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Design of a Car Navigation System that Predicts User Destination

Tsutomu Terada, Masakazu Miyamae, Yasue Kishino, Kohei Tanaka, and Shojiro Nishio
Graduate School of Information Science and Technology
Osaka University
{tsutomu, miyamae, yasue, tanaka.kohei, nishio}@ist.osaka-u.ac.jp

Takashi Nakagawa and Yoshihisa Yamaguchi
Advanced Technology R&D Center
Mitsubishi Electric Corporation
{Nakagawa.Takashi@dy, Yamaguchi.Yoshihisa@dp}.MitsubishiElectric.co.jp

Abstract

Because of advances in information technologies, car navigation systems *have come into widespread use as useful tools to guide drivers where they want to go. Conventional car navigation systems present the most suitable route according to a destination input into the system. However, since the required operation to input the destination costs so much, users do not usually use car navigation systems for daily driving. In this paper, to exploit the effective functions of car navigation systems, we propose a new system that automatically predicts user purpose and destination. The proposed car navigation system presents various information based on predicted purpose without interaction from users.*

1. Introduction

With advances in computer miniaturization and information technologies, *car navigation systems* have come into widespread use as useful tools that support drivers by navigating them where they want to go. Since much work has concentrated on car navigation systems such as the implementation of car navigation systems [1], tracking GPS signals at lower signal strength [3], and map-matching techniques [2, 4], existing systems achieve enough car positioning and routing accuracy for navigation. These conventional car navigation systems are approaching the saturation of navigation functions in response to destinations input into the system. On the other hand, users do not usually input them into the system for the following reasons:

- In daily life, since users usually drive along familiar routes, they do not need routing information to get to destination.
- The operations for inputting destinations into the system cost too much. Users do not want to input the characters to specify a destination, except when they cannot reach it without navigation assistance.

This means that we as drivers do not exploit the full effectiveness of car navigation systems in daily life. We require a convenient car navigation system without stressful work in *non-navigating situations*.

In response to this requirement, we propose a new car navigation system that automatically presents location-aware information by predicting driver purpose and destination. It predicts destination based on a probabilistic model of driving trajectory. Moreover, our prototype system employs real images and several animation animals to show information for effective information presentation and easy information recognizing.

The remainder of this paper is organized as follows. Section 2 outlines our navigation system and presents several scenarios for its use. Section 3 explains the destination prediction mechanism, and Section 4 presents the implementation of a prototype. Section 5 sets forth the conclusion and planned future work.

2. System Design

2.1. Service Senario

We assume that our car navigation system will provide the following services without specific input from users:

- automatically predicts that the user destination is a shopping mall and presents information of another parking lot because the route to the primary parking lot is now congested with traffic.

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- automatically recognizes that the driver is taking friend to the station and presents a train schedule with an estimated arrival time.
- detects the possibility of running out of gas, alerts the driver, and shows information about gas stations along the route.
- recognizes that the user destination is a restaurant and recommends several options.

2.2. System Structure

To achieve these service scenarios, a car navigation system must predict user purpose and destination from the driving trajectory and timely show appropriate information. Figure 1 shows the system structure of our proposed system that has these functions to achieve the service senarios described in Section 2.1. In the figure, *Trajectory DB* records the driving trajectory, to be concrete, data from sensors such as GPS, speedometer, fuel gauge, and in-vehicle camera. *Destination Prediction Part* processes driving trajectory using a probabilistic model to predict user destination. The detailed algorithm is described in Section 3. Prediction results are also stored in *Trajectory DB* to be used in *Purpose Prediction Part*, which recognizes user purpose from sensor data and predicted destinations. Currently, this part predicts user purpose only from predicted destinations. For example, if the system predicts that the user destination is a train station, it recognizes that he/she goes there to pick someone up or send someone off. To construct a sophisticated algorithm is our planned future work. *Information Retrieval Part* retrieves suitable information from the *Navigation Information DB*, which includes various data for supporting the driver, such as route information, traffic jam information, road construction information, parking information, restaurant information, and sightseeing information. This database is frequently updated via internet or other wireless communication methods to get real-time information. *Information Retrieval Part* chooses optimum information based on predicted destination and purpose. For example, if the system predicts that the destination is a train station to send someone off, it presents a train schedule with an estimated arrival time. *Information Display Part* presents retrieved information at a suitable area on the display considering ease of seeing. Currently, the system simply allocates objects to the specific area of the display. We plan to construct a dynamic layout method considering background information and sensor data. The detailed algorithm for object layout will be addressed in the future.

The prototype image of our car navigation system is shown in Figure 2. The navigation window consists of *Map Images Area* and *Real Images Area*. The former displays map images as conventional car navigation systems. The latter is the area specialized to our system. It displays real images for users to grasp information associated with actual buildings and roads, and several characters show various information based on the results of destination predictions.

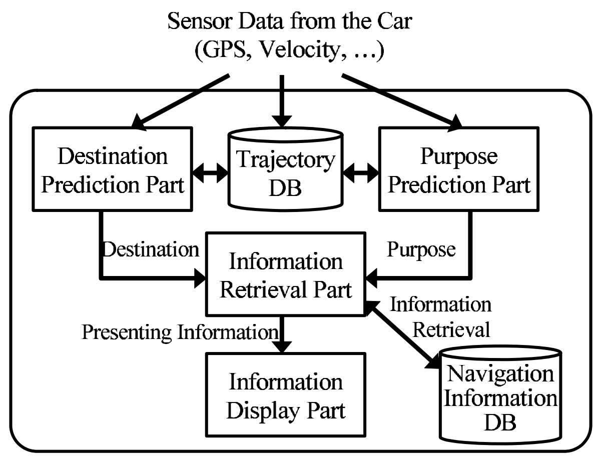

Figure 1. System structure.

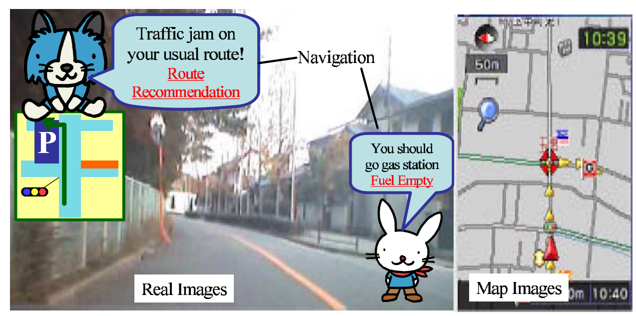

Figure 2. Prototype image.

3. Destination Prediction

The destination prediction algorithm is the most important part of our proposed car navigation system. In this section, we propose a road-link based probabilistic-model to predict user destination.

3.1. Probabilistic Model

Car navigation systems usually manage routes as a set of directed linked graphs, and our system also employs this data model. The system records the transition history of road links, and each road link also stores the frequency of going to each destination by the link. Then, the system cal-

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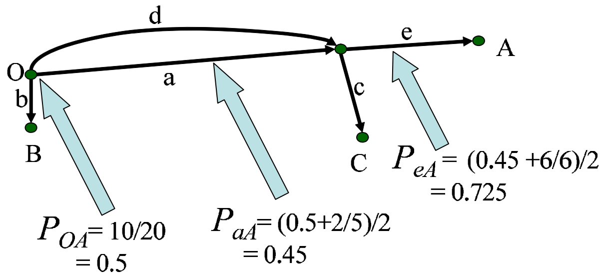

Route record

Route	Count
$O \rightarrow b \rightarrow B$	6
$O \rightarrow a \rightarrow c \rightarrow C$	3
$O \rightarrow a \rightarrow e \rightarrow A$	2
$O \rightarrow d \rightarrow c \rightarrow C$	5
$O \rightarrow d \rightarrow e \rightarrow A$	4

Value of $N_{l_i d}$

$d \setminus l_i$	O	a	b	c	d	e
A	10	2	0	0	4	6
B	6	0	6	0	0	0
C	4	3	0	8	5	0

Figure 3. Prediction example.

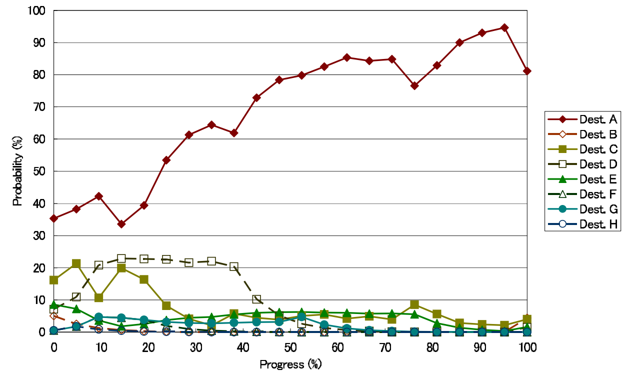

Figure 4. Progress vs. probability for each destination.

culates the concordance rate for each destination by comparing the current driving trajectory with past routes.

Specifically, suppose $\mathbf{L} = (l_0, l_1, l_2, ..., l_i)$ represents the current transition history of road links, and the user is now on link l_i. In this situation, probability $P_{l_i d}$ that he/she at link l_i goes to destination d is expressed as the following formula (1):

$$P_{l_i d} = (1 - \alpha)\frac{N_{l_i d}}{N_{l_i}} + \alpha P_{l_{i-1} d} \qquad (1)$$

Here, N_{l_i} denotes the frequency of the visiting road link l_i in the past. $N_{l_i d}$ also means the frequency of going to destination d by l_i. α is a coefficient to control the weight of considering past routes for calculating $P_{l_i d}$.

We show an example of calculating $P_{l_i d}$. As shown in Figure 3, there are three destinations A, B, and C, and five road links a, b, c, d, and e. We suppose that the car has driven according to the table in the middle of the figure, and the system stored $N_{l_i d}$ shown as the table in the bottom of the figure. In this situation, when the car starts from O, the system predicts that the destination is A because $P_{OA}(= 0.5)$ is higher than $P_{OB}(= 0.3)$ and $P_{OC}(= 0.2)$. Then, when the car is on a migrating from O, it also predicts that his/her destination is A because P_{aA}, P_{aB}, and P_{aC} are 0.45, 0.15, and 0.4 respectively. Correspondingly, P_{eA}, P_{eB}, and P_{eC} are 0.725, 0.075, and 0.2, respectively, when the car reaches e. In this way, the system predicts the possibility of visiting destinations using trajectory data. In this example, we use 0.5 as the value of α. This method is simple but effective. We show the accuracy of the proposed algorithm in the next section.

3.2. Accuracy

To show the effectiveness of the proposed algorithm, we evaluate the accuracy of destination prediction. In this evaluation, we use trajectory data accumulated from a one year GPS log of one of the authors. Figure 4 shows the probability for each destination in progressing of the trip to destination A. Note that the user frequently goes there and drives along usual routes to it. In this situation, our method can consistently predict the right destination. Moreover, the probability of the correct destination increases along with the progress of the trip, while others continuously decrease.

For comparison, we also evaluated a prediction method based on *Bayesian Network*, which is widely used to predict phenomenon from statistics of happened events. We construct the network by simply linking each road link to all destinations. The result of the same evaluation is shown in Figure 5. In this figure, although the correct destination gets the highest probability at the final stage of the trip, another incorrect destination reaches almost 100% probability in the middle stage. Moreover, from the start to the middle stage, the probability of a correct destination is too low to provide services according to predicted destinations.

Next, we evaluate the characteristics of our algorithm by testing it in several situations. For evaluation, we chose four situations: (1) and (2) are cases where the user goes to familiar places along usual routes (case (1) is used in the first

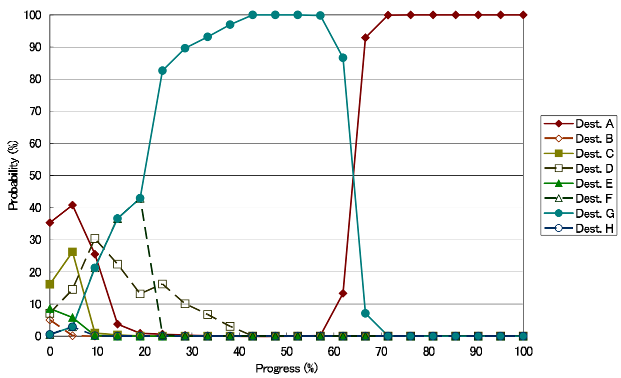

Figure 5. Progress vs. probability for each destination (Bays).

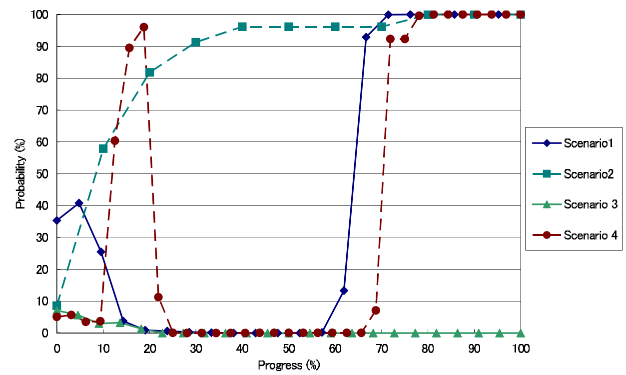

Figure 7. Probability in different scenarios (Bays).

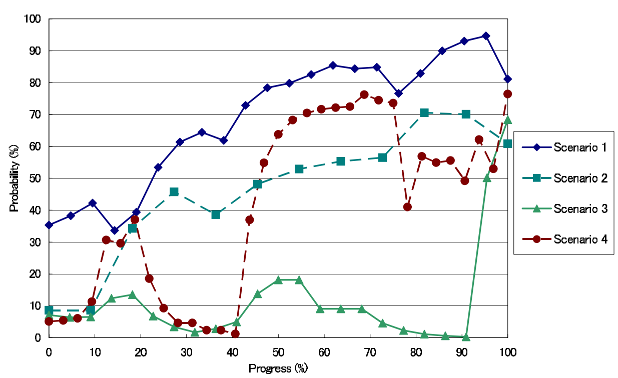

Figure 6. Probability in different scenarios.

Figure 8. Screenshots of prototype (1).

evaluation), and (3) and (4) are cases where the user visits its familiar places along routes that include unusual paths. The evaluation results are shown in Figures 6 and 7.

Using our algorithm, situations (1) and (2) shown in Figure 6 achieve sufficient accuracy without erratic behavior. In situations (3) and (4), especially (4), the probability of a correct destination is low. However, the probability rises at a certain place that may be on a usual path to the destination. On the other hand, using Bayesian Network as shown in Figure 7, since the impact of unusual paths is so large, the probability changes drastically. Especially, in situation (4), the probability decreases from 95% to 10% and increases from 8% to 92% immediately. Moreover, the probability remains around 0% in situation (3).

When driving in daily life, users sometimes stray from their usual route to a destination. Therefore, our approach works better than a Bayesian Networking approach to show destination-aware information.

4. Implementation

We implemented a prototype car navigation system with *Microsoft Visual C++.NET Enterprise Architect* on a *IBM ThinkPad X31 (PentiumM 1.7GHz, 2GByte memory)*. As navigation system hardware, we employ a *Sony VAIO type U VGN-U71P (PentiumM 1.1GHz, 512MByte memory)* with a GPS unit *RIGHT STUFF GPS-USB-RA*. We store a total of approximately 670 hours of driving trajectory data from three people. In the prototype, we prepared several data for realizing the applications described in Section 2 and confirmed the effectiveness of predicting user destination.

Figures 8-10 are screenshots of the prototype system.

Figure 9. Screenshots of prototype (2).

Figure 10. Screenshots of prototype (3).

Figure 8 shows the usual situation of the prototype, where some cartoon animals make their predictions and offer information according to the predicted destination. If the system detects a traffic jam on route to the predicted destination, it automatically calculates another route and shows it graphically, as shown in Figure 9. The detection of traffic jams and the calculation of alternative routes are already implemented in conventional car navigation systems. When the system detects the possibility of running out of gas, it shows an alert message and recommends the nearest gas station on the way to the predicted destination, as shown in Figure 10. Fuel information is acquired from the sensor attached to the car for the navigation system.

We attached various sensors to get more detailed information from the car and to provide more useful applications, such as speed, direction, blinkers, and shifting information, as shown in Figure 11. The system can use such information not only for providing useful applications but also for improving prediction accuracy. We plan to improve accuracy by exploiting sensor information.

Figure 11. Hand wiring for sensors.

5. Conclusion

In this paper, we proposed a car navigation system that predicts user destination and provides various services based on predicted destination. Using our system, the user can acquire various services without high-cost operations such as inputting characters. On the other hand, many problems remain that must be resolved for our system to reach the stage of actual use. Future work to address these problems includes the following:

- **Improved prediction method:** even though the proposed algorithm that predicts user destination is quite simple, it can be improved further. We plan to enhance the method by using other sensor data and metadata such as time and weather. Moreover, currently we are addressing a two-layered destination prediction algo-

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rithm that can achieve higher accuracy by integrating a road-link based approach and wide-area movement analysis.

- **Purpose prediction:** even if the system can predict user destination, it is difficult to show effective contents according to user purpose. For example, when the system recognizes that the destination is a train station, it should present a train schedule when the user wants to take a train. However, if the user wants to go shopping near the train station, the system should present shopping or parking information around the shopping area. We plan to construct a mechanism to predict user purpose by calculating several sensor data such as a load sensor on the passenger seat.
- **Information layout method:** in our system, the number of displaying data increases because it displays several predicted data concurrently for covering information less than the second best. Therefore, the system should filter/allocate such information for users to view without much distraction. We plan to construct an object layout method that considers the background image of the system and a filtering method that considers user mental strain.
- **User evaluation:** we have to evaluate the effectiveness of our system qualitatively with accuracy and subjectively with its actual use.

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