Analysis of Smartphone User Mobility Traces for Opportunistic Data Collection[☆]

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Abstract

Considering that smartphones are tightly-coupled with their users, the interaction between smartphones and wireless sensor networks will play a very important role in pervasive computing for improving our daily life. Instead of using smartphones to access the services provided by various wireless sensor networks, we focus on using smartphones to collect data from sensor nodes opportunistically. In this paper, through analyzing the dataset from Mobile Data Challenge by Nokia, we validated the feasibility of opportunistic data collection through smartphones and identified several important characteristics of smartphone users' mobility, such as the strong spatial and temporal localities that should be considered when designing protocols and algorithms for opportunistic data collection.

Keywords: Human Mobility, Smartphone, Wireless Sensor Network, Opportunistic Data Collection

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1. Introduction

As wireless sensor networks mature, we expect to see many long-term and large-scale deployments for various applications, such as environmental monitoring, domestic utility meter reading, urban monitoring, etc. For example, millions of water meters will be installed across Republic of Ireland in the near future and many air quality monitoring systems will be deployed in large cities of Europe to satisfy EU regulations. Considering that the increasingly ubiquitous smartphones are tightly-coupled with their users, the interaction between smartphones and wireless sensor networks will play a very important role in future pervasive computing. For instance, a smartphone can get various information (temperature, air quality, etc.) from sensor nodes around its user and assist in making informed decisions. Here, it is normally assumed that smartphones and sensor nodes can communicate through some low power radios, such as Bluetooth and ZigBee [1]. In this paper, instead of the above classical paradigm, we focus on letting smartphones provide a service to wireless sensor networks, i.e., using smartphones to collect data from sensor nodes opportunistically.

Due to the limited computing capability and storage size of sensor nodes, these nodes normally send their data to an application server through some dedicated static sink nodes with the aim of further processing [1]. However,

[1] Bluetooth is distributed with almost all smartphones and it is also adopted by many sensor nodes, such as IMote and BTnode. ZigBee is the most widely used radio on sensor nodes and it starts to appear on smartphones. In Mobile World Congress 2012, TazTag released the first smartphone with both ZigBee and NFC (Near-Field Communication) interfaces (http://www.taztag.com/).

due to environmental constraints and/or cost issues, sensor nodes tend to be deployed sparsely and these networks tend to be partitioned. Consequently, deploying large numbers of static sink nodes for collecting sensor data from these sensor nodes would incur prohibitive costs in terms of deployment, maintenance, and data back-haul. The cost of equipping each sensor node with cellular network interface is even higher.

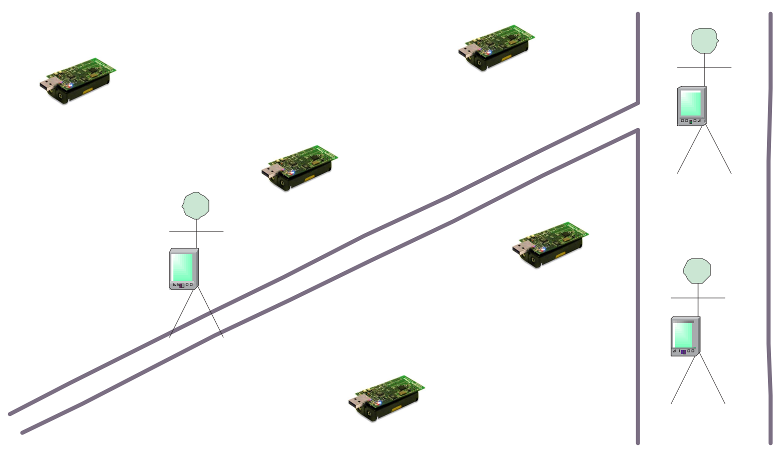


Figure 1: Data Collection through Smartphones

As illustrated in Figure 1, it has been proposed to use smartphones carried by people in their daily life to collect sensor data opportunistically [2][3][4][5]. Under this scenario, smartphones will gather data from sensor nodes automatically and accidentally (without any user intervention or route change). To participate in opportunistic data collection, a smartphone user just needs to run a background application on the phone, and many users could be motivated with a very low reward. For instance, the owners of wireless sensor networks could reward these users by allowing them to access the current sensor readings (temperature, humidity, etc.). In case that the sensor readings are not needed by smartphone users or the sensor readings cannot be publicized due to confidential and privacy reasons, these users could be rewarded by a small amount of virtual/real money through cellular network system. More discussion about the incentive, security, and privacy issues arising in opportunistic data collection through smartphones can be found in [5]. Consequently, the cost of data collection can be reduced through exploiting the uncontrolled mobility of smartphone users.

Apart from reducing the cost significantly, opportunistic data collection through smartphones also has the benefits of adopting mobile sinks, such as the increased network reliability through removing the dependency on static sink nodes and the extended network lifetime through removing hot-spots near the static sink nodes [6][7]. Although data delivery latency could be long in opportunistic data collection, there are many promising wireless sensor network applications which are delay-tolerant. For example, analysis of environmental monitoring data is rarely urgent and meter readings for billing purposes can be delayed by weeks. Hence, it is worthwhile to study how to improve the performance of opportunistic data collection, especially for wireless sensor networks in which sensor nodes are duty-cycled aggressively for longevity.

Considering that the main point of opportunistic data collection is to exploit the *uncontrolled* mobility of smartphone users, it becomes necessary to analyze their mobility traces for answering the following important questions.

1. In opportunistic data collection, is the smartphone's overhead (energy consumption, CPU, etc.) low enough so that the participation of smartphone users could be motivated with a very low reward?

2. For each encounter between a smartphone and a sensor node, does the smartphone stay in the communication range of the sensor node long enough for collecting data opportunistically?
3. Could smartphone users visit a sensor node frequently enough to support a variety of applications?
4. How does the smartphone users' mobility distribute in time and space? How do these distributions influence the design and operation of the protocols and algorithms for opportunistic data collection?

Based on the dataset from Mobile Data Challenge by Nokia [8], the mobility traces of 37 smartphone users are studied in this paper for answering these questions. This paper is organized as follows. The analysis methodology is first introduced in Section 2. We also describe how the dataset is trimmed. The results of analysis are then presented and discussed in Section 3. Finally, Section 4 discusses related works and Section 5 concludes this paper with several key findings, such as the feasibility of opportunistic data collection through smartphones and the strong spatial and temporal localities that should be considered when designing the protocols and algorithms for opportunistic data collection.

2. Data Preparation

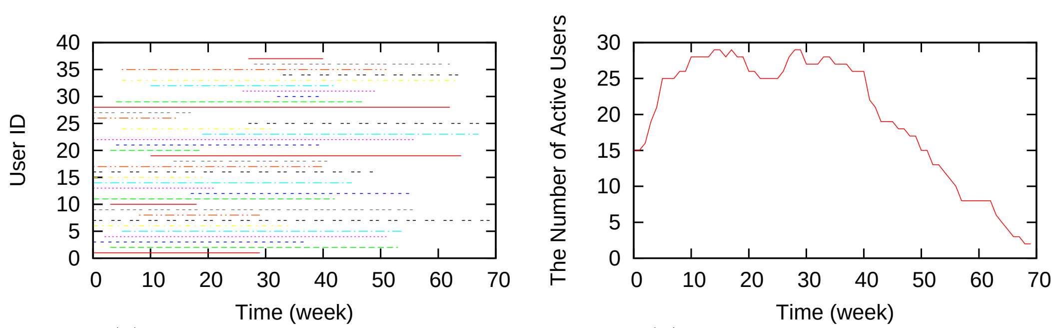
In this paper, the mobility of smartphone users is studied through analyzing the dataset from Mobile Data Challenge by Nokia. Although a lot of information had been collected for each smartphone user, we are mainly interested in the GPS readings recorded when a user was moving around outside. More specifically, we only use the following information of a GPS reading, <*time*, *latitude* and *longitude*, *speed*>, i.e., the time, the location, and the movement speed when this GPS reading was logged.

For opportunistic data collection, we hope to know how the encounters between smartphones and sensor nodes distribute in both space and time. Hence, the area visited by smartphone users is divided into cells[2] with a size of 0.001 (Latitude) * 0.001 (Longitude). Approximately, a cell is a rectangle with a size of 185m * 126m and it matches well with the outdoor communication range of the current sensor node platform [9]. The duration of the Data Collection Campaign by Nokia is also divided into slots in the unit of hour, day, or week based on the analysis to be carried out. The distributions of GPS readings in time and space are then calculated and analyzed in this paper.

Before carrying out analysis, the dataset is first trimmed. We have removed a few GPS readings that are far away from the Lake Geneva region so that the number of cells to be considered can be reduced significantly. For reducing the number of time slots to be considered, the GPS readings which were logged when most of users had quit the Data Collection Campaign by Nokia are also removed. Hence, the analysis can be carried out in a short time. Through removing these GPS readings, we can also avoid that the conclusions are skewed by the large areas and long periods in which the level of user participation is very low. The GPS readings, which have been truncated for user anonymity, are also removed since we cannot associate such a reading to a specific cell.

[2] Note that a cell here is just a small area and it is totally different from the cell in cellular networks.

Consequently, 893,920 GPS readings from 37 smartphone users are used in our analysis[3]. The latitude range is [46.1, 46.8], the longitude range is [6.4, 7.4], there are totally 700,000 cells, and the whole area is referred as the Lake Geneva Region. Sometimes, we only analyze the cells of the Lausanne Urban Area (one major city of the Lake Geneva Region), in which the latitude range is [46.50 46.55], the longitude range is [6.54, 6.66], and there are 6,000 cells. As for the duration, it is from 05/09/2009 to 07/01/2011 and the time span is 70 weeks. Considering that smartphone users may not participate during the whole period, based on the timestamps in their GPS readings, Figure 2(a) plots the periods that these 37 users participate the Data Collection Campaign by Nokia. The level of user participation, i.e., the number of active smartphone users, is also plotted in Figure 2(b).



(a) Users' active periods

(b) Active users vs. time

Figure 2: The participation of 37 smartphone users

[3]In the dataset obtained from Nokia, there are totally 1,553,154 GPS readings from 38 smartphone users. 491,566 GPS readings are purged because they have been truncated for user anonymity. Since only GPS readings in a few sensitive locations are truncated, these purged data does not affect the analysis results in this paper.

3. Results of Analysis

3.1. Percentage of Movement Time

Considering that a sensor node is normally powered by un-chargable battery, its radio must be duty-cycled for longevity. Hence, it is preferred to let a smartphone with re-chargable battery always keep its radio on so that they can discover each other in a timely manner [3]. However, the energy consumed by a smartphone's radio for opportunistic data collection might become a serious concern.

Fortunately, we can reduce its energy consumption based on context information. It has been reported that a smartphone can deduce whether it is moving through accelerometer [10][11]. A smartphone can then keep its radio on only when its user is moving around. In case that its user is static, the smartphone can turn on its radio occasionally for collecting data and turn off its radio in most of the time for saving energy. To study the energy overhead with this scheme, we need get to know the percent of time that a smartphone user is moving around.

In the dataset, a GPS reading is recorded every 10 seconds only when a user is moving around outside. Hence, if the interval between two consecutive GPS readings is too long (>300s), we assume that the user is static and the radio can be turned off during that interval[4]. We then calculate the percentage of movement time for each smartphone user. Figure 3 plots the cumulative distribution function (CDF) of the percentage of movement

[4]Note that GPS readings could be absent due to many reasons. Here, we assume the dominant reason is that a smartphone user stops to move.

time across 37 users. It shows that for most of smartphone users, the movement time is less than 10%. Hence, smartphone users are static and the radio for opportunistic data collection can be turned off most of the time. In another word, the overhead of opportunistic data collection in terms of energy consumption could be low for a smartphone, thus encouraging user participation.

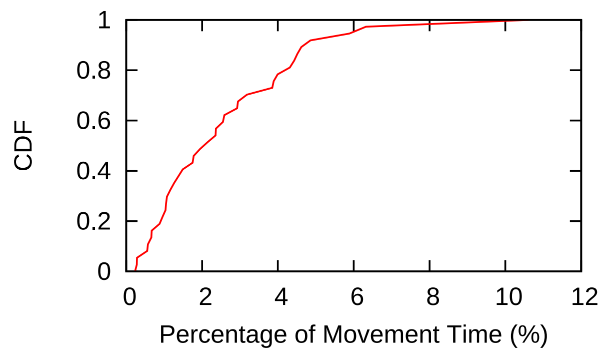


Figure 3: CDF of the percent of movement time

3.2. Movement Speed

Since a sensor node is normally duty-cycled, a smartphone still needs to take time to discover a sensor node even when they are in close proximity. Furthermore, a smartphone and a sensor node normally belong to different authorities, and authentication must be carried out before collecting data. Hence, for opportunistic data collection, it is desired that a smartphone could stay in the communication range of a sensor node for a period that is sufficient for discovery, authentication, and data collection.

To check this issue, the cumulative distribution function of the movement speed in these smartphone users' GPS readings is plotted in Figure 4.

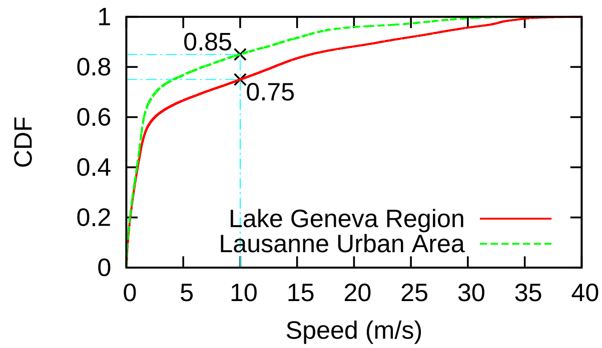


Figure 4: CDF of movement speed

This plot indicates that the movement speed is quite low in many cases. In Lausanne Urban Area, the speed of 85% GPS readings is less than 10m/s. Even for the much larger Lake Geneva Region with many roads, there are still 75% GPS readings whose speed is less than 10m/s. Considering that the outdoor communication range of a sensor node is around 100m, a lot of data could be collected during the encounter between a smartphone and a sensor node. With the assumptions that ZigBee radio is used (the data rate is 250Kbps) and the duration for data collection is 10 seconds, 312K bytes can be collected per visit. Considering that the size of a sensor reading is normally small, thousands of sensor readings can be collected per visit.

Figure 4 also indicates that the movement speed can be high with non-negligible probability, even when only the Lausanne Urban Area is considered. This fact justifies our sensor node-initiated probing mechanism for timely discovery between smartphone and sensor node [3].

3.3. Per-cell's GPS Reading Distribution among Smartphone Users

As mentioned earlier, a smartphone and a sensor node normally belong to different authorities, and some authentication schemes based on public key cryptography are needed for secure data collection. Hence, a smartphone and a sensor node may consume too much CPU, time, and energy for carrying out the related public key operations. In case that a sensor node is repeatedly visited by a few smartphones, hash-chain-based authentication scheme could be used by them to avoid carry out public key operations during each encounter [12]. To verify whether hash-chain-based authentication scheme should be applied, for each cell that is visited at least once per day and is visited by more than one user, we calculate the relative standard deviation of its GPS reading distribution among these users[5].

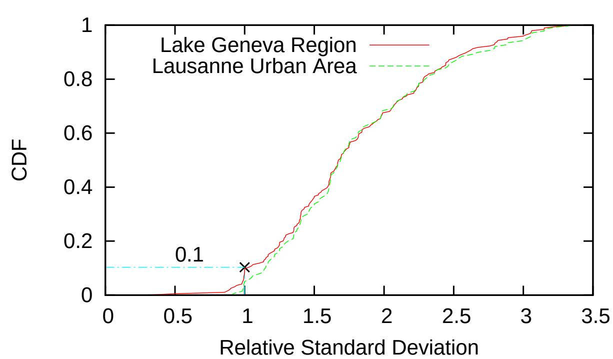


Figure 5: CDF of relative standard deviation for per-cell's GPS reading distribution among smartphone users

[5]Among 700,000 cells in the Lake Geneva region, 16,687 cells are visited by more than one users. As for 6,000 cells in the Lausanne urban area, 2815 cells are visited by more than one users.

Figure 5 plots the CDF of the relative standard deviation across these cells. It indicates that for most cells, the GPS reading distribution among users has a large variance (>1.0), i.e., the visits to a cell are mainly contributed by a few users. Hence, hash-chain-based authentication scheme could be used in opportunistic data collection and the overhead of authentication could become quite low.

3.4. Spatial Analysis

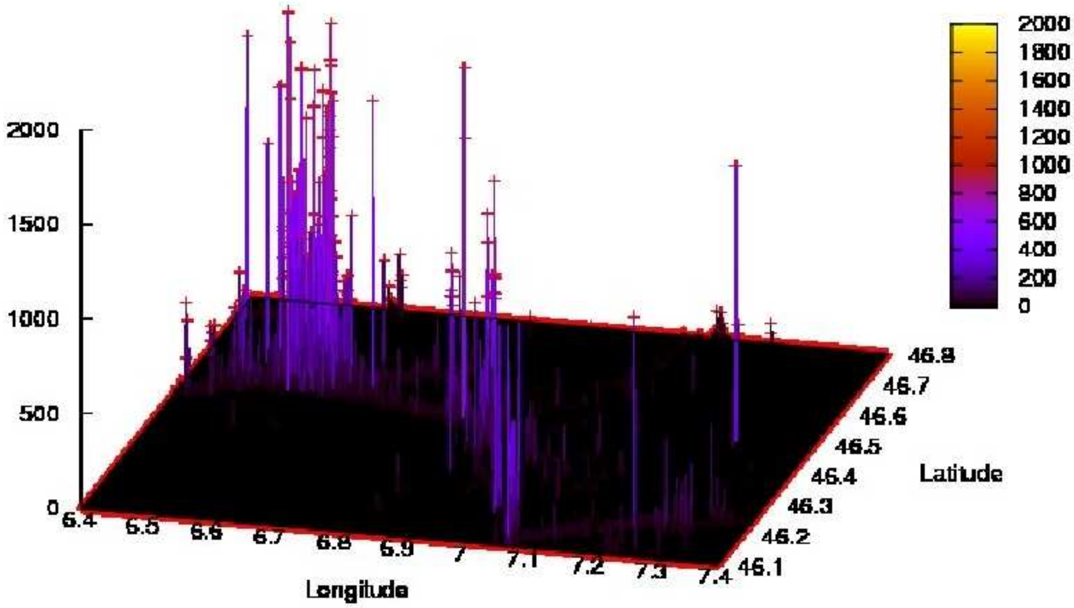
3.4.1. Spatial Distribution

In the following analysis, we first calculate the number of GPS readings in each cell. We then plot the spatial distribution of GPS readings among all cells of the Lake Geneva Region in Figure 6(a). The spatial distribution among cells of the Lausanne Urban Area is also plotted in Figure 6(b).

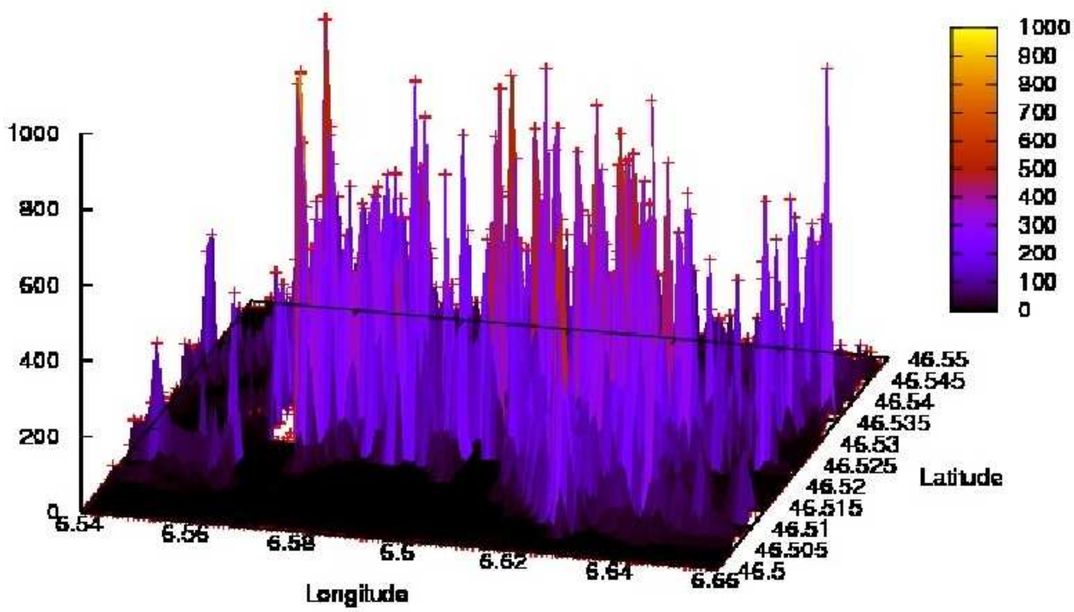
Figure 6(a) shows that the mobility traces of just 37 smartphone users still could cover a large area. Figure 6(b) indicates that the cells in an urban area are visited frequently even when there are only 37 smartphone users. Our analysis shows that 19% of cells in the Lausanne Urban Area are visited at least once per week and 2.466% of cells are visited at least once per day. Hence, we can expect that opportunistic data collection through smartphones can support many applications, especially when sensor nodes are deployed in urban areas where we live in most of the time.

3.4.2. Spatial Locality

Figure 6(a) and 6(b) also indicate that a strong spatial locality exists in these distributions of GPS readings and different cells are visited by smartphone users with different frequencies. Through checking the map of Lake



(a) Lake Geneva Region



(b) Lausanne Urban Area

Figure 6: Spatial distributions of GPS readings

Geneva Region shown in Figure 7, we find that Figure 6(a) clearly illustrates that most of these GPS readings are within the towns alongside the A9 motorway of Switzerland. Figure 6(b) indicates that even in the urban area, there are still some cells that have never been visited. There are also some *hot* cells that are visited much more frequently than other *cold* cells. To study the spatial locality quantitatively, we have calculated the relative standard deviation of the distribution of GPS readings in the Lausanne Urban Area and it is as high as 5.23. Hence, a strong spatial locality is identified and sensor data should flow among sensor nodes to improve the performance of opportunistic data collection through exploiting this spatial locality [4].

Figure 7: The Map of Lake Geneva Region

To study the feasibility of exploiting spatial locality, for the Lausanne Urban Area, a cell is marked as a *hot* cell if it is visited at least once per day. Otherwise, the cell is marked as *cold* cell. We then calculate the distance between a *cold* cell and its nearest *hot* cell. The cumulative distribution function of these distances is plotted in Figure 8 and this plot shows that for 63.5% *cold* cells, the distance is less than ten cells. The distance could be reduced if the mobility traces of more users are considered. However, considering that human mobility is normally constrained by roads and streets, *cold* cells should continue to exist. Hence, sensor data should be exchanged among sensor nodes for exploiting spatial locality and the data could reach a *hot* cell through a few hops.

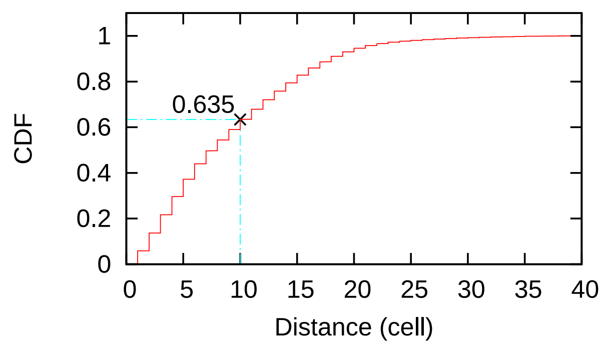


Figure 8: CDFs of the distance between a cold cell and its nearest hot cell

We have also calculated the distance between a *hot* cell and its nearest *hot* cell. The result in Figure 9 shows that for most of *hot* cells, one of its direct neighbors is also a *hot* cell. Hence, opportunistic data collection through smartphones is robust to the failure of sensor nodes in a *hot* cell. It also indicates that the neighboring *hot* cells tend to be visited sequentially and this characteristic should be exploited if the duty cycle of sensor nodes isn't too low.

3.4.3. Seasonal Changes

To exploit the spatial locality for opportunistic data collection, a *hot* cell should continue to be a *hot* cell for a long time so that sensor data won't chase the moving *hot* cells and consume too much energy to arrive at a *hot*

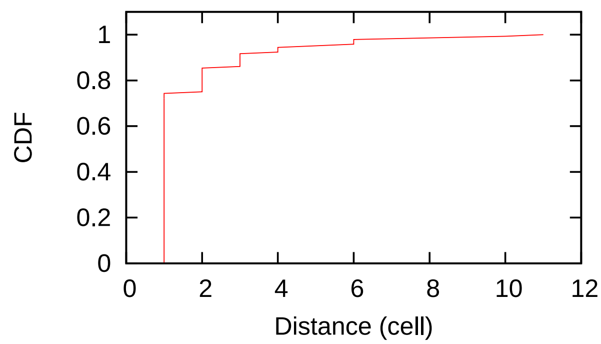


Figure 9: CDFs of the distance between a hot cell and its nearest hot cell

cell and be collected by a smartphone in that cell. Hence, for each week, we calculate the number of GPS readings for each cell and these numbers have been plotted into a 3-D figure. Several animations are then produced based on these figures to demonstrate the changes of the spatial distribution with the elapse of the time. These animations are available at the official webpage of the Mobile Data Challenge by Nokia [13].

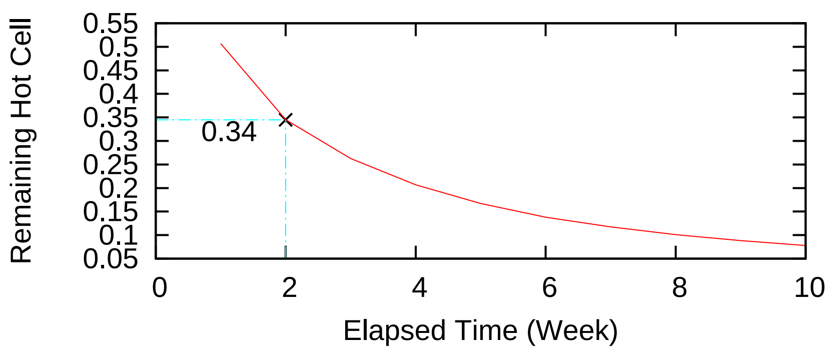


Figure 10: The invariability of *hot* cells

To study the seasonal changes of *hot* cells quantitatively, for each week, a cell in the Lausanne Urban Area is first marked as a *hot* cell if it is visited at least once per day. We then plot the percent of *hot* cells that continue to be *hot* cells with the elapse of time. Figure 10 shows that 34% of *hot* cells are still *hot* cells after two weeks. Hence, spatial locality is quite steady and it could be exploited in opportunistic data collection. However, it also indicates that seasonal changes do exist and sensor nodes must learn and exploit the spatial locality online.

3.5. Temporal Analysis

To carry out temporal analysis, the whole duration is divided into time slots of one-hour length. The number of GPS readings in each time slot is then counted and this temporal distribution is plotted in Figure 11.

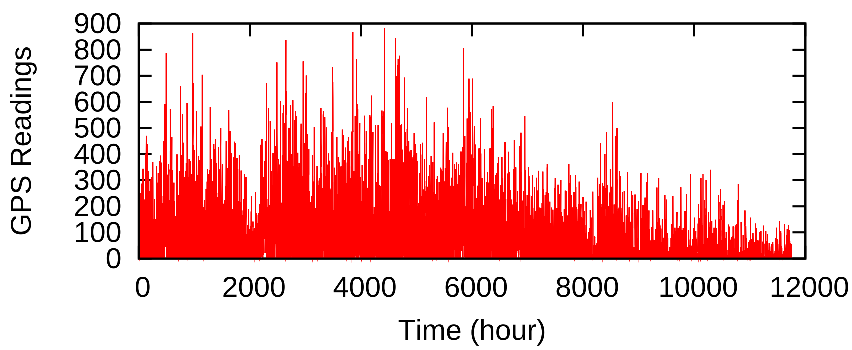


Figure 11: Temporal Distribution

3.5.1. Period Analysis

Previous studies find that human mobility normally follows some repeated patterns (diurnal, etc.) [14]. To check whether repeated patterns exist in smartphone users' mobility, autocorrelations of the above time series are calculated with different time lags and the results are plotted in Figure 12. This

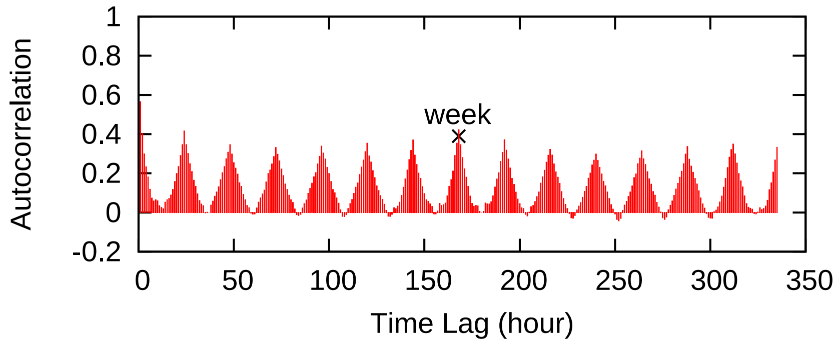


Figure 12: Autocorrelations with different time lags

plot indicates that the mobility of smartphone users does have a repeated pattern whose epoch length is 24 hours.

However, the diurnal pattern isn't obvious since there is no negative autocorrelation with a 12-hours lag. As illustrated in Figure 2(b) and Figure 11, one potential reason is that the number of active users and the number of GPS readings are reduced significantly in the late phase of the Data Collection Campaign by Nokia. Hence, period analysis is carried out again for the GPS readings between the 15th and the 35th week (2520-5880 hours) during which the number of active users and the number of GPS readings are stable. The corresponding results of period analysis are then plotted in Figure 13, which demonstrates the existence of the diurnal pattern clearly.

Furthermore, both Figure 12 and 13 don't show the common weekly pattern. When the time lag is one week (7*24=168 hours), the autocorrelation is only slightly higher than other time lags. This issue will be discussed later when we carry out per-cell analysis.

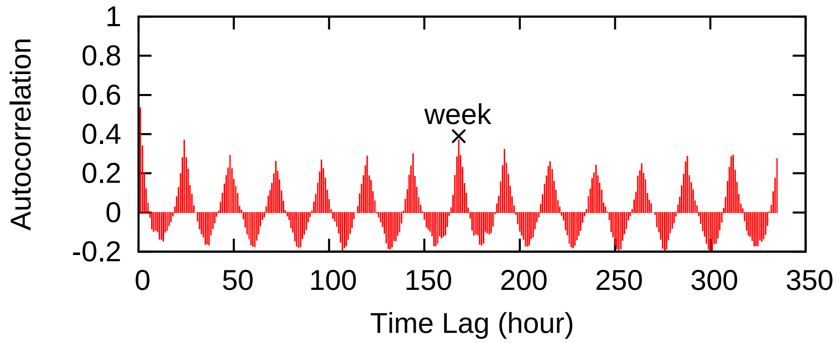


Figure 13: Autocorrelations (15th – 35th weeks)

3.5.2. Temporal Locality

In opportunistic data collection, if there are *rush* hours in which a sensor node is visited by smartphones much more frequently, a sensor node can discover smartphones mainly during *rush* hours so that it can upload the same amount of data with much less energy consumption [2]. Hence, we will check the existence of *rush* hours, i.e., temporal locality, in the mobility of smartphone users. Considering that the mobility of smartphone users has a strong diurnal pattern, the distribution of all GPS readings among 24 hours of a day is then calculated and plotted in Figure 14. This plot indicates that *rush* hours do exist in the morning (8am) and evening (4–6pm).

If an hour continues to be a *rush* hour for many days, a sensor node can learn and exploit the temporal locality easily. To study this issue quantitatively, for each day, an hour is marked as a *rush* hour if its number of GPS readings is one time more than the average across 24 hours. This large threshold is used to avoid that too many hours are marked as *rush* hours. Figure 15 then plots the percent of *rush* hours that continue to be *rush* hours

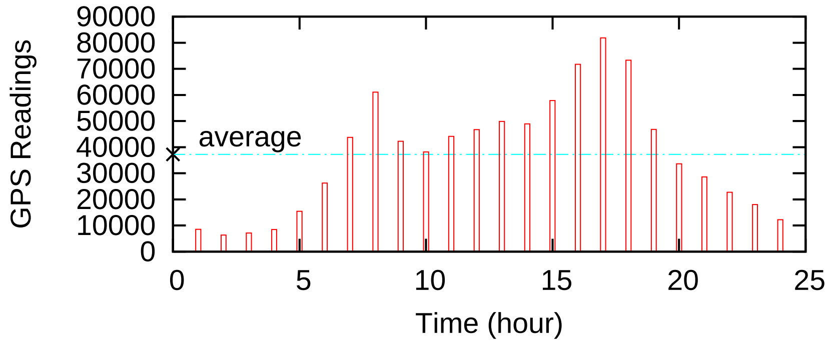


Figure 14: The existence of temporal locality

with the elapse of time. It shows that 56% of *rush* hours are still *rush* hours even after 20 days. Hence, temporal locality is quite steady and it should and could be exploited. However, Figure 15 also indicates that *rush* hours stop to be *rush* hours after a long period, seasonal changes do exist, and a sensor node should learn and exploit *rush* hours autonomously.

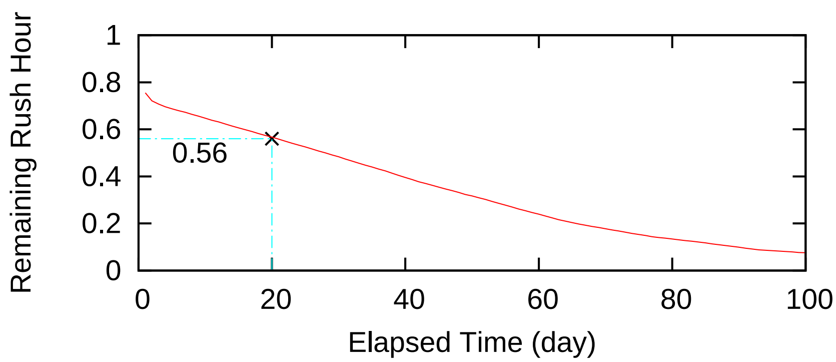


Figure 15: The invariability of *rush* hours

3.5.3. Per-cell Analysis

We notice that in Figure 14, the number of GPS readings in a *rush* hour isn't much higher than the average. The possible reason is that the *rush* hours of various cells are different. They will cancel each other since we study the temporal locality for the whole area. To validate this conjecture, we carried out the following per-cell temporal analysis.

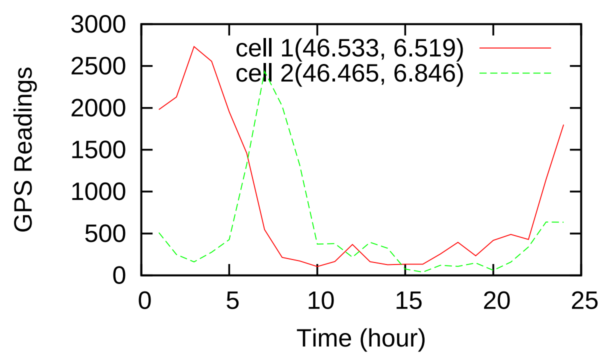


Figure 16: Daily distribution of two cells

For two cells that are visited frequently, their distributions of GPS readings among 24 hours of a day are calculated and plotted in Figure 16. This plot clearly validates the above conjecture since these two cells do have different *rush* hours.

In the above period analysis, we also notice that the common weekly pattern doesn't exist in both Figure 12 and Figure 13. This issue might be caused by the same reason, i.e., the period analysis is carried out for the whole area. Hence, for the above two cells, their distributions of GPS readings among 7 days of a week are also plotted in Figure 17. This plot shows that cell 1 is visited more frequently in weekdays and cell 2 is visited

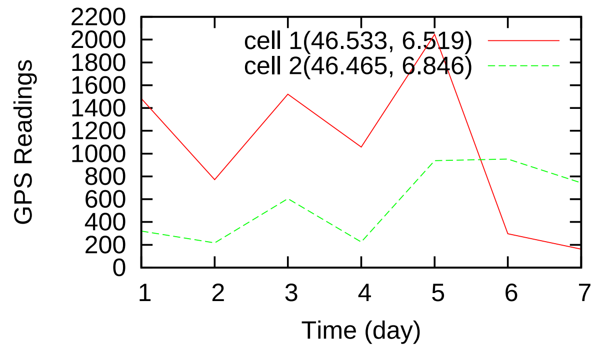


Figure 17: Weekly distribution of two cells

more frequently in weekends. Hence, weekly pattern may exist for some cells. However, due to the small numbers of GPS readings per cell, per-cell period analysis doesn't produce any meaningful results and these results aren't reported here.

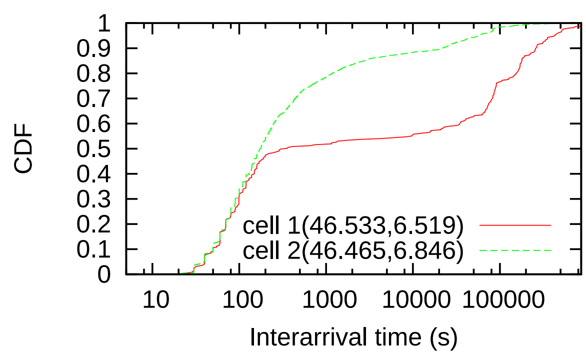


Figure 18: CDF of the inter-arrival time

For carrying out contact probing efficiently, it could be helpful to design the scheme based on the distribution of the inter-arrival time among nodes [15]. Hence, for each of the above two cells, we also calculate the intervals between the consecutive visits of smartphone users. Figure 18 plots the cumulative distribution functions of their inter-arrival time. It indicates that the smartphone arrival patterns observed by cells are location-dependent. Instead of designing a probing scheme for all sensor nodes, it's better to let each sensor node adapt to its own situation.

In summary, the results of per-cell analysis indicate that there are no common repeated pattern, temporal locality, and inter-arrival time across all cells and a sensor node must autonomously learn and exploit the temporal distribution of its own location.

4. Related Work

4.1. Mobile Data Collection

In [16][17][18][6][7][19], the use of mobile nodes has been proposed to move around in the deployed area and collect data from sensor nodes. Depending on the applications, their mobility can be either controlled or not, and these mobile nodes may collect data from sensor nodes within the range of one or multiple hops. In [20], the use of mobile phones had also been proposed to collect data from static sensor nodes purposely or opportunistically. However, none of them had studied the scenario when the uncontrolled mobility of the public is considered.

In [2][3][4][5], we have carried out research on opportunistic data collection through smartphones, and several protocols have been designed for efficient data collection through exploiting the temporal and spatial locality of human mobility. The findings in this paper validate the assumptions used by us in a more appropriate spatial granularity and provide more directions to improve the performance of opportunistic data collection through smartphones.

4.2. Human Mobility Analysis

Based on the history that users visit two Wi-Fi access points (one is deployed in a residence building and the other is deployed in an academic building), human mobility has been studied in [21]. It is confirmed that *rush* hours, i.e., temporal locality, does exist in human mobility. As for seasonal changes of *rush* hours, the existence depends on the locations of access points.

The mobility datasets of phone users have also been studied by the research community [14][22][23], and it has been pointed out that their mobility follows some repeated patterns and demonstrates strong temporal and spatial localities. However, in these datasets, only the current base station is recorded when a phone user communicates through a cellular network (call, short message, etc.). Hence, the phone user's location accuracy is as coarse as several kilometers or even tens of kilometers due to the large communication range of a base station. Although the mobility analysis based on these datasets is valuable for urban planning, the location accuracy is too coarse for opportunistic data collection since the communication range of a sensor node is normally less than 100m [9].

We believe that our study based on the dataset from Mobile Data Challenge by Nokia is extremely valuable to opportunistic data collection through smartphones. It is the mobility traces of *smartphone users* that are analyzed in this paper and the location accuracy of GPS readings could be tens of meters, that should be enough for opportunistic data collection.

5. Conclusions

For the purpose of opportunistic data collection through smartphones, the smartphone users' mobility traces from Mobile Data Challenge by Nokia are analyzed in this paper and our findings are summarized below.

1. Opportunistic data collection through smartphones should be a very promising solution. The overhead on smartphone in terms of energy consumption and CPU can be very low and the mobility of smartphone users could provide a performance level that is sufficient for many wireless sensor network applications, especially when sensor nodes are deployed in urban areas.
2. The mobility of smartphone users follows some repeated patterns (diurnal, etc.) and the distributions in time and space have strong localities. When designing the protocols and algorithms for opportunistic data collection, these localities should be considered and exploited. For instance, a sensor node should try to discover smartphones mainly during *rush* hours [2], and sensor data should also be exchanged among sensor nodes for exploiting the spatial locality of smartphone users' mobility [4]. Due to the existence of seasonal changes and the location-dependent mobility patterns observed by sensor nodes, sensor nodes should learn and exploit these localities autonomously.

In this paper, the used dataset only includes the mobility traces of 37 smartphone users. Some planned analysis (per-cell period analysis, etc.) cannot produce any meaningful results since there is insufficient data. In the case that a larger dataset becomes available, we will carry out this analysis to get more extensive results. Based on the above findings, we will refine our protocols proposed for opportunistic data collection through smartphones [2][3][4]. With the dataset from Mobile Data Challenge by Nokia, these proposals will also be re-evaluated through trace-based simulations.

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