Location and Motion Prediction of Consumers in a Large Shopping Mall

Zeyu Zhang
International School of Software
Wuhan University
Wuhan, China
Email: zhangzeyu@whu.edu.cn

Weiping Zhu*
International School of Software
Wuhan University
Wuhan, China
Email: wpzhu@whu.edu.cn

***Abstract*—People hope to predict the future location and motion (e.g. staying in stillness, walking or running etc.) of consumers in a large shopping mall to take convenience to consumers and boost the earnings of stores. When a consumer passes through mall regions, the indoor positioning system records those regions to form an ordered region sequence. Because so many former Apriori-based approaches for mining sequential patterns cannot be used to mine ordered region sequences, we proposed a new Apriori algorithm variation. The association rules mined out from those ordered region sequences can be used to predict the future locations of consumers. We can predict more than one shopping mall regions the consumer may pass one by one in order in the next time. We also design a special association rule querying method for location prediction and a special tree storage structure that is specifically aimed to meet the need of our location prediction method. With our new Apriori algorithm variation and existing technologies, such as the indoor positioning method and the user motion recognition method, we construct the whole location and motion prediction system for consumers in a large shopping mall.**

***Keywords*—location prediction, motion prediction, apriori variation, sequential pattern mining, large shopping mall**

I. Introduction

In modern society, doing the shopping in a large shopping mall in spare time is very common for people. With the increase of the demands of people for individualized consumption, a great variety of commodities and goods appear in shopping malls. However, it becomes more and more difficult for people to find and choose what they really like and really want.

In order to take convenience to those consumers shopping in the mall and boosting the earnings of stores, shopping malls need to predict consumers future behavior according to their historical behavior. Therefore, we hope to be able to predict the following things:

- One or more possible future continuous regions a consumer may appear in the next time.
- The motion of this consumer in those future regions (e.g., remaining stationary, walking and running).

In this paper, to construct this location and motion prediction system, we use the indoor positioning method to locate the consumer and use this positioning records to generate ordered region sequence. In order to avoid the "data distortion" of the ordered region sequence, we take measure to eliminate outliers in the positioning data. Then mine ordered region sequence set using Apriori algorithm variation designed by myself to get association rules. In the next time, the association rules will be stored into a specifically designed tree structure for later prediction. And the prediction algorithm is proposed then. Finally, we use a 3-axis acceleration sensor in mobile phone or use the RFID method to detect the motion of the consumer and record it into the database for later motion prediction.

When a consumer is doing the shopping in a large shopping mall, if we find out the future regions in which he or she may appear and the main motion state of him or her in those regions through this prediction system, we can easily know which shopping mall region may catch his or her eyes and recommend new products for this consumer or advertise the new shopping mall services according to our judging results. It can not only stimulate the spending power of consumers, but also can increase the profits of shopping malls.

In summary, this paper makes the following contributions.

- We design a method to eliminate the outliers in the consumer positioning data records which is generated by the indoor positioning method, and use the processed positioning data records to generate all ordered region sequences for later location prediction.
- We proposed a new Apriori algorithm variation for mining ordered region sequences. It can effectively mine out frequent ordered region sequences and corresponding association rules for the prediction of more than one locations of a consumer in a large shopping mall.
- We design a special association rule querying method for location prediction, and design a special tree storage structure that is specifically aimed to meet the need of our location prediction method. This tree storage structure stores all association rules mined out using our new Apriori algorithm variation.
- We add the motion prediction function into the location prediction system to make the whole prediction system can not only predict locations of a consumer but also can predict his or her possible motions in some shopping mall region.

*Corresponding Author. Email: wpzhu@whu.edu.cn

The rest of the paper is organized as follows: Section II introduces the existing work that does trajectory prediction and the existing Apriori variations that are proposed for sequential pattern mining. In section III of this paper, we propose the location prediction method in shopping mall, and section III is divided into 4 subsections. They are Generate Ordered Region Sequences, Mine out Association Rules, Store All Association Rules for Later Prediction and Location Prediction Method. Section IV explains the motion prediction method in shopping mall. Experiments and evaluation is in section V. Section VI makes conclusions.

II. Related Work

There are lots of indoor positioning methods that are very effective, such as the fingerprinting-based Wi-Fi positioning method, the RFID positioning method, the ultrasonic-based positioning method, the infrared positioning method and so on. Before choosing one to use, we need to consider the hardware cost, the feasibility of implementation, and the influence of obstacles in shopping mall in advance. Then we some indoor positioning methods to locate consumers in the shopping mall and use positioning records to generate ordered region sequences for later association rule mining.

There are lots of work studying on trajectory prediction methods. In general, those prediction methods are 2 types. One is using motion function, such as the work [14] and [16], and the other is using moving pattern such as [10], [12], [13] and [15]. The methods based on moving pattern is often better than those based on motion function [9]. So we choose to use moving pattern and we consider using some Apriori algorithm variation to do location prediction according to the conclusions of the work [11].

There are so many researches having proposed kinds of trajectory prediction methods, such as [10], [12], [13], [14], [15] and [16], but no one concentrates on the exactly ordered and continuous region sequence, and no one gets one or more consecutive shopping mall regions as the location prediction result. So we propose a new Apriori algorithm variation to mine ordered region sequences and to get the location prediction result in the form of the sub-region-sequence like "*Region 3 → Region 5 → Region 1 → Region 2*".

For mining ordered region sequences, Apriori algorithm needs to be modified to be able to do sequential pattern mining. In order to avoid duplicate work, we have searched lots of papers that have come up with many Apriori variations to do sequential pattern mining. However, these Apriori variations cannot be used to mining ordered region sequences here because of the following things. The work [1] and the work [2] both mine sets to get association rules and there is a totally-ordered relation on those sets. Subset $< a, c >$ of set $< a, b, c >$ and subset $< a, c >$ of set $< a, c, e >$ are the same. For ordered region sequence $a - b - c$ and $a - c - e$, sequence $a - c - e$ has subsequence $a - c$, but sequence $a - b - c$ does not have subsequence $a - c$. The work [3], [4], [5], [6] and [7] also mine sets but only parts of elements in those sets are ordered. The work [8] also studies on trajectory prediction of moving objects. However, it records the location points of a moving object and clusters them into many frequent regions, and each frequent region has to be associated with a specific time. The region in ordered region sequence in this paper is not the same with frequent region. It is not formed by clustering location points and it is not associated with a specific time. It just has a relative position in the ordered region sequence with other region elements. And the work [8] mines out all association rules in advance and later prune invalid rules whose elements are not in time order. This two-step association rule mining method, however, wastes too much time and memory space. We want to use one-step method to directly gain all valid association rules, so, we propose a new Apriori algorithm to mine ordered region sequences and use it in location prediction of consumer in shopping mall.

The work [9] uses a 3-axis acceleration sensor in mobile phone to decide whether a person is staying in stillness, walking or running. And the accuracy of its recognizing method is up to 96%. Also, the RFID recognizing method is very effective for recognizing the motions of consumers. We construct a motion prediction system of shopping mall based on those motion recognizing methods.

III. Location Prediction in Shopping Mall

A. Generate Ordered Region Sequences

Let an ordered region sequence L be $L = r_1 - r_2 - r_3 - ... - r_4$. And r_n denotes a region. L records all regions a consumer passes through from entering the mall to leaving the mall. All L of consumer C can form a historical data set H_C, and $H_C = \{L_1, L_2, L_3, ..., L_n\}$. The historical data set H_C is the input parameter of Apriori algorithm variation.

Using the indoor positioning method can record the location area. For instance, in the indoor positioning record $< A, A, A, A, A, B, B, B, B, B, B, C, C, C, C, C, C, C, C >$, A, B and C are three different shopping mall regions. This indoor positioning record can generate an ordered region sequence $A - B - C$.

Due to the impact of positioning errors when a consumer gets close to the edge of a shopping mall region, outliers may appear in the indoor positioning records. Now we still take the indoor positioning record above as an example. If the consumer gets too close to the edge of region B while passing through B, the indoor positioning system may get a positioning record like $< A, A, A, A, A, B, B, B, \boldsymbol{X}, \boldsymbol{X}, B, B, B, C, C, C, C, C, C, C, C >$ instead of $< A, A, A, A, A, B, B, B, B, B, B, C, C, C, C, C, C, C, C >$. Region X are the outlier in this record and it is the shopping mall region that is next to the shopping mall region B. Using this wrong positioning record we can generate a wrong ordered region sequence $A - B - X - B - C$, not $A - B - C$. So it is in importance to eliminate this outlier. In this paper, we set a threshold to eliminate those outliers in advance and use the filtered new record to generate an ordered sequence. Because the number of consecutive occurrences of one outlier region is always far less than that of other normal regions, the experiments show that this simple outlier filtering method is very effective.

B. Mine out Association Rules

Before we explain our Apriori algorithm variation, some concepts need to be mentioned first.

All shopping mall regions in a large shopping mall can constitute a region set R_{ALL}.

One ordered region sequence of consumer C can be represented as $L = r_1 - r_2 - r_3 - ... - r_n$. And r_n denotes a shopping mall region. The ordered region sequence L records all shopping mall regions a consumer passes through from entering the mall to leaving the mall.

All ordered region sequences L-s of consumer C can form a historical data set H_C, and $H_C = \{L_1, L_2, L_3, ..., L_n\}$. The historical data set H_C is the input parameter of our Apriori algorithm variation.

For the historical ordered region sequence data set H_C, the shopping mall region set $R_C = \{r \mid \exists L \in H_C, r \in L\}$.

Association rule $r_i - r_{i+1} - ... - r_{i+m} \xrightarrow{c} r_j - r_{j+1} - ... - r_{j+n}$ means when a consumer passes region $r_i, r_{i+1}, ..., r_{i+m}$ successively, he or she has c probability to pass region $r_j, r_{j+1}, ..., r_{i+n}$ successively then. Probability c is called confidence.

Support: The support of a sub ordered region sequence equals the number of ordered region sequences that contain this sub ordered region sequence.

Confidence: The confidence of association rule $r_i - r_{i+1} - ... - r_{i+m} \xrightarrow{c} r_j - r_{j+1} - ... - r_{j+n}$ equals the support of $r_i - r_{i+1} - ... - r_{i+m} - r_j - r_{j+1} - ... - r_{j+n}$ divided by the support of $r_i - r_{i+1} - ... - r_{i+m}$.

In the Apriori algorithm variation we need to define the minimum support and the minimum confidence. They are $minsup$ and $minconf$ respectively.

The frequent ordered region sequence is the ordered region sequence that the support of it is not less than $minsup$.

K frequent ordered region sequence: the frequent ordered region sequence that contains K region elements is called K frequent ordered region sequence. Simply we call the K frequent ordered region sequence as a K frequent sequence.

All K frequent ordered region sequences can constitute a set LS_K.

Combine two K-1 frequent ordered region sequences into one K candidate frequent ordered region sequence cd_K. And C_K denotes the set of all cd_K.

1) Mining out All Frequent Ordered Region Sequences:

The pseudocode of the process of mining out all frequent ordered region sequences is showed in Algorithm 1.

The pseudocode of function candidate-gen() is showed in Algorithm 2.

Algorithm 1: Find out All Frequent Ordered Region Sequences

Function: getAllFrequentOrderedRegionSequences(H_C)
LS_1 = {All 1 frequent sequences of Consumer C};
for *(k = 2; $LS_{k-1} \neq \emptyset$; k++)* **do**
    C_K = candidate-gen(LS_{k-1}); /* The main difference between our Apriori variation and original Apriori is in candidate-gen(). Function candidate-gen() will be explained later. */
    foreach $L \in H_C$ **do**
        foreach $cd_k \in C_k$ **do**
            if *L contains subsequence cd_k* **then**
                $cd_k.count$++; /* The initial value of $cd_k.count$ is 0. */
            end
        endfch
    endfch
    $LS_k = \{cd_k \in C_k \mid cd_k.count \geq minsup\}$;
end
return $\bigcup_k LS_k$;

Algorithm 2: Generate Candidate Frequent Ordered Region Sequences

Function: candidate-gen(LS_{k-1})
$Answer = \emptyset$;
for *(m = 1; m $\leq LS_{k-1}.size$; m++)* **do**
    for *(n = m + 1; n $\leq LS_{k-1}.size$; n++)* **do**
        Let $LS_{k-1}.get(m)$ represent the region sequence $r_i - r_{i+1} - ... - r_{i+k-2}$; /* $LS_{k-1}.get(x)$ is used to get the x-th element of LS_{k-1}. The index of elements in LS_{k-1} starts form 1 not 0. */
        Let $LS_{k-1}.get(n)$ represent the region sequence $r_j - r_{j+1} - ... - r_{j+k-2}$;
        if *the subsequence $r_{i+1} - r_{i+2} - ... - r_{i+k-2}$ of $LS_{k-1}.get(m)$ is exactly the same with the subsequence $r_j - r_{j+1} - ... - r_{j+k-3}$ of $LS_{k-1}.get(n)$* **then**
            $Answer.append(r_i - r_{i+1} - ... - r_{i+k-2} - r_{j+k-2})$;
        end
        if *the subsequence $r_i - r_{i+1} - ... - r_{i+k-3}$ of $LS_{k-1}.get(m)$ is exactly the same with the subsequence $r_{j+1} - r_{j+2} - ... - r_{j+k-2}$ of $LS_{k-1}.get(n)$* **then**
            $Answer.append(r_j - r_i - r_{i+1} ... - r_{i+k-2})$;
        end
    end
end
return $Answer$;

Compare this Apriori algorithm variation with the original Apriori algorithm, we can find that the original Apriori algorithm needs two prune step to delete non-frequent K itemset from the candidate frequent K itemset, but our Apriori algorithm variation only needs one prune step. The original Apriori algorithm firstly examines whether any K-1 sub-itemsets of the candidate frequent K itemset is frequent or not, then, secondly calculates the support of the candidate frequent K itemset to examine whether the support of it is greater than $minsup$ or not. However, our Apriori algorithm variation only needs to calculates the support of the K candidate frequent ordered region sequence to examine whether the support of it is greater than $minsup$ or not.

2) Discovering Rules from All Frequent Ordered Region Sequences:

The process of discovering all association rules from all frequent ordered region sequences is similar to the process of discovering rules in the original Apriori algorithm.

In our work, the left part and right part of an association rule must be two consecutive ordered region sequences. For example, for the ordered region sequence $r_1 - r_2 - r_3 - r_4 - r_5$, the association rule $r_1 - r_2 - r_3 \xrightarrow{c} r_4 - r_5$ is a valid rule of $r_1 - r_2 - r_3 - r_4 - r_5$, however, the association rule

Algorithm 3: Discover Association Rules from All Frequent Ordered Region Sequences

Function: discoverAssociationRules($\bigcup_k LS_k$)
$Answer = \emptyset$;
foreach *frequent region sequence* $l \in \bigcup_k LS_k$ **do**
  $k = l.length$;
  Let sequence $r_i - r_{i+1} - ... - r_{i+k-1}$ represent the frequent region sequence l;
  for *(m = 0; $m < k - 1$; m++)* **do**
    Association Rule $ar = r_i - r_{i+1} - ... - r_{i+m} \xrightarrow{c} r_{i+m+1} - r_{i+m+2} - ... - r_{i+k-1}$;
    c =the confidence of Association Rule ar;
    if $c \geq minconf$ **then**
      $Answer.append$(Association Rule ar);
    end
  end
endfch
return $Answer$;

$r_1 - r_2 \xrightarrow{c} r_5$ and $r_3 - r_2 - r_1 \xrightarrow{c} r_4 - r_5$ are not valid rules of $r_1 - r_2 - r_3 - r_4 - r_5$.

The pseudocode of the process of discovering all association rules from all frequent ordered region sequences is showed in Algorithm 3.

C. Store All Association Rules for Later Prediction

Suppose we have got all association rules using Apriori algorithm variation. They are $r_1 - r_2 - r_4 \xrightarrow{0.76} r_8$, $r_1 - r_4 \xrightarrow{0.8} r_5$, $r_1 - r_4 \xrightarrow{0.6} r_5 - r_7$, $r_3 - r_7 - r_1 - r_4 \xrightarrow{0.69} r_9$, $r_5 - r_7 - r_1 - r_4 \xrightarrow{0.73} r_8$, $r_5 - r_7 - r_1 - r_4 \xrightarrow{0.55} r_8 - r_{10}$, $r_6 - r_5 \xrightarrow{0.92} r_3$ and $r_2 - r_5 \xrightarrow{0.81} r_7$. Then we need to store them in a tree structure specifically designed for the association rule indexing and for the location prediction. This tree structure in showed in Fig. 1.

The red rectangle nodes in the tree structure showed in Fig. 1 store the right parts of association rules and their confidence. To pass through oval tree nodes one by one from the oval tree node that has red rectangle node to the tree root, we can get the left part of association rules.

This special storage structure is specifically designed aimed to meet the need of prediction method. For a shopping mall region sequence a consumer recently passed through, such as $r_3 - r_7 - r_1 - r_4 - r_5$, we can get 5 different types of left parts of association rules. They are r_5, $r_4 - r_5$, $r_1 - r_4 - r_5$, $r_7 - r_1 - r_4 - r_5$ and $r_3 - r_7 - r_1 - r_4 - r_5$. If possible, we need to find out all association rules whose left parts are the same with those 5 kinds of left parts above. Then, those association rules found above can be used to do location prediction according to different forward prediction region number querying conditions.

D. Location Prediction Method

The pseudocode of querying association rules from the tree structure is showed in Algorithm 4.

Given forward prediction region number k, first we find out all rules whose right parts are all k region sequences from association rules returned. If no one meets the need, then we only find out all rules whose right parts are the longest. Then, from them we choose one rule whose confidence is maximal

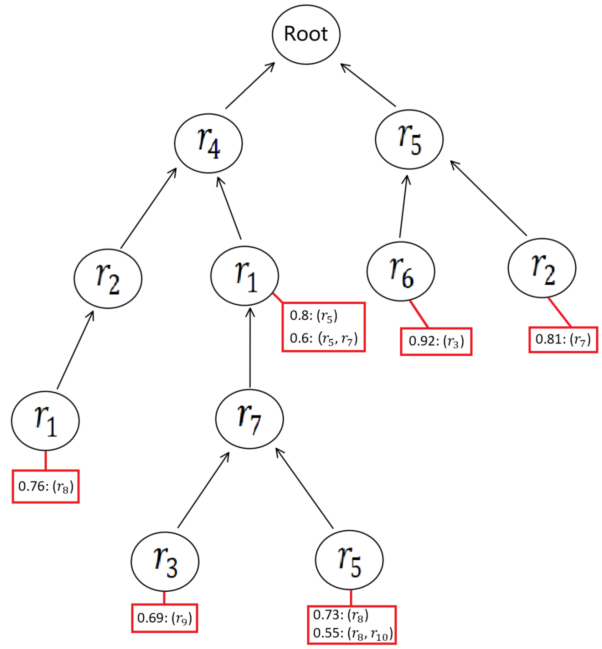

Fig. 1. Tree structure that stores associations rules.

Algorithm 4: Get Prediction Association Rules for Location Prediction

Function: getPredictionAssociationRules(region sequence $r_i - r_{i+1} - ... - r_{i+m}$)
/* The region sequence $r_i - r_{i+1} - ... - r_{i+m}$ represents the regions that the consumer recently passed through in the shopping mall. */
$Answer = \emptyset$;
T = Tree structure that stores all association rules;
$Node = T.Root$; /* $Node$ now is tree root of T. */
for *(k = i + m; $k \geq i$; k = k - 1)* **do**
  if *one node n among subnodes of $Node$ contains region r_k* **then**
    $Node = n$;
    if *$Node$ has red rectangle node* **then**
      $Answer.append$(association rules that consist of left part $r_k - r_{k+1} - ... - r_{i+m}$ and right parts stored in red rectangle node with confidence);
    end
  else
    break;
  end
end
return $Answer$;

as prediction reference data. For instance, given the following returned association rules $r_1 - r_4 \xrightarrow{0.8} r_5$, $r_1 - r_4 \xrightarrow{0.6} r_5 - r_7$, $r_5 - r_7 - r_1 - r_4 \xrightarrow{0.73} r_8$ and $r_5 - r_7 - r_1 - r_4 \xrightarrow{0.55} r_8 - r_{10}$, if k = 1, we can find out $r_1 - r_4 \xrightarrow{0.8} r_5$ and $r_5 - r_7 - r_1 - r_4 \xrightarrow{0.73} r_8$. Among them, $r_1 - r_4 \xrightarrow{0.8} r_5$ has the maximum confidence. Then we use r_5 as prediction result. If k = 3, we cannot find out rules that meet the need so we just find out rules whose right parts are the longest. They are $r_1 - r_4 \xrightarrow{0.6} r_5 - r_7$ and $r_5 - r_7 - r_1 - r_4 \xrightarrow{0.55} r_8 - r_{10}$. Among them, $r_1 - r_4 \xrightarrow{0.6} r_5 - r_7$ has the maximum confidence. Then we use $r_5 - r_7$ as prediction result. It shows the consumer has probability 0.6 to pass through region r_5 and region r_7 in order in the next time.

IV. Motion Prediction in Shopping Mall

The work [9] has proposed a method that uses a 3-axis acceleration sensor in mobile phone to decide whether a person is staying in stillness, walking or running. And the accuracy of its recognizing method is up to 96%. Also, the RFID recognizing method is very effective for recognizing the motions of consumers. So we construct a motion prediction system of shopping mall based on those motion recognizing methods.

For every time windows that has 64 continuous data samples of the 3-axis acceleration sensor, we use the method proposed in the work [9] to decide which motion tag to be attached to this 64-sample-time-window and use the indoor positioning system to decide which region id tag to be attached to this 64-sample-time-window. Then, those data will be stored into the motion database.

Here, we use the recognizing method which is based on the 3-axis acceleration sensor in the mobile phone to explain our motion prediction approach. When the motion prediction system got the location prediction result (the prediction result is in the form of a sub ordered region sequence) from the location prediction system, for every shopping mall region in this result, we query the specific data from the motion database to find out the number of every motion tag in this shopping mall region, and choose one or two tags that the proportion of the number of them exceeds a given threshold as motion references in that region for motion prediction later.

V. Experiments and Evaluation

The new Apriori algorithm variation aimed to mine ordered region sequences is proper for ordered and consecutive region prediction in a large shopping mall. We construct the whole location and motion prediction simulation system in a large shopping mall to test the effectiveness of the location and motion prediction system. And the main structure of this whole prediction system is showed in Fig. 2.

The indoor positioning system provides the ordered region sequence set and the location data of a consumer to association rule mining system and motion recognizing and recording system respectively. There are two databases, association rule database and consumer motion database, and, respectively, association rules and consumer motion data are stored in them. The prediction system uses the data of both databases to do location and motion prediction.

To evaluate the effectiveness of this prediction system, we design a shopping context of a consumer who has a specific shopping habit for prediction simulation. The shopping context is showed in in Fig. 3. In Fig. 3, a circle with a number is a shopping mall region. Region 1 and region 2 are two entrances of this shopping mall. And region 3 and region 4 are two exits of this shopping mall. The red path and the dark blue path are two main paths the consumer often passes through. Paths with other colors are those that the consumer not often passes through but actually does. The number of paths is totally ***100***

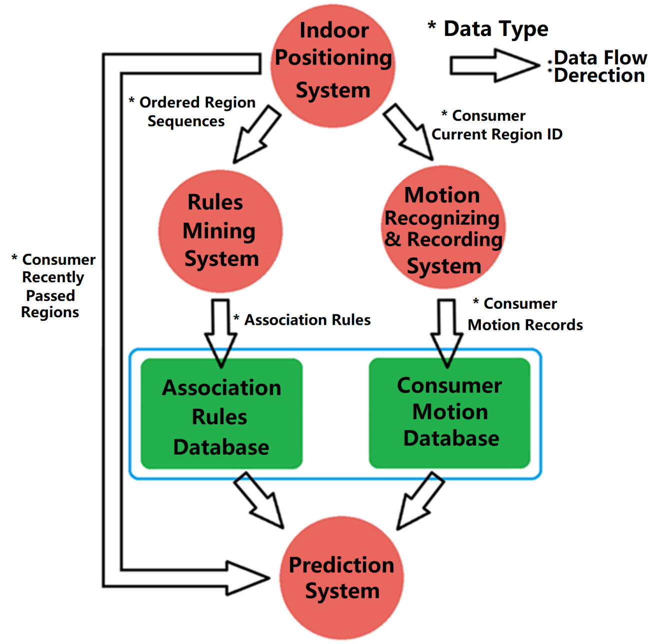

Fig. 2. Location and motion prediction system structure diagram.

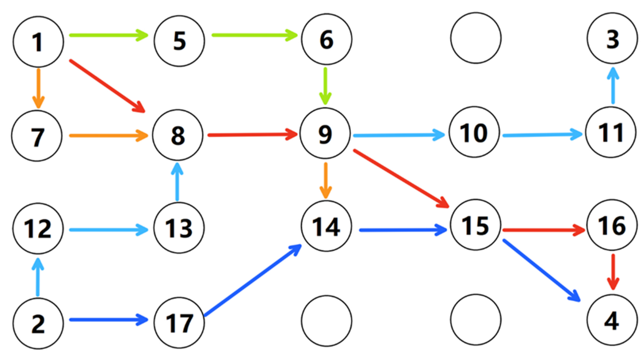

Fig. 3. Habitual shopping paths of a consumer in one large shopping mall.

for simulating shopping activities that basically happen about 2 times a week in one year. Meeting-point regions are region 8, region 9, region 14 and region 15, and the main motion states of this consumer in those regions are mainly remaining stationary or walking slowly. The final simulation test results are showed in Fig. 4.

The simulation results show that the location prediction is very accurate because the actual location prediction results are all the same with the expected location prediction results.

For 8→9, when the forward prediction region number is 1, the prediction system considers the region 15 as the future passing region with probability 0.610. Because 8→9 is a red path, it is a main path. The consumer then is more likely to reach region 15 along the red path 9→15.

When the forward prediction region number is up to 2 for path 8→9, due to the low confidence that is not greater than $minsup$, it can only predict one region not two regions in the

Recently Passed Regions	minsup	minconf	Forward Prediction Region Number	Expected Location Prediction Result	Actual Location Prediction Result	Result Confidence	Motion Prediction Result
8→9	10	0.4	1	15	15	0.610	**15:** not moving or walking
8→9	10	0.4	2	15→16	15	0.610	**15:** not moving or walking
8→9→10	10	0.4	2	11→3	11→3	0.987	**11:** walking **3:** walking
13→8→9	10	0.4	1	10	10	0.856	**10:** walking
2→17	10	0.4	3	14→15→4	14→15→4	0.769	**14:** walking **15:** not moving or walking **4:** walking

Fig. 4. Simulation experiments results.

future. So the prediction result is still region 15.

For recently passed region sequence 8→9→10, because the consumer has passed through the light blue path 9→10, the prediction system then considers the light blue path 10→11→3 as the prediction result with confidence 0.987 when the the forward prediction region number is 2.

Given recently passed regions 13→8→9, the prediction system does not give out a wrong location prediction result "region 15" through the red main path, but successfully give out a correct prediction result "10" because the consumer has passed through a light blue path from region 13 to region 8 and he or she is more likely to pass through a light blue path again from region 9 to region 10.

When the forward prediction region number is 3, considering the dark blue path 2→17, along the whole dark blue path, the prediction system gives out the prediction result with confidence 0.769, and the prediction result is the dark blue path 14→15→4, not the dark blue and red path 14→15→16.

In addition, the motion prediction result can reflect the attraction of regions to the consumer. Most of motions in those meeting-point regions have "not moving" tag, it shows that the consumer may be interested in those regions and actually he or she is.

VI. Conclusions

In this paper, we use the indoor positioning method to generate ordered region sequences, and use a new Apriori algorithm variation to mine out association rules from those ordered region sequences to do location prediction in large shopping mall. A special tree structure for storing association rules is specifically designed aimed to meet the need of our location prediction method. The mobile sensor or the RFID method can be used to recognize the motion of a consumer and then the system stores them into the database as historical data for later motion prediction. The whole location and motion prediction system can effectively predict the future path of a consumer in a large shopping mall and predict the motions the consumer may have in corresponding regions. The new Apriori algorithm variation is aimed to mine ordered and consecutive region sequences and also can be used to mine other ordered and consecutive sequences in other work.

Acknowledgment

This research is supported in part by the National Natural Science Foundation of China No. 61502351, the Nature Science Foundation of Hubei No. 2015CFB340, the Outstanding Young Academic Talents Start-up Funds of Wuhan University No. 216-410100004, and the 2016 National Innovation Project of Wuhan University No. 201610486094.

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