Automatic Labeling and visiting Patterns from Longitudinal axis using Android mobile device

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Abstract—*Wireless sensor network has gained increasing attention from the research community and people. Location aware systems are blooming on a variety of platforms from laptops to cell phones. A place is a locale that is important to a user and which carries a particular semantic meaning such as my workplace, the place we live, or favorite walking place. Most bright decisions can make by mobile devices about how to behave when they are equipped with this higher-level information. We experimentally evaluate the techniques with real, long-term data gathered from particular participants using a Place Labeling. In place of monitoring raw geographic coordinates, we are focused on human mobility patterns based on sequences of place visits most daily activities. This paper survey on place characterization in people's everyday life related to data recorded simultaneously by android mobile devices. And understand human mobility from series of place visits, as well as visiting patterns in the distinct place. Then, we state the problem of automatic place Labeling from android mobile device data without using any geographic location information.*

Keywords—smartphone data, human mobility, place extraction, place visit, place labeling, prediction

1. INTRODUCTION

Location is a key feature for context-aware mobile facilities. In specific, the places in everyday life are the anchors around which social networks like Four Square and location distributing services like Facebook Places have been constructed and are broken, enabled by the widespread usage of smartphones, which allow to provide location explicitly (via check-ins) or to conclude it from sensors [1], [2]. Agreed the importance that places play in our lives, it is not surprising that recent research is investigative methods to automatically describe places and recognize their functions – from private to professional spaces and from transportation hubs to freedom sites [3], [4]. The accessibility of various forms of geolocation data coming from mobile phones has allowable investigators to investigate human movement at large scale in recent years. Human routes were used to describe a law of human motion from mobile cell-tower data in [5], however the variances in travel distances and the inherent anisotropy of each trajectory must be altered in order to detect recurrent travel patterns. With the growth of GPS and mobile technologies, it becomes much easier to monitor human mobility. Humans move has attracted specific interest in recent years, due to the data accessibility and to the relevance of the topic in numerous domains. Most of recent investigation has dedicated on how expectable people's movements are and how long will people stay in the present place. In the research of separate mobility estimation, the main task is to sense the period hidden in the observations. For this problem, we elect to effort on the identification and construction of valuable features that could be used for prediction, rather than on emerging new prediction algorithms. Semantic place labeling is the method of giving a significant name to a location. For example, the method might give the label "home" to the geographic place where a person lives, "work" to their workplace (Figure 1), "school" to school, and so on. Place labels have also been projected for automatically updating a person's status on social networking sites, such as the CenseMe scheme [1], and automatically annotating check-ins. Friendly names for locations are much easier to recognize than latitude/longitude or street addresses. Semantic place labels can similarly help as input to automatic activity inference. However both coordinate-based and landmark-based location schemes can support a variation of applications, they do not gladly deliver a means for working with a user's notion of "place". A place is a locale that is significant to a separate user and which brings significant semantic meaning such as my place of work, the place we live, or favorite walking spot. Mobile devices can provide additional intelligent decisions on how to perform when they have this higher-level information. To translate coordinates produced by the underlying location detecting technologies into places, we need to define the places of attention in terms of those coordinates. For example, a user's work place can be characterized as a rectangular region around her office and distinct with bounding coordinates; then if the present reported location is inside the "office rectangle" (taking the resolution of the location scheme into account), she is measured to be at her work place. In this project, we label an system for automatically identifying and extracting significant places from a trace of coordinates. In addition, we estimate the algorithm experimentally with actual, long term traces collected from three members using a Place Lab client [15], a software client that calculates location coordinates by attending for RF emissions from known radio beacons in the atmosphere (e.g. 802.11 access points, GSM cell towers).

2. RELATED WORK

A. *The GPS Communication*

The benefit of GPS is that it is a consistent, globally available location system that can be simply adapted for use in a variation of contexts. Potential problems of GPS contain its incapability to function well indoors, its occasional lack of accurateness due to the geometry of observable satellites, and harm of signal in urban canyons and other “shadowed” zones.. In that effort, sets of significant coordinates are recognized as those at which the GPS signal reappears after an absence of 10 minutes or longer. Each place is visited one or more times, and at each visit a variety of information such as day, time, exposed networks, applications used, and calls sent/received is collected. Distinct training and test data sets were provided. The test set contains data related to a collection of time intervals just before a user transitions to a new place.

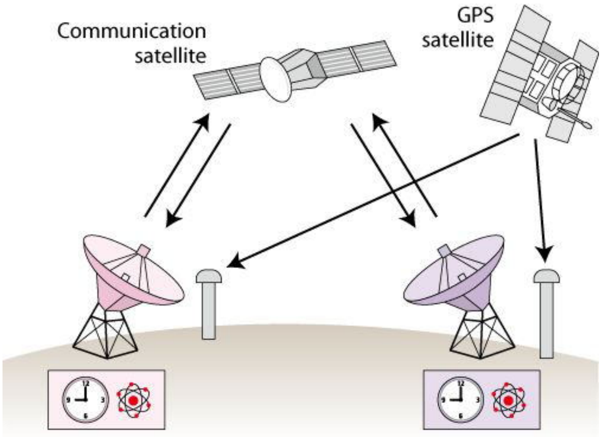

Fig.1. The GPS Communications

B. Spcification For Automatic place Labeling

.Using GPS the user Location traced and stored in database. And stored data extracted by place extraction to predict user location by place prediction method. The specification are given in bellow table1.

Table 1.Specifications ForAutomatic place Labeling

MODULES	ITEMS	SPECIFICATIONS
GET User loaction	GPS	GPS 18x series For mobile device
Share User Location	Database	Unlimited Cloud Storage
Survey of User Location data	Cell ID	Android Mobile device 4.2.2
Automatic place Labeling	Patterns	Unlimited Storage in cloud server

C. Location-aware System

Location-aware systems are proliferating on a variety of platforms from laptops to cell phones. These systems express location in one of two main ways: by coordinate, or by landmark. For example, coordinate based schemes can be used for trip planning and navigation assistance, while landmark-based schemes are valuable for more local or personal requests, such as finding friends that may be in the vicinity of the similar landmark

3. ANALYSIS

A. Place Visting Pattern

Our analysis starts with basic statistics of places and their dynamics. We statement the following questions: How many places do people go to in everyday life? How frequently are these places visited? How often do people visit new places? What are the effects of demographics and calendar in the dynamics of place visits? How many places do people visit? Figure 1(left) illustrates the cumulative distribution of users with respect to the average number of visits per day, showing that a large fraction of people visited from 2 to 4 places per day. Memo that the typical home work-home every day routine corresponds to 2 visits per day since we only count the check-in time of visits: one at Work in the morning, and one at Home in the evening. Associated to previous studies on human dynamics, our data is additional complete and appears to reasonably reflect actual user mobility trends. For instance, the foursquare data in [32] is highly sparse, with one check-in every five days on average, while in [5], [23], location data is only accessible when people make calls or send SMS . While people can easily provide a list of frequently visited places in their lives, it would be inflexible to accurately recall the list of places visited only a few times, even for those that correspond to valuable experiences. Reviewing the set of places that people visited during one year and a half, we found a simple description to this observation: there are a massive number of infrequently visited places compared to a few places that people usually go.

B. Automatic Place Labeling

The set of marked up places allow us to study the task of automatic place labeling in a supervised learning framework. We deliberate the place labeling task as a multi class classification task with 10 place categories. Our place labeling systems employ a random forest [37] as basic classifier. Feature selection was done using greedy forward search with cross validation accuracy as standard. While random forests can deal with multiclass classification tasks, we observed that the multi-class random forest is biased by general categories (e.g. Home or Work) and does not effort on discriminating rare categories. For this purpose, we also trained a one-vs-all random forest for each category, and then collective the votes of one-vs-all random forests to choose the winner class. In this setting, feature selection was run distinctly for each one verses all problems. All evaluation measures are calculated in a leave-one user-out setting, i.e., the system is skilled on annotated places of 113 users, then verified on the annotated places of the remaining user.

C. Place Extraction

The raw location traces were represented as orders of geographic coordinates obtained from GPS sensors or localized Wi-Fi access points (based on co-occurrence of the AP and GPS data). In our context, a place is defined as a small circular region (radius 100 meters) that has been visited for a significant amount of time.Our choice of region size was motivated by the existence of noisy data at some places.Then actual visits risk being segmented into multiple short visits. Note that the selected region size is similar to the one reported in previous work on place recognition [28] with GPS data, which studied 3 dissimilar sizes: 200m_200m, 300m_300m, 400m_400m in which 300_300 was regarded as a reasonable choice. We use a recent place extraction method [29] which consists of two steps. In the first step, the raw location trace is segmented into stay points and transitions. A stay point corresponds to a subsequence of the location trace for which the user stayed within a small circular regions(radius=100 meters) for at least 8 minutes. Note that a place (e.g., a restaurant) that the user visited multiple times corresponds to multiple stay points, having similar geographic regions but vary in the timestamp of the visit. In the second step, a grid clustering algorithm is applied on the canters of these stay points, which results in a list of places. The clustering algorithm splits the space with a unchanging grid, where each cell is a square region of side length equal to 30 meters. It starts with all stay points in the working set and an empty set for stay regions. At each iteration, the algorithm looks for the 5 _ 5-cell region that covers most stay points and removes the covered stay points from the working set. This process is repeated until the working set is empty. Finally, the canters of 5 _ 5-cell regions are then used to define circular stay regions that we called places. In our agenda, the place extraction is done for each user distinctly. The place extraction step outputs more than 10,000 distinct places for the set of 114 users. By mapping the raw trajectory data between these places, we attain a sequence of check-ins and check-outs on the set of places.After cleaning out short duration visits of less than 10 minutes, the whole data contains 106,000 visits with total stay duration of 618,000 hours, covering 65% of the time when the sensing software was live.

4. EXPERIMENTAL OUTCOME

This study contributes to our understanding of places in people's daily lives and to the possibility of inferring place classes from Smartphone data. Our study is based on the LDCC mobile sensing framework that extracts automatically places that people visit. While people usually follow simple routines involving a few frequent places, we perceive that most of them keep exploring new places,

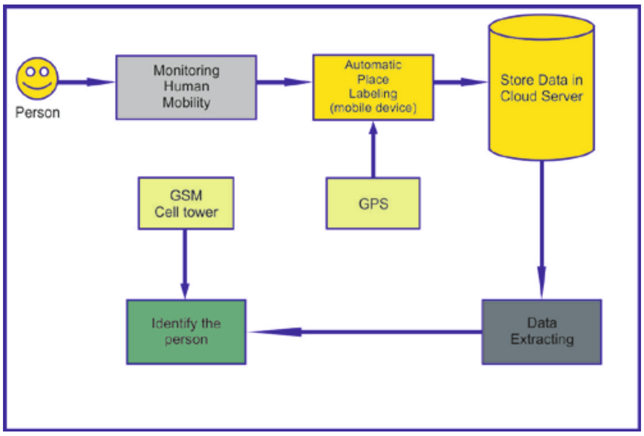

Fig. 2.Over all Architecture Diagram For Transmission

resulting in a large number of places for many individuals. If people could receive relevant recommendation for new places (e.g., restaurants, leisure-related places, etc.), the number of visited places could be even higher. We experimentally estimate the techniques with real, long-term data collected from particular participants using a Place Labeling. In place of monitoring raw geographic coordinates, we are focused on human mobility patterns based on sequences of place visits most daily activities. Our results in this paper show that it is not easy to identify the semantic meaning for a large number of places in our lives if the actual physical location is not known. Frequently visited places such as home, work or the home of a friend can be reliably documented using only location sensitive Smartphone data. As people spend most time in these frequent places, the place category can be recognized exactly. However, the recognition rate for infrequent places is comparatively low due to many features including the current privacy-sensitive data we use. When the mobile phone is disconnected from the internet at time we extract the data from cloud server then we find the person's location based on the GSM Cell tower.

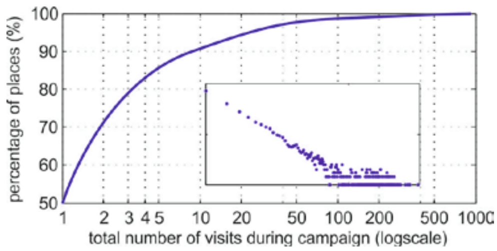

Fig. 3.Cumulative distribution of places

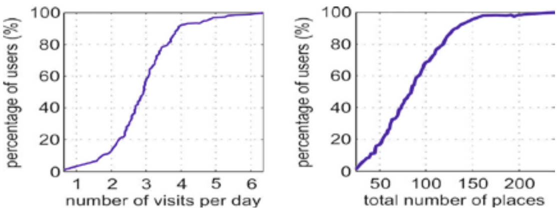

Fig. 4.Cumulative distribution of User

5. CONCLUSION

The labelled about understanding of places in people's daily lives and Place categories from Smartphone data. Our analysis is based on the person daily activities where he spends more time such as favourite walking place. For that we have made effort on the human mobility from where he frequently visiting including the patterns. By using the geo-location to trace his original position. Then we focus on the automatic place labelling to label the user's location each and every 10sec and that will be stored in cloud server. When the mobile is disconnected from the internet or it's in offline we can't find the user's location. By using Place Extraction, extract the data from cloud server and predict the user's location with help of GSM cell tower. In future we can improve the accuracy of finding the user's location.

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