Mobile Location Prophecy: An analytical review

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***Abstract*—In mobile communication, objects may or may not remain stationary. Location management of such objects is an interesting research subject addressed by research community and communication industry. In location management, prediction of mobile next location is one of the most important aspects as it is helpful to increase speed, resource allocation and reduce the chances of hand off. The field of location prediction is rapidly expanding through exploration of different approaches like data mining, neural networks, AI, fuzzy logic and many more. In this paper, an attempt has been made to take an account of various approaches undertaken so far on Next Location Prediction In Mobile Communication and present their comparative analysis and analytical review. This will be beneficial to the community interested in exploring and extending such approaches further.

***Keywords*—Location management, next location prediction, mobile user pattern mining, mobility prediction, neural network, data mining, fuzzy logic Wireless technology, Mobile computing,**

I. Introduction

Mobile communication is fast growing filed in terms of its usage and technology development. One of the areas of research in this field is Location management of mobile objects. Prediction of mobile next location is one of the important aspects of location management as it is helpful to increase speed, resource allocation and reduce the chances of hand off. The field of location prediction is rapidly expanding by exploring various approaches like data mining, neural networks, AI, fuzzy logic and many more. Many conferences and workshops are being held to focus on research on next location prediction.

For an example, Nokia Mobile Data Challenge 2012 Workshop was organized in connection with the Pervasive 2012 in Newcastle, UK. Dedicated track 2 - Next Location Prediction. Various studies have been conducted under different scenarios to improve performance of wireless network under various mobility models.

Accurate and efficient Next location prediction will resolve the real life problems like location-aware mobile advertisements, management of real time traffic, path prediction for the network and services to further enhance the QoS levels.

As there are various tools and techniques being used for the purpose, it is quite helpful to compare all the related work. This paper gives an analytical look at the research work done so far on next Location Prediction In Mobile Communication.

It is known that result of predictions will be based on assumption that data pattern are regular. However what if patterns are random? This paper also focuses on drawback of current systems of location management with respect to the patterns.

The rest of the paper is organized as follows: The Section II describes basic cellular mobile system and location management. Section III presents related work available in literature of major next location prediction models. Section IV presents comparison and analysis of various approaches in tabular format with accuracy index. Section V draws concluding remarks and further work.

II. LOCATION MANAGEMENT

For understating the need of next location prediction and various techniques, it is necessary to understand the basic operation of cellular network. The operation of a cellular mobile system can be described as five major functionalities and four additional utilities. All the functions together make a complete mobile cellular system. (ref fig :1)

A. Mobile unit initialization

- When mobile unit is turned on, it scans and selects the strongest setup control channel used for system.
- Cells with different frequency bands repetitively broadcast on different setup channels.
- The receiver selects the strongest setup channel and monitors that channel.
- With this the mobile station has automatically selected the BS antenna of the cell within which it will operate.
- Then handshake takes place between the mobile unit and MTSO controlling this cell through the BS in this cell.
- Handshake is used to identify the user and register its location.
- As long as the mobile station is on, scanning is repeated periodically to account for the motion of the unit.

- If the unit enters a new cell, then a new BS is selected.

B. Mobile-originated call

- A mobile unit originates a call by sending the number (Mobile Identification Number, MIN) of the called unit on the preselected setup channel.
- The receiver of mobile unit checks if the forward channel (from BS) is idle.
- If idle the mobile may transmit over the reverse channel(To base station)
- BS sends request to the MTSO.

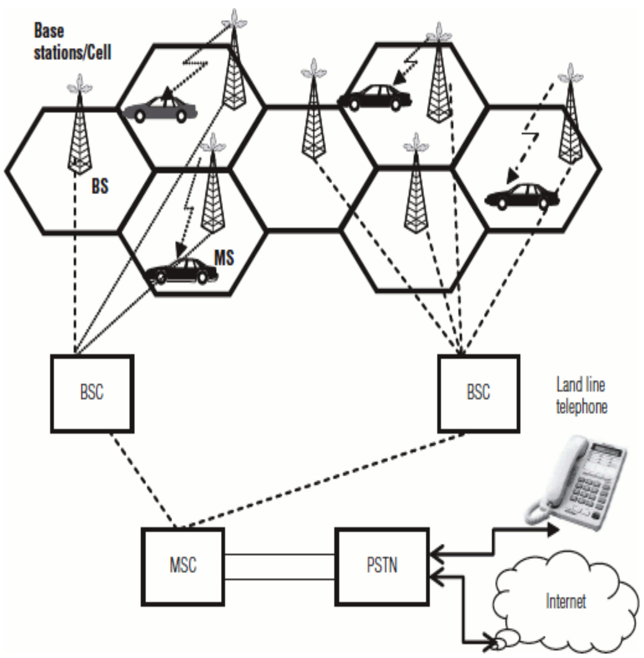

Fig 1: Cellular Network

C. Paging

- MTSO attempts to complete connection
- MTSO sends a paging message to certain BSs depending on called mobile number.
- BS sends paging signal on its own assigned setup channel.

D. Call accepted

- Called mobile unit recognizes its number on the setup channel being monitored and responds to that BS, which sends the response to the MTSO.
- MTSO sets up a circuit between calling and called BSs.
- MTSO selects available traffic channel within each BS's cell and notifies each BS, which in turn notifies its mobile unit (a data message called alert is transmitted over FVC to instruct the mobile to ring).
- The two mobile units tune to their respective channels.

E. Ongoing call

- While connection is maintained, two mobile stations exchange voice or data, through BSs and MTSO as shown in fig 1.

F. Handoff

- If a mobile unit moves from range of one cell to another the traffic channel has to change.
- System makes this change without either interrupting the call or alerting the user as shown in the fig 2.

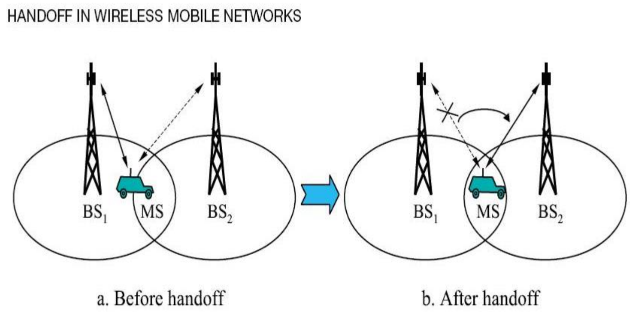

Fig 2: Handoff between the MS and BS

Call blocking: If all traffic channels are busy even after multiple attempts a busy tone is returned.

Call termination: When one of the users hangs up, MTSO is informed and the traffic channels are released

Call drop: during a connection if because of interference or weak signal spots, the BS can't maintain the minimum required signal strength for a certain period of time the traffic channel is dropped and MTSO is informed.

Calls to/from fixed and remote mobile subscriber: MTSO connects to the public switched telephone network. Thus it can setup calls b/w mobile user in its area and fixed subscriber via telephone network, remote MTS

As per the above details we can say that the major feature of wireless networks is mobility support, which enables mobile users to communicate with others, regardless of location. Location management is very critical but essential task in mobile communication to find user Mobile Node (MN) location. It is divided into two operation 1) location updating 2) location prediction.

G. Location updating

MN periodically performs location registration (i.e., location update) where it is explicitly notify the network of its new access point and store changes to its user location profile. Following are some update location strategy available, in which one of it is implemented for location update.

- Instant update
- Movement based update
- Distant based update
- Time based update

These strategies are time consuming and costly because every time we need to update location even though MN is idle and call is not forwarded or received. On the contrary, this is most reliable method for uninterrupted communication because exact location of the user's MN is available whenever required. Location update scheme are often partitioned into static and dynamic. A location update is static if a predetermined set of cell location updating occur on either same intervals or upon every cell change. On the other hand dynamic location management is an advanced concept where the parameters of location management can be modified to be best fitted for individual users and conditions [1].

H. Location prediction

MOBILITY predictions of wireless devices helps the users in smart access and useful to the service provider in planning of the infrastructure and to provide better quality of service (QoS) [1]. Two classes of location (path) prediction schemes can be found in the current, mobile computing, literature. The first class includes schemes based on extensive historical data of the user movement. Such a scheme can be characterized as stateful. Contrary to the stateful scheme, a stateless model does not take into account extensive historical movement information for the prediction process. Instead, it uses short sliding window of historical movement information.

III. DIFFERENT METHODS OF NEXT LOCATION PREDICTION

Considerable amount of research has been done in mobility prediction. Some of the related works are discussed here. This section is divided into 3 parts where some similar approach is used for mobility prediction.

A. Mobility prediction using data mining

Mr. Mohammad Waseem et al (2013), have used both spatial and temporal information and showed that the simple approach of computing by applying standard graph matching algorithms and the DBMS primitives of grouping, sorting, and joining could be utilized to yield efficient match join operations. Moreover, a novel mining scheme was proposed to mine associated trees so that they can locate user behaviour patterns [2]. The approach does not support location independent queries.

Joao Bartolo Gomes et al (2013), have proposed Next Location a personalized mobile data mining framework - that not only uses spatial and temporal data, but also other contextual data such as accelerometer, Bluetooth and call/sms log. In addition to this they have also proposed new paradigms for privacy-preserving next place prediction as the mobile phone data is not shared without user permission. This paper also reports on their experiments, analysing data from the Nokia Mobile Data Challenge (MDC). The results on MDC data show great variability in predictive accuracy across users, where irregular users are very difficult to predict while for most regular users it is possible to achieve more than 80% accuracy using the proposed model [3].

Thuy Van T. Duong et al (2012), gave two characteristics of mobility behaviour. They were location and time-of-day. Finally, they have derived temporal weighted mobility rules [4].They have generated their own dataset using personal mobility behaviour of a lecturer in a campus wireless network and got experimental results. Their experimental results were two-fold. First, they show that use of temporal attribute was necessary for improving the prediction accuracy. Second, they show that the prediction accuracy was not affected by regular rate of movements; it means that their mining algorithms were suitable for mobility prediction in wireless networks. They would be working further on developing group mobility based on clustering mobility patterns will be their future work.

Huiji Gao et al (2012), introduced "HPY Prior Hour-Day" (HPHD) model to capture the spatio-temporal trajectory of user visits, which considered not only the spatial historical trajectories, but also the temporal periodic patterns. They also employed nine baseline models (HPY prior Model, HPY prior hourly model, PHY prior daily model etc.,) to evaluate given proposed method [5]. Models were spatial based, time based and spatio- temporal based. Author has used Mobile data set provided by Nokia Mobile Data Challenge, which contains 80 users over one year of time. The accuracy in the spatio-temporal based HPHD model was 50%. Extension of the work would be to consider social network information together with spatio-temporal patterns of visiting trajectories to achieve better performance of location prediction.

Le-Hung Tran et al (2012), have applied user specific decision tree model for location prediction. The feature extraction and data pre-processing were done carefully to increase the effectiveness of the model. Additionally, optimizer was implemented to find the best parameter combination for each user since users had widely varying behaviour. Finally, C4.5 decision tree algorithm was implemented using Weka tools to generate the decision tree. Model [6] has generated results with an accuracy of 61%.

Gokhan Yavas et al (2005), have proposed a model based on mining the mobility patterns of users, forming mobility rules from these patterns, and finally predicting a mobile users next movements by using the mobility rules. Performance of algorithm evaluated using simulation and compared the obtained results with the performance of two other prediction methods, Mobility Prediction based on Transition Matrix (TM) and Ignorant Prediction [7].

Through accurate prediction of mobile user movements this algorithm enables the system to allocate resources to users in an efficient manner, thus leading to an improvement in resource utilization and a reduction in the latency in accessing the resources and also enable the system to produce more accurate answers to location-dependent queries that refer to future positions of mobile users.

B. Markov model for prediction

Jorge Alvarez-Lozano et al (2013), have presented a spatio-temporal prediction model to forecast user location in a medium-term. Author was taking advantage of the Markovian property shown in user's mobility. Proposed system identified Point of Interest (POI) using location data corresponding to a sliding window. Finally, they have defined Hidden Markov Model (HMM) [8] by considering user mobility among POIs. Once the HMM was defined, they made some predictions. Finally, the prediction model was updated using the most recent mobility data. The focus of the work was in updating the prediction model taking into account changes in user mobility.

Model obtained 30% of accuracy by averaging the accuracy for the three different clusters radius with sliding window of eight weeks.

This method cannot be applied to everyone; there are people with frequent random pattern, and the mobility patterns they exhibit are much more complicated. In such cases, they obtained a very low accuracy.

George Liu et al (1996), have proposed Mobile Motion Prediction (MMP) model for the prediction of the future location of a roaming user according to his movement history patterns. The model consists of Regularity Pattern Detection (RPD) algorithms and Motion Prediction Algorithm (MPA). Regularity Detection was used to detect specific patterns of user movement from a properly structured database (IPB: Itinerary Pattern Base). Three classes of matching models were used for the detection of patterns, namely the state matching, the velocity or time-matching and the frequency matching. The Prediction Algorithm (MPA) [9] was invoked for combining regularity information with stochastic information (and constitutional constraints) and thus, reach a decision - prediction for the future location (or locations) of the terminal.

Simulations of the proposed scheme have shown a maximum prediction efficiency of 95% but it was reported that as the random movements of the user increase, the performance of MMP decreases linearly.

C. Mobility prediction using neural network

Smita Parija. et el (2013), have proposed a neural network scheme using back propagation technique for location prediction of mobile hosts. The future position of a mobile terminal was predicted by the algorithm based on the previous record of its movement pattern.

To solve the proposed method [2], an ANN methodology (Multi-Layer Perceptron) was adopted. That entire simulation was done using the MATLAB simulation environment. The proposed system was simulated with the help of Pentium Core due Processor 3.2 GHz CPU, 2 GB based RAM and 300 GB storage capacity based Personal Computer. As a result the overall training and testing accuracy was found 85% and 84% respectively.

It will be a good research work in the direction of Fuzzy and Neuro-Fuzzy which do not have any well-defined pattern. This paper was worked for the subscriber which shows the uniform and regular movement pattern, but this work can be extended for random data.

Velmurugan. L. et al (2012) have used one month trace data of Dartmouth College available in the public domain to evaluate their hypothesis. The classification accuracy of the mobility predictions was evaluated using different classification methods [10] like Naive Bayes, CART, Multilayer Perceptron and Feed Forward Neural Network.

Authors conclude that classification accuracy of the Neural Network classifier was higher than other probability or decision tree based classifiers.

Jingjing Wang et al (2012), were predicting the next destination using the current context and for that they built user specific model for each user. Considering two types of input for models and algorithms:1) all transitions 2) only trusted transition which gives frequent pattern. The proposed system [11] was first applied periodicity based model to find the frequently visited places and then model that task into a multi-class classification problem by feeding all user information. After that, they have proposed six algorithms based on the multi-class classification model. Experiments conducted on Radial basis function (RBF) and support vector machine (SVM) with different feature sets and different transition sets in MATLAB.

Result shows that trusted data performed well in system compare to all available data.

Saikath Bhattacharya et al (2011), have classified users in three categories.1) Class A: highly predictive, 2) Class B: highly random 3) Class C: a real life user as they follow a certain path on weekends or once in a week or month goes to a new location. Based on given classification, user's movement was collected for 3 days i.e. 50 data set and during the training the cell id and the corresponding time of visit was fed into the network. The results were simulated and the prediction pattern was observed for radial base functional neural network (RBF) and back propagation neural network (BP) for all three categories [12]. One of the most important factors while training a neural network was to take care of over- learning. They have assumed the learning goal of 0.001

and a learning rate of 0.2 while training. The number of hidden layers was 15.

Authors have concluded that radial base neural network was more efficient than back propagation because it provides satisfactory result even with the class B user.

In their future work, they want to use Mobile assisted prediction where a smart phone can use neural network in the background application for creating a user and send the results to the Mobile Switching Centre.

Sherif Akoush Ahmed et al (2007), have proposed a traditional method for topology independent user tracking where geographical coverage and street network are not considered. They organized Bayesian learning for neural networks for both locations and service prediction. It was a hybrid model making use of Bayesian inference in artificial neural networks.

Results show that prediction accuracy of this model [13] was outperforming all other discussed standard neural networks. Enhancing prediction accuracy by including cells geographical coverage and street network can extend our work.

Studying service prediction relation to location prediction is interesting feature suggested as future research.

D. *Mobility prediction using fuzzy logic*

Sajal Saha et al (2010), proposed a new fuzzy logic based intelligent paging scheme. They use a fuzzy inference system to depict the user's usual movement schedule. Here, users were classified in different categories like Manager, Professional, Housekeeper /senior citizens and students/others. They have done their survey over the region of Saltlake city, Kolkata, India. They have randomly chosen 500 mobile users and collected data about their movement in 7 x 24 hour basis. The users consist of 81 businessmen, 242 corporate users, 48 HouseKeeper/Senior Citizens, 19 Field Worker and 12 Student & others.

Simulation has been carried out using MATLAB R2008b. They have created five different rule bases corresponding to five different categories of users in MATLAB fuzzy logic toolbox. Historical data of user movement was fed into the rule base to produce the LA with respect to the cell number. In this scheme, their rule base was fed offline by the movement of large number of users.

However, efficiency of the scheme [14] was highly dependent on the size of the rule base. This scheme reduces the paging cost of the local MSC for a new call and save the radio bandwidth resource. Prediction accuracy was also been enhanced by minimizing the standard deviation.

Maryam Borna et al (2011), proposed model [15] for location estimation, tracking and mobility prediction in cellular networks in dense urban areas using neuro-fuzzy networks apply tracking and post-processing method to estimated locations. For mobility prediction purpose the use of ANFIS neuro-fuzzy was implemented. For training the network, 20% of the beginning of the travelled path with 2 delays was selected as input and the same path with one precession as output. The remaining 80% of the path was used for testing. In this way trained network would be able to predict next location by knowing the present and one previous location of user.

Author have concluded that applying ANFIS post-processing by approximating user's movement function, decreased high errors. The accuracy of proposed mobility prediction by ANFIS with respect to radius of cells in most cities that are about 100 to 150 m makes it useful in anticipation of user's next cell to be causing decrement in costs of location update and paging procedure.

N. Mallikharjuna Rao et al (2012), proposed intelligent location management schemes [16]; it can reduce the cost of maintaining location of mobile users by using Fuzzy Logic and Fuzzy databases for call registration and call delivery procedure of a mobile station for describing location and a call setup.

In the future they will further improved on mobility management using fuzzy logic and fuzzy databases.

E. *Mobility prediction using artificial intelligence*

As task 1 Ying Zhu et al (2013), proposed methods to predict the semantic meaning of the “important places” and the users' next destination in Nokia MDC dataset. Method first extracts the feature data like visit location, Bluetooth, accelerometer, address book, call log etc., after that two types of prediction methods [17] proposed: rule based and machine learning based. As task 2 prediction of next location takes place.

A preliminary result shows that maximum accuracy 72% and observed that proposed methods can achieve reasonable prediction accuracy if the number of instances in the training data is sufficient.

F. *Mobility prediction using Fusion Model*

Vincent Etter et al (2013), have built user-specific models [18] that learn from their mobility history. Changes in the users' behaviour were detected and adapted using aging technique. Developed several mobility predictors, based on graphical models, neural networks, and decision trees and finally combined these predictors using different blending strategies.

Their predictors reach an average prediction accuracy of more than 56%, yet they observed a high variance between users.

IV. COMPARATIVE STUDY AND ANALYSIS

Comparison Study of various Mobile prediction methods are given in TABLE: 1 along with their accuracy measurements.

TABLE 1: COMPARISON STUDY OF VARIOUS MOBILE PREDICTION METHOD

Approch Used	Year	Author	Proposed Model	Dataset Used	Accuracy
Data Mining	2004	[Gokhan Yavas]	Mining user mobility patterns from graph traversals	Single user data	_
	2012	[Thuy Van T. Duong]	Spatiotemporal Data Mining	Own Dataset	70% with best input
	2012	[Huiji Gao]	"HPY Prior Hour-Day" model to capture the spatio-temporal trajectory	Nokia MDC Dataset	50%
	2012	[Le-Hung Tran]	User-specific decision Tree	Nokia MDC Dataset	Maximum average accuracy 61.1%
	2013	[Mr. Mohammad]	Association rule mining	_	_
	2013	[Joao Bartolo]	classification techniques using WEKA tool	Nokia MDC Dataset	overall accuracy is 17%
Markov Model	1996	[George Liu]	Mobile Motion Prediction Model	Itinerary Pattern Base database	depends on no of random user record
	2013	[Jorge Alvarez-Lozano]	HMM model	GPS trajectories of 178 users collected in a period of over 4 years	30%
Neural Network	2007	[Sherif Akoush Ahmed]	Bayesian Learning Neural Network	It contain over 500,000 hours (~60 years) of continuous	_
	2011	[Saikath Bhattacharya]	Multi-Layer Neural network (BP, RBF)	single user data	RBF using class A give better accuracy
	2011	[Maryam Borna]	Adaptive Neuro-FuzzyInference Structure	self-generated data	_
	2012	[Velmurugan. L]	(Naive Bayes, CART, Multilayer Perceptron and FFNN)	syslog data of Dartmouth college	78.50%
	2012	[Vincent Etter]	Dynamical Bayesian Network, Artificial Neural Networks and Gradient Boosted Decision Trees	Nokia MDC Dataset	56.22%
	2013	[Smita Parija]	Artificial neural network model (MLP-BP)	_	0.84
Artificial Intelligence	2012	[Jingjing Wang]	multi-class classification via SVM with RBF	Nokia MDC Dataset	50%
Fuzzy Logic	2010	[Sajal Saha]	Fuzzy Interface system Algorithm	Saltlake city, Kolkata, India randomly 500 mobile user data	Efficiency dependent on the size of the rule base.
	2012	[Ying Zhu]	Rule Based Method and Machine Learning Method	Nokia MDC Dataset	72%
	2012	N. Mallikharjuna Rao, Prof M. M Naidu	Fuzzy logic and fuzzy databases.	_	_

Here, it can be seen that different strategies have been used for mobile next location prediction to reduce resource cost and call latency period. In all the above Data mining algorithms, the data set used contain regular patterns and hence promise good accuracy. These systems do not support location independent queries.

For the group which belongs to neural network, we have seen that authors have divided dataset in different classes, they have also categorized users and applied different neural network model like feed forward, back propagation, radial base functional model, Naive Bayes, CART, Multilayer Perceptron etc. They have also done comparative study between two or more neural model and search out the results but still data is good enough for regular pattern, not for random one. In group with fuzzy logic, in absence of adequate data an attempt has been done to predict user's next location. Although their proposed system reduced the database overhead because queries are not directly fired for central database like HLR but system is again not giving satisfactory results for random users. Markov chain model which is basically for the random pattern but still result are found depend on the size of random data set.

V. CONCLUSION

In view of the above, it can be observed that each and every proposed model is appropriate for regular pattern but not for random one. In addition to this, in all of the above work, only one dataset is used so it will give user behavior pattern of that region , hence it may not applied for another region. To check the efficiency of the model if different datasets of various region are used than more we can check the accuracy of the model effectively.

We have been working to extend this research further by focusing on random patterns and using multiple datasets to study user behavior patterns.

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