Motion detection based fine grained place extraction on mobile cellular phone

Shuangquan Wang[1], Zhenyu Chen[1], Yiqiang Chen[1], Kuifei Yu[2]
[1]*Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China*
{wangshuangquan,chenzhenyu2010,yqchen}@ict.ac.cn
[2]*Nokia Research Center, Beijing*
kuifei.yu@nokia.com

Abstract

Location-based services (LBS) are proliferating in the field of mobile and pervasive computing. Normally, locations are expressed as coordinates or landmarks, which are geography related and hardly to be understood by average user. Recent researches pay much attention to extracting personally meaningful places where one works, lives or plays, using mobile phone as the platform. With the advantages of universal availability and low energy consumption, Global System for Mobile Communication (GSM) based method is more attractive than using GPS or Wi-Fi. However, because of large coverage and overlap of cells, existing methods can only extract coarse grained places and have a limit capability to discriminate the places closed with each other. This paper proposes a motion detection based fine grained place extraction method to discover meaningful places for individual user using GSM information. The proposed method can detect the user's motion states through analyzing the fluctuation of GSM received signal strength (RSS) and divide the cell trace into moving segments and stationary segments. Each stationary segment is represented as a time-weighted cell ID vector, which can confine the places to a small area. Experimental results indicate that the proposed method has strong capability to discriminate places closed with each other and, compared with existing method, extract finer grained places.

1. Introduction

The past decade has seen the emergence and fast growing of location-based services (LBS) on mobile platform. These location-aware applications mainly express locations as coordinates [1] or landmarks [2] and provide localization, navigation and trip planning services. Such location data are geography related and hardly to be understood by average users, who are used to thinking in terms of meaningful places, such as "home", "office", "super market", "bus station", "bank", etc. According to [3], a place is a locale that is important to an individual user and carries important semantic meanings such as being a place where one works, lives, plays, meets socially with others, etc. The semantic information contained in the places can be mashed up with other context information and widely used to develop user-centric services on the mobile devices, such as local search, advertising, social networking, etc.

GPS is the dominant technology in localization and is firstly used in place extraction. Marmasse and Schmandt [4] propose comMotion system, which detects the lost and recovery of GPS signal within a certain radius and considers this region as an indoor place. Ashbrook and Starner [5] use GPS data to infer significant locations when the time interval of signal lost or moving speed is less than one mile per hour is larger than 10 minutes. Then, these locations are clustered into places using a variant of K-means clustering algorithm. Above two methods apply to indoor place extraction, but cannot discriminate indoor places. In addition, they may draw false conclusion because of GPS shadows when the user is at outdoor environment. Kang et al [3] propose an algorithm for extracting significant places from a trace of GPS coordinates. This simple algorithm clusters the locations along the time axis and extracts the clusters depend on two parameters: distance threshold and time threshold. The distance threshold determines the size of clusters and the time threshold determines the number of significant places. [6] uses hierarchical Markov model to learn and infer user's daily movements, and identify significant places where user frequently changes transportation mode, using GPS data logs without requiring any manual labelling. These two methods can only identify outdoor places. Besides, continuous GPS data collection and analysis

978-1-4577-0208-2/11/$26.00 ©2011 IEEE

will bring challenge of heavy energy consumption and computation cost.

Another approach for place extraction is measuring the connection information of Wi-Fi access points (APs). [7] proposes LOCADIO system which uses Wi-Fi signal strengths from existing APs measured on the client to infer the user's motion states and locations using hidden Markov model (HMM). However, this method needs to map Wi-Fi MAC address to its corresponding geo-coordinates. In addition, Wi-Fi based place extraction method requires wireless network infrastructure and device penetration. It would be invalid if the places are outside the network coverage or the client device has no Wi-Fi component.

Compared with GPS and Wi-Fi based methods, Global System for Mobile Communication (GSM) based place extraction is much more attractive. All cell phones can obtain GSM data conveniently and directly from the operating system, with little energy consumption. GSM network has most extensive coverage and can be accessed almost anywhere and anytime. [8] proposes an on-device algorithm which can learn personally important places and routes between them without the knowledge of the physical topology of the network. Based on a time-stamped sequence of transitions between cells, the proposed algorithm constructs a cell graph to abstractly represent the cell topology and partitions the cell graph into cell clusters. Then, clusters that have shared cells are recursively combined into distinct locations. Places are defined as locations where the user spends a large portion of his time, and an aging algorithm is applied to gradually purge non-recurring places. Different from [8], Yang [9] proposes a temporal correlation based clustering algorithm to extract user's significant places. He observed that, because cells are often deployed with overlapping to enhance connectivity robustness, the cell phone may jump to a different cell and come back shortly even the user stay at one place. The proposed algorithm scans the cell trace and finds out all minimum circular sub-sequences (MCS). A MCS means that the cells in it are co-located or close to each other. Then, all MCS that have shared cells are recursively combined into distinct locations, same as the procedure in [8]. Places are defined as locations where user spends a significant amount of time or visits frequently. However, above two methods both represent place as a set of cell IDs of geographically co-located or nearby cells. As cell coverage can be large and overlap with the ones nearby, these two methods can only identify coarse grained places which cover very large areas, from several to over ten kilometres in diameter.

This paper proposes a motion detection based fine grained place extraction method using only GSM data. The proposed method uses motion detection algorithm to extract stationary segments of the cell trace. Different from [8] and [9] which represent place as a set of cell IDs of geographically co-located or nearby cells, our method represents place as a time-weighted cell ID vector which can confine the place to a very small region and increase the discrimination capability for closed places. Experimental results demonstrate the proposed method can extract finer grained places than Yang's method in [9].

The rest of the paper is organized as follows. Section 2 describes the rationale of proposed method in detail. Experimental results will be illustrated in Section 3 and some related topics will be discussed in Section 4. Finally, we conclude this paper in Section 5.

2. Motion detection based fine grained place extraction

In today's mass market, most mobile phones can only obtain GSM data of the cell it currently connects to. We assume that the proposed place extraction method applies to mainstream cell phones. The place extraction method for cell phones which can obtain information of multiple GSM cells simultaneously will be investigated in the near future.

With sample rate s, the obtained GSM data is a sequence of N observed cell IDs and RSS readings, along with timestamps. Denote cell IDs, RSS readings and corresponding timestamps as ID_i, RSS_i and T_i, $i = 1,2,\cdots,N$. Our goal is to extract user's personal meaningful places from the cell trace.

2.1 Cell trace segmentation

GSM is the most widespread cellular telephony standard in the world. A GSM base station is often equipped with a number of directional antennas that define sectors of cells [10]. As indicated in [11], the RSS observed from fixed sources are consistent in time, but variable in space. Therefore, fluctuation of RSS can be a clue to infer user's mobility. In fact, RSS has been used to recognize user's activities [10], transportation modes [12] or estimate one's moving speed [13].

We use a sliding window of size M to extract raw RSS readings from the trace, as shown in Figure 1. The fluctuation of RSS in this sliding window is calculated as $f = \sum_{j=i+1}^{j=i+M-1} \left| RSS_j - RSS_{j-1} \right|$. Assume the threshold of RSS fluctuation is f_{thres}, $f > f_{thres}$ indicates the user is moving at timestamp $i + M - 1$ and otherwise the user is stationary. Accordingly, the cell trace can be divided into moving segments and stationary segments. The stationary segment whose length is larger than length threshold, len_{thres}, represents a stop point at someplace and will be reserved for subsequent processing.

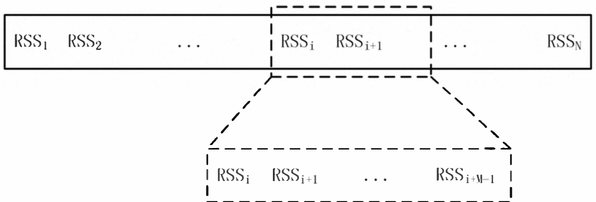


Figure 1. Sliding window for raw RSS reading extraction

2.2 Stop point representation

According to the basic theory of mobile communication, the mobile phone can connect to one cell only when it is in the cell's coverage. If a stop point contains two or more different cell IDs, it is easy to infer that the mobile phone must be located in the overlap area of these cells, as illustrated in Figure 2. Thus, at the first step, all cell IDs can form a cell ID vector to confine the region of stop point.

A stop point contains a sequence of cell IDs and each cell ID can occur repeatedly. Suppose all base stations have equal transmitting power, then the closer mobile phone and one cell tower are, the more time mobile phone connects to this cell. Therefore, at the second step, occurrence number of cell ID can also used to further confine the region of stop point.

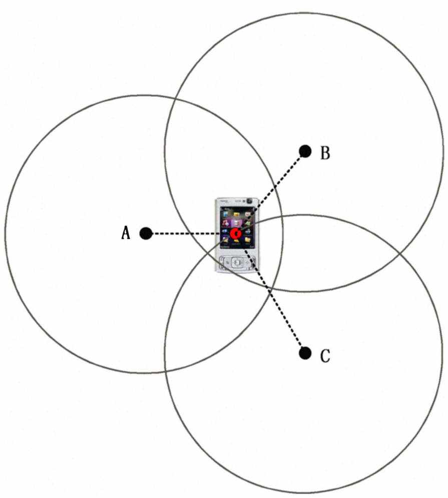


Figure 2. Cell coverage and phone location

We merge the same cell ID in one stop point and weight it with the occurrence number. Cell IDs are sorted in ascending or descending order. Then, this stop point is transformed into a time-weighted cell ID vector $\langle ID_{(1)}(\omega_{(1)}) \quad ID_{(2)}(\omega_{(2)}) \quad \cdots \quad ID_{(k)}(\omega_{(k)})\rangle$, $ID_{(k)} \in \{ID_i, i = 1,2\cdots,N\}$. For example, stop point "AAABBAAAAC" can be expressed as $\langle A(7) \quad B(2) \quad C(1)\rangle$. In order to compare stop points with different time lengths, the weights can be normalized by replacing occurrence number with occurrence ratio, i.e. $\frac{\textit{Occurrence number of } ID_{(k)}}{\textit{Length of the sequence}}$. Thus, above stop point is represented as $\langle A(0.7) \quad B(0.2) \quad C(0.1)\rangle$.

2.3 Distance metric definition for stop points

Time-weighted cell ID vector cannot be used directly to calculate the distance between two stop points. In order to quantify the proximity of two stop points, the distance metric is defined as follows.

Assume that two stop points, $\langle ID_{(1)}(\omega_{(1)}) \quad ID_{(2)}(\omega_{(2)}) \quad \cdots \quad ID_{(k)}(\omega_{(k)})\rangle$ and $\langle ID_{(1)}(\omega'_{(1)}) \quad ID_{(2)}(\omega'_{(2)}) \quad \cdots \quad ID_{(k)}(\omega'_{(k)})\rangle$, contain same cell IDs. If one cell ID only presents in one stop point, it will be filled up in the other stop point with weight 0. The similarity of these two stop points on $ID_{(i)}$, $i = 1,2,\cdots,k$ can be expressed as $\min(\omega_{(i)}, \omega'_{(i)})$. Then, the similarity of two stop points, Sim, can be defined as

$$Sim = \sum_{i=1}^{k} \min(\omega_{(i)}, \omega'_{(i)}) \tag{1}$$

The value range of Sim is $[0,1]$. 0 indicates these two stop points have no overlap and 1 indicates these two stop points are located at absolutely same position. Based on the similarity definition, the distance of two stop points is defined as

$$Dis = \frac{1}{Sim} - 1 \tag{2}$$

The value range of distance is $[0,+\infty)$.

2.4 Stop point clustering based place extraction

Based on the distance metric defined above, all stop points are clustered using a density-based clustering algorithm similar to DBSCAN [14]. The clustering algorithm starts with an arbitrary starting point that has not been visited and retrieves all neighbour points whose distance to the starting point is less than threshold Dis_{thres}. All these points form a cluster. If a point is found to be part of this cluster, its neighbour points whose distance to it less than Dis_{thres} are also part of this cluster. This process continues until the cluster is completely found. Then, a new unvisited point is retrieved and processed, leading to the discovery of a further cluster.

3. Evaluation

3.1 Data collection

We develop a data collection software in Python and install it on author's Nokia N95 mobile phone. The software calls the Nokia Python S60 sensor module over Symbian platform and retrieves GSM data once every 5 seconds. Each data point consists of Unix timestamp, mobile country code, mobile network code, location area code, cell ID, number of signal bars and RSS reading.

GSM data is collected for 26 consecutive days. The phone is turned on most of the time during the day and turned off normally at night, giving a coverage of about 361 hours. The author keeps a diary to log visited places and time intervals, which is used as the ground truth for performance evaluation.

3.2 Stop point detection

The stop points are detected according to the method introduced in subsection 2.1. The size of sliding window is set as $M = 5$ and the threshold of RSS fluctuation is set as $f_{thres} = 5\ dbm$. Correlation between number of stop points and length threshold, len_{thres}, is shown in Figure 3.

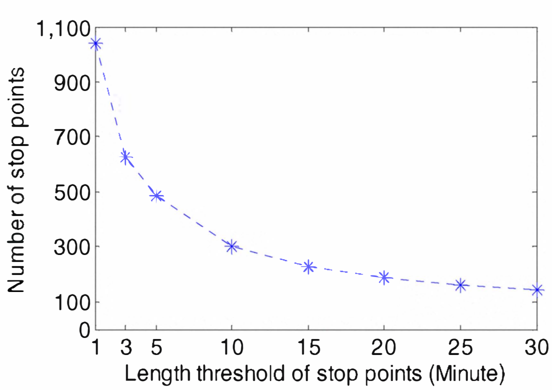


Figure 3. Correlation between number of stop points and length threshold

When $len_{thres} = 1$ minute, the proposed method extracts more than one thousand stop points. With the increase of length threshold, the number of stop points decreases rapidly and approaches 300 when $len_{thres} = 10$ minutes. Then, the decrease speed slows down and reaches about 140 when $len_{thres} = 30$ minutes.

Comparing ground truth with detected stop points, we find that small length threshold causes high detection rate and false alarm rate simultaneously, and large length threshold results in the reverse. Length threshold should be deliberately chosen to balance the detection rate and the false alarm rate. According to our experiences and the experimental results in Figure 3, we set $len_{thres} = 10$ minutes in following experiments.

3.3 Place extraction

Based on the detected stop points, density-based clustering algorithm is used to extract meaningful places. The clustering parameter, Dis_{thres}, is set to 1, which means the similarity between two stop points should no less than 0.5. In order to evaluate the performance of the proposed method, Yang's place discovering method with same parameter setting in [9] is reimplemented and executed on the same GSM data. Experimental results of these two methods will be presented and compared as following.

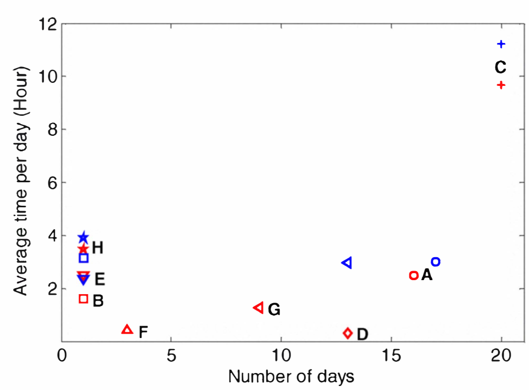


Figure 4. Significant places extracted by proposed method and Yang's method

Totally, the proposed method extracts 64 different places. Figure 4 shows eight significant ones using different marks. Red marks are places extracted by the proposed method and blue marks are places extracted by Yang's method. The ground truth of these places is described in Table 1. From Figure 4 we can see that 1) proposed method identifies all eight places, but Yang's method misses "Canteen" and "Girlfriend's office", which are only several hundred meters away from "Office" and "Girlfriend's home", respectively; 2) generally, the average time duration at one place of Yang's method is a little larger than that of proposed method; 3) at some places (e.g. "Girlfriend's home"), Yang's method detects more occurrence days.

Table 1. Ground truth and description of eight significant places

Label	Place	Description
A	Home	Reside in most time
B	Fragrant Hills Park	Visit at weekend
C	Office	Work place on workdays
D	Canteen	100m away the Office, have lunch on workdays
E	Football field	Visit at weekend, far away from Home or Office
F	Girlfriend's office	Visit occasionally
G	Girlfriend's home	200m away Girlfriend's office, reside in sometimes
H	Tsinghua University	Academic visit occasionally

Table 2. Number of cell IDs used to represent place

	Proposed method	Yang's method
Place	Avg. number for each stop point	Number of Cell IDs in the cluster
Home	1.98	12
Fragrant Hills Park	6.5	11
Office	1.58	22
Canteen	1.36	/
Football field	6	3
Girlfriend's office	3	/
Girlfriend's home	2.07	22
Tsinghua University	1.5	5

Table 2 shows the number of cell IDs used to represent each place. Averagely, the proposed method only uses a few cell IDs to identify each stop point, which is much smaller than that of Yang's method. As explained in subsection 2.2, proposed method locates the mobile phone at the overlap area of involved cells. Yang's method locates the mobile phone at the union area of all involved cells, which is much larger than that of our method. This is the key point deciding the performances of these two methods.

Then, let's review three observations in Figure 4. 1) "Canteen" is only 100 meters away from "Office". As shown in Table 2, "Office" identified by Yang's method involves 22 cells, which span a large area. "Canteen" is covered and identified with "Office" as one place. "Girlfriend's home" and "Girlfriend's office" are in the same situation; 2) because of its large coverage, it is reasonable that the time duration at one place of Yang's method is larger than that of proposed method. This also can be used to explain observation 3). Yang's method defines big place area and cannot detect user's movement. It may consider passing by a place as one stop.

Figure 5 shows the percentage of occurrence time of one dominant cell for each place. For places A, C, D and H, the percentages almost approach 100%; for the other four places B, E, F and G, the average is about 70%. Figure 5 indicates that, though one place may be covered by many different cells, the mobile phone normally connects to one dominant cell in most of the time. This proves that time-weighted cell ID vector is useful to confine a place to a much smaller area than cell union in Yang's method.

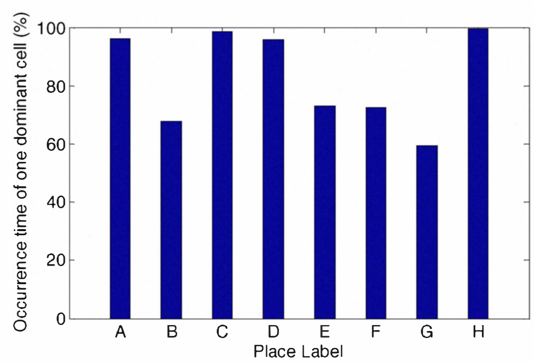
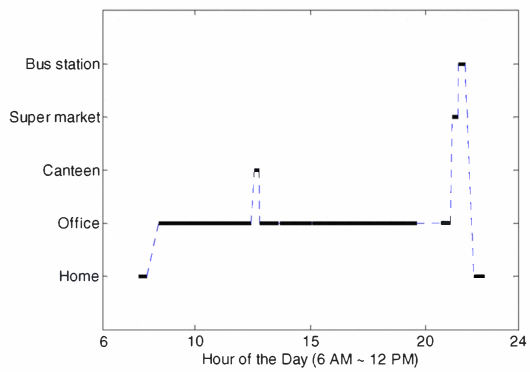
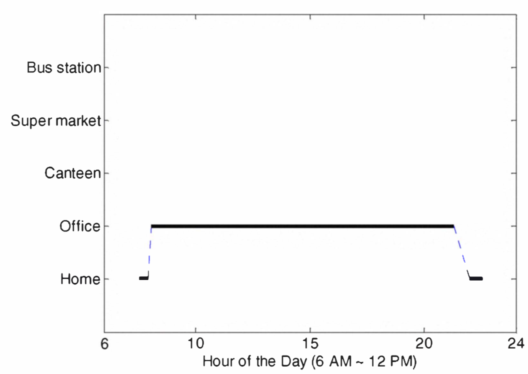


Figure 5. Percentage of occurrence time of one dominant cell for eight places

Figure 6 and Figure 7 show the extracted places and transit of typical workday and weekend for these two methods. The thick solid lines represent places and dotted lines mean transit processes between places. As shown in these two figures, 1) the proposed method extracted more places than Yang's method. In workday, the proposed method not only identifies "Office", but also "Canteen", "Super market" and "Bus station", which are all near "Office"; in weekend, the proposed method not only identifies "Home" and "Football field", but also "Night market" near "Home"; 2) for "Office" and "Home" extracted by proposed method, there are some discontinuous points, which indicate author's movements at these time. Checking with the ground truth confirms this judgement. During workday, the author may have a coffee break at the coffee bar near the "Office" or have a short discussion in the meeting room at next floor; during weekend, the author may go to convenient store beside "Home" to buy some vegetables or get some money from ATM nearby.

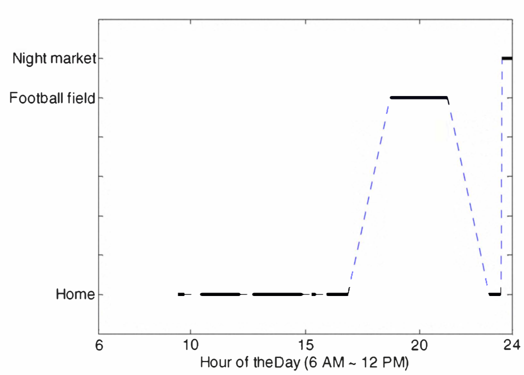


(a)

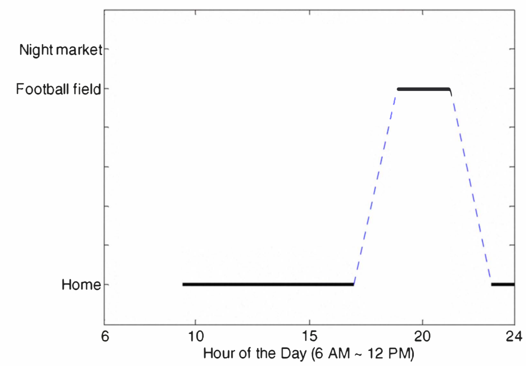


(b)

Figure 6. Extracted places and transit of typical workday. (a) proposed method; (b) Yang's method



(a)



(b)

Figure 7. Extracted places and transit of typical weekend. (a) proposed method; (b) Yang's method

From above analysis we can see that 1) motion detection algorithm can segment the cell trace accurately; 2) time-weighted cell ID vector can be used to confine the place in a small area; and 3) the proposed method extracts finer grained places and outperforms Yang's method.

4. Discussion

[11] indicates that, when the position of mobile phone is fixed, the RSS observed from one cell should be consistent. From raw GSM data we find that, although there is no movement, the RSS readings of one cell occasionally have a sudden change of several dbm. This change may exceed the threshold f_{thres} and divide one stop point into two neighbor stationary segments, with an interval of several seconds. This problem can be solved by merging neighbor segments if they belong to the same place and the interval between them is small enough.

We check all stop points in 26 days and find that there are a few false stop points. The ground truth and raw GSM data show that the author is moving slowly at that time but coincidentally there is no obvious RSS change. These stop points often have small time length and no obvious dominant cell. Thus, they can be eliminated by checking the time length and occurrence ratio of each cell.

5. Conclusion

This paper presents a motion detection based fine grained place extraction method, using mobile phone as the platform. The proposed method divides the cell trace into moving segments and stationary segments according to the RSS fluctuation. Each stationary segment indicates a stop point and is represented as a time-weighted cell ID vector to confine it to a very small region. Based on the defined distance metric, all stop points are clustered to extract meaningful places. Comparative experiments are conducted and the results demonstrate that the proposed method outperforms Yang's method and can extract fine grained places accurately.

Acknowledgment

This work was supported in part by the National Basic Research Program of China (973 Program) under Grant No.2011CB302803, the Natural Science Foundation of China under Grant No.61070110 and No.90820303, and Beijing Natural Science Foundation under Grant No.4112056.

Reference

[1] B. Schilit, et al., "Challenge: Ubiquitous Location-Aware Computing and the Place Lab Initiative", in *Proceedings of the 1st ACM International Workshop on Wireless Mobile Applications and Services on WLAN*, San Diego, CA, September 2003, pp. 29-35.

[2] J. Krumm, and K. Hinckley, "The NearMe Wireless Proximity Server", in *Proceedings of The Sixth International Conference on Ubiquitous Computing (UbiComp'2004)*, Nottingham, England, September 2004, pp. 283-300.

[3] J. H. Kang, W. Welbourne, B. Stewart, and G. Borriello, "Extracting Places from Traces of Locations", in *Proceedings of the Second ACM International Workshop on Wireless Mobile Applications and Services on WLAN Hotspots*, Philadelphia, Pennsylvania, USA, October 2004, pp. 110-118.

[4] N. Marmasse and C. Schmandt, "Location-aware information delivery with ComMotion", *Handheld and Ubiquitous Computing*, Springer-Verlag, 2000, pp. 157-171.

[5] D. Ashbrook and T. Starner, "Learning Significant Locations and Predicting User Movement with GPS", in *Proceedings of the 6th International Symposium on Wearable Computers (ISWC'02)*, Seattle, Washington, October 2002, pp. 101-108.

[6] L. Liao, D. Fox, and H. A. Kautz, "Learning and Inferring Transportation Routines", in *Proceedings of 19th National Conference on Artificial Intelligence (AAAI 2004)*, San Jose, California, 2004, pp. 348-353.

[7] J. Krumm, E. Horvitz, "LOCADIO: Inferring Motion and Location from Wi-Fi Signal Strengths", in *Proceedings of International Conference on Mobile and Ubiquitous Systems Networking and Services (MobiQuitous'04)*, Boston, MA, 2004, pp. 4-14.

[8] K. Lassonen, M. Raento, H. Toivonen, "Adaptive On-Device Location Recognition", in *Proceedings of PERVASIVE 2004*, LNCS, vol.3001, pp. 287–304.

[9] G. Yang, "Discovering Significant Places from Mobile Phones - A Mass Market Solution", in *2nd International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments (MELT'09)*, Orlando, FL, 2009, pp. 34-49.

[10] T. Sohn, et al., "Mobility Detection Using Everyday GSM Traces", in *Proceedings of the Eighth International Conference on Ubiquitous Computing*, Irvine, California, 2006, pp. 212-224.

[11] V. Otsason, A. Varshavsky, A. LaMarca, and E. de Lara, "Accurate GSM Indoor Localization", in *Proceedings of Seventh International Conference on Ubiquitous Computing (UbiComp 2005)*, Tokyo, Japan, September 2005, pp. 141-158.

[12] M. Mun, et al., "PEIR, the Personal Environmental Impact Report, as a Platform for Participatory Sensing Systems Research", in *Proceedings of the 7th international conference on Mobile systems, applications, and services (MobiSys'09)*, Kraków, Poland, 2009, pp. 55-68.

[13] G. Chandrasekaran, et al., "Vehicular Speed Estimation using Received Signal Strength from Mobile Phones", in *Proceedings of 12th ACM International Conference on Ubiquitous Computing*, Copenhagen, Denmark, 2010, pp. 237-240.

[14] M. Ester, H. P. Kriegel, J. Sander, X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise", in *Proceedings of the 2nd international Conference on Knowledge Discovery and Data Mining (KDD 96)*, Portland, Oregon, 1996, pp. 226-231.