Predicting Human Movement Based on Telecom's Handoff in Mobile Networks

Yi-Bing Lin, *Fellow*, *IEEE*, Chien-Chun Huang-Fu, and Nabil Alrajeh

Abstract—Investigating human movement behavior is important for studying issues such as prediction of vehicle traffic and spread of contagious diseases. Since mobile telecom network can efficiently monitor the movement of mobile users, the telecom's mobility management is an ideal mechanism for studying human movement issues. The problem can be abstracted as follows: What is the probability that a person at location A will move to location B after T hours. The answer cannot be directly obtained because commercial telecom networks do not exactly trace the movement history of every mobile user. In this paper, we show how to use the standard outputs (handover rates, call arrival rates, call holding time, and call traffic) measured in a mobile telecom network to derive the answer for this problem.

Index Terms—Human movement, Little's Law, mobile computing, mobility management

1 Introduction

Prediction of human movement behavior is important for studying issues such as prediction of vehicle traffic and spread of contagious diseases, which requires tracing the movement of people. In [1], a wireless sensor network technology is utilized to obtain high-resolution data of close proximity interactions which cause the spread of most contagious diseases. However, this method needs extra effort to distribute the senor network motes, and is constrained in a small area (e.g., a campus).

An alternative to investigate user movement can be achieved through mobile telecom service. In a mobile telecom network (e.g., UMTS, cdma2000, and GSM [6]), the users are tracked by the mobility management mechanism so that the network can connect incoming calls to the users through base stations (BSs) [2]. For this purpose, BSs in the service area (SA) are grouped into *location areas* (LAs). The users are tracked at the accuracy of an LA coverage, and when an incoming call arrives, all BSs in that LA will page the user. Since this mobility management mechanism provides the position information of a user at the accuracy of one LA coverage that may include 10-100 BSs, it cannot be used for location-based applications that require position accuracy within the size smaller than a *cell* (the radio coverage of a BS or a sector of the BS). Location-based services that need to accurately track the position of a user require specific techniques described in 3GPP TS 25.305 [3]. Details of these methods were described in [4], and are elaborated here for the reader's benefit.

The Cell-ID-based method determines the mobile user's position based on the coverage of SAs. An SA includes one or more cells. At most one-cell-sized accuracy (about 500 meters) can be achieved when the SA includes only one cell. The *observed time difference of arrival* (OTDOA) method utilizes trilateration to determine the mobile user's position. At least three concurrent downlink signals from different cells are measured by the mobile phone. The time differences among the signal arrivals are calculated to form hyperbolic curves. The intersection of these curves is then used to indicate the mobile user's position. This method provides location accuracy within 50-150 meters. The *assisted global positioning system* (A-GPS) method speeds up GPS positioning by downloading GPS information through the radio access network (RAN). Execution of A-GPS positioning only requires several seconds while execution of normal GPS positioning requires 30 seconds to several minutes. GPS modules are installed in both the mobile phone and the RAN. This method provides location accuracy within 5-15 meters. The *uplink time difference of arrival* (U-TDOA) method evolves from OTDOA, which utilizes uplink signals instead of downlink signals. A normal uplink signal from the mobile user is measured in different cells, and no extra signal is required. Same calculation process as OTDOA is then conducted to find out the mobile user's position. Since the measurement and the calculation process are exercised only in the RAN, this method does not require any modification to the mobile phone. This method provides location accuracy within 50-150 meters.

The aforementioned techniques can effectively monitor the behaviors of specific mobile users at the cost of modifications to telecom network, which are not appropriate to generate behavior statistics for a large number of users that are typically required to study problems such as pedestrian movement and contagious disease spread. In other words, these techniques cannot be used to answer questions like "What is the probability $P_{A,B}(T)$ that a person at location A will move to location B after T hours."

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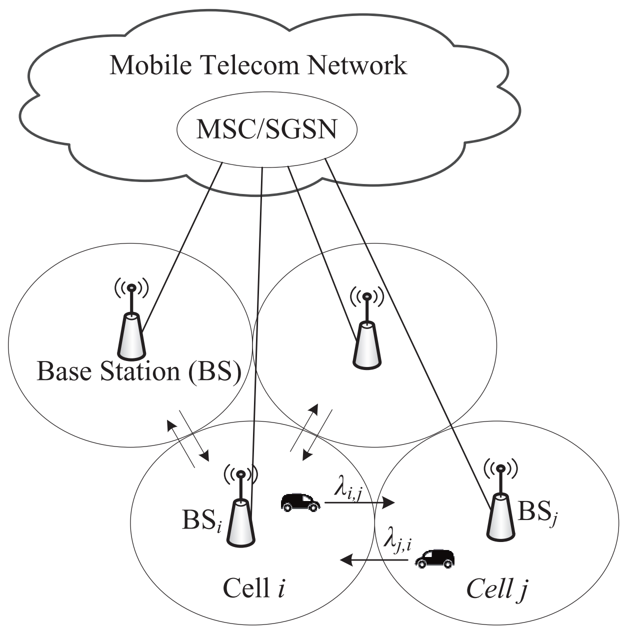


Fig. 1. A simplified mobile telecom network.

In [5], two data sets of the BS locations are utilized to analyze the human mobility patterns. The first data set records the BS locations of 100,000 individuals for six-month when they initiated/received a call or a short message. The second data set captures the BS locations of 206 individuals recorded every two hours for one week. The distribution of the displacements calculated from these two data sets is found to be well approximated by a truncated power-law equation. This method as well as other solutions [9], [10] require quasianonymous phone identities for tracing individual movements which causes extra undesirable overhead for the telecom operators. Furthermore, the data cannot be processed quickly (say, in one day) if the number of mobile users is larger than millions.

In this paper, we propose a novel approach to address the spread problem by only using the statistics from the standard mobile telecom switches such as *mobile switching centers* (MSCs), and *serving general packet radio service support nodes* (SGSNs) [6]. Our approach does not need to identify individual users and, therefore, does not cause any customer privacy problem. The notation used in this paper is listed in Appendix A, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TMC.2012.87.

2 Spread Prediction Model

Fig. 1 illustrates a mobile telecom SA covered by several BSs. In this figure, a cell of a BS is represented by a circle. A mobile user is represented by a vehicle moving around the cells. If a user in conversation moves from one cell to another, then the call connection must be switched from the old cell to the new cell. This switching operation is called a *handover*. When a call arrives at a user or when he/she performs a handover, the activity is recorded at the MSC/SGSN. The mobile telecom network collects the statistics of the activities for every Δt interval typically ranging from 15 minutes to several hours. The mobile operator can then investigate these statistics (output measures) for future network planning.

Four major measures provided by mobile telecom network are the expected call holding time, the numbers of handovers in and out of the cells, the number of new call arrivals of the cells, and the voice/data *traffic* (in Erlang) of the cells. For time τ, define $\Delta\tau$ as the timeslot $(\lfloor \frac{\tau}{\Delta t} \rfloor \Delta t, \lfloor \frac{\tau}{\Delta t} + 1 \rfloor \Delta t)$. Suppose that a mobile user in conversation moves from cell i to cell j at time τ, then he/she contributes to one handover out of cell i, and one handover into cell j in time slot $\Delta\tau$. The mobile telecom network measures $\lambda_{i,j}(\tau)$, the number of handovers from cell i to cell j in timeslot $\Delta\tau$. Note that it is meaningless that a call hands over to the same cell, and therefore $\lambda_{i,j}(\tau) = 0$. A mobile user resides at cell i in time slot $\Delta\tau$ may receive an incoming call or originate an outgoing call. Such "new calls" are counted by the measure $\alpha_i(\tau)$.

In telephony engineering, an Erlang represents the continuous use of one voice path. Let $\rho_i(\tau)$ be the measure of the Erlang traffic of cell i in $\Delta\tau$. Then, $\rho_i(\tau)$ is the number of calls arriving at cell i in $\Delta\tau$ times the expected call holding time. Practically, the mobile telecom network measures $\rho_i(\tau)$ by summing up all conversation minutes of cell i in $\Delta\tau$. The expected call holding time $\mathrm{E}[t_c]$ is the average of all collected call holding times over a long observed period.

Consider a cell as the granularity of location coverage. The movement of a mobile user is described as follows: The user stays at one cell for a period of time, and then moves to the next cell. If we sum up the *residence times* of the cells he/she visited, then we know exactly which cell the user visited after a specific elapsed time. Unfortunately, the above task cannot be achieved because the standard outputs $\mathrm{E}[t_c]$, $\lambda_{i,j}(\tau)$, $\alpha_i(\tau)$, and $\rho_i(\tau)$ cannot tell you how a specific mobile user moves exactly. On the other hand, these outputs can be used to derive the probability that where and when a user moves. When a user arrives at cell i in time slot $\Delta\tau$, let $R_i(\tau)$ be the average residence time before the user moves out of the cell. Let $p_{i,j}(\tau)$ be the transition probability that a user moves from cell i to cell j in time slot $\Delta\tau$. If both $R_i(\tau)$ and $p_{i,j}(\tau)$ are known, then we can predict the probability of the user's location at time $\tau + R_i(\tau)$. That is, the user moves to cell j with probability $p_{i,j}(\tau + R_i(\tau))$. Note that $p_{i,i}(\tau) = 0$ because $\lambda_{i,i}(\tau) = 0$. We use a prediction model to approximate $R_i(\tau)$ and $p_{i,j}(\tau)$ by using $\mathrm{E}[t_c]$, $\lambda_{i,j}(\tau)$, $\alpha_i(\tau)$ and $\rho_i(\tau)$, and show how the model computes $P_{i,j}(T)$, the probability that starting from cell i, a user will move to cell j after a time period T.

The concept behind the prediction model is Little's Law [7], which says that the expected number N of users in a system is the arrival rate λ of the users times the expected response time R that a user stays in the system, i.e.,

$$N = \lambda R. \tag{1}$$

Equation (1) is used to compute $R_i(\tau)$. We first derive the average number $N_i(\tau)$ of users at cell i in time slot $\Delta\tau$. The intuition behind the derivation of $N_i(\tau)$ is the following: If everyone at cell i makes at most one call in $\Delta\tau$, and every call takes $\mathrm{E}[t_c]$ minutes, then $N_i(\tau) = \rho_i(\tau)/\mathrm{E}[t_c]$. Let t_R be the "true" cell residence time. Assume that $\Delta t < \mathrm{E}[t_R]$ (we will discuss what happens if this assumption is violated later). When $\mathrm{E}[t_c] \gg \Delta t$, the conversation minutes contributed by the user is Δt, therefore the denominator of the $N_i(\tau)$ equation is adjusted by $\min(\mathrm{E}[t_c], \Delta t)$, and the equation is rewritten as

$$N_i(\tau) = \frac{\rho_i(\tau)}{\min(\mathrm{E}[t_c], \Delta t)}.$$

When $\mathrm{E}[t_c] \ll \Delta t$, most calls occurring in Δt are new calls (Section 3 will show in (13) that handover calls rarely occur when $\mathrm{E}[t_c]$ is small), and their call holding times are completely measured in $\rho_i(\tau)$ before Δt ends. Therefore, above equation is reasonably accurate when $\mathrm{E}[t_c] \gg \Delta t$ or $\mathrm{E}[t_c] \ll \Delta t$. When $\mathrm{E}[t_c] \approx \Delta t$, many ongoing calls (either in or out of the cell) are observed in the beginning or the end of Δt, and such a call contributes much less conversation minutes than $\min(\mathrm{E}[t_c], \Delta t)$. Therefore, we scale down the conversation minutes by a linear factor β expressed as

$$\beta = \frac{|\mathrm{E}[t_c] - \Delta t|}{\max(\mathrm{E}[t_c], \Delta t)} + \delta\left[1 - \frac{|\mathrm{E}[t_c] - \Delta t|}{\max(\mathrm{E}[t_c], \Delta t)}\right],$$
$$\text{where } 0 \le \delta \le 1.$$

Note that when $\mathrm{E}[t_c] \ll \Delta t$ or $\mathrm{E}[t_c] \gg \Delta t$, $\beta \approx 1$, and the conversation minutes are $\min(\mathrm{E}[t_c], \Delta t)$. When $\mathrm{E}[t_c] \approx \Delta t$, $\beta \approx \delta$, the conversation minutes are $\delta\{\min(\mathrm{E}[t_c], \Delta t)\}$ for "incomplete" calls that do not begin or end in Δt. The final $N_i(\tau)$ equation in our prediction model is

$$N_i(\tau) = \frac{\rho_i(\tau)}{\beta\{\min(\mathrm{E}[t_c], \Delta t)\}}. \quad (2)$$

Based on the above discussion, accuracy of (2) is affected by two effects.

Effect 1 (multiple-calls-per-cell effect on $N_i(\tau)$). If a user generates *multiple calls per cell*, then (2) overestimates $N_i(\tau)$.

Effect 2 (observed time slot). If $\Delta t < \mathrm{E}[t_R]$, (2) is more accurate when $\mathrm{E}[t_c] \gg \Delta t$ or $\mathrm{E}[t_c] \ll \Delta t$. When $\mathrm{E}[t_c] \approx \Delta t$, the conversation minutes of a call should be scaled down.

Basically, it is reasonable to assume that an "incomplete" call contributes half of the conversation minutes (i.e., $\delta = 0.5$) in Δt. If $\Delta t > \mathrm{E}[t_R]$ and $\mathrm{E}[t_c] \gg \mathrm{E}[t_R]$, then the measured conversation minutes of a call should be $\min(\mathrm{E}[t_c], \mathrm{E}[t_R])$, and (2) will underestimate $N_i(\tau)$. In Section 3, we show that this error can partially corrected by selecting a smaller δ value (e.g., $\delta = 0.4$).

In time slot $\Delta\tau$, the number of handovers flowing into cell i is

$$\lambda_i(\tau) = \sum_{j,j \ne i} \lambda_{j,i}(\tau). \quad (3)$$

Four types of users are observed at cell i. In time slot $\Delta\tau$, a *type 1* user moves into the cell when he/she is in phone conversation (and a handover occurs). A *type 2* user is not in phone conversation when he/she moves into the cell, and then has phone calls at this cell in $\Delta\tau$. A *type 3* user moves in and/or out of cell i without any call activity. A *type 4* user arrives at cell i earlier than $\Delta\tau$, and then has at least one phone call at this cell in $\Delta\tau$.

The number of type 1 users moving into cell i in timeslot $\Delta\tau$ is $\lambda_i(\tau)$. If multiple-calls-per-cell effect does not exist, then $\alpha_i(\tau)$ is the number of type 2 and type 4 users of cell i in time slot $\Delta\tau$.

According to (1), the average residence time $R_i(\tau)$ of a user arriving in cell i in time slot $\Delta\tau$ is approximated as

$$R_i(\tau) = \frac{N_i(\tau)}{\lambda_i(\tau) + \alpha_i(\tau)}.$$

From (2), we have

$$R_i(\tau) = \frac{\rho_i(\tau)}{\beta\{\min(\mathrm{E}[t_c], \Delta t)\}[\lambda_i(\tau) + \alpha_i(\tau)]}, \quad (4)$$

where $\lambda_i(\tau)$ in (4) is computed from (3).

Effect 3 (multiple-calls-per-cell effect on $\alpha_i(\tau)$). If Effect 1 is significant, i.e., a user tends to make multiple calls in a cell, then $\alpha_i(\tau)$ overestimates the number of type 2 users.

Note that due to Effect 1, (4) overestimates the cell residence time. Due to Effect 3, (4) underestimates the cell residence time.

Effect 4. A type 4 user is not supposed to contribute to the arrival rate λ in (1). However, a type 4 user does contribute to $\alpha_i(\tau)$, and therefore (4) underestimates the cell residence time.

If $\Delta t > \mathrm{E}[t_R]$, a type 4 user becomes a type 2 user. Note that type 3 users contribute to neither $\rho_i(\tau)$ nor $\alpha_i(\tau)$, and are reasonable to be ignored in computing (4). The predicted routing probability $p_{i,j}(\tau)$ is expressed as

$$p_{i,j}(\tau) = \frac{\lambda_{i,j}(\tau)}{\sum_{j,j \ne i} \lambda_{i,j}(\tau)}. \quad (5)$$

However, behavior of Type 3 users does affect the routing probability, which results in the following effect.

Effect 5. Movement of type 3 user is not included in $\lambda_{i,j}(\tau)$, which affects the accuracy of (5).

By using (4) and (5), $P_{i,j}(T)$ can be expressed recursively as

$$P_{i,j}(T) = \sum_{k,k \ne j} P_{i,k}(T') p_{k,j}(T), \quad (6)$$

where $T = T' + R_k(T')$. For $T \le 0$,

$$P_{i,j}(T) = \begin{cases} 1, & \text{for } j = i, \\ 0, & \text{for } j \ne i. \end{cases}$$

The recursion stops when $T' \le 0$. We note that the above recursive algorithm is given for the description purpose. In our implementation of the prediction model, an iterative algorithm is used to compute (6), where the details are given in Appendix B, available in the online supplemental material.

3 Numerical Examples

We have collected $\lambda_{i,j}(\tau)$, $\rho_i(\tau)$, $\mathrm{E}[t_c]$, and $\alpha_i(\tau)$ statistics from a commercial mobile telecom SA in Hsinchu, Taiwan. The statistics were measured when $\Delta t = 1$ hour, which can be translated into $\Delta t = 15$ minutes, and are listed below:

- $\mathrm{E}[\lambda_{i,j}(\tau)]$: 3.3725 movements per 15 minutes (13.49 movements per hour).

- $\mathrm{E}[\rho_i(\tau)]$: 1.0325 Erlangs per 15 minutes (4.103 Erlangs per hour).
- $\mathrm{E}[t_c]$: 1-5 minutes for voice calls and 10-20 minutes for data sessions.

Due to the Personal Information Protection Act in Taiwan, we are not allowed to publish the mappings between the collected statistics and the BS in that area. Therefore, we assume that the cell layout is of the Manhattan Street fashion with 7×7 cell structure, where every cell has four neighbors (the boundary cells have two or three neighbors and the users visiting these cells will bounce back).

We consider a baseline scenario where call arrivals are a Poisson process with the expected intercall arrival time $\mathrm{E}[t_a] = 2$ hours, and the call holding time is exponentially distributed with the mean $\mathrm{E}[t_c] = 2$ minutes. Based on these assumptions as well as the $\mathrm{E}[\lambda_{i,j}(\tau)]$ and the $\mathrm{E}[\rho_i(\tau)]$ statistics obtained from the commercial mobile telecom network, we select the number of users as follows: The total call traffic generated in this system is $\mathrm{E}[\rho_i(\tau)] \times 49 = 4.103 \times 49 = 201.05$ Erlangs per hour. The Erlang traffic generated from a user is $\frac{\mathrm{E}[t_c]}{\mathrm{E}[t_a]} = \frac{1}{60}$. Therefore, the number of users in the system is $201.05 \div (\frac{1}{60}) = 12{,}062.82$. The numbers of users considered in our experiments are 12,000 and 24,000, respectively. Also, as a baseline scenario, the expected cell residence time $\mathrm{E}[t_R]$ can be selected as follows: Since we assume that every cell has four neighbors, the handover rate out of a cell is $\mathrm{E}[\lambda_{i,j}(\tau)] \times 4 = 13.49 \times 4 = 53.96$ per hour. The expected number of users in a cell is $12000 \div 49 = 244.9$. Since every user leaves the cell with rate $1/\mathrm{E}[t_R]$, and such cell crossing is a handover with probability $\frac{\mathrm{E}[t_c]}{\mathrm{E}[t_a]+\mathrm{E}[t_c]} = (\frac{1}{61})$, we have

$$244.9 \times \left(\frac{1}{\mathrm{E}[t_R]}\right) \times \left(\frac{1}{61}\right) = 53.96.$$

That is, $\mathrm{E}[t_R] = 0.08$ hours or 4.8 minutes. Our experiments consider $\mathrm{E}[t_R] = 5$, 10, 15, and 20 minutes.

Based on the above parameters, we simulate user movement and call activities for 24 hours. The cell residence time t_R has an arbitrary distribution (we specifically consider Gamma, Normal, and Weibull distributions; the results for Gamma distribution are elaborated in this paper, other distributions show similar results and are not presented). In our experiments, the cell residence times $\mathrm{E}[t_R]$ and the routing probabilities $p^*_{i,j}(\tau)$ are given. Probabilities $p^*_{i,j}(\tau)$ are randomly generated to avoid homogeneous routing; i.e., our experiments arrange that $p^*_{i,j}(\tau) \neq p^*_{i,k}(\tau)$ for cell i's neighboring cells $j \neq k$. At the end of a simulation run, we obtain the "real" probabilities $P^*_{i,j}(T)$ for $T = 6$, 12, 18, and 24 hours). During the experiments, the simulated mobile telecom network produces $\lambda_{i,j}(\tau)$, $\rho_i(\tau)$, t_c, and $\alpha_i(\tau)$ in every 15 minutes (i.e., $\Delta t = 15$ minutes). Then we use the prediction model to compute $p_{i,j}(\tau)$, $R_i(\tau)$, and $P_{i,j}(T)$, and compare them with the "real" values $p^*_{i,j}(\tau)$, $\mathrm{E}[t_R]$, and $P^*_{i,j}(T)$.

In our experiments, phone calls (connected to the MSC) are represented by $\mathrm{E}[t_c] \leq 5$ minutes, and data sessions (connected to the SGSN) are represented by $\mathrm{E}[t_c] \geq 10$ minutes. The accuracy of the prediction model is investigated through the following measures (where the number of users is 24,000 and the expected intercall arrival time $\mathrm{E}[t_a] = 2$ hours).

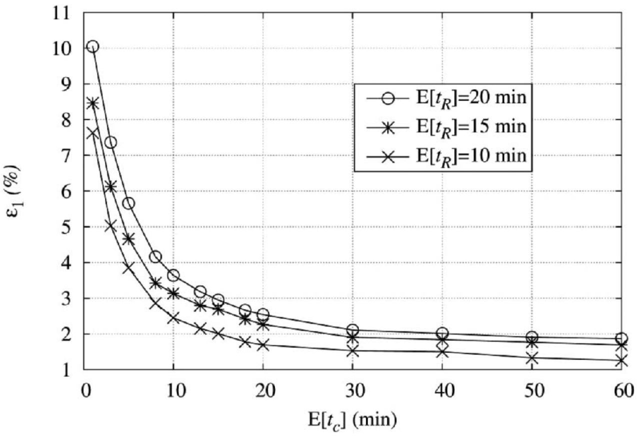


Fig. 2. Accuracy of routing probability prediction ($\mathrm{E}[t_a = 2]$ hours).

Measure ε_1 is the average error between the predicted and the real routing probabilities. Let $\varepsilon_{i,j}$ be the error between the predicted routing probabilities $p_{i,j}(\tau)$ and the real values $p^*_{i,j}(\tau)$. That is,

$$\varepsilon_{i,j} = \frac{p_{i,j}(\tau) - p^*_{i,j}(\tau)}{p^*_{i,j}(\tau)}.$$

Then, we have

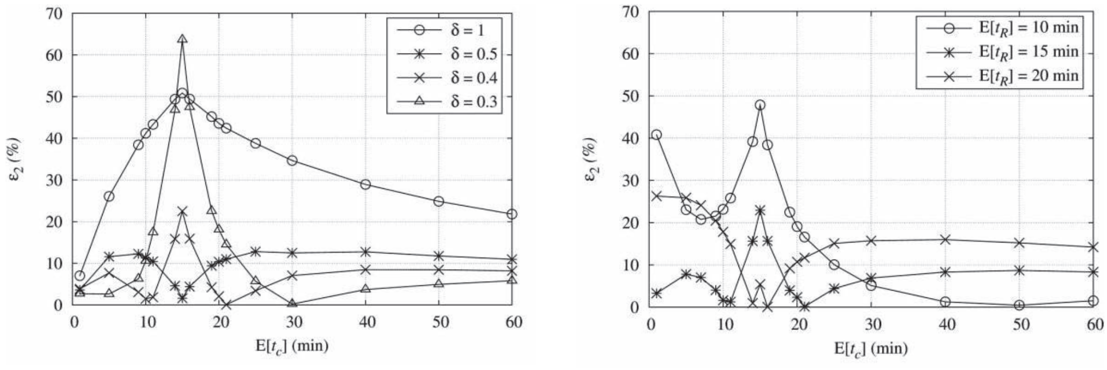
$$\varepsilon_1 = \frac{\sum_{i=1}^{N} \sum_{j \in S_i} \varepsilon_{i,j}}{\sum_{i=1}^{N} |S_i|},$$

where N is the number of cells in the mobile network, and S_i is the set of neighboring cells of cell i.

As pointed out in Effect 5, the users who do not make calls when they cross the cells also affect $p^*_{i,j}(\tau)$, which are not captured by (5). If t_c increases, t_a decreases, or t_R decreases, more users are in conversation when they move into a cell (see (13) and (14)), and therefore there are more handovers. Having more handovers means that the effect of the users who do not make calls when crossing the cells becomes insignificant and the measured $p_{i,j}(\tau)$ is more accurate, as indicated in Fig. 2.

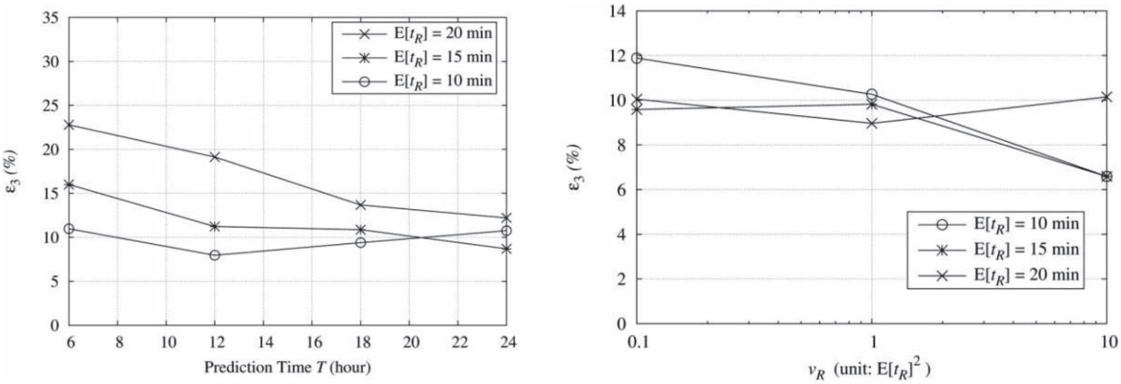
Measure ε_2 is the error between the real cell residence time $\mathrm{E}[t_R]$ and the predicted cell residence time $R_i(\tau)$ computed by (4), which is mainly caused by Effects 1, 2 (on (2)), 3 and 4. Fig. 3a plots ε_2 against δ where $E[t_R] = 15$ minutes. The figure indicates that when $\delta = 1$ (i.e., no adjustment), the largest $\varepsilon_2 = 50$ percent occurs at $E[t_c] = \Delta t = 15$ minutes. This result is exactly what we expected (see Effect 2). When $\delta < 0.4$, β over compensates (4), which results in high error when $\mathrm{E}[t_c] \geq \Delta t$. When $0.4 < \delta < 0.5$, the overall ε_2 performance is better than other δ values, which is also consistent with the intuition mentioned in Section 2. Fig. 3b plots the ε_2 curves for $\delta = 0.4$. When $\mathrm{E}[t_R] \geq \Delta t$, ε_2 is limited to 25 percent. When $\mathrm{E}[t_R] < \Delta t$ and $\mathrm{E}[t_c] \gg \Delta t$, ε_2 are limited to 5 percent. Therefore, reasonably small ε_2 can be achieved when $\mathrm{E}[t_R] < \Delta t$. If both $\mathrm{E}[t_c]$ and $\mathrm{E}[t_R]$ are smaller than Δt, large errors are observed.

Accuracy of our model is enhanced if a user does not generate more than one call at a cell. In Appendix C,



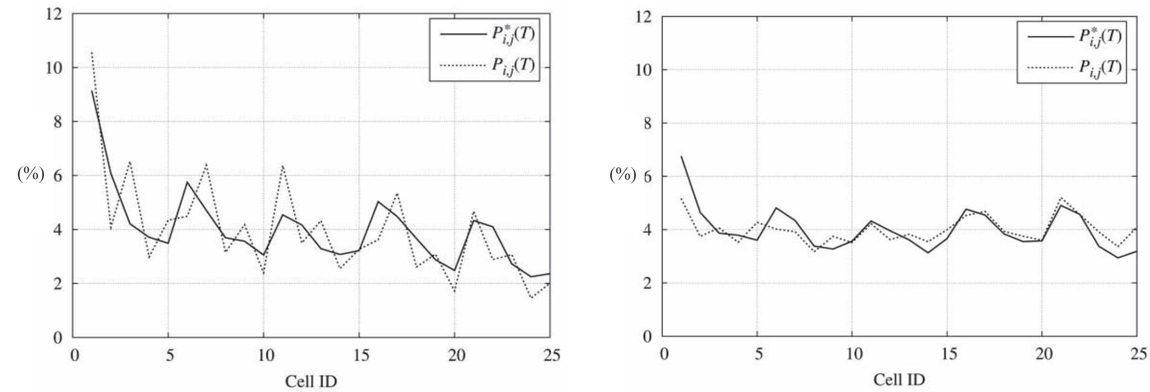
(a) $\mathrm{E}[t_R]$=15 minutes (b) $\delta = 0.4$

Fig. 3. Accuracy of cell residence time prediction ($\mathrm{E}[t_a = 2]$ hours, $\Delta t = 15$ minutes).



(a) Impact of T ($\mathrm{E}[t_c]$=1 minute, v_R= $\mathrm{E}[t_R]^2$) (b) Impact of v_R (T=24 hours, $\mathrm{E}[t_c] = 15$ minutes)

Fig. 4. The ε_3 measure. ($\mathrm{E}[t_a = 2]$ hours, $\Delta t = 15$ minutes, $\delta = 0.4$).



(a) T= 6 hours (b) T= 24 hours

Fig. 5. $P_{i,j}(T)$ versus $P^*_{i,j}(T)$ ($\mathrm{E}[t_a] = 2$ hours, $\Delta t = 15$ minutes, $\mathrm{E}[t_c] = 15$ minutes, $v_R = \mathrm{E}[t_R]^2, \delta = 0.4$).

available in the online supplemental material, we provide a detailed analysis of the multiple-calls-per-cell effect, which summarizes the results in Effect 6 stating that the multiple-calls-per-cell effect is more significant as $\mathrm{E}[t_a]$ decreases, $\mathrm{E}[t_c]$ decreases, or $\mathrm{E}[t_R]$ increases. Effect 6 can be partially explained by a simple (30) derived in Appendix C, available in the online supplemental material, which assumes that t_a, t_c, and t_R are exponentially distributed. Define $\mathrm{r_a} = 1/\mathrm{E}[t_a]$, $\mathrm{r_c} = 1/\mathrm{E}[t_c]$, and $\mathrm{r_R} = 1/\mathrm{E}[t_R]$, (30) expresses the probability that multiple-calls-per-cell effect does not occur as

$$\frac{r_R(r_c + r_a + r_R)}{(r_c + r_R)(r_a + r_R)}.$$

From the above expression, Effect 6 states that the multiple-calls-per-cell effect is more significant as $\mathrm{E}[t_a]$ decreases, $\mathrm{E}[t_c]$ decreases, or $\mathrm{E}[t_R]$ increases. Fig. 3b indicates that, in general, for $\mathrm{E}[t_c] > \Delta t$, ε_2 decreases as $\mathrm{E}[t_R]$ decreases due to Effect 6. The above statement is also true for $\mathrm{E}[t_c] < \Delta t$ if $\mathrm{E}[t_R] \geq \Delta t$.

Measure ε_3 is the error between $P_{i,j}\ (T)$ and $P^*_{i,j}(T)$, which is caused by the inaccuracy of (11). Fig. 4a shows that ε_3 decreases as T increases in general. In other words, our model provides better prediction for far future than near future. From Effect 6, ε_3 decreases as $\mathrm{E}[t_R]$ decreases. When $\mathrm{E}[t_R] < \Delta t$, ε_3 may become large for long T.

Little's Law is entirely independent of any of the detailed probability distributions involved, and hence requires no assumptions about the schedule according to which customers arrive or are serviced. To investigate how our application on Little's Law is affected by the distributions, we have experimented on Weibull, Gamma, and truncated Normal distributions. Effect 6 in Appendix C, available in the online supplemental material, suggests that Effect 1 is more serious as the variance v_R of the t_R distribution is larger. However, Fig. 4b shows that v_R does not have significant impact on ε_3.

Fig. 5 plots $P_{i,j}(T)$ and $P^*_{i,j}(T)$ for $1 \leq i, j \leq 25$. The figure indicates that $P_{i,j}(T)$ nicely captures the trends of $P^*_{i,j}(T)$.

4 Conclusions

Based on Little's Law, this paper proposed a model to predict how people spread from one location to another after a period of time. This information is very useful to investigate issues such as prediction of vehicle traffic and spread of contagious diseases. The standard statistics provided by a commercial mobile telecom network are used as inputs of our prediction model. Experiments indicate that if the measured time slot is smaller than the expected cell residence time, and is not close to the expected call holding time, then good accuracy of the prediction model can be expected. For all parameters considered in this paper, the errors of the prediction are limited to 20 percent and are less than 10 percent in most cases. In the future, we will continue to improve the accuracy of prediction.

As we mentioned in Section 1, existing solutions cannot answer the question "What is the probability that a person at location A will move to location B after T hours?" with statistics of large samples of human movements. Our solution is the first work that can statistically answer this question by effectively utilizing the statistics collected from millions of mobile users. As a final remark, this work is pending US and Taiwan patents.

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