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Future Location Prediction in Wireless Network Based on Spatiotemporal Data Mining

Cong Hung Tran[1], Thuy Van T. Duong[2] and Dinh Que Tran[1]

1. Department of Information Technology, Post and Telecommunication Institute of Technology, Ho Chi Minh city 70000, Vietnam

2. Department of Information Technology and Applied Mathematics, University of Ton Duc Thang, Ho Chi Minh city 70000, Vietnam

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Abstract: Handover latency is the time interval during which a mobile node cannot send or receive any packets. How to improve the latency is one of the major problems in Mobile Internet Protocol version 6 (MIPv6). One of the solutions for reducing the handover latency that has attracted various research interests is to predict mobility of mobile node. Several approaches to prediction have been proposed such as Hidden Markov models, machine learning, data mining, and so on. The approach in data mining investigates the log file of node mobility history to predict the next move of mobile node. However, such conventional studies do not consider simultaneously spatial and temporal attributes of data. In the context of wireless network, the spatial attributes of a mobile node are changing over time, therefore time constraints between locations play an important role in considering its mobility. This paper proposes a data mining based approach that utilizes spatio-temporal attributes to predict the movement of mobile node.

Key words: Data mining, prediction, handover, mobile node, wireless network.

1. Introduction

In the recent years, the need of Internet connection "everywhere and at any time" has become more and more popular with IEEE (Institute of Electrical and Electronics Engineers) 802.11 wireless local area networks (WLAN) Standards. In 802.11 WLAN components, Access Points (AP) (also known as Base Stations) are stations providing services of distributed systems and they are connected to each other via a fixed wired network. APs with parameters such as name of networks and the channel used by AP, etc., offer wireless connection with the mobile nodes such as laptops, Personal Digital Assistants (PDAs) or mobile phones. A handover (handoff) is the transfer of a communication from one AP to another AP as the mobile node moves [1]. During a handover, a mobile node (MN) cannot send or receive any packets thus the packet loss may occur as well [2]. There has been a considerable amount of research on handover latency. They strive to reduce the delay in handover in order to achieve a seamless handover with the meaning that the user is unware of such status [3].

In 802.11 WLAN, the mobile nodes gain access to the network through an AP by scanning all available channels with active or passive types to find an AP to associate with [3]. This task takes a lot of time and becomes the main factor contributing to the handover latency [1]. One way to solve this problem is to guess the next AP of the mobile node so as to take active scanning. Predicting the next location of the mobile node can reduce the handover delay mainly by detecting the identity of the future AP prior to the

Thuy Van T. Duong, graduate student, research fields: artificial intelligence, data mining, wireless networks. E-mail: vanduongthuy@yahoo.com.

Dinh Que Tran, Ph.D., associate professor, research fields: artificial intelligence, data mining, agent, semantic web. E-mail: tdque@yahoo.com.

Corresponding author: Cong Hung Tran, Ph.D., associate professor, research fields: B – ISDN performance parameters and measuring methods, QoS in high speed networks, MPLS. E-mail: conghung@ptithcm.edu.vn.

actual handover [3]. The information of the future AP can be used in handover preparation such as providing the channel information required to reduce the scanning delay. Therefore, movement prediction of a MN plays a key role in optimizing handovers.

The wireless networks consist of a number of APs which are called cells. Each AP transmits on one assigned channel and periodically broadcast a beacon frame on this channel. Therefore, the MN which is currently in this cell and listening to the broadcast channel will know in which cell they are now. The movement of a MN from his current cell to another cell will be recorded in a database which is called the log file of mobility history [4]. Each mobility history contains the identification (ID) of the cell which the MN is connected and the timestamp of this connection. According to Refs. [1, 3-6], data mining has been a useful approach to mobility prediction based on the log file of node mobility history. However, the conventional studies do not consider spatial and temporal attributes of data simultaneously.

This study finds that the spatial attributes of a mobile node are changing over time, therefore, time constraints between locations need to be considered in predicting the mobility. Then, we survey and analyze some movement prediction proposals based on spatiotemporal data mining technique. According to this, this paper proposes an approach to predict the movement of a mobile node based on spatial and temporal attributes of data in the wireless network. The remainder of this paper is organized as follows. Section 2 is the related works on mobility prediction. Section 3 presents the system architecture and problem definition. Section 4 is our proposed approach. Finally, discussion and conclusion are presented in Section 5 and Section 6, respectively.

2. Related Works

Various data mining techniques have been used widely to implement the prediction algorithm. Sequential pattern mining is one of the most important techniques in discovering the trends [4-5] and used widely to predict customer behaviour in business [7] or user behaviour in web systems [8], to determine the location of moving objects [9] or to guess the next location of a mobile node in mobile environments [4]. It is the process of extracting certain sequential patterns whose support exceeds a predefined minimal support threshold (min_{supp}) [10]. The min_{supp} is a pruning mechanism that is used to reduce the number of sequences to a certain level of interest and make the process more efficient [5].

Xiaobai Yao [11] indicates the need of temporal extensions of the most spatial data mining techniques. According to the work, knowledge extracted from spatio-temporal data will help us to have better prediction of spatial processes or events. The use of spatio-temporal data mining to predict the user movement is shown in Table 1. However, these proposals focus on the physical movements of users but do not really pay attention to user mobility from the perspective of a wireless network. What required in a wireless networks is for the mobility prediction scheme to predict the next AP through which the MN will connect to the network. In an ideal environment, the handover would be to the closest AP. However, AP overloading and anomalous propagation effects frequently result in handovers to APs other than those adjacent to the current cell [12]. This is the cause of differences between user behaviour patterns and user mobility patterns which are illustrated in Fig. 1. To overcome this problem, we determine a user's movement patterns in wireless networks through a sequence of IDs of AP instead of a sequence of locations which are measured in 2-dimensional coordinates as in Refs. [9, 13].

In summary, because of the differences between user behaviour patterns and user mobility patterns, the data mining based approaches shown in Table 1 can be successfully utilized for location prediction for

Table 1 A brief description of some spatio-temporal data mining based movement prediction proposals.

Proposed scheme	Prediction approach and user mobility model	Type of improvement and prediction accuracy
Frequent pattern based prediction model [9]	The approach simplifies original trajectories and clusters them into spatio-temporally meaningful regions. A original trajectory is a temporally ordered sequence, consisting of spatial locations that are measured in 2-dimentional coordinates at each time-stamp. After approximating original trajectories into the simplifies sequences and finding frequent patterns from the sequences, a prediction model is constructed based on these patterns and the best match for an object's location is determined among all the possible paths in the model.	Improving the quality of location based services (LBS) such as traffic management or route finding system. Predicting a future location accurately even though the query time is far in the future.
Temporal moving pattern mining [13]	This work defines individual users as the moving objects, and spatial locations of moving objects are represented in coordinate system with x- and y-axis. Moving objects' location is transformed into area using spatial operation in order to discover significant information. Next, applying time constraints between locations of moving objects to make valid moving sequences. Finally, the frequent moving patterns are extracted from the generated moving sequences.	Providing knowledge applicable to improving the quality of LBS. Algorithm efficiency has a negative relation with its support level but positive relations with the length of moving sequences and the size of the moving objects database.
Movement pattern mining [7]	The proposal predicts the next movement for individual mobile users based on user movement database (UMD). Each cell in the UMD represents a coordinate which identifies the current position of a mobile user at the given time. UMD is transformed into location movement database (LMD) which details the movement sequences. The movement pattern can be mined from the LMD in order to determine how mobile users travel through the location of interest from base location to another base location via multiple intermediate locations.	Opening up a new future for the prediction of the movement for the individual mobile user.
Path prediction through data mining [14]	Using the user historical context in order to predict the future location based on two classification schemes: the cell-based classification scheme and the cluster-based classification scheme. The approach uses temporal context to enhance the prediction accuracy.	The model can be enhanced with more semantics and context data such as application context (e.g., service requests), proximity of people (e.g., social context) and destination and velocity of the user movement.
Data mining approach for location prediction [4]	Predicting the next inter-cell movement of a mobile user in a Personal Communication Systems (PCS) network. History of mobile user trajectories is utilized for user mobility patterns mining. Next, a set of the mobility rules are extracted from these patterns. Finally, predicting a mobile user's next movement by using the mobility rules.	Mobility prediction enable 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.

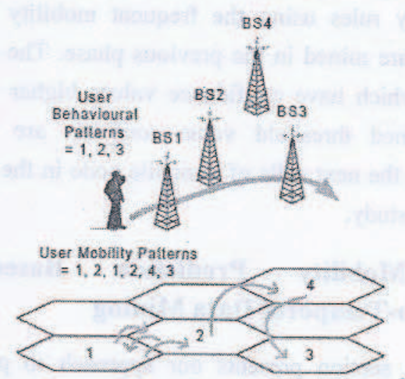

Fig. 1 Differences between user behaviour patterns and user mobility patterns [12].

other types of moving objects, e.g., vehicles or even human, and are unsuitable for location prediction for MN in wireless networks.

3. System Architecture and Problem Definition

3.1 System Architecture

Fig. 2 shows the system architecture for the proposed mobility prediction mechanism. The workflow of the system consists of four phases: Database generation phase, mining phase, rules generation phase, and prediction phase.

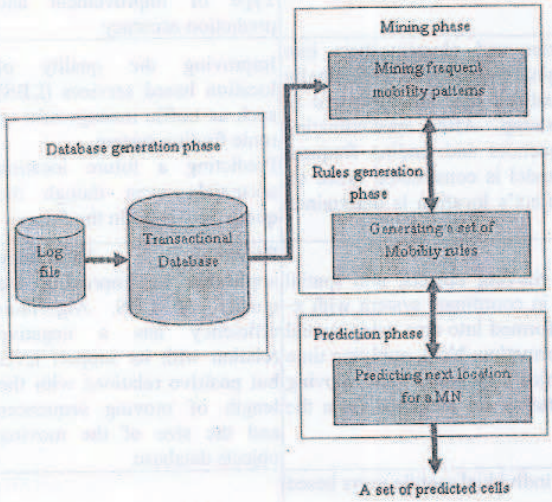

Fig. 2 System architecture.

3.2 Problem Definition

Given a directed graph G, where each vertex is a cell in the coverage region and the edges of G are formed as follows: if two cells, say A and B, are neighboring cells in the coverage region then G has a directed and unweighted edge from A to B and also from B to A. These edges demonstrate the fact that a mobile node can move from A to B or B to A directly. The mobile node can travel around the coverage region corresponding G.

Let c be the ID number of the cell to which the mobile node connected at the timestamp t, we define a point as follows:

Definition 1: Let C and T be two sets of ID cells and timestamps, respectively. The ordered pairs $p = (c, t)$, in which $c \in C$ and $t \in T$, is called a point. Denote P the set of all points, then:

$P = C \times T = \{(c, t) \mid c \in C \text{ and } t \in T\}$.

Definition 2: The trajectory of the mobile node is defined as a finite sequence of points $\{p_1, p_2, \ldots, p_k\}$ in $C \times T$ space, where point $p_j = (c_j, t_j)$ for $1 \le j \le k$.

Definition 3: A mobility pattern $B =< b_1, b_2, \ldots, b_m >$ is a sub-pattern of another mobility pattern $A =< a_1, a_2, \ldots, a_n >$, where a_i and b_j are points, written as $B \subset A$, if and only if there exists integers $1 \le i_1 < \ldots < i_m \le n$ such that $b_k = a_{ik}$, for all k, where $1 \le k \le m$. Here, A is called the super-pattern of B.

For example, given $A =< (c_4, t_2), (c_5, t_3), (c_6, t_4), (c_8, t_5) >$ and $B =< (c_5, t_3), (c_8, t_5) >$. Then B is a sub-pattern of A and conversely, A is super-pattern of B.

Definition 4: Let $D = \{S_1, S_2, \ldots, S_N\}$ be a transaction database which contains N mobility patterns. The support of pattern S is defined as

$$\text{support}(S) = \frac{|\{S_i \mid S \subset S_i \text{ and } 1 \le i \le N\}|}{N} \quad (1)$$

Definition 5: A mobility rule has the form $R: A \rightarrow B$, in which A and B are two frequent mobility patterns and $A \cap B = \varnothing$. Then, A is called the head of the rule, and B is called the tail of the rule.

Each rule $R: A \rightarrow B$ has a confidence value which is determined by the formula

$$\text{confidence}(R) = \frac{\text{support}(A \cup B)}{\text{support}(A)} \quad (2)$$

Problem definition: The problem of mobility prediction in wireless networks based on spatiotemporal data mining is defined as follows. Given a coverage region directed graph G, a log of a node's mobility history, a maximal time gap, *max_gap*, a minimum support threshold *supp_min*, and a minimum confidence threshold *conf_min*, the first phase of the problem is to generating transactional database from a log of a node's mobility history. The second phase of this problem is to discover all frequent mobility patterns in transactional database satisfying *supp_min*. The third phase is generating all mobility rules using the frequent mobility patterns which are mined in the previous phase. The mobility rules which have confidence values higher than the predefined threshold value *conf_min* are used to predict the next cells of a mobile node in the last part of this study.

4. Mobility Prediction Based on Spatio-Temporal Data Mining

This section presents our approach to predicting mobility of MN that consists of four algorithms: (1) Generating transactional database from a log file of node mobility history; (2) Mining frequent mobility patterns (FMP); (3) Generation of mobility rules using the mined FMPs; and (4) the mobility prediction based on the mobility rules. Due to the restriction of the paper, we focus to the first and the last algorithm.

4.1 Generating Transactional Database

Mining sequences with time constraints allows a more flexible handling of the transactions. In this phase, we use temporal attribute to generate transactional database. Each node has a log file of mobility history. It is created whenever a node performs a handover to a new cell. For example, a part of a log file of node mobility history is show in Table 2. The work in Ref. [5] proposed to generate the transactional database using a log of a node's mobility history as follows: a new transaction is started every *T* seconds to indicate the beginning of a new mobility session. Due to the various reasons of data missing such as loss of connection, delaying of update in application environment, etc., Ref. [13], the transactional database obtained by the above procedure may be incorrect. In order to tackle this problem, we apply the time constraints between locations of a node to make valid transactions. Time constraints restrict the time gap between two locations in a transaction. The occurrence time point of consecutive movements is denoted by t_j, t_{j+1}. The maximal time gap, *max_gap*, is defined as follows:

$$t_{j+1} - t_j \leq \text{max\_gap}$$

The pseudo-code for generating transactional database is as following:

```
Generate_Transaction(file Log){
for (i=1; end of a log of//mobility history; i++)
{
if (tj+1- tj > max_gap)
Insert with new transaction id
}
return a set of transactions;
}
```

Table 3 shows an example transactional database which is extracted from the log of mobility history in Table 2. In this example, we assume that *max_gap* is 30 mins. The time gap between the third and the fourth location exceeds the *max_gap* of 30 min, thus generating a new transaction.

Table 2 A Log file of Node Mobility History.

Time	Location
2011/8/10/13/10	2
2011/8/10/13/20	5
2011/8/10/13/25	1
2001/8/10/13/58	7
2011/8/10/14/15	6
2011/8/10/14/55	8
2011/8/10/15/10	2

Table 3 A Transactional Database.

ID	Transactions
1	2, 5, 1
2	7, 6
3	8, 2

4.2 Mobility Prediction

Our approach to mining frequent mobility patterns from the transactional database is based on the work by Yavas et al. [4]. The mobility pattern mining algorithm is based on Apriori algorithm which is one of the most important algorithms of sequential pattern and association rule mining techniques. In this mining algorithm, a mobility pattern is a *trajectory* of the mobile node which contains a sequence of neighboring cells in the coverage region directed graph *G*. For example, in the mobility pattern P = <(a_1, t_1), (a_2, t_2), (a_3, t_3),..., (a_{i-1}, t_{i-1}), (a_i, t_i)>, a_1 is the neighbor of a_2, a_2 is the neighbor of a_3,..., and a_{i-1} is the neighbor of a_i.

Now, we summarize how the frequent mobility patterns (FMPs) are mined. In the *(k-1)*st run of the while loop in the mining algorithm, all the length-*k* subsequences of all sequences in the transactional database are generated and these subsequences are used to count the supports of the length-*k* candidate patterns. After counting the supports of all the candidates, the candidates which have a support higher than the predefined threshold value ($supp_{min}$) are selected and called the *length-k frequent mobility patterns* (L_k). Then, L_k is added to the set *L* in which all the frequent mobility patterns are maintained. L_k is also used to generate lengh-*(k+1)* candidate patterns which are utilized for the next step in the algorithm. A candidate *(k+1)*-pattern is created by adding to the end of a frequent *k*-pattern a neighbor cell in the consideration of the time constraint. Let F = <(c_1, t_1), (c_2, t_2), …, (c_k, t_k)> be a frequent *k*-pattern, $V(c_k)$ be a set of cells which are neighbors of c_k in *G*. For each $v \in V(c_k)$, generating all point (v, t_i) where $<(v, t_i)>$ is a frequent 1-pattern and $t_i > t_k$:

$$P(c_k) = \{(v, t_i) \mid <(v, t_i)> \in L_1 \text{ and } t_i > t_k\}$$

For each point $p \in P(c_k)$, a candidate *(k+1)*-pattern is generated by attaching $p = (v, t_i)$ to the end of *F*: <(c_1, t_1), (c_2, t_2), …, (c_k, t_k), (v, t_i)>. This procedure is repeated for all the frequent *k*-patterns in L_k in order to generate all candidates *(k+1)*-pattern.

However, the mobility rule generation algorithm and the mobility prediction algorithm [4] are extended to the temporal attributes. In the third phase, a set of the mobility rules is extracted from the frequent mobility patterns which are mined in the previous phase. According to the work in Ref. [4], assume that we have a FMP F = <(c_1, t_1), (c_2, t_2), …, (c_k, t_k)>, where $k > 1$. All the possible mobility rules which can be extracted from such a pattern are:

$$<(c_1, t_1)> \rightarrow <(c_2, t_2), \ldots, (c_k, t_k)>$$
$$<(c_1, t_1), (c_2, t_2)> \rightarrow <(c_3, t_3), \ldots, (c_k, t_k)>$$
$$<(c_1, t_1), (c_2, t_2), \ldots, (c_{k-1}, t_{k-1})> \rightarrow <(c_k, t_k)>$$

Each rule has a confidence value which is determined through the formula in ***definition*** 5. By using the mined FMPs, all possible mobility rules are generated and their confidence values are calculated. Then the rules which have a confidence higher than a predefined confidence threshold are selected to use in the mobility prediction algorithm.

Howerver, Yavas et al. [4] has not yet considered the temporal attributes of the rules. The rules, which are extracted from recent movement patterns, should be more important than the rules extracted from older movement patterns.

Definition 6: Assume that we have two rules r_1: <(a_1, t_1), (a_2, t_2),…, (a_j, t_j)>→ <(a_{j+1}, t_{j+1}), (a_{j+2}, t_{j+2}),…, (a_k, t_k)>; and r_2: <(b_1, t'_1), (b_2, t'_2),…, (b_i, t'_i)> → <(b_{i+1}, t'_{i+1}), (b_{i+2}, t'_{i+2}),…, (b_l, t'_l)>. r_2 is a older rule if the timestamp of the last position of its tail is smaller than the timestamp of the last position of the tail of r_1 ($t'_l < t_k$). In this case, r_1 is known as the recent rule.

For an accurate prediction, recent rules should have a greater importance than older rules and w_i, weight for rule r_i, is used for this purpose. Each rule is assigned a weight value when it is generated. The w_i is determined through the timestamp of the last position of the rule's *tail* (t_k). Therefore, all the rules extracted from a FMP have a same weight value.

The frequent mobility patterns and mobility rules are discovered periodically in an offline manner while the last phase is performed online. In the last phase, the next movement of the node is predicted based on the set of the mobility rules which are generated in the third phase. This paper reveals that if the timestamp of the last position of the head of the rule (t_j) is far away from the query time (t_{i-1}), the prediction result cannot be accurate. Thus, T_{diff} is included to incorporate temporal similarity to the query time.

According to the above analyses, the proposed mobility prediction algorithm is presented in Fig. 3. The algorithm extends the problem of matching the current trajectory of a node to the rule's head and finding the best matching using the time constraints. The best matched rule is temporally closest to the query time.

5. Discussion

Mining sequences with time constraints allows a more flexible handling of the transactions. Our paper uses temporal attributes to generate transaction database. Each mobile node has a log file of mobility history. It is created whenever a mobile node performs a handover to a new cell. The work in Ref. [5] proposed to generate the transaction database using a log of a node mobility history as follows: a new transaction is started every *T* seconds to indicate the beginning of a new mobility session. Due to the various reasons such as loss of connection or delaying

Mobility Prediction()

Input: Current trajectory of the user, $P = \langle (c_1, t_1), (c_2, t_2), \ldots, (c_{i-1}, t_{i-1}) \rangle$

Set of mobility rules, R

Maximum predictions made each time, *m*

Output:Set of predicted cells, *Pcells*

PCells = ∅//Initially the set of predicted cells isempty

$k = 1$

for each rule $r : \langle (a_1,t'_1),(a_2,t'_2) \ldots,(a_j,t'_j) \rangle \rightarrow \langle (a_{j+1},t'_{j+1}),\ldots,//(a_i,t'_i) \rangle \in R$

{

//check all the rules in *R* find the set of matchingrules

if $\langle (a_1,t'_1), (a_2,t'_2) \ldots, (a_j,t'_j) \rangle$ is contained by

$P = \langle (c_1, t_1), (c_2, t_2), \ldots, (c_{i-1}, t_{i-1}) \rangle$ and $a_j = c_{i-1}$

{

$T_{diff} = 1/(t_{i-1}-t'_j)$

r.matchingscore = r.w+T_{diff}

r.score= r.confidence+r.support+r.matchingscore

//Add the rule into the set of matching rules

MatchingRules ←*MatchingRules* ∪ *r*

//Add the (a_{j+1}, *r.score*) tuple to the *Tuples* array

TupleArray[k] = (a_{j+1}, *r.score*)

$k = k+1$

}

}//end for

//Now sort the *Tuples* array w.r.t. the score of the

//corresponding rule) in descending order

TupleArray ←*sort(TupleArray)*

index = 0

//Select the first *m* elements of the *Tuples* array

while (*index* < *m* && index < *TupleArray*.length)

{

PCells←*PCells* ∪ *TupleArray[index]*

index = *index*+1

}

return *Pcells*

Fig. 3 Mobility prediction algorithm.

of update in application environment, the transaction database obtained by the above procedure may be incorrect. In order to tackle this problem, we apply the time constraints between locations of a node to make valid transactions. Time constraints restrict the time gap between two locations in a transaction. The occurrence time point of consecutive movements, which are denoted by t_j and t_{j+1}, satisfies:

$$t_{j+1} - t_j \leq max\_gap$$

Moreover, our approach to generating frequent mobility rules is based on the work by Yavas et al. [4]. However, rather than neglecting the temporal factor of rules, the rules which are extracted from the mobility patterns are assigned a weight value with time. Since in our viewpoint, the rules from the recent patterns should be more important than the rules extracted from older mobility patterns.

Our work also reveals that if the timestamp of the last position of the head of the rule t_j is far away from the query time t, the prediction result may not be accurate. Thus, T_{diff} is included to incorporate temporal similarity to the query time. The algorithm extends the problem of matching the current trajectory of a node to the rule head and finding the best matching using the time constraints. The best matched rule is temporally closest to the query time.

6. Conclusions

The spatial attributes of a mobile node are changing over time, therefore, time constraints between locations play an important role in considering its mobility. This paper presents a mobility prediction approach based on spatiotemporal data mining. While various studies on mobility prediction focus on types of moving objects with only location, our work integrates time into rules to facilitate prediction of location of mobile nodes in wireless networks. Implementing the prediction algorithm and performing comparison evaluation with other work is currently examined and will be presented in our further work.

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