure vehicle speeds to assist drivers in estimating travel times and to avoid traffic jams. To provide this service, an ITS server is responsible for collecting and computing vehicle speeds. This traffic information can be accessed by users through networks such as the Internet.

The ITS server can obtain traffic information from a mobile telecommunications network. The intuition behind this approach is described as follows. When a person runs faster, the person passes telephone poles on the side of the road more frequently. Similarly, when a car travels down a road, it will pass cell phone towers [base stations (BSs)] more often. The length of time a cell phone is connected to a particular BS will vary inversely with speed. In fact, the speed of the vehicle can be estimated just by dividing the length of the road covered by a particular BS by the difference between the time when it left the cell (radio coverage of the BS) and when it entered that cell.

Information about when "handing over" from one BS to another is available in the mobile telecommunications network so that the speed can be estimated if the intersections of cells relative to the road on which is being travelled is also known. Of course, the vehicle itself already has more accurate means of estimating its velocity, but speedometer readings are not typically accessible externally. In addition, the *Global Positioning System* (GPS) provides a much more accurate method of estimating speed, but running GPS continuously takes a lot of power, and some cell phones do not even have a GPS receiver. The alternative method based on frequency of handovers could provide speed estimation for map-based information on traffic to other travelers. Such a system would require installation of a central server (i.e., the ITS server) to gather all the information and to make the resulting summary traffic information available over the Internet. These statistics include 1) the number of handovers into each cell, 2) the number of handovers out of each cell, and 3) the total voice traffic. Here, voice traffic is measured as the sum of the call holding times for all calls.

Our previous work [1]–[3] proposed the *Lin–Chang–Huangfu* (LCH) scheme to estimate the cell residence time (the time periods that user equipment (UE) stays in the cells) by the ratio of the voice traffic and the number of handovers into the cell. The cell residence time in turn can be used to estimate the speed. This paper is a major extension of our previous conference paper [4]. We compute the cell residence times of the LCH scheme to estimate the vehicle speeds and validate the LCH scheme with the vehicle detector (VD) measurements at National Highway 3, Longtan Township, Taoyuan County, Taiwan. A major contribution of this paper is the investigation on the bias for the cell residence times computed by the LCH scheme. This kind of bias derivation has not been found in the literature, which shows that the LCH scheme is an appropriate approach to vehicle speed estimation.

This paper is organized as follows. Section II describes the related work. Section III describes how the LCH scheme computes the cell residence times. Section IV derives the bias of the cell residence times computed by the LCH scheme. Section V proposes several techniques for improving the

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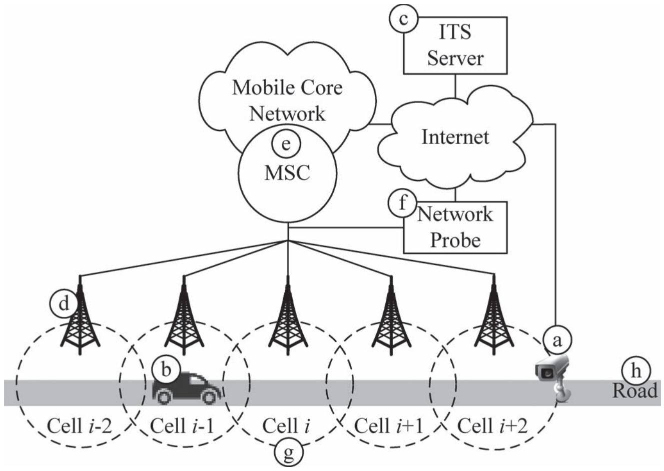

Fig. 1. Simplified mobile telecommunications network architecture.

accuracy of the vehicle speed estimation. Section VI investigates the performance of the LCH scheme by numerical examples, and the conclusions are given in Section VII.

II. Related Work

The vehicle speed measurement approaches can be classified into three categories.

- VDs [5]: The VDs [see Fig. 1(a)] are installed in roads to measure the speeds of the vehicles [see Fig. 1(b)], and the speeds are reported to the ITS server [see Fig. 1(c)] through a wireline or a wireless network.
- *GPS-based vehicle probes* (GVPs) [6], [7]: The *user equipment* (UE; i.e., mobile devices) in the vehicles are equipped with GPS receivers, which send the GPS coordinates and time information through the mobile telecommunications network [i.e., the BSs in Fig. 1(d) and the *mobile switching center* (MSC) in Fig. 1(e)] to the ITS server. The ITS server computes the speeds according to the received GPS coordinates.
- *Cellular floating vehicle data* (CFVD) [8]–[10], [16], [17]: The network probes [see Fig. 1(f)] are installed to monitor the signals between the BSs and the MSC and then to send them to the ITS server. The network probe also replaces the user identities and the phone numbers in the signals by their hash values from the one-way hash function to protect the user privacy [18]. Based on the call activities of the UE devices, the ITS server tracks the locations of the UE devices at the cell level and estimates the cell residence times of the UE devices to derive their moving speeds.

The VD approach is typically deployed by the transportation department of the government. On the other hand, the GVP and CFVD approaches are typically developed by the telecommunication operators. The VD approach suffers from high construction and maintenance costs for detectors [8], [10]. The GVP approach requires that the UE devices are equipped with the GPS receivers, and it consumes extra radio resources to transmit the GPS data. Furthermore, our experience (with Chunghwa Telecom) indicates that not many vehicles with GPS receivers travel in some suburb/country roads, and the traffic information for these roads is difficult to obtain from the GPS data. Therefore, the GVP approach is typically used in urban areas. For suburb/country areas, the vehicle speeds are obtained by the CFVD approach, which requires extra signaling links and network probes in the mobile telecommunications network to monitor the signaling messages delivered between the UE devices and the mobile core network.

Our previous work [1]–[3] proposed the LCH scheme. The LCH scheme derives the cell residence times from the standard counter values that are automatically and periodically collected by the MSCs. The details of the LCH scheme will be described in Section III.

III. Lin-Chang-Huangfu Scheme

The LCH scheme was described in [1], and the details are reiterated here for the reader's benefit. In Fig. 1, the MSC [see Fig. 1(e)] is responsible for the call processing and mobility management [11]. The MSC is connected to a group of BSs. The radio coverage of a BS is a cell [see the dashed circles in Fig. 1(g)]. During a phone conversation, the UE in a cell connects to the MSC through the BS. If the UE in conversation moves from one cell to another, then the call path is switched from the old cell to the new cell. This process is referred to as *handover*.

In a standard commercial mobile telecommunications operation, the MSC records the call activities of the UE devices (e.g., when the UE makes/receives a call or when the UE in a conversation hands over from one cell to another). The MSC collects the statistics of the activities in each cell for every Δt interval that are typically ranging from 15 min to several hours. Two of the statistics are the number of handovers in and out of the cells and the voice traffic (in Erlang) of the cells. Consider a time point τ. We define $\Delta\tau$ as the time slot $(\lfloor(\tau/\Delta t)\rfloor\Delta t, \lfloor(\tau/\Delta t)+1\rfloor\Delta t)$. For purposes of description, we define the road segment for speed estimation as the *target road segment* [see Fig. 1(h)]. The average cell residence time of cell i [see Fig. 1(g)] is derived as follows. Let $\rho(\tau)$ be the carried traffic of cell i in $\Delta\tau$. In other words, $\rho(\tau)$ is the number of calls arriving at cell i in $\Delta\tau$ multiplied by the expected carried call holding times (in minutes). The carried call holding time is different from the offered call holding time. The offered call holding time is the duration (in minutes) of a call if there were unlimited radio channels in all BSs and if the new calls and the handovers are always successful. In reality, the capacity of a BS is limited; therefore, a call attempt may be blocked at the beginning or may be forced to terminate in a handover. For a call that is connected, the call minutes are actually measured at the MSC in the $\rho(\tau)$ statistics and are defined as the carried call holding time t_c. In the duration t_c of a carried call measured in the MSC, the call is not blocked at the beginning and is not forced to terminate at handovers occurring in t_c (although it may be forced to terminate at the end of t_c). Let $\gamma(\tau)$ denote the number of handovers into cell i in $\Delta\tau$. Let t_m be the cell residence time. In [1], we estimated the cell residence time $t^*_m(\tau)$ of the UE arriving at cell i in time slot $\Delta\tau$ as

$$t^*_m(\tau) = \frac{\rho(\tau)}{\gamma(\tau)}. \quad (1)$$

Based on (1), the average vehicle speed of the one-way target road segment is derived as follows. Suppose that the vehicle with the UE [see Fig. 1(b)] in cell $i-1$ moves to cell $i+1$ through cell i. Let x be the length of the target road segment covered by cell i. From (1), the average vehicle speed $v(\tau)$ of the target road segment in $\Delta\tau$ can be computed as

$$v(\tau) = \frac{x}{t_m^*(\tau)} = \frac{x\gamma(\tau)}{\rho(\tau)}. \quad (2)$$

Now consider a two-way road. To compute the average speed of each direction in the two-way road, we first determine the moving directions of the UE devices by their handover sequences of cells. Then, based on the moving directions, we compute the $\gamma(\tau)$ and $\rho(\tau)$ of each direction. The average speed of each direction is computed by the $\gamma(\tau)$ and $\rho(\tau)$ of each direction by using (2).

In the following, we derive the bias of the cell residence times computed by the LCH scheme. The bias will indicate that the LCH scheme is a good measure for estimating the vehicle speeds.

IV. Bias of the Cell Residence Time Estimation

Here, the accuracy of the LCH scheme is evaluated by estimating the bias of this scheme. We will show that the LCH scheme has a smaller bias for the vehicle speed estimation than the general cell residence time estimation; therefore, the LCH scheme is an appropriate approach to estimate the vehicle speeds.

Let t_m be the real cell residence time and $t_m^*(\tau)$ be the estimator of t_m. Then, the bias of the cell residence time estimator is defined as

$$b_{t_m}\left(t_m^*(\tau)\right) = E\left[t_m^*(\tau)\right] - E[t_m]. \quad (3)$$

Note that, in statistics, the bias and the error are not the same. The bias of an estimator is the difference between the estimator's value and the real value [12]. On the other hand, the error is the discrepancy between an exact value and its approximation. In the following, we first derive $\gamma(\tau)$ and $\rho(\tau)$ constrained by $\Delta\tau$. Then, we express the cell residence time estimator $t_m^*(\tau)$ by the derived $\gamma(\tau)$ and $\rho(\tau)$. Finally, (3) is used to compute the bias.

Fig. 2 shows the timing diagram of the activities of six UE devices in an observation time period $[t_0, t_{19}]$. For example, consider the behavior of UE 3. UE 3 moves to cell i at t_8 (marked by △), and a call is connected to UE 3 at t_{11} (marked by ○). UE 3 leaves cell i at t_{13} (marked by ▲), and the call for UE 3 is completed at t_{15} (marked by ●). The cell residence time for UE 3 is $t_m = t_{13} - t_8$. The carried call holding time for UE 3 is $t_c = t_{15} - t_{11}$.

Consider time slot $\Delta\tau = t_{19} - t_5$ (see the gray area in Fig. 2). A call observed in cell i in $\Delta\tau$ can be one of the following three types:

- a *new call* that is originated in $\Delta\tau$, e.g., the call arrivals at time t_{10} for UE 6 and time t_{11} for UE 3 in Fig. 2;
- an *existing call* that is already connected in cell i at the beginning of $\Delta\tau$, e.g., the call for UE 1 originated at t_4 before time slot $\Delta\tau$ when UE 1 was in cell i; in other words, UE 1 arrived at cell i before t_5, and the call started in the cell at $t_4 < t_5$ is still in progress;
- a *handover call* that is switched from another cell to this cell, e.g., the handovers at time t_6 for UE 2, t_9 for UE 4, and t_{12} for UE 5.

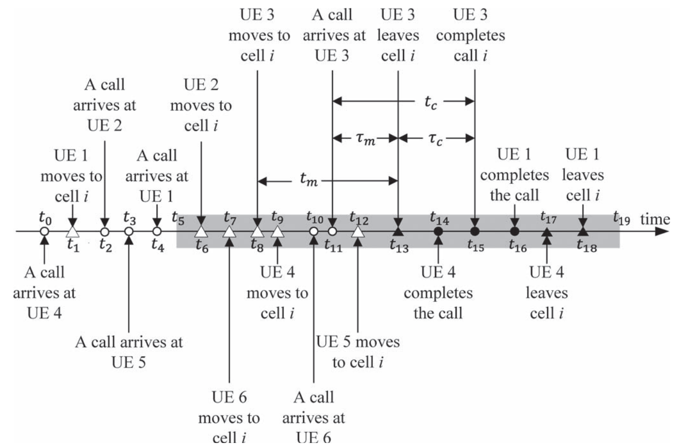

Fig. 2. Timing diagram for UE movements and call arrivals (△: UE moves to cell i; ▲: UE leaves cell i; ○: a call arrives; ●: a call completes; ■: $\Delta\tau$).

Let $\alpha(\tau)$, $\beta(\tau)$, and $\gamma(\tau)$ be the numbers of new calls, existing calls, and handover calls in $\Delta\tau$ in cell i, respectively. In Fig. 2, $\alpha(\tau) = 2$ (i.e., the calls that originated at t_{10} and t_{11}), $\beta(\tau) = 1$ (i.e., the call that originated at t_4), and $\gamma(\tau) = 3$ (i.e., the calls that were handed over at t_6, t_9, and t_{12}). Let λ be the call arrival rate. It is clear that

$$E\left[\alpha(\tau)\right] = \lambda\Delta\tau. \quad (4)$$

Let t_m be a random variable with mean $1/\eta$ and t_c be a random variable with mean $1/\mu$. In the Appendix, we prove five facts that lead to the following important theorem.

Theorem 1: Assume that t_c and t_m have arbitrary distributions with the means $1/\mu$ and $1/\eta$, respectively. If time slot $\Delta\tau = 1/\delta$ is fixed and if we observe the call activities for a long period t, then

$$b_{t_m}\left(t_m^*(\tau)\right) = \frac{\mu\delta}{\lambda\eta^2}. \quad (5)$$

Equation (5) indicates that the LCH scheme has better accuracy when the call holding time is long (i.e., μ is small), $\Delta\tau$ is long (i.e., δ is small), the call arrival rate λ is large, or the cell residence time is short (i.e., η is large). Because the vehicles typically have much shorter cell residence times (i.e., higher speeds) than the pedestrians, (5) indicates that the LCH scheme has higher accuracy in estimating the vehicle speeds than the general cell residence time estimation that also includes pedestrians.

V. Techniques for Improving the Accuracy of the Vehicle Speed Estimation

Several techniques are described here to further improve the accuracy of the vehicle speed estimation expressed in (2). We first introduce two filtering techniques to exclude the UE

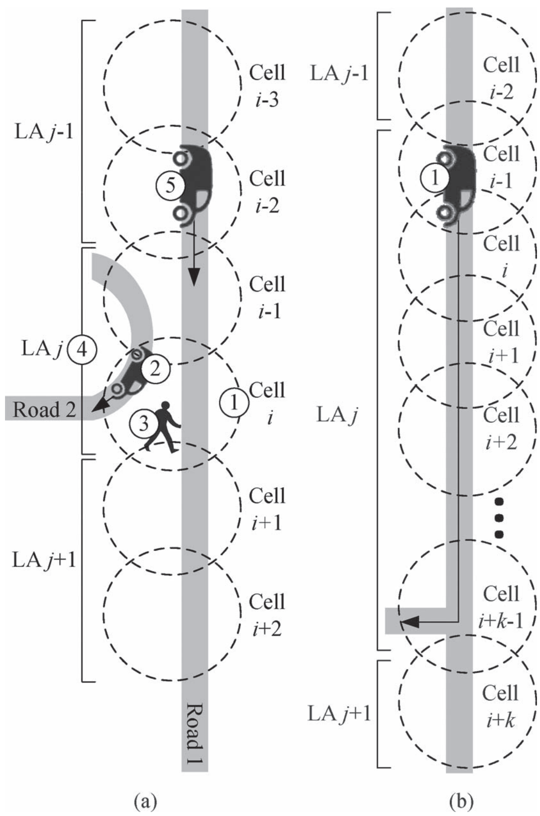

Fig. 3. Two scenarios that affect the accuracy of the vehicle speed estimation. (a) Cell may cover several roads and pedestrians. (b) Vehicle may move to another road without leaving the la of a cell.

devices that are not in the target road segment. Then, we describe two compensation techniques to increase the number of observed calls based on the leaky-bucket integration strategy [15]. Note that these techniques may not cover all realistic road configurations. Here, we demonstrate that the accuracy of speed estimation can be improved by the concepts of "filtering" and "compensation." Based on the filtering/compensation concepts, we can further develop other potential techniques to improve the accuracy and hope that these concepts can be used to develop appropriate techniques in user's scenarios.

If cell i [① in Fig. 3(a)] also covers the area other than the target road segment [② and ③ in Fig. 3(a)], $\gamma(\tau)$ and $\rho(\tau)$ also include the call activities of the UE devices that are not in the target road segment. These activities may reduce the accuracy of (2). To resolve this issue, we first introduce the standard location update procedure in a mobile telecommunications network and then show how to identify the UE devices in the target road segment from the UE devices outside the target road segment but in cell i. In the mobile telecommunications network, the cells are grouped into *location areas* [LAs; e.g., LA j contains cells $i-1$ and i. See ④ in Fig. 3(a)]. When a UE [⑤ in Fig. 3(a)] moves from one LA to another, the UE executes the location update procedure to inform the MSC of its new LA [11], [14]. The location update messages are delivered from the BS to a mobility database (specifically, a *visitor location register*) through the MSC. Based on the location update, we propose the following technique to identify the UE devices in the target road segment.

Filtering Technique 1. For every UE that has call activities in cell i, let cell A be the cell where the UE performs the location update when entering the LA of cell i, and let cell B be the cell where the UE performs another location update when leaving the LA of cell i. If both cells A and B cover the road, then the UE is identified as in the target road segment.

For example, when the UE moves from LA $j-1$ to LA $j+1$ through LA j [see ⑤ in Fig. 3(a)], one location update is performed in cell $i-1$ of LA j (i.e., cell A), and another location update is performed in cell $i+1$ of LA $j+1$ (i.e., cell B). Because both cells $i-1$ and $i+1$ cover the road, the UE is identified as a vehicle moving in the target road segment.

Depending on their destinations, some vehicles may be stopped within the LA of cell i or may have moved from the target road to another road [see ① in Fig. 3(b)]. Those UE devices may not be identified by filtering technique 1 but can be detected by the following technique.

Filtering Technique 2. For every UE that has the call activities in cell i, if the UE's handover sequence of cells contains at least three cells which cover the road, the UE is identified in the target road segment.

In Fig. 3(b), if the UE's handover sequence of cells contains cells $\{i-2, i-1, i\}$, cells $\{i-1, i, i+1\}$, or cells $\{i, i+1, i+2\}$, the UE is identified in the target road segment.

For the UE devices identified by filtering techniques 1 or 2, we use their handover information and call holding times in cell i to compute $\gamma(\tau)$ and $\rho(\tau)$ of the target road segment. Then, the average speed of the target road segment is computed by using (2).

Although these two filtering techniques effectively exclude the UE devices that are not in the target road segment, they also reduce the number of the observed calls. It is clear that, if few calls are observed in $\Delta\tau$, the samples cannot reflect the actual vehicle speeds of the target road segment. To resolve this issue, we consider the far-history and near-history compensation techniques based on the leaky-bucket integration strategy. The far-history compensation technique uses the "same $\Delta\tau$" on the same days of the past weeks to compensate for the number of the observed calls. On the same days of the past weeks, the traffic patterns are typically similar, e.g., the traffic patterns of this Monday are similar to those of last Monday. Similarly, for national holidays (e.g., the New Year's day), we may use far-history compensation of the last national holiday (e.g., the last New Year's day). For time slot $\Delta\tau$, let $\Delta\tau_k$ be the same time slot on the same day of the most recent kth week, and let $\Delta\tau_0 = \Delta\tau$. For example, if $\Delta\tau$ is the time slot on this Monday, then $\Delta\tau_1$ is the same time slot on last Monday. The far-history compensation technique guarantees that $v(\tau)$ is computed by at least K_h samples of handovers. The details are given in the following.

Far-History Compensation Technique. The average speed of the target road segment with the threshold K_h is computed as

$$v(\tau) = \frac{x\left[\sum_{k=0}^{K} \gamma(\tau_k)\right]}{\sum_{k=0}^{K} \rho(\tau_k)} \tag{6}$$

where

$$K = \min\left\{N : \sum_{n=0}^{N} \gamma(\tau_n) \geq K_h\right\}. \tag{7}$$

Note that, in (7), if $\gamma(\tau)$ is no less than K_h, (6) is the same as (2) (i.e., no historical datum is used).

Because the MSC collects $\rho(\tau)$ and $\gamma(\tau)$ for every Δt interval, some calls may cross the time slot (i.e., the existing calls). These "crossing time slot" calls may cause a nonsmooth effect on the consecutive time slots. The leaky-bucket strategy can smooth the results if the traffic patterns of the consecutive time slots do not significantly change. However, if the speeds of the consecutive time slots dramatically change (e.g., the difference between these two speeds is larger than a threshold V_s), then this technique should not be used. The details are described in the following.

Near-History Compensation Technique. The average speed of the target road segment is computed as

$$v(\tau) \leftarrow \begin{cases} Wv(\tau) + (1-W) \\ \quad \times v(\tau - \Delta t), & \text{for } |v(\tau) - v(\tau-\Delta t)| < V_s \\ v(\tau), & \text{for } |v(\tau) - v(\tau-\Delta t)| \geq V_s \end{cases} \tag{8}$$

where $0 \leq W \leq 1$ is a weighting factor, $v(\tau - \Delta t)$ is the speed of the preceding time slot of $\Delta\tau$, and V_s is the threshold to detect the significant traffic change.

In (8), a larger W value means that the past speed $v(\tau - \Delta t)$ has less of an effect on the current speed $v(\tau)$.

VI. Numerical Examples

Here, the vehicle speeds derived from the LCH scheme and those measured by the VD scheme are compared. We have obtained the vehicle speed data of National Highway 3 at Longtan Township, Taoyuan County, Taiwan [see Fig. 4(a)]. The speed data were published by the Ministry of Transportation and Communications of Taiwan, which were measured by the VD at the 66 km of the highway [see Fig. 4(b)]. The *wideband code-division multiple-access* BSs are deployed along the highway. From a sector (cell) of a BS at Longtan Township [about 66.8 km of the highway, which is about 800 m away from the VD; see Fig.4 (c)], we utilize the LCH scheme with filtering techniques 1 and 2, and far-history and near-history compensation techniques to estimate the vehicle speeds from a cell of length $x = 1$ km and $\Delta t = 1$ h. The x length is obtained through measurement [16], [17]. We use the average of the numbers of handovers into the cell and out of the cell to estimate the speeds. Our experiments indicate that, using the average of the numbers of handover into and out of the cell has better accuracy for the LCH scheme. To eliminate the ping-pong effect, we adopt the algorithm in [9] to filter out the interhandover intervals, which are less than 10 s. In this paper, we consider $K_h = 10$, $V_s = 40$ km/h, and $W = 0.5$.

Let v_s be the vehicle speeds measured by the VD ($s = \text{VD}$) and computed by the LCH scheme ($s = \text{LCH}$), respectively. Fig. 5(a) and (b) plot v_s from 8:00 to 20:00 on

Fig. 4. Experimental environment in National Highway 3 at Longtan Township, Taoyuan County, Taiwan. (The VD is marked by ×, and the BS is marked by ○.)

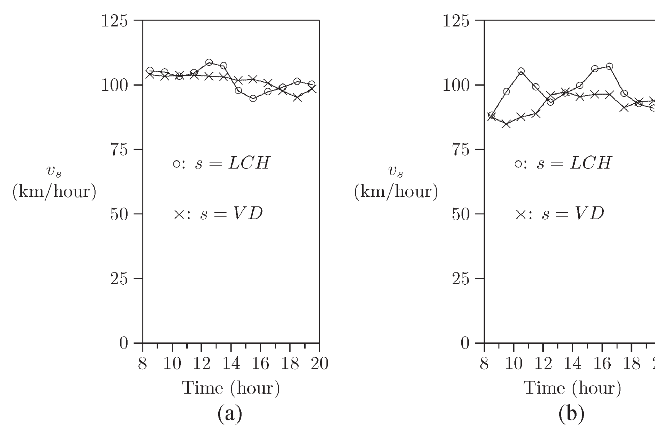

Fig. 5. Vehicle speeds of the VD and LCH schemes on September 16, 2011 ($\Delta t = 1$ h and $x = 1$ km). (a) Northbound. (b) Southbound.

September 16, 2011, in the northbound and southbound directions, respectively. In these figures, both the VD and the LCH approaches indicated that the traffic did not significantly vary from 8:00 to 20:00 (i.e., $v_s > 75$ km/h). Fig. 6(a) and (b) plots v_s from 8:00 to 20:00 on September 25, 2011, in the northbound and southbound directions, respectively. In Fig. 6(a), both approaches captured a traffic jam occurred from 18:00 to 20:00 (i.e., $v_s < 60$ km/h). In Fig. 6(b), both approaches indicated that the traffic did not significantly vary during 8:00 to 20:00 (i.e., $v_s > 75$ km/h). Figs. 5 and 6 show that the trends of speeds of the LCH scheme are consistent with those of the VD scheme in both directions.

We further define the discrepancy ϵ as

$$\epsilon = \left|\frac{v_{\text{LCH}} - v_{\text{VD}}}{v_{\text{VD}}}\right|. \tag{9}$$

Based on Figs. 5 and 6, Fig. 7 plots the ϵ curves in the observation time periods. The figure indicates that ϵ are reasonably small in most cases. When the traffic jam occurs, [in Fig. 7(b), the ○ curve from 19:00 to 20:00], ϵ is slightly larger. The reason is that, when the traffic jam occurs, the cell residence times of

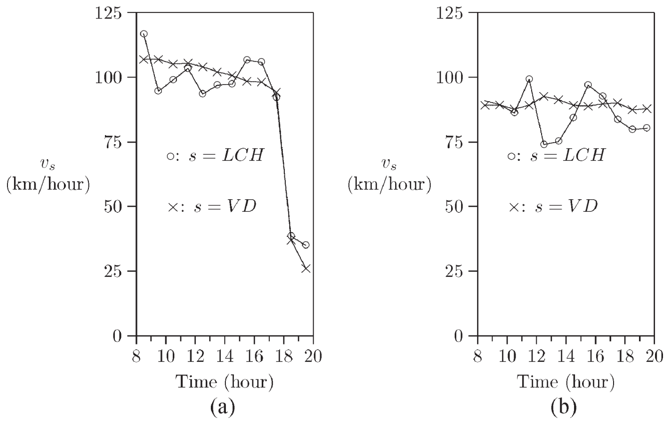

Fig. 6. Vehicle speeds of the VD and the LCH scheme on September 25, 2011 ($\Delta t = 1$ h and $x = 1$ km). (a) Northbound. (b) Southbound.

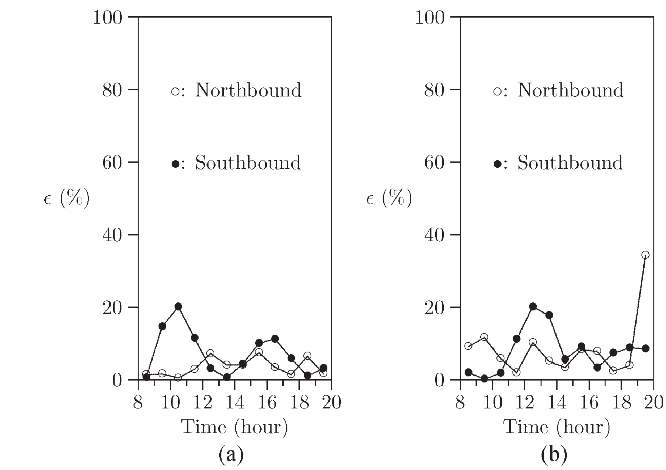

Fig. 7. Discrepancy between the LCH and the VD schemes ($\Delta t = 1$ h and $x = 1$ km). (a) Experiment on September 16, 2011. (b) Experiment on September 25, 2011.

the vehicles are typically longer, and (5) already implies that the LCH scheme has lower accuracy for longer cell residence times.

We have also collected $\gamma(\tau)$ and $\rho(\tau)$ statistics during 8:00 to 20:00 over 49 days (from September 13, 2011 to October 31, 2011) from the mobile telecommunications network. Based on the observed data, this paper indicates that $E[\epsilon]$ is 14.46% if none of the techniques in Section V is applied, $E[\epsilon]$ is reduced to 12.7% if filtering techniques 1 and 2 are applied, and $E[\epsilon]$ is further reduced to 7.51% if both filtering and compensation techniques are all applied.

VII. Conclusion

This paper extended the previously proposed *LCH* scheme [1], [2] to derive the vehicle speeds. The bias analysis indicated that the LCH scheme is an appropriate approach to vehicle speed estimation (as compared with the pedestrian speed estimation). We further utilized several techniques to improve the accuracy of the LCH scheme and then compared the vehicle speeds derived from the improved LCH scheme with those measured by a VD installed by the government. The comparison study showed that the trends of speeds derived from the LCH and VD schemes are consistent, and the discrepancies between these two schemes are reasonably small in most cases, where the average discrepancy $E[\epsilon]$ is 7.51%. Our study indicates that the LCH scheme can appropriately capture the vehicle speeds of the roads and can avoid expensive deployment costs of existing approaches (e.g., sensor deployment of the VD scheme).

One potential issue of CFVD methods is that it only applies to cell phones that are actually connected. This will be typically only a fraction of the cell phones within the cell. This paper has indicated that the number of the connected phones is reasonably large to produce data for our measurements and compensation techniques. Another potential issue is the selection of the time interval Δt for statistical data collection. One may question that speed calculated in a period of 15 min or longer is not real time. Our experience indicates that the 15-min interval (or even longer) is appropriate. The traffic information broadcast from the government in Taiwan uses the 15-min interval or longer. Many GVP approaches also use similar intervals to report the traffic information.

In the future, we will investigate the speed estimation in the *Long-Term Evolution* environment and evaluate the performance of the LCH scheme based on packet-switching data connections. We will also develop more techniques to enhance the accuracy of the speed estimation for several scenarios (e.g., parallel road effect, few LA crossings, tourist effect, etc.).

Appendix
Detailed Proof of Theorem 1

Here, we describe the proof for Theorem 1. We first prove the following facts.

Fact 1: Assume that t_c is exponentially distributed and t_m has arbitrary density function $f_m(t_m)$ with rate η. If time slot $\Delta\tau$ has an arbitrary distribution with mean $1/\delta$, then $E[\beta(\tau)] = \lambda/\mu$, and $E[\gamma(\tau)] = (\lambda\eta)/(\delta\mu)$.

Proof: Consider the start time of time slot $\Delta\tau$ (e.g., t_5 in Fig. 2). This time point observes the call activities of cell i. The expected number $E[\beta(\tau)]$ of existing calls is proportional to $E[\alpha(\tau)]$ and the expected call holding time $1/\mu$ and is inversely proportional to the expected length $E[\Delta\tau]$ of the time slot. Therefore, we can express $E[\beta(\tau)]$ as

$$E\left[\beta(\tau)\right] = \frac{E\left[\alpha(\tau)\right](1/\mu)}{E[\Delta\tau]} = \frac{\lambda}{\mu}. \quad (10)$$

Intuitively, if $(1/\mu) < E[\Delta\tau]$, then $1/(\mu E[\Delta\tau])$ is the probability that a call is an existing call in $\Delta\tau$. Then, the total number of existing calls $E[\beta(\tau)]$ is $E[\alpha(\tau)]$ multiplied by $1/(\mu E[\Delta\tau])$, which results in (10).

Obviously, $E[\gamma(\tau)]$ can be expressed as $E[\alpha(\tau)]$ multiplied by the average number of handovers of a call, Due to the memoryless property of the exponential distribution, the residual call holding time (e.g., $\tau_c = t_{15} - t_{13}$ in Fig. 2) of a handover call is also exponential with the same mean $1/\mu$. Let the distribution function of t_m be $F_m(t_m)$. Let τ_m (e.g., $\tau_m = t_{13} - t_{11}$ in Fig. 2) be the residual cell residence time. According to the *residual life theorem* [13], the density function of τ_m is $(1 - F_m(t_m))/(1/\eta) = [1 - F_m(t_m)]\eta$. Note that the measured t_c periods are carried call holding times. Therefore, if a handover occurs, a radio channel is available in the new cell, and the handover is always successful. Define P_i as the probability that a new call completes after it has handed over i times. Define $q_1 = \Pr[t_c > \tau_m]$ as the probability that a new call is handed over, and define $q_2 = \Pr[\tau_c > t_m]$ as the probability that a call is handed over under the condition that it has been handed over before. Let $P_i = q_1 q_2^{i-1}(1-q_2)$ where $i \geq 1$. Then, the average number of handovers of a call can be expressed as

$$\sum_{i=1}^{\infty} iP_i = \sum_{i=1}^{\infty} iq_1 q_2^{i-1}(1-q_2) = \frac{q_1}{1-q_2}. \tag{11}$$

In (11), probability q_1 is derived as

$$\begin{aligned} q_1 &= \Pr[t_c > \tau_m] \\ &= \int_{\tau_m=0}^{\infty} \int_{t_c=\tau_m}^{\infty} \mu e^{-\mu t_c} \left[1 - F_m(\tau_m)\right] \eta dt_c d\tau_m \\ &= \int_{\tau_m=0}^{\infty} e^{-\mu \tau_m} \left[1 - F_m(\tau_m)\right] \eta d\tau_m \end{aligned} \tag{12}$$

and $1 - q_2$ can be expressed as

$$\begin{aligned} 1 - q_2 &= \Pr[\tau_c < t_m] \\ &= \int_{\tau_c=0}^{\infty} \int_{t_m=\tau_c}^{\infty} \mu e^{-\mu \tau_c} f_m(t_m) dt_m d\tau_c \\ &= \int_{\tau_c=0}^{\infty} \mu e^{-\mu \tau_c} \left[1 - F_m(\tau_c)\right] d\tau_c \\ &= \left(\frac{\mu}{\eta}\right) q_1. \end{aligned} \tag{13}$$

From (12) and (13), the average number of handovers of a call is $q_1/(1-q_2) = \eta/\mu$. In a typical vehicle environment, the average number of handovers of a call is between 2 and 3. The expected number $E[\gamma(\tau)]$ can be derived as

$$E\left[\gamma(\tau)\right] = E\left[\alpha(\tau)\right] \left(\frac{\eta}{\mu}\right) = \frac{\lambda \eta}{\delta \mu}. \tag{14}$$

From the given proof, the derivation of $E[\alpha(\tau)]$, $E[\beta(\tau)]$, and $E[\gamma(\tau)]$ are independent of the $\Delta\tau$ distribution. ■

Based on Fact 1, we have Facts 2 and 3.

Fact 2: Assume that both t_c and $\Delta\tau$ are exponentially distributed with means $1/\mu$ and $1/\delta$, and t_m has arbitrary density function $f_m(t_m)$ with rate η. Then, $E[\rho(\tau)] = \lambda/(\delta\mu)$.

Proof: As defined in Fact 1, let the residual life of t_c be τ_c, and let the residual life of t_m be τ_m. For time slot $\Delta\tau$ of cell i, $\rho(\tau)$ is contributed by the conversation minutes of new, existing, and handover calls. Consider the new call for UE 3 during the time slot $\Delta\tau$ in Fig. 2. This call arrives at t_{11} with $t_c = t_{15} - t_{11}$. At t_{11}, the residual life of UE 3's cell residence time is $\tau_m = t_{13} - t_{11}$. Since the call arrivals are a Poisson process, t_{11} is a random observer of UE 3's cell residence time t_m. The time point t_{11} is also a random observer of $\Delta\tau$. From the residual life theorem and the memoryless property of the exponential distribution, the residual life $\Delta\tau_n$ of $\Delta\tau$ seen by t_{11} is also exponentially distributed with the mean $1/\delta$. Therefore, the expected call minutes $E[\rho_n(\tau)]$ of this new call in $\Delta\tau$ is

$$\begin{aligned} E\left[\rho_n(\tau)\right] &= E\left[\min(t_c, \tau_m, \Delta\tau_n)\right] \\ &= E\left[\min\left(\min(t_c, \Delta\tau_n), \tau_m\right)\right]. \end{aligned} \tag{15}$$

Clearly, random variable $x_n = \min(t_c, \Delta\tau_n)$ is exponentially distributed with the rate $\mu + \delta$. Let the Laplace transform of $f_m(t_m)$ be $f_m^*(t_m)$. From the derivation in [14], (15) is rewritten as

$$\begin{aligned} E\left[\rho_n(\tau)\right] &= E\left[\min(x_n, \tau_m)\right] \\ &= \frac{1}{\mu+\delta} - \left[\frac{\eta}{(\mu+\delta)^2}\right]\left[1 - f_m^*(\mu+\delta)\right]. \end{aligned} \tag{16}$$

Now consider the existing call for UE 1 during $\Delta\tau$ in Fig. 2. This call arrives at t_4, At t_5, the residual call holding time is $\tau_c = t_{16} - t_5$, and the residual life of UE 1's cell residence time is $\tau_m = t_{18} - t_5$. Since t_5 can be considered as a random observer of UE 1's call holding time t_c, τ_c is exponentially distributed with mean $1/\mu$. Then, the expected call minutes $E[\rho_e(\tau)]$ of this existing call in $\Delta\tau$ is

$$E\left[\rho_e(\tau)\right] = E\left[\min(\tau_c, \tau_m, \Delta\tau)\right].$$

Since both τ_c and $\Delta\tau$ are exponentially distributed with the rates μ and δ, $E[\rho_e(\tau)]$ can be expressed as (16); in other words, $E[\rho_e(\tau)] = E[\rho_n(\tau)]$.

Finally, consider the handover call for UE 4 during $\Delta\tau$ in Fig. 2. This user moves to cell i at t_9 with the cell residence time $t_m = t_{17} - t_9$. At t_9, the residual life of the call holding time is $\tau_c = t_{14} - t_9$. Since t_9 is a random observer of UE 4's call holding time t_c, which is exponentially distributed with mean $1/\mu$, τ_c has the same distribution as t_c. The time point t_9 is also a random observer of $\Delta\tau$, and the residual life $\Delta\tau_h$ of $\Delta\tau$ seen by t_9 is also exponentially distributed with mean $1/\delta$. Therefore, the expected call minutes $E[\rho_h(\tau)]$ of this handover call in $\Delta\tau$ is

$$\begin{aligned} E\left[\rho_h(\tau)\right] &= E\left[\min(\tau_c, t_m, \Delta\tau_h)\right] \\ &= E\left[\min\left(\min(\tau_c, \Delta\tau_h), t_m\right)\right]. \end{aligned} \tag{17}$$

Let $x_h = \min(\tau_c, \Delta\tau_h)$, which is exponentially distributed with the rate $\mu + \delta$. Then, similar to the derivation of (16), (17) is rewritten as

$$\begin{aligned} E\left[\rho_h(\tau)\right] &= E\left[\min(x_h, t_m)\right] \\ &= \left(\frac{1}{\mu+\delta}\right)\left[1 - f_m^*(\mu+\delta)\right]. \end{aligned} \tag{18}$$

From (4), (16), (18), and Fact 1, $E[\rho(\tau)]$ is expressed as

$$\begin{aligned} E\left[\rho(\tau)\right] &= E\left[\alpha(\tau)\right] E\left[\rho_n(\tau)\right] + E\left[\beta(\tau)\right] E\left[\rho_e(\tau)\right] \\ &\quad + E\left[\gamma(\tau)\right] E\left[\rho_h(\tau)\right] \\ &= \left(E\left[\alpha(\tau)\right] + E\left[\beta(\tau)\right]\right) \\ &\quad \times \left\{\frac{1}{\mu+\delta} - \left[\frac{\eta}{(\mu+\delta)^2}\right]\left[1 - f_m^*(\mu+\delta)\right]\right\} \\ &\quad + E\left[\gamma(\tau)\right]\left\{\left(\frac{1}{\mu+\delta}\right)\left[1 - f_m^*(\mu+\delta)\right]\right\} \\ &= \frac{\lambda}{\delta\mu}. \end{aligned} \tag{19}$$

In (19), $E[\rho(\tau)]$ is independent of the t_m distribution.

Fact 3: Let $\Delta\tau$ be a fixed value $(1/\delta)$. If the call holding time t_c and the cell residence time t_m are exponentially distributed, then $E[\rho(\tau)] = \lambda/(\delta\mu)$.

Proof: Like the proof of Fact 2, $\rho(\tau)$ is contributed by the conversation minutes of new, existing, and handover calls. The expected call minutes $E[\rho_n(\tau)]$ of the new call in $\Delta\tau$ is

$$E[\rho_n(\tau)] = E[\min(y_n, \Delta\tau_n)] = E[\min(\min(t_c, \tau_m), \Delta\tau_n)] \quad (20)$$

which is the same as (15), except that $\Delta\tau_n$ is uniformly distributed over the interval $[0, (1/\delta)]$ with density function δ. Since both t_c and τ_m are exponentially distributed with rates μ and η, respectively, random variable $y_n = \min(t_c, \tau_m)$ is exponentially distributed with rate $\mu + \eta$, and (20) is rewritten as

$$\begin{aligned} E[\rho_n(\tau)] =& \int_{\Delta\tau_n=0}^{\frac{1}{\delta}} \int_{y_n=0}^{\Delta\tau_n} \delta y_n(\mu+\eta)e^{-(\mu+\eta)y_n} dy_n d\Delta\tau_n \\ &+ \int_{\Delta\tau_n=0}^{\frac{1}{\delta}} \int_{y_n=\Delta\tau_n}^{\infty} \delta\Delta\tau_n(\mu+\eta)e^{-(\mu+\eta)y_n} dy_n d\Delta\tau_n \\ =& \left(\frac{1}{\mu+\eta}\right)\left[1 - \frac{\delta}{\mu+\eta} + \frac{\delta e^{-\left(\frac{\mu+\eta}{\delta}\right)}}{\mu+\eta}\right]. \end{aligned} \quad (21)$$

Now, consider the expected call minutes $E[\rho_h(\tau)]$ of the handover call in $\Delta\tau$, i.e.,

$$E[\rho_h(\tau)] = E[\min(\tau_c, t_m, \Delta\tau_h)]. \quad (22)$$

Both τ_c and t_m are exponentially distributed with the rates μ and η, and $\Delta\tau_h$ is uniformly distributed over the interval $[0, (1/\delta)]$. Therefore, (22) can be expressed as (20); in other words, $E[\rho_h(\tau)] = E[\rho_n(\tau)]$. The expected call minutes $E[\rho_e(\tau)]$ of the existing call in $\Delta\tau$ is

$$E[\rho_e(\tau)] = E\left[\min\left(y_e, \frac{1}{\delta}\right)\right] = E\left[min\left(\min(\tau_c, \tau_m), \frac{1}{\delta}\right)\right] \quad (23)$$

where $y_e = \min(\tau_c, \tau_m)$ is exponentially distributed with the rate $\mu + \eta$, and (23) is rewritten as

$$\begin{aligned} E[\rho_e(\tau)] =& \int_{y_e=0}^{\frac{1}{\delta}} y_e(\mu+\eta)e^{-(\mu+\eta)y_e} dy_e \\ &+ \int_{y_e=\frac{1}{\delta}}^{\infty} \left(\frac{1}{\delta}\right)(\mu+\eta)e^{-(\mu+\eta)y_e} dy_e \\ =& \left(\frac{1}{\mu+\eta}\right)\left[1 - e^{-\left(\frac{\mu+\eta}{\delta}\right)}\right]. \end{aligned} \quad (24)$$

From (4), (21), (24) and Fact 1, $E[\rho(\tau)]$ is expressed as

$$\begin{aligned} E[\rho(\tau)] =& E[\alpha(\tau)]E[\rho_n(\tau)] + E[\beta(\tau)]E[\rho_e(\tau)] \\ &+ E[\gamma(\tau)]E[\rho_h(\tau)] \\ =& (E[\alpha(\tau)] + E[\gamma(\tau)])\left(\frac{1}{\mu+\eta}\right) \\ &\times\left[1 - \frac{\delta}{\mu+\eta} + \frac{\delta e^{-\left(\frac{\mu+\eta}{\delta}\right)}}{\mu+\eta}\right] \\ &+ E[\beta(\tau)]\left(\frac{1}{\mu+\eta}\right)\left[1 - e^{-\left(\frac{\mu+\eta}{\delta}\right)}\right] \\ =& \frac{\lambda}{\delta\mu}. \end{aligned}$$

■

Fact 4: Assume that $\Delta\tau$, t_c, and t_m have arbitrary distributions with means $1/\delta$, $1/\mu$, and $1/\eta$, respectively. Then, $E[\gamma(\tau)] \approx (\lambda\eta/\delta\mu)$.

Proof: Consider a long observation time period $t \gg 1/\delta$, $1/\mu$. Let t^* be the time that is occupied by the calls to a user during period t. Then, there are $\lceil(t^*/(1/\mu)\rceil = \lceil\mu t^*\rceil$ call arrivals within t. Note that the user is expected to move across cells $\lfloor t/(1/\eta)\rfloor$ times in period t, and among these crossings, $\lfloor t^*/(1/\eta)\rfloor$ of them occur during conversations. Therefore, the number of handovers is $\lfloor t^*/(1/\eta)\rfloor = \lfloor\eta t^*\rfloor$, and the average number of handovers of a call is $E[n_1] = (\lfloor\eta t^*\rfloor)/(\lceil\mu t^*\rceil)$. Clearly, $\lim_{t^*\to\infty} E[n_1] = \eta/\mu$; therefore, if t is long enough, we have

$$E[\gamma(\tau)] = E[\alpha(\tau)]E[n_1] \approx \frac{\lambda\eta}{\delta\mu}. \quad (25)$$

The result of Fact 4 is consistent with that of Fact 1. ■

Fact 5: Assume that $\Delta\tau = 1/\delta$ is fixed, and t_c and t_m have arbitrary distributions with means $1/\mu$ and $1/\eta$, respectively. Let t be the observation period. Then, $\lim_{t\to\infty} E[\rho(\tau)] = \lambda/(\delta\mu)$.

Proof: We assume that the UE devices are moving around n_2 cells, and their behaviors are observed in a long time period $t \gg n_2/\delta$, n_2/μ. Since the UE devices will not leave n_2 cells, handovers of these calls (therefore, the t_m distribution) will not affect the statistics of call minutes. There are $\lceil\lambda t n_2\rceil$ calls that arrive in n_2 cells during period t. Some of the calls are initiated before the beginning of t, which are not counted (we call it the initial effect). Some of the counted calls do not complete at the end of t (we call it the end effect). Let $t_{c,i}$ be the call holding time of the ith call, and let $f_c(t_{c,i})$ be the density function of the call holding time of the ith call with the rate μ. Then, the measured call minutes θ of these n_2 cells during t can be approximated as

$$\theta = \sum_{i=1}^{\lceil\lambda t n_2\rceil} \int_{t_{c,i}=0}^{\infty} t_{c,i} f_c(t_{c,i}) dt_{c,i} = \frac{\lceil\lambda t n_2\rceil}{\mu}.$$

There are a total of $n_2\lceil t/(1/\delta)\rceil = \lceil n_2 t\delta\rceil$ time slots. Since $E[\rho(\tau)]$ is the expected call minutes of traffic in $\Delta\tau$ of cell i, it can be approximated as $E[\rho(\tau)] \approx \theta/(\lceil n_2 t\delta \rceil)$. If t becomes large, the initial and end effects become insignificant, and

$$\lim_{t\to\infty} E\left[\rho(\tau)\right] = \frac{\lambda}{\delta\mu}. \tag{26}$$

Note that the result in Fact 5 is the same as those in Facts 2 and 3. These results are also consistent with the Erlang equation, which defines the traffic per minute as λ/μ. Therefore, $\lambda/(\delta\mu)$ is the traffic in time slot $\Delta\tau$. ■

Theorem 1: Assume that t_c and t_m have arbitrary distributions with the means $1/\mu$ and $1/\eta$, respectively. If time slot $\Delta\tau = (1/\delta)$ is fixed and if we observe the call activities for a long period t, then $b_{t_m}(t_m^*(\tau)) = (\mu\delta)/(\lambda\eta^2)$.

Proof: Suppose that we observe the call activities for a long period $t \to \infty$. Since the measurements of the LCH scheme are conducted in $\Delta\tau$, from (25) and (26), both $E[\gamma(\tau)]$ and $E[\rho(\tau)]$ go to infinity if $1/\delta$ becomes infinity, and (1) cannot be used to compute $t_m^*(\tau)$. To fix this problem, let $c_1 = (E[\rho(\tau)])/(1/\delta) = \lambda/\mu$ and $c_2 = (E[\gamma(\tau)])/(1/\delta) = (\lambda\eta)/\mu$. Then, we can rewrite (1) as function $f(r,s)$, such that

$$t_m^*(\tau) = f(r,s)|_{r=c_1,s=c_2} = \left(\frac{r}{s}\right)\Big|_{r=c_1,s=c_2}. \tag{27}$$

To compute (27), we use the Taylor series for $f(r,s)$ around the point (c_1, c_2), which is shown in the following:

$$\begin{aligned} f(r,s) = f(c_1,c_2) &+ \left[\frac{\partial f(r,s)}{\partial r}\Big|_{r=c_1,s=c_2}\right](r-c_1) \\ &+ \left[\frac{\partial f(r,s)}{\partial s}\Big|_{r=c_1,s=c_2}\right](s-c_2) \\ &+ \left(\frac{1}{2}\right)\left[\frac{\partial^2 f(r,s)}{\partial r^2}\Big|_{r=c_1,s=c_2}\right](r-c_1)^2 \\ &+ \left[\frac{\partial}{\partial s}\left(\frac{\partial f(r,s)}{\partial r}\right)\Big|_{r=c_1,s=c_2}\right](r-c_1)(s-c_2) \\ &+ \left(\frac{1}{2}\right)\left[\frac{\partial^2 f(r,s)}{\partial s^2}\Big|_{r=c_1,s=c_2}\right](s-c_2)^2 + \cdots. \end{aligned} \tag{28}$$

Since we consider the $f(r,s)$ function around point (c_1, c_2) and the expected value $E[r] = c_1$ and $E[s] = c_2$, we have

$$E[r-c_1] = 0,\ E[s-c_2] = 0 \tag{29}$$

$$E\left[(r-c_1)(s-c_2)\right] = 0. \tag{30}$$

In addition, from (27), we have

$$\frac{\partial^2 f(r,s)}{\partial r^2}\Big|_{r=c_1,s=c_2} = 0 \tag{31}$$

$$\frac{\partial^2 f(r,s)}{\partial s^2}\Big|_{r=c_1,s=c_2} = \frac{2c_1}{c_2^3}. \tag{32}$$

From (29)–(32), the expectation of (28) can be written as

$$\begin{aligned} E\left[f(r,s)\right] &= f(c_1,c_2) + \left(\frac{1}{2}\right)\left[\frac{\partial^2 f(r,s)}{\partial s^2}\Big|_{r=c_1,s=c_2}\right] \\ &\quad \times E\left[(s-c_2)^2\right] \\ &= \frac{c_1}{c_2} + \left(\frac{c_1}{c_2^3}\right)E\left[(s-c_2)^2\right] \\ &= \frac{1}{\eta} + \left(\frac{\mu^2}{\lambda^2\eta^3}\right)E\left[(s-c_2)^2\right]. \end{aligned} \tag{33}$$

In (33), $E[(s-c_2)^2] = \mathrm{Var}[\gamma(\tau)/(1/\delta)] = \delta^2\mathrm{Var}[\gamma(\tau)]$. From (14), $\gamma(\tau)$ is a Poisson random variable with the mean $E[\gamma(\tau)] = (\lambda\eta)/(\delta\mu)$ and variance $\mathrm{Var}[\gamma(\tau)] = (\lambda\eta)/(\delta\mu)$. Therefore, (33) is rewritten as

$$\begin{aligned} E\left[f(r,s)\right] &= \frac{1}{\eta} + \left(\frac{\mu^2}{\lambda^2\eta^3}\right)\mathrm{Var}\left[\frac{\gamma(\tau)}{\left(\frac{1}{\delta}\right)}\right] \\ &= \frac{1}{\eta} + \frac{\mu\delta}{\lambda\eta^2}. \end{aligned} \tag{34}$$

Since the mean of t_m is $1/\eta$, from (3) and (34), $b_{t_m}(t_m^*(\tau))$ is

$$\begin{aligned} b_{t_m}\left(t_m^*(\tau)\right) &= E\left[t_m^*(\tau)\right] - E[t_m] \\ &= \left[\frac{1}{\eta} + \frac{\mu\delta}{\lambda\eta^2}\right] - \frac{1}{\eta} = \frac{\mu\delta}{\lambda\eta^2}. \end{aligned} \tag{35}$$

■

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References

[1] Y.-B. Lin, M.-F. Chang, and C.-C. Huang-Fu, "Derivation of cell residence times from the counters of mobile telecommunications switches," *IEEE Trans. Wireless Commun.*, vol. 10, no. 12, pp. 4048–4051, Dec. 2011.

[2] Y.-B. Lin, C.-C. Huang-Fu, and N. Alrajeh, "Predicting human movement based on telecom's handoff in mobile networks," *IEEE Trans. Mobile Comput.*, to be published.

[3] C.-C. Huang-Fu and Y.-B. Lin, "Deriving vehicle speeds from standard statistics of mobile telecom switches," *IEEE Trans. Veh. Technol.*, vol. 61, no. 7, pp. 3337–3341, Sep. 2012.

[4] R.-H. Liou, Y.-B. Lin, Y.-L. Chang, and M.-F. Chang, "Deriving the vehicle speeds from mobile telecommunications network," in *Proc. 12th Int. Conf. ITST*, Nov. 2012, pp. 429–432.

[5] S. J. Park, T. Y. Kim, S. M. Kang, and K. H. Koo, "A novel signal processing technique for vehicle detection radar," in *Proc. IEEE MTT-S Int. Microw. Symp.*, 2003, pp. 607–610.

[6] A. Poolsawat, W. Pattara-Atikom, and B. Ngamwongwattana, "Acquiring road traffic information through mobile phones," in *Proc. 8th Int. Conf. ITST*, 2008, pp. 170–174.

[7] R. L. Cheu, C. Xie, and D.-H. Lee, "Probe vehicle population and sample size for arterial speed estimation," *Comput.-Aid. Civil Infrast. Eng.*, vol. 17, no. 1, pp. 53–60, Jan. 2002.

[8] C.-Y. Chiang, J.-Y. Chuang, J.-K. Chen, C.-C. Hung, W.-H. Chen, and K.-R. Lo, "Estimating instant traffic information by identifying handover patterns of UMTS signals," in *Proc. 14th Int. IEEE Conf. ITSC*, 2011, pp. 390–395.

[9] K.-R. Lo, C.-Y. Chiang, J.-Y. Chuang, J.-K. Chen, C.-C. Hung, and W.-H. Chen, "Feasibility analysis of UMTS handover logs for traffic state estimation," in *Proc. 11th Int. Conf. ITST*, 2011, pp. 684–690.

[10] B.-Y. Lin, C.-H. Chen, and C.-C. Lo, "A traffic information estimation model using periodic location update events from cellular network," in *Communications in Computer and Information Science*. New York, NY, USA: Springer-Verlag, 2011, pp. 72–77.

[11] Y.-B. Lin and A.-C. Pang, *Wireless and Mobile All-IP Networks*. Hoboken, NJ, USA: Wiley, 2005.

[12] J. L. Devore, *Probability and Statistics for Engineering and the Sciences*. Pacific Grove, CA, USA: Duxbury, 2011.

[13] L. Kleinrock, *Queueing Systems, Vol. I, Theory*. New York, NY, USA: Wiley, 1976.

[14] Y.-B. Lin, "Performance modeling for mobile telephone networks," *IEEE Netw.*, vol. 11, no. 6, pp. 63–68, Nov./Dec. 1997.

[15] Y.-B. Lin and I. Chlamtac, *Wireless and Mobile Network Architectures*. Hoboken, NJ, USA: Wiley, 2000.

[16] D. Gundlegard and J.-M. Karlsson, "Handover location accuracy for travel time estimation in GSM and UMTS," *IET Intell. Transp. Syst.*, vol. 3, no. 1, pp. 87–94, Mar. 2009.

[17] H. Bar-Gera, "Evaluation of a cellular phone-based system for measurements of traffic speeds and travel times: A case study from israel," *Transp. Res. Part C: Emerg. Technol.*, vol. 15, no. 6, pp. 380–391, Dec. 2007.

[18] D. Valerio, T. Witek, F. Ricciato, R. Pilz, and W. Wiedermann, "Road traffic estimation from cellular network monitoring: A hands-on investigation," in *Proc. IEEE 20th Int. Symp. Pers., Indoor Mobile Radio Commun.*, 2009, pp. 3035–3039.

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