A Destination Prediction Method Using Driving Contexts and Trajectory for Car Navigation Systems

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ABSTRACT

Car navigation systems provide the best route to a destination quickly and effectively. However, during daily driving, this information is not necessary since drivers already know the route to the destination very well. In addition, it is time-consuming for drivers to input the destination. Thus, our research group has proposed a new car navigation system that provides information related to the destination by predicting the user's destination automatically. We propose the use of a new method that predicts the destination on the basis of the driving trajectory and the contexts in which the user drives. A system that uses our method knows the destination without user interaction and provides information related to the correct destination.

Categories and Subject Descriptors

H.4.0 [**Information Systems Applications**]: General; I.5.5 [**Pattern Recognition**]: Design Methodology—*Classifier design and evaluation*; D.2.10 [**Software Engineering**]: Design—*Methodologies*

General Terms

Algorithms

Keywords

Car navigation system, Destination prediction

1. INTRODUCTION

Recently, the car navigation system has become more and more popular all over the world. It consists of various functions, such as vehicle positioning, route retrieval for the destination, map database management, and visualization. Many researchers and companies have developed mechanisms for these functions and applied them to navigation systems.

These mechanisms are used only in the navigated situation where the user does not know the route to the destination and the system navigates the user to the destination. However, in daily driving i.e., to work or for shopping we are mostly in a non-navigated situation where we are very familiar with the route to the destination. Most these functionalities are not used in everyday driving.

Therefore, our research group has developed a new navigation system that predicts the driver's purpose and destination, and automatically presents information that is valuable even in a non-navigated situation. For example, when the system predicts the destination as *Train Station 'X'*, it presents the train schedule at the estimated arrival time and the traffic information on the predicted route.

The method of predicting the destination that we previously developed had some problems because only the driving trajectory was used. We have investigated the reasons for errors in the previous method, and we propose the use of a new way to predict the destination. This method changes dynamically on the basis of the type of road driven on.

2. DESTINATION PREDICTION FOR CAR NAVIGATION SYSTEM

Our system[4] has a structure as shown in Figure 1. Because of space limitations, we have omitted the details and simply show the key features.

This system is implemented on a PC-based system and a commercial car navigation system using Java.

2.1 Service Scenario

The following are some examples of how our system presents the information related to the destination and the route:

- The system automatically predicts that the user destination is a shopping mall and presents information about another parking lot because the route to the primary lot is now congested.
- The system automatically predicts that the driver is taking their passenger to the station and presents a train schedule with the estimated arrival time.
- The system recognizes that the destination is a restaurant and recommends several menu items.

We assume that the system presents various pieces of information at the same time, which are related to destinations

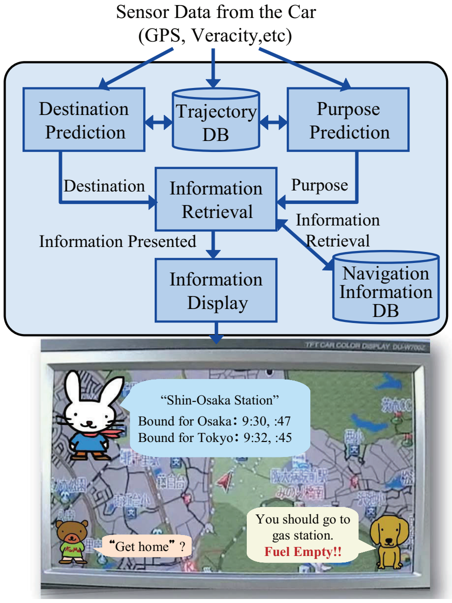

Figure 1: Structure and snapshot of our system

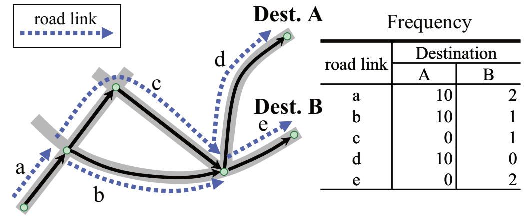

Figure 2: Various of road link

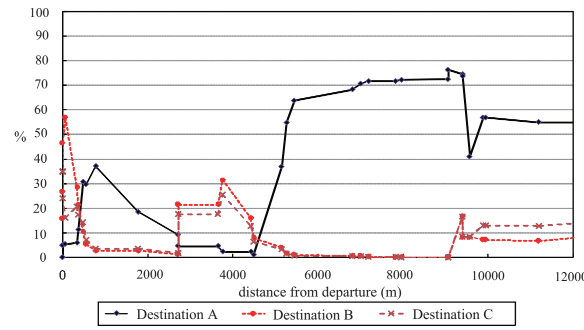

Figure 3: Result of prediction using BM

with higher probability. This is because, while the system does not always predict destinations correctly, its purpose is to present correct information for as long as possible.

As shown in Figure 1, since the system also needs to display the map and the current location of the vehicle, it presents 4 pieces of information at most.

2.2 Conventional prediction of destinations

Our research group has proposed the use of a simple destination prediction method, Basic Method (BM) which calculates the degree of concordance between the route from the departure and stored trajectories. It, as shown in Figure 2, uses a data model that manages routes as a set of directed road links and the system records the transition history of road links. The system predicts destinations by using the following formula (1).

$$P_{ij} = (1-\alpha)\frac{N_{ij}}{N_i} + \alpha P_{(i-1)j} \qquad (1)$$

The probability that user at link i goes to destination j is given by P_{ij}. The past frequency of the visiting road link i is given by N_i, and N_{ij} means the frequency of going to destination j by i. The coefficient to control the weight of considering past routes for calculating P_{ij} is given by $alpha$, and it is set from 0 to 1. The system recalculates the probabilities for all destinations when the user transits to another road link. Note that P_{0j} is the rate of the drives where the destination is j in past drives.

We show an example of calculating P_{ij} in Figure 2. When a user drives along *link a*, P_{aA} and P_{aB} are 83%(= 10/12) and 17%(= 2/12). Next, when he/she arrives at link b, P_{bA} and P_{bB} become 87.1%(= $0.5 \times 10/11 + 83\% \times 0.5$) and 12.9%.

An example of a prediction result using this method is shown in Figure 3. The figure shows the transition of probability for each destination where the correct destination is A. On the right side of the graph, that is near the destination, the probability of the intended destination being destination A is quite higher and the system presents the correct information related to A. On the other hand, when the user is driving around $3000m$ from the departure, the probability of destination A is lower than the others and the system cannot present the correct information.

3. PROPOSED METHOD

We need a way of predicting destination that predicts the correct destination with a higher probability. To do this, we investigated the characteristics of changing the prediction probability through pilot studies, and proposed a new destination prediction method that varies dynamically with the situation.

First, we extracted driving road links that have effect on predictions. From the results of our previous investigation, we confirmed that the prediction result often worsened when we drove along alternative ways or along arterial ways that were frequently used in other drives. In the following sections, we discuss this in detail.

3.1 Using alternative routes

3.1.1 Problems and issues

When we use an alternative way, it has deleterious effect on the accuracy of the prediction. An example is shown in Figure 4; when a user drives along *link c* instead of one that which he/she usually uses, b, the destination prediction highly depends on the record of c and the probability for the correct destination decreases significantly. After that, when he/she arrives at link d, in most cases, the probability is restored. Thus, the probability temporarily decreases. In this example, when the transition between *link a* and c occurs, the probability that he/she goes to destination A changes from 83 to 42% while the probability for B rises to 58% from 17%. Next, when he/she arrives at *link d*, the probability of A is restored to 71%. Since it causes a lack of reliability, incorrect information may thus be presented. As drivers often take a more indirect route for reasons based

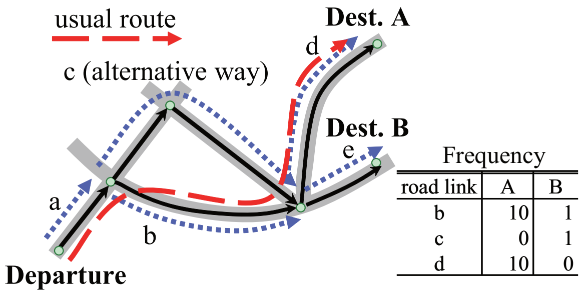

Figure 4: Example of using alternative way

on their experience, such as to avoid a red traffic signal or a traffic jam, the system may present information on an undesired destination.

3.1.2 *Prediction method considering alternative routes*

We propose the use of the *Alternative way Method* (AM) that is suited for use on alternative routes to resolve the problem described. The main idea is that it changes the weight of past prediction probability on the basis of the situation.

Though the weight "α" in Equation (1) is constant in the BM, we change the weight α dynamically to eliminate the loss of predictive accuracy of using the alternative way. In the new method, α and P_{ij} are defined by following equations, respectively.

$$\alpha = \frac{N_{i-1}}{N_{i-1}+N_i} \tag{2}$$

$$P_{ij} = \frac{N_{ij}}{N_{i-1}+N_i} + \frac{N_{i-1}}{N_{i-1}+N_i} P_{(i-1)j} \tag{3}$$

As shown in the equation (2), N_i means the frequency of the visiting road link i in the past. By using this equation, the frequency of using the road is considered as the significant factor.

3.1.3 *Evaluation*

We evaluated the AM by comparing the ratio that the prediction results include the correct destination in the Top-1 or Top-4 accurately predicted distances. In the evaluation, we use the trajectory data of 104 drives by two test subjects during 4 months.

The result is shown in Figure 5. The ratio of Top-1 improves about 2% while, compared with BM, the ratio of Top-4 does not change. In addition, we evaluated the total count of changes in rank for the correct destination. The result is shown in Table 1. Using AM decreases that the rank for the correct destination decreases.

These results mean that the AM is more suitable for predicting destination but the difference in accuracy is not significant.

3.2 Using arterial way

3.2.1 *Problems and issues*

When we use an arterial way that is used a number of times, such as one used on a commute, the prediction probability highly depends on ity and the system cannot predict a less commonly used destination. For example, when a user

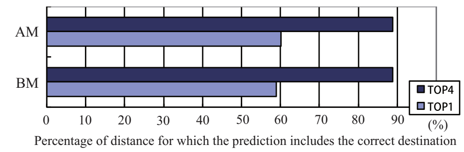

Figure 5: Evaluation result for method using alternative way

Table 1: Probability of changes in rank for correct destination

Rank	BM	AM
up	58.6% (65/111)	61.1% (66/108)
down	41.4% (46/111)	38.9% (42/108)

drives along *link b*, as shown in Figure 6, the probability of *Destination A* decreases significantly since he/she has often used the *link b* to go to *B*. When a user drives along *link a*, the probability of *A* is 83%. Next, when he/she arrives at *link b*, this probability decreases to 46%. As a result, the information presented about destination *A* disappears during the drive on *link b*.

3.2.2 *Prediction method with arterial way*

By using the data for each departure, we may be able to predict the correct destination. We call this method the *Departure Method* (DM). An example is shown in Figure 6. The system predicts the correct destination, *A*, with 83% probability by using the refined data while the prediction rate gained in the BM is 46%.

3.2.3 *Evaluation*

We evaluated the DM by comparing it with the BM using the same data as that used in the evaluation in the last section, which is the trajectory data of 104 drives. To find the difference between both methods, we compared the number times the prediction probability changed.

The evaluation result is shown in Table 2. The probability of the correct destination calculated by the BM decreased more frequently than that calculated by DM. Therefore, the DM predicts the correct destination for a longer time than the BM does. One of the reasons is that the passed route becomes a tree-shaped structure using the DM and it can be used to factor in the user's behavioral characteristics, such as he/she often drops in somewhere on the way home from school.

On the other hand, it is difficult to use the DM to collect data on driving. The data gained from the DM in Table 2 are fewer than those gained from the BM. This fact brings new problems that the DM cannot predict the correct destination where a user has visited it many times from other places but he/she has not been there from the present departure point. Moreover, the prediction result is easier to change since the DM has fewer training data than the BM does.

Thus, both methods have merits and demerits.

3.3 Context based prediction

Though the BM, the AM, and the DM predict the destination using only the driving trajectory, predicting destinations where they are in the same direction or they are

Table 3: Number of visits for each context

Context (time of day, day of week, weather, number of passengers, weight of baggage)	A	B	⋯	Z
(morning, holiday, sunny, single, light)	1	2	⋯	1
(morning, holiday, sunny, single, heavy)	1	4	⋯	1
:			⋯	
(night, workday, rainy, multiple, heavy)	1	3	⋯	5

Table 2: Probability of increase/decrease for correct destination

	BM	DM
Increase	65.0% (316/486)	80.7% (167/207)
Decrease	35.0% (170/486)	19.3% (40/207)

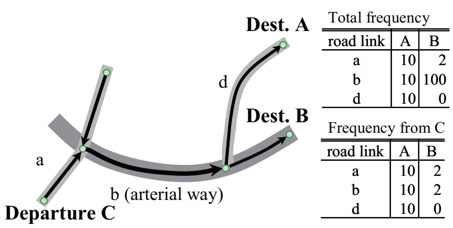

Figure 6: Use of an arterial way

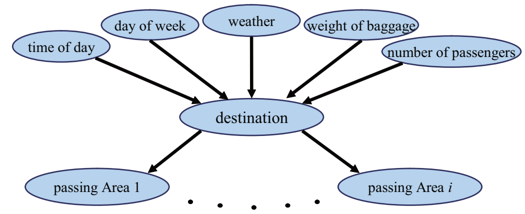

Figure 7: Our structured Bayesian network

Table 4: Particle size of each context

Context	Particle size
time of day	morning, noon, night
day of week	weekday, holiday
weather	sunny, rainy
number of passengers	single, double, multiple
weight of baggage	light, heavy

located close to each other is difficult. Therefore, we propose the use of the *Context Method* (CM) that predicts the destination using driving context such as the time of day, the day of the week, the number of passengers, and the weather. In addition, since the transition sequence of the vehicle's approximate positions also explains the context of driving, we use area transitions by dividing the field into two-dimension lattices.

We made the CM by using a Bayesian network, which is often used to predict user behaviors on the basis of his/her past behaviors. In our method, we structured the network as shown in Figure 7.

This network predicts the destination by using a table that stores the number of visits for every driving context. An example is shown in Table 3, and Table 4 shows the granularity of each context. We supposed that the context can be recognized automatically and confirmed that most contexts can be recognized using by a set of sensors .

3.4 Prediction destination by using Hybrid method

We proposed several destination prediction methods in previous sections. However, they have both merits and demerits in different situations. Therefore, we propose the use of *Hybrid Method* (HM) that changes prediction method dynamically with the type of road driven on. There are several methods finding what road is being used. One of them is by using a map database. Though it is simple, the road is different on every drive and the prediction method may not work well. Thus, we consider that the road type can be classified by the characteristics of the changes in probability for each prediction method. We used the changes of the prediction result gained from the AM and the DM since the CM result is almost constant.

The type of road classified by the change of probability and how often they are used to get to a given destination are shown in Table 5. The probability changes are different for each destination. Therefore, even the same road can be classified as a different type.

3.4.1 Detecting the type of road

First, we used the data from the previous sections to investigate how frequent the change in probability occurs. The result is shown in Table 6. Even for the correct destination, the correctly predicted rate when the prediction probability in both methods increases is only 61.9%. Therefore, it does not necessarily mean that it a predicted destination is the correct one when the probability of both methods increases. On the other hand, when both probabilities decrease, the rate that the destination is correct is 1.2%. Thus, when the probabilities of both methods decrease for a destination, it is not the correct one and the present road is not used to go to that place. The case where the results from the two methods are different rarely occurred; the rate is approximately 4%. From the table, the probability increasing in the DM for the correct destination happens more frequently than that in the AM does in such a situation. Therefore, when the result of both methods is different, the DM predicts the destination more accurately than the AM does.

These results suggest that when both probabilities increase, the prediction method needs to keep the probability. This suggests that the predicted destination is likely to be the correct destination. On the other hand, when both probabilities decrease, the prediction method needs to decline the destination since the probability that it is the

Table 5: Type of the road according to the change of probability

Type of road	AM	DM	Meaning of the road
i	Increase	Increase	often used for the destination
ii	Increase	Decrease	often used from other departures for the destination
iii	Decrease	Incresase	often used for the destination though often used for other places
iv	Decrease	Decrease	rare used for the destination

Table 6: Number of probability changes

Type	All destinations (Occurrence rate)	Correct destination (Correctly predict rate)
i	239 times (12.6%)	148 times (61.9%)
ii	38 times (2.0%)	11 times (28.9%)
iii	33 times (1.7%)	19 times (57.6%)
iv	1586 times (83.6%)	19 times (1.2%)

correct one decreases. When the change in both probabilities is different, the implications for the prediction method are not yet clear. We now discuss the road types as well as the implications of our experiments for which method is better for prediction.

3.4.2 Conducting the hybrid method

Using HM changes the prediction methods dynamically with the road types. Using the same data as those in the pilot study, we applied the prediction methods (AM, DM, and CM) to the each road type. We tried all combinations between the types of road and the methods and found the best combination of the prediction methods. We evaluated them by the ratio that the prediction results include the correct destination in the Top-1 or Top-4 in all the distances driven. The reason is that our navigation system presents some pieces of information about the topside of the prediction results. What is important is not that the correct destination joins the Top-1, but it can be in the top group.

The results are shown in Figure 8 - 11. In the evaluation, we tried all combinations of prediction method and calculated the probabilities. Each figure shows that the average ratio of the driving distance focused on one type of the road. The correct destination is Top-1 or Top-4 when the probabilities of the both methods are increasing, i.e., type (i), is shown in Figure 8. In the same way, Figure 9 shows the results of type (ii), in which the probability of AM increases and the probability of DM decreases. The results of type (iii), in which the AM decreases and the DM increases are shown in Figure 10. The results of type (iv), in which the results of the both methods decrease are shown in Figure 11. From the results, all the prediction methods except CM predict the correct destination move accurately in the type (i) and (iv). In type (ii), there is not much difference of each method. In type (iii), the DM is better adapted to predict for Top-1 and the AM is better for Top-4. Moreover, the DM is the best in type (i), AM is the best in type (iv), and in type (ii) the CM is the best for Top-4 and AM is the best for Top-1 though these results do not show significant

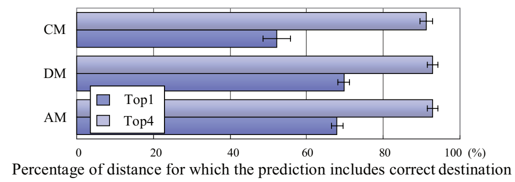

Figure 8: Pprediction results in type (i)

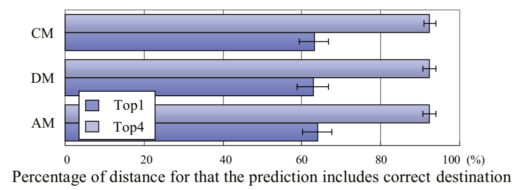

Figure 9: Prediction results in type (ii)

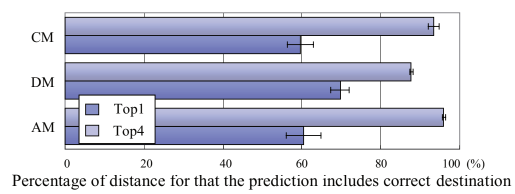

Figure 10: Prediction result in type (iii)

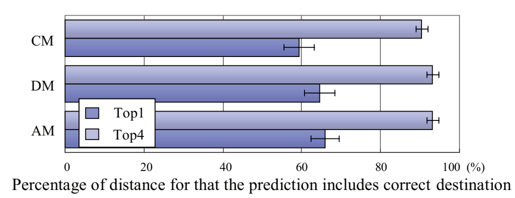

Figure 11: Prediction result in type (iv)

differences.

From these results, we propose the use of HM classified by the Table 7 for Top-4 prediction. Additionally, since predicting the Top-1 group is also important in areas such as using voice guides, we propose the use of HM with the classification shown in Figure 8 for the Top1 prediction.

3.4.3 Evaluation

We have implemented HM on the prototype system. We evaluated the method using half of the data for training and the other data for evaluation. The data is the trajectory for a 4-month period of a single person driving by a person. In other words, we evaluated the effectiveness of our proposed method in the case where the user has used our system for

Table 7: Hybrid method for Top-4 prediction

Type	AM	DM	Prediction method
i	Increase	Increase	DM
ii	Increase	Decrease	CM
iii	Decrease	Decrease	AM
iv	Decrease	Decrease	AM

Table 8: Hybrid method for Top-1 prediction

Type	AM	DM	Prediction method
i	Increase	Increase	DM
ii	Increase	Decrease	AM
iii	Decrease	Increase	DM
iv	Decrease	Decrease	AM

a training term of two months.

The results are shown in Figure 12. It shows how long the information related to the correct destination is presented. We found that both of our methods can predict the correct destination with a rate of accuracy approximately 20% higher than other methods in Top-1 and 10% higher than those used in Top-4.

The reasons why the DM is worse than BM may be that 2 months is not enough collect all the training data needed to to predict the correct destination.

4. RELATED WORK

There are several pieces of research on destination prediction based on driving trajectory. For example, one method is to divide a map into grids by latitude and longitude and transform the driving route to the grids [1]. The current passed grids are compared with the previous passed grid and the concordance is measured. It also supposes that the current position is important and gives a large weight to the current grid like the BM does. Since this method is similar to the BM, it has also the problems when the driver chooses driving alternative and arterial routes.

One method is to use the difficulty of estimating the arrival place as a cross-point as a node of the network and show the difficulty of predicting the destination by using node transitions [5]. Thus, it predicts the destination and it also defines the entropy as the characteristic of difficulty that was calculated by driving times. Using the entropy, we can know the degree of certainty of the prediction.

There is work on a method that is used to learn and infer the user's daily movements using a hierarchical Markov model [2]. This model uses the GPS data logs to accurately predict the goals of a person and recognizes the situations in which the user performs unknown activities. However, their experiments are executed in a specific situation in which the user's movement is only between 5 points. Neither method can adapt to more complex situations such as driving alternative and arterial ways.

There are also many studies that predict user behaviors using his/her locations. One of them describes a way to predict the change of transportation mode using Bayesian networks [3]. Their network is complex and constructed on the basis of general knowledge. If we structure our CM, in this way, the predictive accuracy may not be much higher

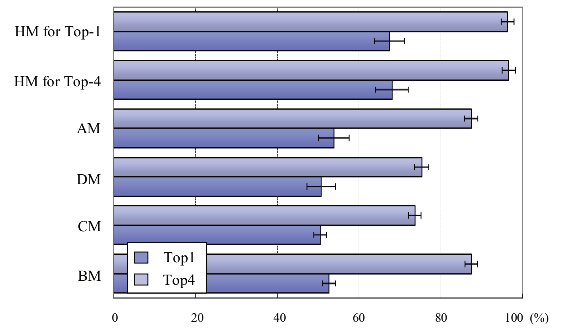

Figure 12: Performance of proposed method

in the early stages.

5. CONCLUSION

We have proposed the use of a new destination prediction method that factors in the driving trajectory and common contexts of daily driving that would be useful to include in a car navigation system. We evaluated the proposed method on the basis of a prototype system. We clarified the situations in which our proposed method works well, and we propose integrating these proposed methods in different ways on the basis of the changes in the situation.

Our future work is to bring out the relation between the amount of training and suitable prediction methods, and we will carry out experiments with more users to evaluate the proposed method.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] M. Kobayashi et al. The arrival place presumption mechanism applied to an information filtering system for in-vehicle navigation systems. *Transactions of Information Processing Society of Japan*, 45(12):2688–2695, 2004.

[2] L. Liao et al. Learning and inferring transportation routines. *Artif. Intell.*, 171(5-6):311–331, 2007.

[3] D. J. Patterson et al. Inferring high-level behavior from low- level sensors. In *Proc. of The Fifth International Conference on Ubiquitous Computing (UbiComp2003)*, pages 73–89, 2003.

[4] T. Terada et al. Design of a car navigation system that predicts user destination. In *Proc. of Int'l Workshop on Tools and Applications for Mobile Contents (TAMC)*, pages 54–49, 2006.

[5] M. Yoshioka and J. Ozawa. Destination entropy for arrival place presumption from car driving route history. *Transactions of Information Processing Society of Japan*, 46(12):2973–2982, 2005.