Human Activity Recognition | Location Information | Behavioral Model

Technology Reports

Human Activity Recognition for Personalized Services

Many mobile terminals have come to be equipped with a GPS function and many services based on location information have come to be provided. To provide mobile terminals that can support the user in all kinds of real-life situations, a system has been developed for estimating user behavior with high accuracy. This system identifies the area in which the user is currently located based on GPS locations and uses behavioral transition patterns defined beforehand for different user attributes. Services that apply human activity recognition are being provided by "My DOCOMO Labs."

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1. Introduction

Recent years have seen an increasing number of mobile terminals equipped with a GPS function and the provision of services that make use of the user's current circumstances estimated from GPS locations. To support the user in all kinds of real-life situations, there is a need for more advanced services that use a more detailed timeline of information achieved, for example, by creating a history of location information.

To meet this need, we have developed human activity recognition for automatically estimating user behavior using information obtained from the mobile terminal.

In this article, we describe a system for estimating user behavior with high accuracy by identifying the area that the user is currently located in from GPS locations and using behavioral transition patterns defined beforehand for different user attributes such as company employee, student, housewife, etc. We also introduce a system for collecting user location information over the long term and estimating everyday and unconventional user-behavior areas, and describe the application of these systems to services provided by "My DOCOMO Labs" [1][2].

2. Development of Human Activity Recognition

The concept of services based on behavior estimation is shown in **Figure 1**. With human activity recognition, advanced services can be created in accordance with the user's current circumstances and behavioral patterns. For example, we can envision a "personal ads service" that provides a user who is heading home after work with information on the neighborhoods of train stations he is approaching but that delivers no information while the user is at work, or a "kid tracking service" that sends an e-mail to the child's family

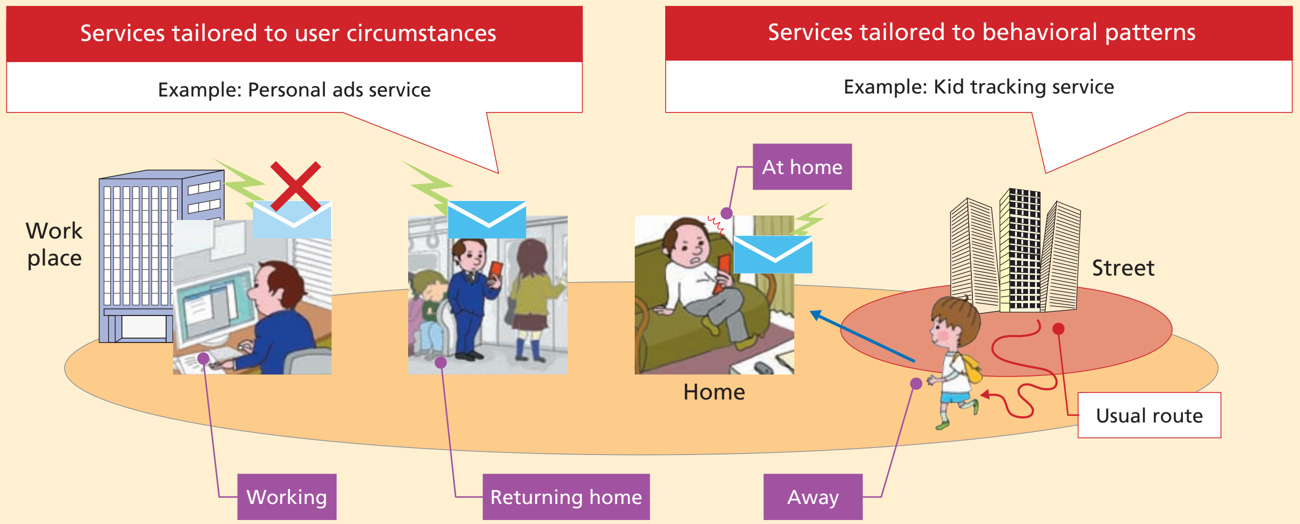


Figure 1 Concept of services based on behavior estimation

only when the child is behaving out of the ordinary compared to everyday behavioral patterns.

2.1 Overview of Human Activity Recognition

The human-activity-recognition technology that we have developed estimates behavior using various types of data. These include data obtained from the mobile terminal such as location information and operation logs, data registered by the user (user-created data) such as area names like "home" and "workplace," the locations of those areas, and time slots for everyday activities like waking up, going to bed, and working, and a previously prepared behavior transition table (behavioral model) that models the transitions that take place in user behavior. Behavior targeted for estimation is classified according to the duration of collecting location information used for estimation and the level of abstraction of the behavior to be estimated (**Figure 2**). Location information, in turn, is classified into the following three types:

- Simple data (Simple GPS location: one set of latitude and longitude)
- Serial data (A sequence of GPS locations: multiple sets of latitude and longitude corresponding to behavior with beginning and ending locations)
- Collected data (Collected GPS locations: multiple sets of latitude and longitude collected over the long term)

Information other than location information used for estimating behavior includes area data registered for locations such as home and workplace and user-created data obtained by user input such as terminal operation logs, time slots for everyday activities, and information on weekdays and holidays.

Behavior to be estimated is classified into "behavioral element," "behavior," and "lifestyle" for each of the three types of location information. Here, the system estimates "behavioral element" from location information and area data. For example, on comparing the location information obtained from GPS with the latitude and longitude of the user's home as set beforehand by the user and stored in a database, the system would estimate the current area as being "home." Next, the system estimates "behavior" from behavioral elements, operation logs and user-created data obtained from the mobile terminal, and a behavioral model using immediately preceding behavior. For example, using the behavioral element of "workplace," user-created data on working hours, the current time, and the immediately preceding behavior of "work-

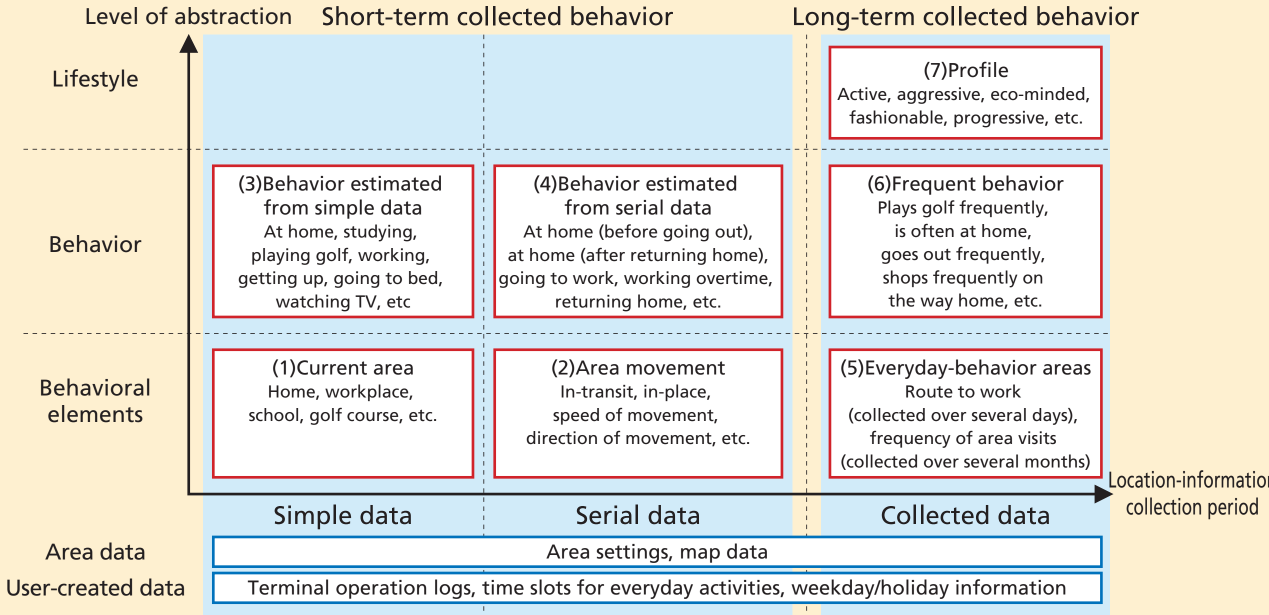


Figure 2 Classification of behavior targeted for estimation

ing," the system would estimate a transition in behavior from "working" to "working overtime" at the same location. Finally, the system estimates lifestyle from behavioral elements, behavior, and the results of collecting user-created data over the long term. For example, a user that has visited many new places on holidays would be estimated as having an "aggressive" lifestyle. Behavior can be classified into short-term collected behavior or long-term collected behavior depending on the period used for collecting location information.

2.2 Technique for Estimating Short-term Collected Behavior

The following technique is used for estimating short-term collected behavior.

1) Estimating Current Area (Fig. 2 (1))

The current area is a behavioral element estimated from simple data and is essentially the place where the user is currently located. Areas that will be used as targets of comparison for establishing the current area are called "significant areas," which are specified by users with names like "home" and "workplace." As user-created data, significant areas are registered in a database beforehand. In determining the current area, current location information is expressed as a circle whose center is GPS latitude and longitude and radius is positioning error. If current location information happens to spatially overlap a significant area, the system considers the user to be present in the significant area, and if there is no overlap, the system considers the user to be outside the significant area.

2) Determining Area Movement (Fig. 2 (2))

Area movement consists of behavioral elements estimated from serial data. Here, the system determines the user state to be either in-place or in-transit, and if in-transit, the route taken, the speed of movement, direction of movement, etc.

To decide between in-place and in-transit, the system treats location information p_i as a reference point, obtains n points of past location information $\{p_{i-n}, p_{i-n+1},\ldots, p_{i-1}\}$, and checks to see whether all location information $\{p_{i-n},\ldots, p_{i-1}\}$ overlaps with p_i. If all n

points do, the system considers the user to be in-place, and if they do not, the system considers the user to be in-transit.

3) Behavior Estimated from Simple Data and Behavior Estimated from Serial Data (Fig. 2 (3)(4))

Behavior can be determined on the basis of a behavioral model that models transitions in behavior using, as input, current area estimation, area movement estimation, time slots for everyday activities, and immediately previous behavior as determined by the system. Simple data can be used to estimate behavior taking place at one location, such as working (at one's workplace) and golfing (at a golf course), while serial data can be used to estimate behavior that is accompanied by movement through multiple locations (from an initial location to a final location) as in "commuting to work" and "returning home."

However, a person's behavior cannot generally be determined in terms of only one type of behavior. Rather, it can be defined in terms of multiple types of behavior such as "at home" and "eating," "away" and "shopping," etc. Here, to simplify the reuse and extension of defined behavior and systematize the expression of composite behavior, we classify behavior derived from simple data and serial data into three hierarchical levels (**Figure 3**). In this hierarchical setup, behavior corresponding to a node on one level may possibly occur in parallel under the behavior of a parent node on the next upper level. Defining behavior in such a hierarchical manner makes it possible to add new types of behavior for estimation by altering only part of the tree structure. This makes for greater generality and reusability. At the same time, the meaning of locations may differ depending on the user's living patterns or attributes. For example, "commuting to work" in the case of a company employee would be "commuting to school" for a student. In short, the content of a tree structure can vary according to lifestyle and must therefore be defined for each lifestyle.

2.3 Evaluation Experiment on Short-term Collected Behavior

To examine the performance of the proposed system for estimating short-term collected behavior, we used mobile terminals equipped with a GPS function and evaluated current-area determination, in-place/in-transit determination, behavior estimated from simple data, and behavior estimated from serial data. In the experiment, two subjects were used to collect data over a total of 14 days. The location measurement interval was 5 minutes for current-area determination and in-place/in-transit determination and 10 minutes for behavior estimated from simple data

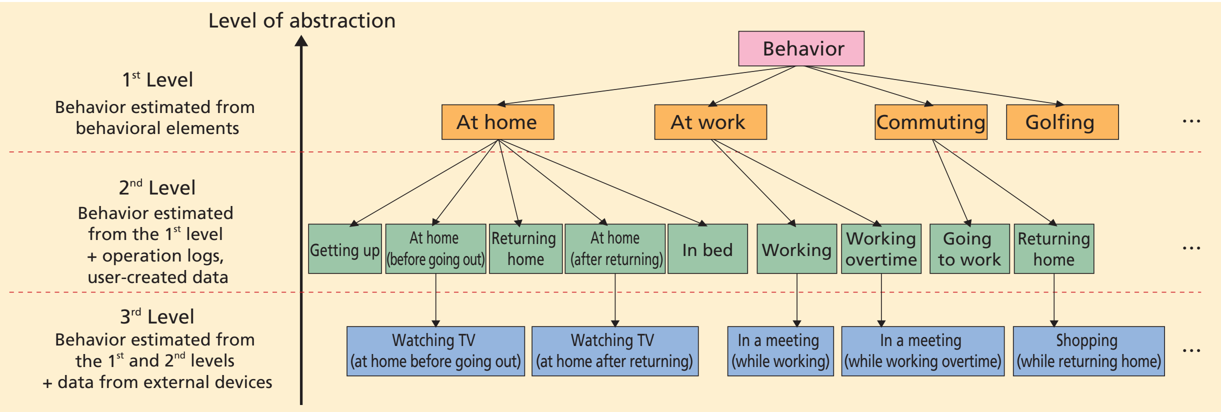


Figure 3 Example of hierarchical behavior

and behavior estimated from serial data. The parameter *n* in in-place/in-transit (area-movement) determination was set to 2.

Data recording actual behavior of subjects were compared with the results of determining behavior using human activity recognition. The accuracy rate of the latter was then computed as shown in **Table 1**.

In current-area determination, an accuracy of 97% or greater was obtained in estimating whether a subject was at home or at work. In in-place/in-transit determination, in which the targets of estimation were commuting or in-place at home or work, an accuracy of 97% was obtained in estimating in-place location, but in estimating in-transit, an accuracy of only 70% was obtained. This is because the system considers the user to still be in-transit for up to two location-information measurements after arriving at home or work with parameter *n* set to 2.

The results of determining behavior estimated from simple data and behavior estimated from serial data revealed an accuracy of no more than 70% in estimating "going to work" and "returning home" behavior. The reason for this relatively low score is the same as that given above for estimating in-transit.

These issues can be solved by shortening the location measurement interval, but as this would increase battery consumption in the mobile terminal, it would be necessary to control this interval dynamically according to the type of behavior being estimated (for example, the measurement interval could be lengthened during the nighttime when the user is at home and shortened during the daytime when the user is apt to be moving).

2.4 Human Activity Recognition based on Long-term GPS Locations

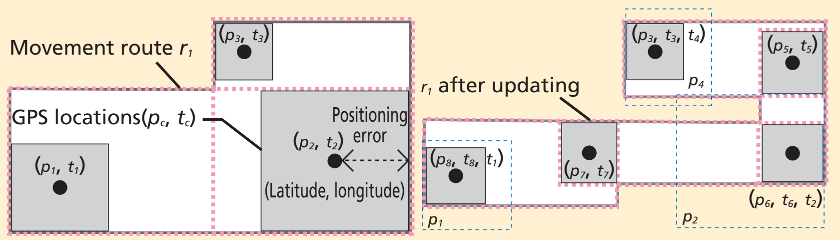
Estimation targets for long-term behavior are everyday-behavior areas, frequent behavior, and profile. Since the latter two targets are in the process of being evaluated, the following focuses on explaining the system for estimating everyday-behavior areas.

1) Estimating Everyday-behavior Areas (Fig. 2 (5))

Everyday-behavior areas are behavioral elements estimated from collected data. They represent locations that are frequently visited by the user based on commuting route, area-visit frequency, etc. Here, we denote GPS locations in terms of position p_c and positioning time t_c. Position p_c constitutes a square whose center is the latitude and longitude and whose side is equal to twice the positioning error (**Figure 4**). The movement route is expressed in terms of Minimum Bounding Rectangles (MBRs), where each MBR contains two adjacent positions, that is, two squares, and a sequence of MBRs follows the location information obtained during movement in positioning-time order. This scheme can reduce the com-

Table 1 Results of evaluating short-term collected behavior

Item	Target	Accuracy
Current-area determination	Home	97%
	Workplace	98%
Area-movement determination	In-place	97%
	In-transit	70%
Behavior estimated from simple data, behavior estimated from serial data	At home	73%
	Going to work	75%
	Working	97%
	Returning home	75%
	In bed	91%
	Away	84%



(a) Results of estimating movement route r_1 by (p_1, t_1), (p_2, t_2), and (p_3, t_3)

(b) Results of updating movement route r_1 by (p_c, t_c), c = 4 – 8

Figure 4 System for estimating movement route

putational complexity of estimating the movement route. An example of movement route r_1 estimated from GPS locations (p_1, t_1), (p_2, t_2), and (p_3, t_3) is shown in Fig. 4(a).

To make a more accurate estimation of a movement route with this technique, the system determines whether a movement route taken by the user in the past is being used again and updates that route using the newly acquired GPS locations. To decide whether the user is retaking a past movement route, the system checks to see whether movement route r_c generated by newly obtained GPS locations coincides even partially with past movement route r_p. Specifically, if the location information configuring either movement route r_c or movement route r_p does not even partially coincide with the other movement route for a certain number of consecutive positions, that movement route is judged to be a new one. Otherwise, r_c and route r_p are judged to be the same movement route and the location information for r_c is used to update r_p.

In updating a movement route, either the route is corrected by replacing location information (p_p, t_p) of r_p with location information (p_c, t_c) of r_c or the route is supplemented by adding (p_c, t_c) to r_p. That is, if two positions p_p and p_c coincide with each other even partially and positioning error p_c is smaller than p_p, p_p is replaced by p_c. At this time, an association is made and recorded between positioning time t_p (of p_p) and t_c and p_c so that the movement route can be corrected while storing user time points in passing along this route. The results of updating movement route r_1 of Fig. 4(a) with location information p_4, p_5, p_6, p_7 and p_8 when the user retakes that route is shown in Fig. 4(b). Here, a complete overlap occurs between positions p_4, p_6 and p_8 and p_3, p_2 and p_1, respectively, and as a result, p_4, p_2 and p_1 as the larger positioning errors are deleted and their positioning times t_4, t_2 and t_1 are attached to positions p_3, p_6 and p_8. This eliminates location information with large positioning errors thereby enabling the movement route to be corrected.

If, on the other hand, position p_c does not spatially overlap the location information of r_p at all, the system will add p_c to r_p. In doing so, however, the problem arises as to where to add p_c in the r_p location information sequence. The simplest method would be to find the nearest point to p_c in the r_p location information sequence and then add p_c either before or after that point. This approach, however, would not support curved routes of movement. For example, the nearest point to p_7 in Fig. 4(b) is p_3, and by the above method, p_7 would be added between p_3 and p_5 resulting in an erroneous movement route.

Since r_c and r_p are the same movement route, we can consider that the movement route before and after updating does not, in general, undergo much change. Accordingly, this movement route estimation technique adds p_c so as to minimize the change in the length of the movement route when making an update. To this end, we first find the set of N nearest points to p_c denoted as $\{{}^c p_1, .., {}^c p_N\}$ from the r_p location information sequence. Then, denoting the distance between ${}^c p_n \in \{{}^c p_1, .., {}^c p_N\}$ and adjacent point p_a on the movement route as dis(${}^c p_n$, p_a), we find (${}^c p_n$, p_a) that minimizes equation (1) and add p_c between those two points.

$$\begin{aligned}&\text{dis-variation}(p_c, {}^c p_n, p_a)\\&= \text{dis}(p_c, {}^c p_n) + \text{dis}(p_c, p_a) - \text{dis}({}^c p_n, p_a)\end{aligned} \quad (1)$$

Taking point p_7 in Fig. 4(b) again as an example, we let N=2 so that the set of nearest points is $\{p_3, p_8\}$ and the problem becomes whether to add p_7 between p_3 and p_5 or between p_8 or p_6. In this case, p_7 is added between p_8 and p_6 since dis(p_8, p_6) minimizes dis-variation(p_7, p_8, p_6) (**Figure 5**). In this way, a movement route can be supplemented by adding newly obtained location information for that route.

2) Estimating Frequent Behavior (Fig. 2 (6))

Frequent behavior is behavior estimated from collected data, that is, behavior that the user frequently engages in such as playing golf, going shopping on the way home from work, etc. To estimate frequent behavior, the system collects behavior data obtained from behavior estimation in steps (3) and (4) of Fig. 2 and tabulates the frequency of each type of behavior. The system considers behavior (or a behavioral sequence extracted by pattern extraction technology) whose frequency of occurrence is above a certain threshold to be frequent behavior.

3) Estimating Profile (Fig. 2 (7))

Profile corresponds to the user's lifestyle estimated from collected data. It expresses characteristics of the user's behavior such as "active," "aggressive," etc. After defining characteristic behavior or behavioral elements suitable for a profile, the system estimates profile based on the results obtained in steps (5) and (6) of Fig. 2. For example, an active person is defined as someone who enjoys visiting a variety of places. The system determines whether a person is active based on the number of in-place areas tabulated for that person.

2.5 Evaluation Experiment on Long-term Collected Behavior

We performed an evaluation experiment using a GPS-equipped mobile terminal to examine the performance of the movement route estimation method described above as a technique for estimating everyday-behavior areas. In the experiment, we obtained GPS locations in five-minute intervals and travelled along the same route six times. The route estimated after one trip and that after six trips are shown in **Figure 6** [3]. The movement route estimated after one trip features location information with large positioning errors resulting in large MBRs. In contrast, the movement route estimated after six trips features more location information that enables location information with large positioning errors to be replaced by more accurate location information and smaller MBRs. It can therefore be seen that a more detailed movement route can be estimated if that route is frequently taken by the user. It can also be seen that a large MBR still exists despite taking the route six times. This portion of the route corresponds to a tunnel inside of which GPS positioning cannot be performed.

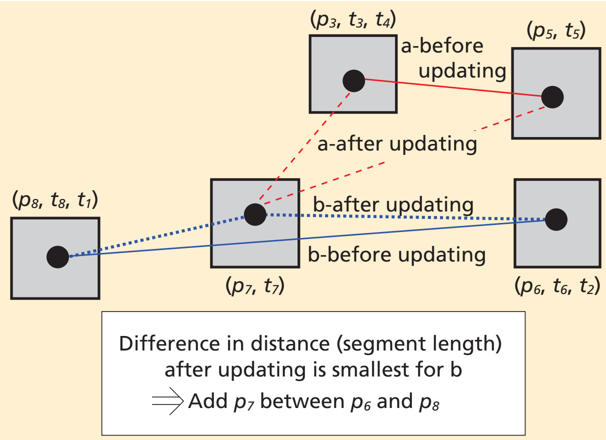


Figure 5 Method for determining position for adding p_7 to movement route r_1

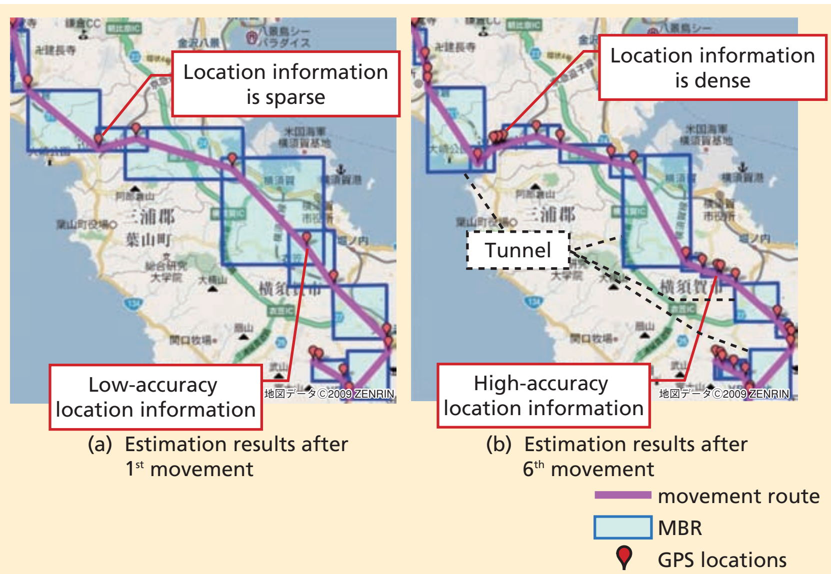


Figure 6 Movement-route estimation experiment

3. Development of Behavior Estimation Services

Various services have been developed using human activity recognition (**Figure 7**). These services, which are provided by My DOCOMO Labs, automatically estimate user behavior and behavioral patterns and aim to provide detailed and appropriate support for the user's lifestyle (Fig.7).

3.1 Spirit Boosting Agent

The Spirit Boosting Agent service (that goes by the name of Kokoropitan at NTT DOCOMO) provides the user with soothing words from Kokoropitan, an agent that personifies a mobile terminal, in relation to the user's current behavior. For example, the agent may sympathize with the user when working long overtime hours or offer some words of encouragement to motivate the user. The service is also equipped with a flexible dialog function that learns the user's everyday behavioral patterns and uses that data to support the user, such as by expressing concern or asking about the user's health when the user is getting little sleep or working extra hours.

3.2 Look and Connect Tool

The Look and Connect Tool displays the avatars[*1] and current state of family members or friends on the terminal's standby screen as well as the user's behavioral state determined by human activity recognition. It enables each member of the group to check on each other's condition on opening his or her terminal. Although instant messenger services are similar in nature, the content displayed by this service on the standby screen is automatically estimated by human activity recognition in the terminal. The Look and Connect Tool, which is implemented by a standby i-appli, estimates 15 types of behavior. Members of the group register beforehand by a mutual-authentication mechanism using e-mail addresses. This prevents strangers from discovering a user of this tool and registering with the group without permission. The service also provides a dedicated site for users to view their behavior history. A user can map personal behavior history onto a geographical map and inspect that history on a day-by-day basis with a calendar. The site supports viewing from either a mobile terminal or PC thereby promoting ongoing use of the service.

3.3 TPO UI

TPO UI is a service that aims to improve the operability of a user's terminal. It provides a user interface from which a variety of services can be quickly launched in accordance with time, place, and occasion (TPO). By applying user behavior and the user's operation logs as well as information related to the operation logs of other users deemed to have similar preferences to the target user, this service can flexibly switch the information and function/service shortcuts displayed on the terminal's screen according to the

(a) Spirit Boosting Agent (b) Look and Connect Tool (c) TPO UI

Figure 7 Screen shots of services using human activity recognition

*1 **Avatar**: A character figure representing oneself on a terminal screen.

user's current circumstances. For example, the information displayed when the user is at home and likely to use e-mail would differ from that displayed when the user is commuting to work and likely to be in need of news and train-transfer information.

4. Conclusion

This article outlined newly developed human activity recognition, described behavior estimation techniques and evaluation results, and introduced services that apply human activity recognition. We plan to conduct trials to evaluate these services and, with an eye to the future, to continue our research of more functional and more accurate behavior-related services through the learning of behavioral patterns from long-term behavior history, the analysis of user profiles, etc.

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