LOCATION BASED PREDICTIVE MODELLING OF HANDOFF MANAGEMENT IN WIRELESS NETWORK

Ms. Vandana Kaushik[1], Dr. J.S.Sodhi[2]

[1, 2] ASET Amity University, (India)

ABSTRACT

Location based internet application has taken over as the internet become more mobile. When a mobile system moves from one cell to another it is called handover or handoff, the cell handover all the information to the new cell on which the mobile node is connected. There are many prediction schemes are already proposed to perform the reservation of resource so as to reduce latency. Data can be hugely collected with the advancement of wireless technology and positioning services. The trajectory patterns which are evoked from historical trajectories of the objects which moving from one cell to another can tell the important information about the behaviour for the location based services and for location prediction also. I propose in this paper a new approach which uses constant trajectory figures or patterns to predict the current location. The proposed method uses the line specification to simplify the trajectories making clusters out of them in spatio-temporal regions. I analyzed that the method which I proposed is efficient enough for discovering trajectory pattern to predict a near location accurately whether the query has been made for the same or not.

KEYWORDS: Trajectory Pattern, Spatio-Temporal Data Mining, Location Prediction

I. INTRODUCTION

There are much advancement going on in today's life in positioning services and wireless technology. For e.g. users who are having smart phones or the phones which are GPS enabled can log their positions on time interval which is fixed in nature and transmit to the server, in fixed intervals, of wireless carrier. Location Based Services which are reliable and having high quality, for e.g. managing the traffic on network or finding the appropriate route or route system, requires the current as well as the future locations. Now if the current location is not available of a moving object, an authentic method for predicting the location is required [1]. In the process of handover a moving node is not able to send or receive any packet or message what so ever, so the packet loss is likely to occur [2]. A huge amount of work has already been done in handover latency. The work is based upon to reduce the delay in handover so that seamless handover can be achieved plus the user should not be interrupted because of handover [3].

The wireless network is composed of various APs called cells. Each n every AP is given one channel to transmit and broadcast an echo frame on this channel. So the mobile node can easily determine in which cell it is. The movement of mobile node from one cell to another can be recorded in a database which is usually known as log file [4]. In lieu of Ref [1, 3-6], data mining has been a new and potential approach to predict the mobility of node based on log file history.

This paper will clearly define the prediction of a moving object with spatio and temporal attributes. Further this paper is organized as: Part 2 indicates the related work on prediction of moving object. Part 3 will tell about the architecture and the problem definition. Part 4 is the approached given by me. And lastly conclusion and references.

II. RELATED WORK

There are various work has already been done on prediction of moving object. There are various techniques of data mining that have been used to implement the prediction algorithm. The widely known technique of data mining is sequential pattern. It is used to discover the trend [4-5] and also used to predict the customer or user behaviour [7-8]. It is also used to determine the exact location of an object or guessing the next location also [9, 4]. The whole process is to extracting the pattern which is sequential in nature whose support exceeds a predefined minimal support ($supp_{min}$) [10].

In another study by Yao [11] says that information extracted from spatio and temporal data will give better prediction of events. Following are some related work which indicates the spatio temporal data mining based movement prediction.

1. Temporal Weighted Mobility Rule [12] says that the mined mobility rules will be utilized in predicting the next location of a mobile node. The proposed algorithm is implemented on various parameters.
2. Temporal moving pattern mining [13] says that the moving objects like individual user are represented in x and y axis coordinates. Moving objects location is transformed into the area and by using of spatial operation can get the related information.
3. Prediction Model for moving object [14] says that the location of a moving object can be predict through trajectory pattern. These patterns allow us to predict accurate location of moving object.

III. ARCHITECTURE AND PROBLEM DEFINITION

3.1) Fig 1 shows the architecture of prediction management. It consists of 4 phases, database phase, mining phase, rules generation phase and prediction phase.

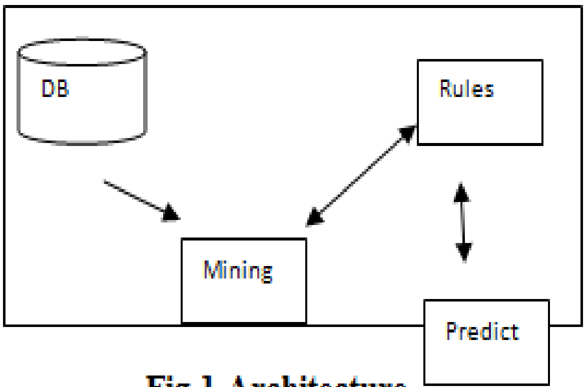

Fig 1 Architecture

Database Phase is divided into two parts. When a moving object sends or receives any data it will go into the log file and then converts it into the transactional database.

Mining phase mines the frequent pattern.

Rules Generation Phase generates the mining rules.

Prediction phase is for predicting the next location.

3.2) Problem Definition

The problem of prediction in mobility in wireless based network on spatio temporal data mining is as defined: Given a directed graph DG, a log of mobility, time gap or max_gap, minimum support min_supp, confidence min_conf, the first phase which based on database, generate the transactional database from the history of log file. Second phase is to identify all mobility patterns which are occurring frequently in transactional database should also satisfy min_supp. Now the third phase is to generate all the rules which is used for a node mobility and which should also be mined in the previous phase. In fourth and the last phase the mobility rule having the maximum confidence value are used to predict the next cell.

IV. PROPOSED PREDICTIVE HANDOFF TECHNIQUE

The proposed handover scheme may used with any network although we use LTE (Long Term Evolution) network to explain the scheme

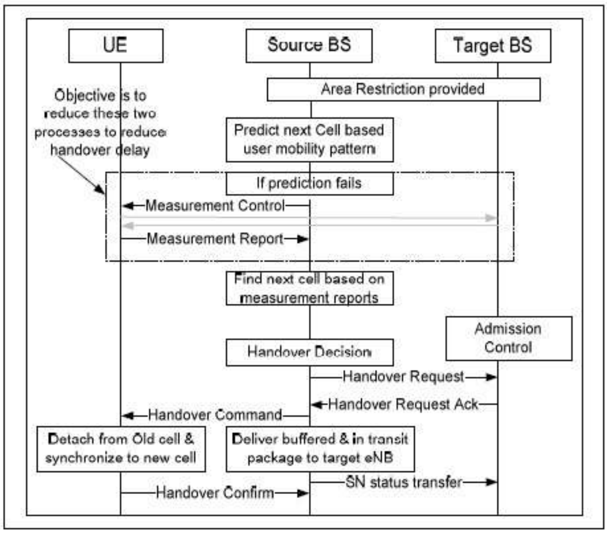

Fig 2 Handoff Management Process

Fig 2. illustrates the handoff procedure used in the proposed handoff scheme [15]. The proposed handoff management system uses a prediction technique which tries to estimate the best handoff target cell and the best handoff time for fast and seamless handoff. This prediction is based on the mobility pattern of the UE, which has been recorded for certain time duration. MFNN (Multilayer Feed-forward Neural Network) with back propagation algorithm is used as a predictive model to predict the best handoff target cell and best handoff time. A prefix tree sequence mining algorithm (PTSMA) is applied on the raw data set to eliminate the outliers. This refined data set is then given to MFFN for target cell prediction.

If a UE initiates connection to a BS, the BS checks whether that UE can connect to it or not. Checking is based on area restriction information. If connection authenticates, the UE can connect to the BS and process will be initiated. By the time the UE is connected, the BS will have information in which cell, the UE is likely to move next and at what time. Also, when handoff is taking place from a BS to another BS, the prediction process will be going to predict the UE's next cell and handoff time. The technique which is proposed also has a backup mechanism in case prediction fails. Prediction may fail when any of the following happens:

- The predicted target BS is not in the neighbourhood of the source BS
- Insufficient number of datasets to discover a pattern.
- The mobility pattern changes frequently

In above situations when prediction fails, the normal handoff procedure will continue as shown in Fig 2. The source BS will take measurement reports from the UE and decides if handoff is required or not. If handoff is required, the source BS will communicate with a target BS to which the UE has to be handoff and thus the normal handoff procedure takes place. In case, the mobility pattern has changed, the new mobility pattern will be learned by the predictive model so that it can predict a similar pattern later. Thus the system is flexible enough to be trained dynamically.

V. DEVELOPMENT OF SUGGESTED LTE HANDOVER SCHEME

Our suggested handover scheme is applied on the broadband wireless networks. The aim of this scheme is to reduce the delay incurred during handover to minimize call dropping and packet loss. In our suggested scheme the source BS predicts the time state of the handover and initiates the handover procedure with the target BS. The proposed scheme is based on the generation of mobility profiles using a statistical technique and using these profiles to predict the handover of a UE using neural networks. The suggested handoff scheme involves the following three steps, 1) input data preparation, 2) predicting target BS using MFFN, 3) initiating handover procedures.

5.1) Creating MFFN Input Data

The generation of mobility profiles involves the collection of input data and eliminating outliers and less frequent datasets. The input data collection and data reduction is done at the mobility management entity. The reduced data is then sent to each BS which does the next cell prediction. To collect the input data, the data is obtained from the mobility management entity by recording the entry time of a node and exit time of a node. From this data the fix time (Fi) of a UE at each cell is calculated as

$$Fi = ExitTime_{cell\text{-}n} – EntryTime_{cell\text{-}n}$$

The collected input data over period of time will have the data of all visited BSs during a given period for a particular UE.

Data is collected in a specific form which is given below

UE id	$CellId_1$	F1	$CellId_2$	F2	$CellId_3$	F4

Table: 1) Input data

Mobility pattern (Pn) is the history of recent movements' pattern of a UE recorded over a period of time T during which the UE is in active state. Let the mobility pattern Pn= {p1, p2,….pn} be recorded for a UE, where pi indicates the movement of a UE during time period ti when the UE makes call. The mobility pattern Pn is defined in terms of the cell number and the time duration in seconds spend in that cell. Pi is represented by a pair (ci, ti). ci is the cell number where the UE for time duration ti. For example if there are 16 BSs in a region, then ci ϵ {1, 2, 3…..16}. If a UE is in cell 2 then ci=2; t2 is the time duration (in terms of seconds) a UE spends in cell 2 while in active state.

If a pattern is of mobility is recorded for 3 transition (n=3) from cell 1 to cell 3 and the time recorded is 5 mins, 30 mins, 25 mins, then the pattern of mobility is

P3={p1,p2,p3}={(c1,f1),(c2,f2),(c3,f3)}={(1,5),(2,30),(3,25)}.

5.2) Predicting Target BS using Sequence Mining Algorithm

The objective of data preparation is to reduce the volume of the input data and prepare in the required format to be put in MFFN. The task of sequence mining is to find out a set of shared attributes in a large number of objects in a given database. Prefix tree Sequence Mining Algorithm is an algorithm that finds all the frequent sequential patterns that satisfy a given length-decreasing support constraint. It is used as a row reduction technique to reduce the number of rows in the dataset to be fed to the MFNN. The problem of finding frequent sequences patterns given a constant minimum support constraint is defined as:

Given s sequential database D and a minimum support $\sigma(0 \leq \sigma \leq 1)$ find all sequences each of which is supported by at least $[\sigma|D|]$ sequences in D. Computationally efficient algorithms for finding frequent item sets or sequences in very large data base is the essential characteristic of a sequence mining algorithm in this context. Once we find that a sequence of length l is infrequent, we know that any longer sequences that include these particular sequences cannot be frequent, thus can eliminate such sequences from further consideration. This is the general principle of any prefix tree based sequence mining algorithm. The algorithm starts from the root node and expands to create the children nodes that correspond to the frequent items as shown in Fig 3. Each child node is recursively visited in a depth first order and expands to the child nodes that represent frequent sequential patterns. Each node in the tree represents

a frequent sequential pattern. The relation between the sequential pattern represented at a particular node at level k and that of its parent at level k -1 is that they share the same k -1 prefix. Thus the child's pattern is obtained from the parent by adding one item at the end. For example if an itemset contains < (1), (2, 3)>, its parent node is < (1), (2)>. At the root of the tree is the null sequence with no itemset.

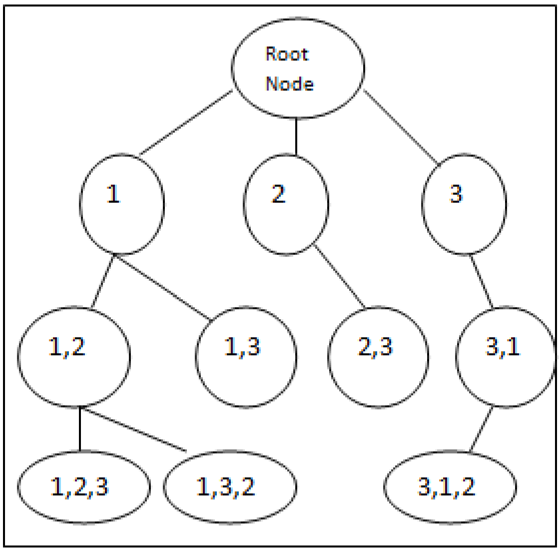

Fig. 3. Prefix Tree Algorithm

5.3) Handover Procedure using MFNN

A multilayer perceptron is used in this model to create a predictive model. The MFNN model that is considered for prediction consists of three layers: input, hidden and output. The number of neurons is chosen through experimentation by trial and error to have more generalization capability for the MFNN model. Also, while choosing the number of input and hidden layer neurons, care must be taken to avoid any under-learning or over-fitting of the training data. For example, Table 2 below shows that the number of movements considered in the input training data is 4, i.e. k = 4, and each movement Pj requires two quantities to represent cell number and time of a UE. But in this work, cell number and time are fed at a time to one neuron. Hence, the number of input layer neurons for the above representation is equal to k=4. The number of neurons in the hidden layer depends on the length of the sub-pattern and the number of subpatterns provided for training. The number of neurons in the hidden layer is initially chosen to be 3. This is just a preliminary value and will be changed based on requirements. The number of output layer neurons depends on the output movement parameters and their representation. In this case, cell number and time are considered as the movement parameter. Hence, there are two output neurons.

Sub pattern	Input 1	Input 2	Input 3	Input 4	Input 5
1	P_1	P_2	P_3	P_4	P_5
2	P_2	P_3	P_4	P_5	P_6
3	P_3	P_4	P_5	P_6	P_7

Table 2: Data Format for MFNN

The value of parameter is decided after trial and error. It is found that for the designed MFNN, the learning Parameter (input layer to hidden layer) is set to 0.7 and the learning parameter (hidden layer to output Layer) is set to 0.007. The activation function used is a tanh. The error tolerance is set to about 0.001. To avoid the MFNN from getting stuck at local minima, numbers of iterations is chosen to be 20,000.

The mobility pattern of a UE travelled over a period of time is recorded and is processed to construct predictive model for mobile movement prediction. If a UE is active and attached to a particular cell, the system predicts the UE's next possible cell location along with the amount of time likely to be spent in that cell based on previous mobility pattern of that UE. Amount of time likely to be spent includes the handoff time and the duration for which the UE stays in that cell. The process of predicting a UE's next cell location is explained with the following example. In this example, an array of 7 cells is considered, constituting the mobile network topology as shown in Fig. 4.

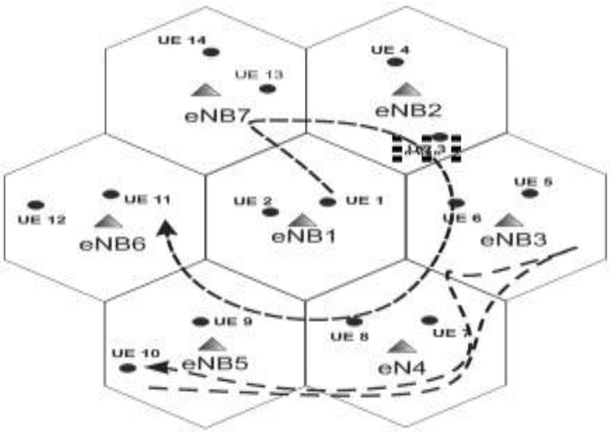

Fig 4 Structure of Cell with Node Movement

Also, it is assumed that a central BS is surrounded by the other 6 BSs. The BSs are assigned a BS number. In this example, it is assumed that BS1 is surrounded by BS2-BS6. The UE movements are recorded in terms of cell number and time spent in that cell at every handoff. The recorded mobile movements are pre-processed to obtain the mobility pattern as described in section 4. B. From the cell-based mobility pattern, the pattern for UE1 and UE10 are derived for prediction as follows. For UE1, the mobility pattern is

Pi = {(1, f1), (7, f2), (2, f3), (3, f4), (4, f5), (5, f6), (6, f7)}, with seven handoffs. For UE10, the mobility pattern is

Pi = {(5, f1), (4, f2), (3, f3), (4, f4), (5, f5)}, with five handoffs.

By observing the patterns for each user, the corresponding sub patterns are obtained. These patterns are recorded for certain duration of time. In the recorded patterns, many incomplete patterns or irrelevant data may be present. These incomplete or irrelevant patterns are eliminated using prefix tree sequence mining algorithm. These sub patterns are then used for training the predictive model. Consider UE 1 to extract the training data set for the predictive model. The mobility pattern of UE1 is arranged in the form given in Table 2. It is arranged in a form suitable for training the predictive model. This training data is fed to the predictive model. Here, Pattern No.1 and Pattern No.2 are the training pattern while Pattern No.3 is considered as the test pattern. P1 to P4 are fed as the input to the predictive model while P5 is considered to be the desired output. It is assumed that the above 3 patterns has occurred many times in the recorded mobility history of UE 1. The network is trained using a number of iterations until the error reduced below the error tolerance value of 0.001. The trained network is tested on the testing data for prediction.

VI. ALAYSIS OF THE SUGGESTED HANDOFF SCHEME

Testing of the proposed Wireless handoff scheme is done for LTE Network [15] on ns2 simulator. All the Wireless layers namely, PDCP, RLC, RRC, MAC, X2, S1 and

Physical are implemented on the ns2 simulator. The test scenario models a 7 cell hexagonal network model where all the cells experience interference characteristics. All the BSs are connected to the gateway node via a wired link. The experimental parameters are as given below in Table 3.

Parameter	Settings
Cell Radius	1.5 km
Speeds	Upto 100 km/hr
Mobility	Random
Cell Deployment	7 cell ring
Experiment Duration	250 sec

Table 3) Simulation Parameter

Figure 5 shows the cumulative call dropping count comparison with and without using Predictive model. As shown in Figure 5, the prediction starts only when there is sufficient data that can be used for training the neural network. Without using predictive model we see that call dropping count is higher compared to when predictive model is used. The reason for this behavior can be attributed to overlapping cells where the UE is handed over to any adjacent BS without being aware of the subsequent movement of the UE and resource availability at target BSs. Using predictive model, the UE is handed over to the appropriate BS based on its trajectory. Thus the number of handovers are reduced which in turn reduces call dropping. Here cumulative call dropping count is obtained by cumulatively adding call drop count over duration of time.

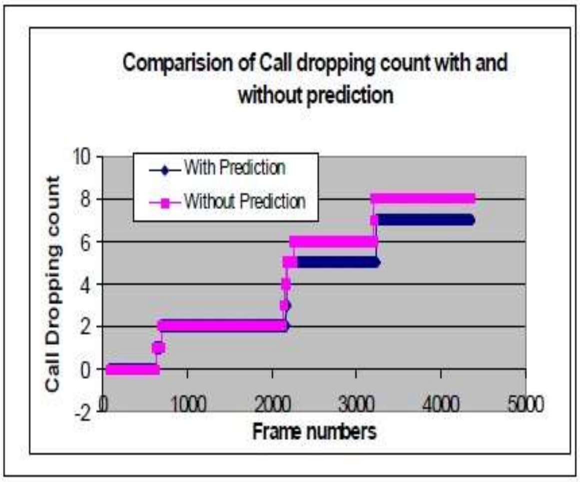

Fig 5 Call Drop With and Without Prediction Modelling

In Table 4 we present the data from our simulation. We define four parameters as given below:

TS: Average Time at which a UE is attached to source BS

TT: Average Time for which threshold level goes down below the handoff trigger threshold

TTR: Average Time at which UE is connected to target BS

TD: Average Handoff delay time

	Time (m/sec)							
	With prediction				Without Prediction			
UE	TS	TT	TTR	TD	TS	TT	TTR	TD
2	59	127	112	42	51	121	126	48
5	116	140	134	54	110	138	147	67
7	143	182	170	27	169	170	176	46
9	99	99	106	44	92	98	100	74

Table 4) Parameters Compared

Table 4 presents the data for different UE in the simulation experiment. From the table we can observe that the reduction in handover delay with the predictive model.

Also the average dwell time of a UE at the BS increases with use of predictive model. We can observe that while using the predictive model handover is performed early when compared to without using the scheme. This enables to minimize call drop. In this current experiment e minimize the effect of false prediction by data preparation process where inconsistent data is removed from the training data set.

VII. CONCLUSION

The handover procedure of wireless networks is successfully modified by adding a prediction model. A Predictive Model based on data mining was designed and developed for making predictions about the next BS Id as well as the optimal time for a proactive handoff to takes place. The average prediction accuracy was measured to be around 84 %. It is said that the suggested method helps in reducing the time of handoff by spirited performing the handoff. The system is able to predict the next best handoff cell location as well as the best handoff time. The benefit of using the proposed data clean up method can be tested with a more complex neural network.

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