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OPTIMIZING THE LOCATION DEPLOYMENT OF DYNAMIC MOBILE BASE STATIONS

Ramkumar.R, Saravanan.M, Vignesh.S, Visvanathan.P, Dept of IT, SKP Engg. College, Tiruvannamalai
Senthil Kumar.G, Assistant Professor, Dept of IT, SKP Engineering College, Tiruvannamalai.

Abstract:

With the rapid adoption of location-enabled smart phones and the proliferation of mobile Internet services, we have seen the emergence of a large number of applications that can sense and share users' location information with others. One objective of our study was to see to what extent this might be the case for location sharing. In order to study the performance of our algorithms in a real deployment, we implement and test their execution efficiency on smart phones. We propose a method for searching the location based on the user location The user location can be fetched Using GPS (Global positioning system)to the location of current user can be fetched as latitude and longitude values.

Keywords – Location enabled, GPS, Longitude.

1. INTRODUCTION

The aim of this project is to identify the location of the employees and to schedule meeting according to that, which satisfies all the employees in the peer group.The location of the employees is tracked using the GPS in smart phones and it gets updated in the Cloud storage. Based on the location of the employees common place is identified using the Google maps and the distance is calculated using Google API to get a centralized place. That particular meeting location and address will send to the corresponding employee mail id. The existing system is used to find the location and to schedule the meeting. But finding the location is not directly tracked from GPS. Since some places are restricted and the correct location cannot be identified, it becomes difficult. The smartphone with mounted camera is used to capture the photo of the physical plane. Using the captured photo, the latitude and longitude of the place is found through GPS receiver. Based on the computed destination cluster, we propose PPM that aims to estimate the path (i.e., subsequent transitions of road segments towards destination) a user would take during his movement from current location towards destination within the time period *dt*. PPM takes into account (a) user's habits in terms of the frequency of using road segments to reach a specific destination (e.g., estimated destination cluster); (b) direction from current location to that specific destination; (c) the current trajectory/path (i.e., sub-sequence transitions of road segments from movement origin to the current location); and (d) spatial conceptual maps. More specifically, at each road junction/intersection, PPM determines the next road segment a user will likely use during his movement towards destination; indeed, PPM selects the potential next road segments among the adjacent road segments of the considered/current road junction according to the current direction (i.e., direction from the last crossed road junction to the current road junction) deviation compared with the estimated destination cluster. Then, making use of filtered historical movement trace, PPM computes, based on an extended second-order Markov Chain, the probabilities of all selected potential next road segments given current trajectory/path and destination; the road segment among the potential next road segments with the highest probability is then selected as the next road segment. Here, the historical movement trace filtering process is based on the day of the week (e.g., weekend, holiday and Labor Day) and the time of the day (e.g., morning, noon, afternoon and night). PPM repeats the same process until the selection of last road segment to the destination cluster.

The predicted user′s path consists of the list of the selected road segments. To the best of our knowledge, this is the first work which takes into account both user′s habits and user′s contextual knowledge to estimate user′s path to destination. In addition, this work is the first to consider destinations clustering to reduce errors using historical and contextual knowledge. More importantly, this work presents one of the few schemes that allow for predicting, without restrictive assumption (e.g., known specific user pattern), the whole path from origin to destination. In this paper, we do not take into account energy consumption of user equipment (UE); indeed, we do believe that energy consumption is not an important constraint for vehicles and the impact on their batteries is expected to be negligible. For users using smart phones on board vehicles, they can always consider charging them while being on the move. In case charging is not possible on board vehicles, users shall be given the flexibility to manually disable DAMP. DAMP can be also automatically disabled if a UE has battery below a predefined threshold, e.g., 20% of the battery. It is worth noting that users who are not in motion do not run DAMP; thus, they do not use UE energy for mobility prediction process. Indeed, for the sake of energy saving, DAMP can be automatically disabled when a UE is moving at a speed lower than a predetermined threshold, e.g., an equivalent of a general pedestrian speed. The remainder of this paper is organized as follows. Section II presents some related work. Section III describes data collection algorithm and database structure, and presents our proposed mobility prediction scheme using second-order Markov Chain. Section IV evaluates the proposed mobility prediction scheme via simulations. Section V concludes the paper.

2. RELATED WORK

Mobility modeling has been extensively studied in many types of wireless networks during the past ten years . Mobility model analysis can be used to create models for predicting user mobility. User mobility prediction allows estimating/predicting the location and trajectory of the user in the future. The commonly used mobility models are random walk, random waypoint, fluid flow, Markovian and activity-based mobility models. The simplest of these models are the random walk and random waypoint models; they were originally proposed to emulate the unpredictable mobility of particles in physics. The other models are used for prediction, such as path prediction. It has been shown that users follow daily routines and that mobility models have cyclic properties . Many researchers rely on such principles to define user mobility prediction models that benefit from the periodic nature of mobility. One of the important fields of users' mobility prediction models is the individual mobility prediction models; basic models are models that employ location, direction, time and conditional probability. Indeed, based on the regularity of user mobility, a conditional probability distribution of next moves is defined considering movement direction and time; the move with the highest value is predicted as the next move. In other words, the cell that was most frequently visited according to the current location, current movement direction and the time of the day is predicted as the next cell. Recent years have seen a considerable amount of work done on developing users' mobility prediction models. Many of these models heavily rely on the availability of prior information on the users' mobility history. Whereas the continuous tracking of mobile users may lead to better predictions in terms of movement, such models suffer from the large overhead accrued due to constant monitoring; obviously, this requires a more detailed analysis of the users' mobility history, and the application of advanced data mining and knowledge discovery techniques. The models presented in are examples in which the prediction requires no knowledge of the users' mobility history; unfortunately, these models are limited to predicting only where a user is likely to move (i.e., user's final destination) instead of the path to reach this final destination. For example, a scheme that incorporates geographic maps with identifiable landmark objects (e.g., schools, malls, gyms, libraries) into the users' IEEE Transactions on Vehicular Technology,Vol.64,No.6,June 2015. mobility prediction models has been proposed in more specifically, the mobility prediction architecture (MPA) gathers the necessary information for the prediction process and analyzes this information using Dempster-Shafer's theory in order to predict future locations of the mobile user. Finally, to determine the user's future predicted location, they combine each pair of hypothesis-belief mass using the Dempster rule of combination; a hypothesis represents a location or a sequence of locations. Indeed, they compute the belief function Bel(Hi) of hypothesis Hi. Bel(Hi) describes quantitatively all the reasons to believe in hypothesis Hi. The location with the highest belief value is the predicted future location of the user. However, this technique (i.e., destination prediction model) is used in certain path prediction models [7, 8] to improve prediction accuracy by eliminating or affirming certain paths according to the predicted destination. However, such models require a vast amount of information (e.g., user's preferences, user's goals and user's schedules) to be collected and processed and may not perform very well with temporary changes of the surrounding infrastructure. A few models consider using both mobility historical data and current conditions in the network. One example is the model proposed in which considers both current trajectory of mobile users (i.e., ordered set of cells already transited) and time-of-day, as well as historical data, to predict the likelihoods of single-cell transition and N-cells transition for an arbitrary user in wireless networks; the prediction model performed quite well for lower values of N (e.g., 2 cells). In a short-term prediction model that employs mobility history for predicting future location of a mobile user while considering the mobile user's current trajectory within the predefined navigation zone was proposed; this model is limited to only next cell prediction. In a long-term mobility prediction model which considers both current trajectory and movement direction, as well as historical data, was proposed; however, the model requires an immense amount of mobility history and a massive processing load. In the following, we briefly overview our previous contributions [7, 8] that are most related to the proposed model. In [7], we proposed a method to estimate a user's future destination based on the use of filtered user's mobility history and contextual knowledge; the filter is based on the type-of-day (e.g., working, holiday and weekend) and the time-of-day (morning, noon, afternoon, evening and busy hours); the proposed model also takes into account the movement direction. The drawbacks of this model are (1) the automatic identification of Frequently Visited Locations (FVLs) has not been taken into account; (2) the databases are not updated according to user's predictability level; predictability level is the degree to which a correct prediction of a user's mobility can be made; this degree is related to the frequency of visited places and transited roads according to the day of week and the time of the day; (3) the frequency function of FVL is not explicitly defined, and the weighted sum of the belief and probability functions is not related to user's predictability level. we proposed an approach which predicts the path the user will use within a time period during his movement from trip origin to destination; the approach makes use of filtered users' mobility history, current movement data (e.g., trip origin and current location) and spatial conceptual maps while assuming a priori knowledge of the destination . More specifically, at each road junction (starting from the location where user first accesses the network), the next road junction the user will likely use during his movement towards the trip destination, is determined. The drawbacks of this approach are (1) the deviation function takes into account the trip origin instead of the previous road junction; and (2) common conditional probability is used instead of second-order Markov Chain that is more appropriate in this type of situations. To conclude, we summarize the limitations of existing mobility prediction models as follows: they are limited to short term (e.g., next cell) mobility prediction they do not consider the temporal context and/or the whole path from trip origin to current location and direction to destination these parameters play a key role in improving prediction accuracy they compute more than on predicted path they incur high processing overhead they require massive data storage space they make restrictive assumptions user's movements follow a specific pattern they solely rely on the history of individual users' movement . In this paper, we propose a model that proposes solutions to overcome these limitations.

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user contextual knowledge, day-of-week and time-of-day in predicting paths; it is a long-term users' mobility prediction model. To limit the impact of using user mobility history (that may change), DAMP considers user knowledge, and regular spatial and temporal patterns for predicting the mobility of users.

3. PROPOSED SYSTEM

The aim of this project is to identify the location of the employees and to schedule meeting according to that, which satisfies all the employees in the peer group.The location of the employees is tracked using the GPS in smart phones and it gets updated in the Cloud storage.Based on the location of the employees common place is identified using the Google maps and the distance is calculated using Google API to get a centralized place.That particular meeting location and address will send to the corresponding employee mail id.

3.1. MODULES

Selecting the users and getting the common places, From the database, the admin will select the group of users for the meeting and their latitude and longitude will be tracked.The common places will be retrieved from the Google Maps and it will be displayed. Getting the venue by prioritizing the vehicle parameter. From the available common places the venue will be selected by using the vehicle parameter. The venue will be sorted in such a way that, the user using 2-wheeler will travel more distance than the user using 4-wheeler.Sending the meeting location via mail, The scheduled meeting will contain the meeting name, organizer, time and venue.

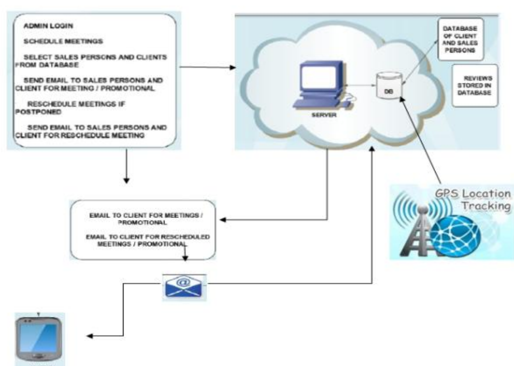

Fig.1. Architecture Diagram

Finally, it will be sent via mail to the selected users. Plotting the location on Google Maps The Google Maps is embedded in the webpage using Google Maps JavaScript API V3.All maps API applications should load the Maps API using an API key. This API key is embedded in the JavaScript which loads the Google maps.

CONCLUSION:

In this paper, we introduced a destination and mobility path prediction model, called DAMP, for predicting subsequent transitions of road segments across the mobility of users within a predefined time period *dt*. DAMP consists of two models: DPM (for predicting user's destination) and PPM (for predicting subsequent transitions of road segments towards predicted destination). We evaluated, via simulations, DAMP and compared it against three related schemes recently proposed in. The simulation results demonstrated that DAMP achieved better accuracy regardless of the predictability level of users, learning phase length, prediction lengths, and already traversed path length. The obtained results also clearly show that the utilization of user context, path traversed from trip origin to current location and movement direction together with fine-grain filtering of historical data (e.g., type of day) greatly increases path prediction accuracy. The findings of this contribution (estimated path) can be used, for example, to better estimate the handoff times along estimated paths . Currently, we are working on integrating the proposed DAMP with a suitable bandwidth-management and admission control scheme; a preliminary version of this scheme can be found in Mobility modeling has been extensively studied in many types of wireless networks during the past ten years [2, 9-27]. Mobility model analysis can be used to create models for predicting user mobility. User mobility prediction allows estimating/predicting the location and trajectory of the user in the future. The commonly used mobility models are random walk, random waypoint, fluid flow, Markovian and activity-based mobility models. The simplest of these models are the random walk and random waypoint models; they were originally proposed to emulate the unpredictable mobility of particles in physics. The other models are used for prediction, such as path prediction. It has been shown that users follow daily routines and that mobility models have cyclic properties [1, 2, 12, 14, 19, 23, 26, 27, 29-33]. Many researchers rely on such principles to define user mobility prediction models that benefit from the periodic nature of mobility. One of the important fields of users' mobility prediction models is the individual mobility prediction models; basic models [1, 2, 12, 14, 19, 23, 26, 27] are models that employ location, direction, time and conditional probability. Indeed, based on the regularity of user mobility, a conditional probability distribution of next moves is defined considering movement direction and time; the move with the highest value is predicted as the next move. In other words, the cell that was most frequently visited according to the current location, current movement direction and the time of the day is predicted as the next cell.

In this work, we assume that the road topology consists of several roads and junctions while the entire network space is assumed to be divided into cells. We refer to the location frequently visited by a user (e.g., home, school, shop, mall and office) as a frequently visited location (FVL). We assume that a road junction or a FVL is represented by a node; each node is identified by a node ID that is related to its geographic coordinates (i.e., latitude and longitude); we refer to data about visited nodes (e.g., time, date and node ID) as mobility data. We refer to the road between two nodes a and b as a road segment, and identify it using a road segment ID that is represented by the node pair (a, b) where . A user's location is identified by his geographic coordinates. The movement of a mobile user through the network can be described by a list that represents the sequence of road segments that was visited by the user throughout the trip. A user's mobility pattern from the network's perspective is determined by the user's terminal (e.g., mobile phone) mobility pattern. The users' mobility history patterns can be periodically recorded using node ID (road junction and FVL).

The mobility history can either be recorded for each user or collectively for all users into a single history profile per location. The latter method is more suitable for situations where all users generally exhibit similar behavior at a given navigation zone and are also not significantly impacted by erratic behaviors from one or more users. Even though different groups of users have different mobility patterns, it can be difficult to address every type of group behavior in a single mobility model. To derive DPM we need contextual knowledge about users; we assume that User Contextual (UC) information is organized into six categories as shown in Table I. The UC database can be built (1) by having users fill in a questionnaire and explicitly express their interests with regard to different places within their living areas; or (2) by having users "continuously" registering both their tasks and scheduled appointments. To implement mobility data collection, we assume that (1) user equipment (UE) maintains a database which records data about the user movements and his living area; (2) static data about geographic maps (topology/map of roads), called Navigation Map (NM), is readily available; and (3) UE embeds technology, such as tachometer and GPS, that samples user velocity and coordinates of places visited by the user, along with the day and the time of the visits. It is also assumed that NM database contains geographic coordinates of nodes (e.g., road junctions and FVLs). A FVL is extracted from UC database shown in Table I or inserted automatically. Indeed, when a user's velocity is 0 and the current location is not a road segment or road junction, we assume that the current location may be a new visited place and insert it in FVL database. User Movement Trace (UMT) database contains user ID, date *d*, time *t* and node ID (a FVL or a road junction) that represents user location at date *d* and time *t*. User Frequently Visited Location Trace (UFVLT) database contains user ID, date *d*, arrival time *ta*, departure time *td* and node ID (a FVL) that represents user location at date *d* from arrival time *ta* to departure time *td*; in other words, arrival time.

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