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Travel Destination Prediction Using Frequent Crossing Pattern from Driving History

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Abstract—**The modeling of user behavior patterns for personalized information services in mobile environments has recently become a popular research theme. Most of the research aims at predicting the user's future behavior (and/or location) by extracting frequent patterns from the history of location data sequences. However, sometimes user behavior changes according to the external information such as date, time, weather, etc., and we cannot accurately predict it based on the location data sequences alone. In this paper, we propose a new travel destination prediction method including day and time as external information. First, the user's travel history information including the location, date and time is stored. Then, from the external information, time/day categories that have correlation to the user's destination based on entropy are determined. Finally, using the categories, a destination that depends on the external information can be successfully predicted. An application of the method to data collected from a car navigation system showed possibility for an improved performance comparing to the conventional methods. Higher destination prediction accuracy during the first several minutes after user's departure was reported.**

I. Introduction

In recent years, mobile internet usage through a cellular phone or PDA (Personal Digital Assistant) has become popular, and users can obtain information anywhere and anytime. While the amount of available information has been increasing, the mobile access of information is becoming more difficult. The terminals are often constrained by the size and the usability of the input/output interfaces that need to be operated on the move or while driving. Therefore, in most cases the mobile terminal information access is restricted compared with a non-portable information terminal. In order to improve the usability, a technology that provides the required information at a suitable timing based on the user's characteristics is needed.

Nowadays, several systems such as car-navigation and mobile phones utilize GPS (Global Positioning System) with an error of less than 10 meters and offer location based information according to the current positions of the users [1] [2]. At the same time, research that uses an agent framework to secure the information response to the services offered by a car navigation as well as research on development of the platform for automotive system is ongoing [3] [4]. From the user modeling point of view, the user's driving history can be analyzed on an automotive platform so the destination and future action of the driver can be predicted. Several approaches have already analyzed the day-to-day modeling of driver route choice behavior [5] [6]. By knowing the destination and the possible route, an appropriate and timely information delivery through the car navigation becomes possible. The history information related to the position and the time the user has spent in one building/place enables analysis of the history behavior of the customer [7] [8] as well as extraction of the similar frequent patterns of behavior using the FP-growth method [9] [10] [11]. Other researchers have analyzed the behavior pattern of the user in a mobile environment by using an episode framework and combining the information on the frequently occurring position [12] [13], by using data allocation schemes by incremental mining [14], or by using Markov Model for prediction and learning the significant locations of the user [15]. However, the current researches analyze the history behavior based only on the past movement history and on the time the user stopped in one place, without considering the external information such as the time of the user movement. Therefore, although they are applicable to the moving predictions for a car navigation service, they cannot guarantee sufficient accuracy. On the other side, using the driving log data of a car navigation system, the existence of a cause-effect relation was confirmed between the next route of the user and the external information such as the driving time, stopping conditions, etc. [16]. If we could extract the external information that is the main cause for a change of users' behavior, we could improve the future movement prediction.

In this paper, we propose a new travel destination prediction method based on the movement history including the external information of time and day of the week. First the complete user's travel history (location, date, time) is stored. Then from the external information, attributes with categories that have correlation to the user's destination based on entropy are extracted. The time and the day of the week attributes were divided in a fixed layered structure and the categories that contribute most for the decision of the future behavior of the user were decided automatically. The proposed method is applied to a driving log obtained by a GPS car navigator that included the information of the position and the time. Using the past history moves, the categories that contain a cause-effect relation with the user's destination were chosen and the efficacy of our method in destination predicting experiments was shown.

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The paper is organized as follows: Section II gives an outline of the characteristics of the user's movements (movement behavior) and the destination prediction. In Section III we explain the method for extraction of the user's history from the GPS data and the database construction. The experiment and the prediction results are presented in Section IV. The conclusion is drawn in Section V.

II. FEATURES OF THE USER'S MOVEMENTS

In this paper we assume the task of prediction of the user's destination based on the history of the past geographical moves. Fig. 1 shows an example of typical user movement within his/her activity area, marking the starting point, the destination, and the cross points. If we consider the start place and the crossings as significant location points - nodes - the user's movement behavior can be expressed as a series of transfers in the nodes' space.

By matching the information of a series of user node-transfer movement with an accumulated movement history data, it is possible to calculate from that point forward the probability of a transfer to another series of nodes towards the destination. Thus it is possible, after a given amount of time or a given number of nodes, to predict the user's route and destination. There are three patterns in the user's movements that can be transformed into nodes, as shown in Fig. 2. Node C indicates the user's current position while the arrows between the nodes show the user's movement direction:

(i) There is only one destination, independent of the previous route until C.

(ii) There are two or more destinations and more then one route to C. Each destination is dependent on the route until C.

(iii) There are two or more destinations although the route until C is unique (only one).

(i) shows that the destination is restricted to C-D-E, independently of the preceding route and nodes until C. In this case, by knowing only the current node C it is possible to accurately predict the further course and the destination.

(ii) shows that there are several possible routes and destinations from C. In this case, by only knowing the current node C it is impossible to predict the later moves. However, if information about the peculiarity of the user's behavior as well as the rules (cause-effect relations between the route until the current node) is available, we might be able to predict the direction. For example:

- If the driver used the A → C route, the following route will be E → G.
- If the driver used the B → C route, the following route will be D → F

(iii) shows that even if there is only one route until C, there are several possible latter moves which are unknown. However, in the case that there are rules related to the external information, such as day, date, time, people together, weather etc., it still might be possible to predict the future movement direction. That is particularly true if we can discover the cause-effect relations between the current external information and the direction to be taken, such as: "If it is a weekday, then the user must go from D to F, while if it is a holiday, then the user must go from E to G".

Up until now, prediction methods based on the extraction of frequent patterns from large time series database have been proposed [13]. Such methods are suitable for extraction of patterns like (i) or (ii) as they aim at efficient discovery of only a sequence or series of data that appear as frequent patterns among large quantity of data. However, it is not suitable for extraction of rules such as in (iii) where the further direction changes based on external information differ from the time series. It can be conjectured that the behavior of persons is very much connected to the situation of that moment. According to Nelson [17], from several pieces of information that are related to a particular situation, a person

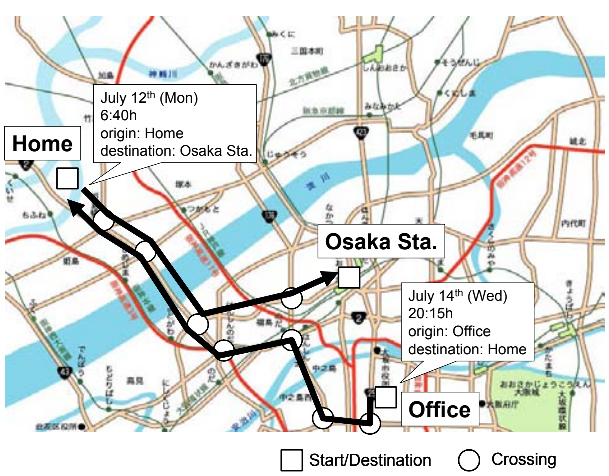

Fig. 1. Significant points in the area of activity of the user

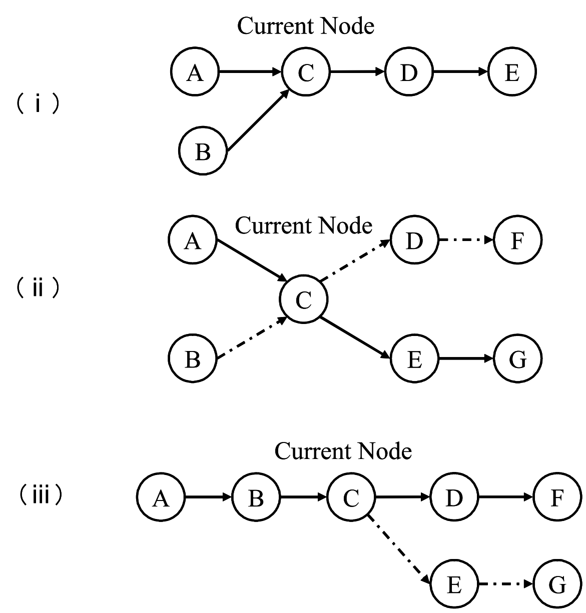

Fig. 2. Features of the user's movements

obtains as a category a combination of the information that is most appropriate for her/his own behavior.

In this paper, based on the history data of the user's moves, we try to find the cause-effect relation between the destination and the external information such as in case (iii). First we try to extract the category that the user obtains and then based on the user's possible change of the route, due to the external information, to predict the destination with high accuracy.

III. Proposed Algorithm

In this section we outline our method for destination prediction using the user travel history. First, we introduce our approach for constructing the database of frequent patterns based on the moving history. Then we include the transition information that is considered as significant when analyzing the moving history. Last, we introduce our algorithm for determining the attribute categories using entropy.

A. Data structure of the moving sequence

Recently, the frequent pattern mining has become an important research area and different techniques and algorithms have been proposed. Han proposed the FP-growth algorithm (FP: frequent pattern) [10] [11], which constructs a highly compact FP-tree usually substantially smaller than the original database. Thus it saves the costly database scans in the subsequent mining processes. However, the FP-tree proposed by the FP-growth method does not consider the time of transition, which in the case of moving sequence is particularly important. Therefore, in this section, we propose construction of a database including the transition information based on FP-tree.

Usually when we leave from one place towards a destination, we move through several significant nodes such as crossings. Therefore our movement can be expressed as a sequence of nodes: start-point → crossings → destination. Fig. 3 shows an example of a user's moving sequence where each node is represented as CP (Crossing Point) with a unique ID: CPn (n = 1, 2, 3...). In this respect, each route of the user can be expressed as node moving sequence, which for the case from the user's home to office would be represented as CP1, CP2, CP3, and CP4. Since only the frequent node will play a role in the frequent pattern mining, it is necessary to perform one scan of the database and eliminate the nodes that are under the minimum support threshold ξ. In this paper we assume $\xi = 4$. The right column of each route shown in Fig. 3 is an example of the moving frequent pattern that met the previous condition. For example CP6 and CP7 in route 8 have been eliminated as the user moved through them less than four times.

The FP-tree structure is constructed using the extracted data series by two operations as shown in Fig. 4:

Operation 1: Each moving sequence S is linked to the Root. In case of adding a new sequence S = {g, h, i}, the new tree structure will connect the sequence S directly to the Root.

Operation 2: In case of a new moving sequence S = {e, b, g}, S' = {e, b} which is part of S is already linked to the Root, therefore {g} is linked to {b}. By performing such operations to all data series, the tree structure shown in Fig. 5 is obtained. Additionally we assign several parameters to each node such as time and day as well as frequency – the number of times the users has gone through that node.

There are clear advantages in constructing and using FP-tree structure regarding the destination prediction. We

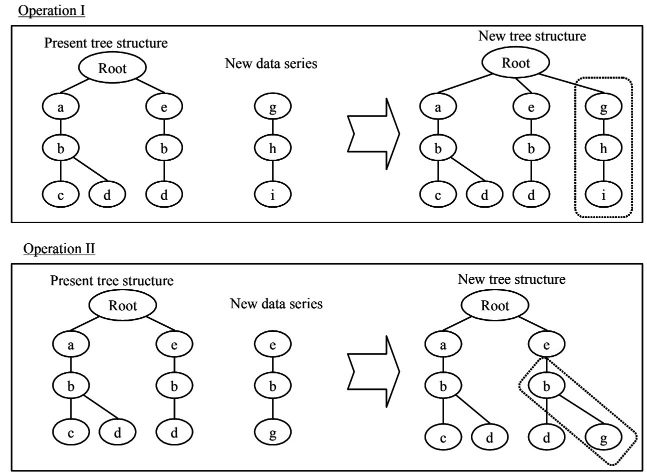

Fig. 4. FP construction method

	Movement history data	High frequency node extracted data
Route 1	Home, CP1, CP2, CP3, CP4, Office	Home, CP1, CP2, CP3, CP4, Office
Route 2	Office, CP4, CP3, CP2, CP1, Home	Office, CP4, CP3, CP2, CP1, Home
Route 3	Home, CP1, CP2, CP3, CP4, Office	Home, CP1, CP2, CP3, CP4, Office
Route 4	Office, CP4, CP3, CP2, CP6, CP7, Supermarket	Office, CP4, CP3, CP2, Supermarket
Route 5	Supermarket, CP7, CP6, CP2, CP1, Home	Supermarket, CP2, CP1, Home
Route 6	Home, CP1, CP2, CP3, CP5, Pool	Home, CP1, CP2, CP3, Pool
Route 7	Pool, CP8, CP9, Supermarket	Pool, Supermarket
Route 8	Office, CP4, CP3, CP2, CP6, CP7, Supermarket	Office, CP4, CP3, CP2, Supermarket
Route 9	Home, CP1, CP2, CP3, CP5, Pool	Home, CP1, CP2, CP3, Pool
Route 10	Pool, CP5, CP3, CP2, CP1, Home	Pool, CP3, CP2, CP1, Home

Fig. 3. Movement history data

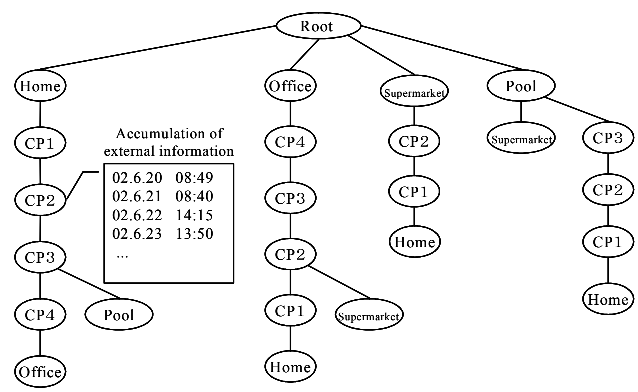

Fig. 5. Example of tree structure of movement history data

avoid the costly search for moving patterns that match the user's current movement, and the probability of destination prediction can be easily calculated at a node until which the sequences were identical, as the possible future routes are minimized. Furthermore, by assigning external information to each node, the destination prediction probability can be calculated considering the condition of the user when he/she has passed through that node.

B. Category determination based on entropy

This section describes the proposed technique for external information category determination based on entropy. It has been shown that the external categories of information such as time, date or even the season have meaningful relation to the user's action [17]. In our work we considered only time and day as external categories.

If user A commutes to her office one day at 8:50 and at 9:10 on another day, we can consider that the category for commuting time for the user A is around 9 o'clock. On the other hand, another user B commutes to his office one day at 8:10 and at 10:10 on another day. We cannot consider 9 o'clock as a category, but the whole period from 8 to 10 o'clock. Obviously, as the categories for commuting time are different for each user, we need to define an appropriate one for each of them. In a similar way we define the categories for the day attribute. For example, if a user A often goes to a supermarket on Saturdays and Sundays, we assume that the weekend/holiday can be considered as a day category for the user A. On the other hand, if the user B goes to supermarket only on Saturday, the category cannot be weekend/holiday but only Saturday. Furthermore, the category that is effective for mining of the user movement is not necessarily only one attribute but a combination of two or more attributes. For example, user A goes to a gym on 20:00 Friday, or user B goes to a particular restaurant 19:00 to 20:00 every weekday etc. From these examples, it is obvious that there are many variations and combinations in the categories and they depend on the lifestyle of each user. Therefore, in order to predict the user destination reliably, it is important to be able to automatically decide the category for each user.

Our proposed algorithm for determination of the category uses entropy as evaluation criteria. First, we define heuristically the tree layered structure for each attribute, where each of them consists of several categories. Two attributes (X_1, X_2) and their respective category structure ($C^k_{i,j}$) are shown in Fig. 6, where k is the attribute number, i is the layer number, and j is the number of categories on i-layer. The flowchart in Fig. 7 outlines the category determination algorithm.

First, we set the initial category (root category), in this case $C^1_{0,1}$ and $C^2_{0,1}$, which are roots of the attributes X_1 and X_2 respectively. The root category includes all the categories (attribute values) of its own attribute, in other words without referring to any external information. Therefore concerning a root category, such as $C^1_{0,1}$, is same as not concerning attribute X_1 as external information. The number of attribute category combinations is one and we define the combination ($C^1_{0,1} \wedge C^2_{0,1}$) as CV_m (m = 1). In general, if the number of total combination is set to M, the standard evaluation value EV_0 can be computed using the EV (evaluation value) equation defined by (1) and (2).

$$EV = \sum_m \sum_n P_{n,m} \log\left(P_{n,m}\right) / M \quad (1)$$

$$P_{n,m} = Freq\left(N_n \mid S \wedge CV_m\right) / Freq\left(S \wedge CV_m\right) \quad (2)$$

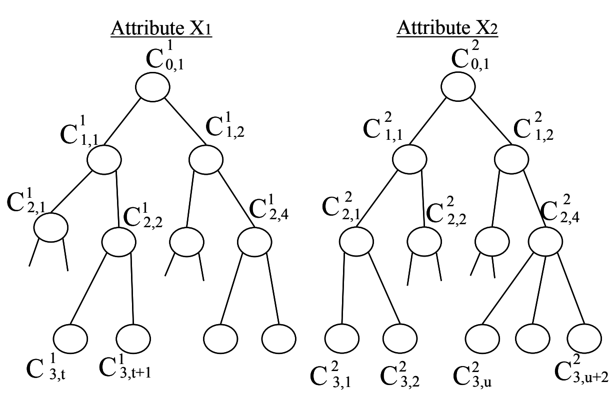

Fig. 6. Hierarchical structure of categories

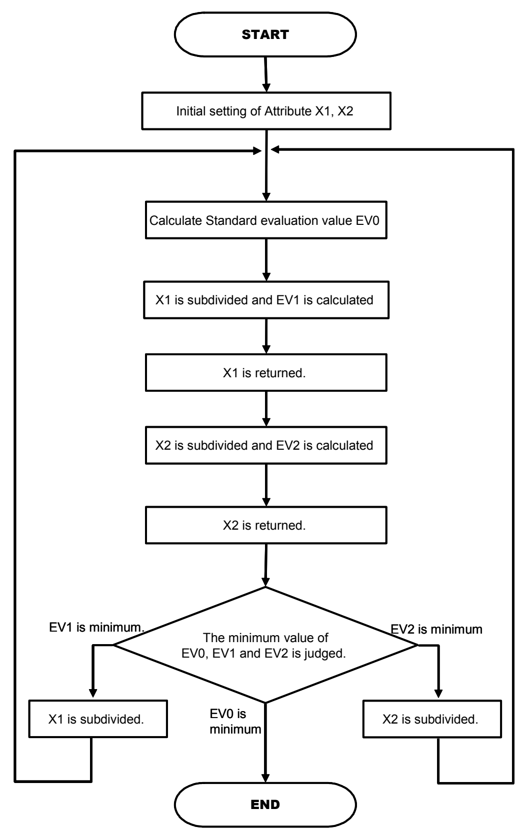

Fig. 7. Flowchart of the category determination algorithm

S is the current node including the route that the user has used, $N_n(n=1,2,.....)$ is the destination that the user has reached through S, and M is the number of combinations. $Freq(S \wedge CV_m)$ is the total frequency of S under the condition CV_m, while $Freq(N_n \mid S \wedge CV_m)$ is the frequency of S for the N_n destination, both of which can be calculated from the user travel history database. With the decrease of the EV value for certain attribute categories as defined by (1), the prediction probability becomes higher. After the initial value EV_0 for the categories $C^1_{0,1}$, $C^2_{0,1}$ is computed, we move one level down in the category structure and calculate the new EV values. First, the attribute X_1 category $C^1_{0,1}$ is subdivided into $C^1_{1,1}$ and $C^1_{1,2}$ while keeping X_2 with the $C^2_{0,1}$ category, so the combinations of attribute categories become $C^1_{1,1} \wedge C^2_{0,1}$ and $C^1_{1,2} \wedge C^2_{0,1}$. For this combination $CV_m(m=1,2)$, we calculate EV_1 according to (1). Then we return the attribute X_1 to $C^1_{0,1}$, while $C^2_{0,1}$ of the attribute X_2 is subdivided into $C^2_{1,1}$ and $C^2_{1,2}$. In this case the attribute X_1 is $C^1_{0,1}$ and attribute X_2 is $C^1_{1,1}$ and $C^1_{1,2}$, so the combination of attribute categories become $C^1_{0,1} \wedge C^2_{1,1}$ and $C^1_{0,1} \wedge C^2_{1,2}$. We calculate the value EV_2 and return the attribute X_2 to $C^2_{0,1}$. Now one of the following relations between EV_0, EV_1 and EV_2 are possible:

(i) $(EV_0 \le EV_1) \quad \wedge \quad (EV_0 \le EV_2)$

(ii) $(EV_1 < EV_0) \quad \wedge \quad (EV_1 < EV_2)$

(iii) $(EV_2 < EV_0) \quad \wedge \quad (EV_2 < EV_1)$

In the case of relation (i), the category division has no effect on the entropy reduction *(EV)* - which means there is no correlation between the subdivided category and the destination - so we quit the subdivision operation. On the other side, in the case of relation (ii) and (iii), there is correlation between the subdivided category and the destination, so it is effective to subdivide the category. For example, let case (ii) be the relation between the values so that attribute X_1 is divided into $C^1_{1,1}$ and $C^1_{1,2}$ while attribute X_2 remains $C^2_{0,1}$. Then EV_1 is set as a new standard evaluation value ($EV_0 = EV_1$) and we repeat the process for the new initial categories $C^1_{1,1}$, $C^1_{1,2}$, and $C^2_{0,1}$ with calculation of the evaluation value for three patterns. The subdivision of the layers is repeated until the relation of each evaluation value, which we denoted previously, satisfies the case (i). When the process is completed, we obtain the categories for which the entropy to the destination candidates becomes the smallest. With this approach, categories having the highest correlation with the user's destination can be determined automatically.

IV. Application Examples

In order to show the results of the proposed method described in Section III, we used the movement history data obtained by a GPS car navigation as an object to a prediction task.

A. History data collection

Here we describe the method of storing the movement history data in a time category. We used a commercial hard disk car-navigation system (Panasonic CN-HD9000WD) to collect the user position information from which the information about the nodes was extracted. Our application program was uploaded to the main car-navigation unit through the SD memory card slot. The car navigation position data obtained by the GPS unit, expressed in latitude and longitude, was sampled in a fixed time interval of 1 second. The 1Hz position data, together with the information related to the day/time the driving occurred, were recorded in time categories in segments "from the start of the engine until the car stops". This segment represents one unit of the history data. Since the sampling time interval is short, the amount of the movement history data recorded on the SD card is extremely big even for short units. As the history position movements consists of many long data sequences that are not always necessary to make a model of the user's behavior, it would be extremely inefficient to consider and process the complete data. This paper focuses only on the significant location points - nodes - whose data we extract from the history data sequences. We define a node as follows:

- *landmarks* as a node – location where the user started the engine (starting point) and the place where the engine was stopped (destination)

- *crossing point* as a node – locations where there is a choice between two or more routes

In the case of landmarks, it is possible to automatically extract the start/end nodes from the engine start/end data in one segment. However, due to the errors in the obtained GPS position data, for an automatic extraction of the crossing points we need some heuristics in addition to a logical algorithm. In our study we graphically visualize and simulate all of the driving routes and move information, so we could manually find the crossing points considered as node objects. Then, the node series are extracted from the history data and are stored together with the time/day information.

B. Destination prediction experiments

Six months of movement history data for three subjects

TABLE I
SUBJECT'S INFORMATION

	Sex	Age	Average running time	Period of history data acquisition	Runs/ day
Subject A	M	20's	20 min	~6 months	2.6
Subject B	M	20's	48 min	~6 months	2.4
Subject C	F	30's	9 min	~6 months	3.7

were used for our experiments. The subjects' information is shown in Table 1.

Two kinds of external information - *day* and *time* attributes - were used as conditions for the prediction with a layered structure of the categories as shown in Fig. 8.

The prediction experiments were conducted using the external information and the information of the driven route for a determined period of time after user's departure from a landmark. The driving route of a subject to the node at a certain time is defined as already discussed in section III-B with categories determined by the minimum evaluation value (1). Then, from the history data combined with the day/time attribute categories, the destination and a group of frequent destinations is extracted. We take the predicted destination as the most frequent among those, and if it is the same as the real destination of the driving data, the prediction is successful. First we investigate the relation between the prediction accuracy and the number of history data used in the study. Sixty of the complete history data of the three users were used as evaluation, while the rest of the history data was studied by adding 20 data each time. The prediction accuracy of the route S was calculated for the following three cases:

- using the route information at the starting point
- using the route information of the first 2 minutes after start
- using the route information of the first 5 minutes after start

For comparison purposes, together with the proposed method, we show the prediction accuracy of the method without external information [13] and the case of using only two and only three layers as described in Fig. 8. The relation between the average prediction accuracy of the subjects and the number of data studied is shown on Fig. 9, Fig. 10 and Fig. 11. Fig. 9 shows the results in the case of prediction using

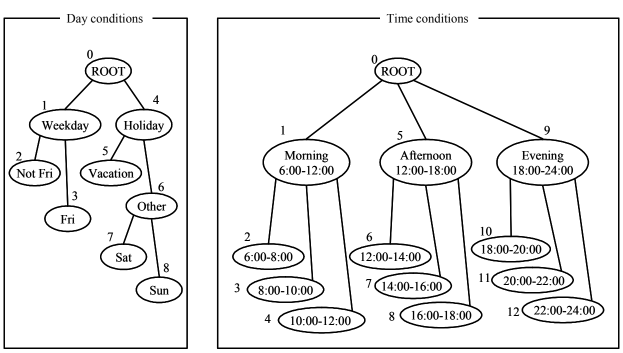

Fig. 8. Layered structure of day and time categories

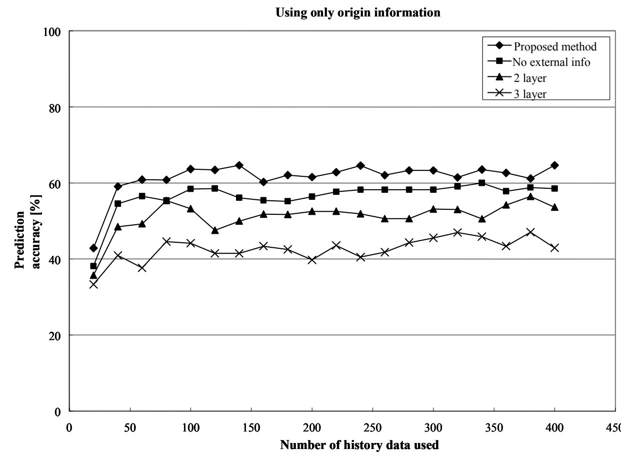

Fig. 9. Prediction results using only the information of the starting point

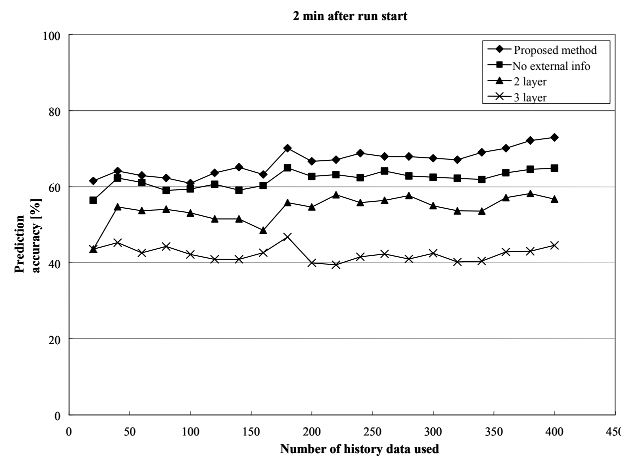

Fig. 10. Prediction results using the information of the starting point and the route of the first 2 min

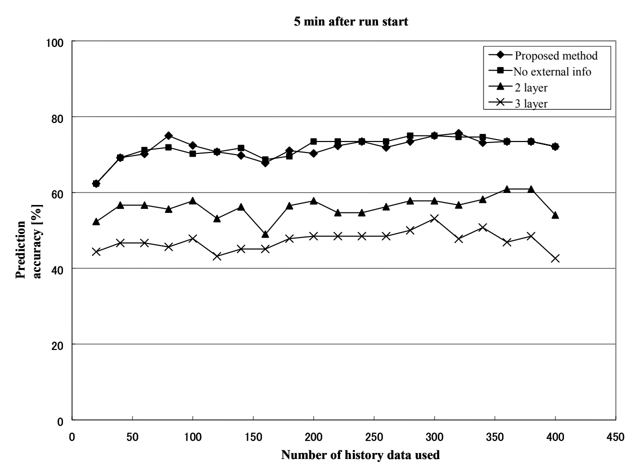

Fig. 11. Prediction results using the information of the starting point and the route of the first 5 min

only the information of the starting point, Fig. 10 shows the results when using the information of the starting point and the route of the first two minutes, while Fig. 11 shows the prediction results using the information of the starting point and the route information of the first five minutes.

According to the results from Fig. 9 to Fig. 11, the prediction accuracy increases with the increase of the time since the engine start, as well as with the increase in the number of history data used. The proposed method shows high accuracy compared to the case of using external information of the 2nd and 3rd layer, which surprisingly is lower than the accuracy without external information. We believe that one reason for this could be the a priori design of the category structure as there are categories without any history data. As this tendency appears more clearly when the layers become deeper and the range of the category becomes smaller, we tried to solve it by increasing the amount of data used in the study. However, our experiment showed that even in that case, the prediction accuracy when deep layers are used was not higher than the proposed method. The drive history tended to accumulate selectively at a certain category, and there were attribute categories that did not contain data. Therefore, in the proposed method, we determine only the category that has meaning for the user and which we believe could improve the prediction accuracy.

When we use the run course of five minutes (Fig. 11), the prediction accuracy of our method hardly differs from the case when external information is not used. However, for short time run courses (Fig. 9 or Fig. 10), the prediction accuracy of our method is clearly superior. Therefore, it is shown that the route information of the first several minutes leaves the possibility of many subsequent destinations, so the exact user's destination cannot be accurately determined only by the route data. In order to make high accuracy predictions, it is necessary to use the external information and analyze the features by acquisition of the categories.

Furthermore, by looking at the figures, we can conclude that the prediction accuracy does not improve much with the increase in the number of history data used. This result is unlike previous studies where the prediction accuracy tends to increase in a linear way with the increase of the quantity of data. We think one reason could be in the nature of the acquired drive data as there are certain examples of being impossible to predict a destination based only on the movement history and the time factor.

We have also investigated the changes of the prediction accuracy and the evaluation value with the change of the running time of the user as shown on Fig. 12. As we can see from the graph, as the user's drive goes on, the prediction accuracy becomes higher while the evaluation index for the category determination decreases. This shows that the evaluation indicator is correlated with the prediction accuracy, and when the index of the indicator becomes small, i.e. the number of possible destination candidates decreases, the prediction accuracy becomes higher.

In order to understand how the category that is chosen based on the moves changes according to the drive of the user, we analyzed the data of subject A as shown in Fig. 13. The indexes of the day/time categories are the same as in Fig. 8. As shown in the figure, in case of route CP1 → CP2 → CP18 → CP19, the external attribute of the day is not chosen and there is subdivision only in the time attribute. The further analysis revealed that it was the most frequent route of subject A in which he leaves his home in the morning and drives to his office. Therefore, in this route there is no dependency on the day, and the time attribute can be considered to be widely effective as the category of the morning. If we look at the CP2 → CP3 movement, both attributes of day and time category are important, while in case of CP18 → CP14 there is no dependency on the time attribute, but only on the category of day. When we looked at the details of CP18 → CP14 route, almost all moves were between 14:00~18:00 so the destination did not depend on the time category, which was more subdivided, but depended on the day of the week.

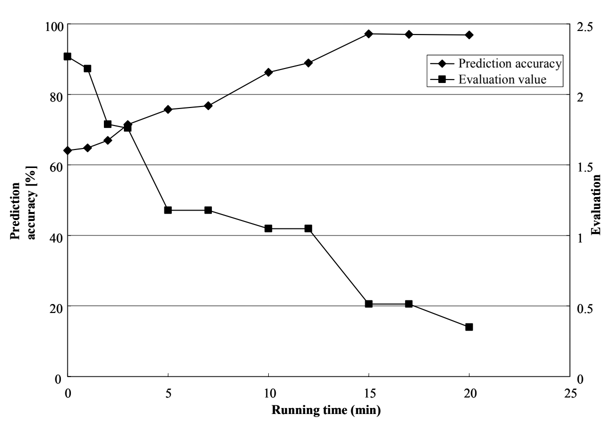

Fig. 12. Changes of the prediction accuracy and the evaluation value

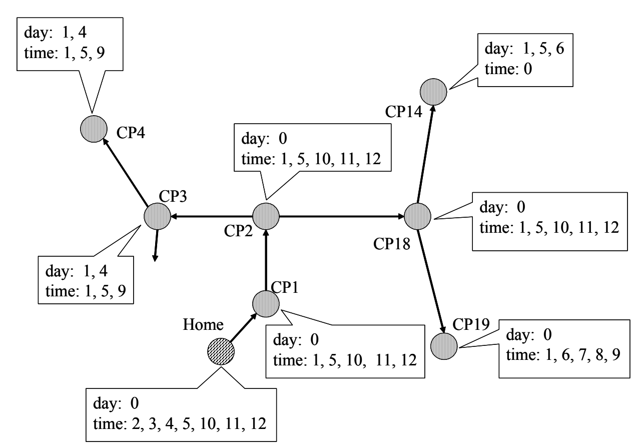

Fig. 13. Changes of the extracted category

The previous results show that for short run-courses our proposed technique performs better than a prediction based on course information only. Moreover, we understood that the user's movements using a vehicle strongly depend on the external information such as day and time, and utilization of this information is effective for route prediction.

V. Conclusion

In this paper we aim at the realization of a system that can offer user personalized information services in a mobile environment. We proposed a high accuracy method for prediction of the user's destination using a concept of external information categories based on the history data of the moves obtained from a car navigator. The extraction of specific patterns of user actions was conventionally performed by paying attention to the co-occurrence of the data series, and it was difficult to predict a user's behavior that changes according to the context. With our evaluation experiments, we applied the proposed method on the history data of the three subjects and we were able to show the validity of the method. We believe that from now on the filtering of only the information related to the destination and the predicted route will become very helpful for support to the information activity of the user in the ubiquitous environment.

Regarding our future work, the first step will be to focus on improving the prediction accuracy. Although our experiments showed that using date and time as external information was an effective method to obtain the categories, in order to improve the accuracy further, we have to use some additional information correlated to the destination. For example, some researchers reported that the information related to the object used by the user may be considered as important external information [18]. Some other researchers already work on knowledge discovery from sequential data based on Markov model by summary and visualization of the characteristics of the database [19]. It would be interesting to compare and analyze that approach combined with external information depending on the user context. The second step in our future work would be the planning of the structure of the layers of the categories. In this study we have defined the layer structure shown in Fig. 8 beforehand, however it does not represent sufficiently the category candidacy. For example, in case of the category 14:00~16:00, other categories such as 14:00~15:30 or 15:30~16:30 might be more appropriate. Therefore it is also necessary to automatically determine the range of category from the history data.

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