# Detection of User Mode Shift in Home

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**Abstract.** A ubiquitous environment enable us to enjoy various services "anytime" "anywhere". However, "everyone" is not realized. We research an intelligent space "everyone" can enjoy services. This paper proposes a method to detect user behavior to provide services according to user context in home. We focus on scenes user's mode significantly changes, such as going out and going to bed. People often have characteristic behavior in these scenes. Our method extracts this characteristic as a behavioral pattern and detects user behavior in these scenes by matching current user behavior online with it. The method characterizes each scene with kind of objects a user touched and the order of them. The method realizes early start of providing services by creating a behavioral pattern from user behavior logs in short duration. The experiment proves the high potency of our method and discusses its weakness at the same time.

**Keywords:** intelligent space, ubiquitous, context, behavior, RFID.

## 1 Introduction

A ubiquitous environment enables us to enjoy many kinds of services with information devices such as a cellular phone and information appliances. However, a user must actively access to the environment by operating such devices. It means there are actually a lots of users such as old people who can not enjoy services, because they are unfamiliar with information devices and are not able to use these devices. A variety of intelligent spaces are researched as an environment in which everyone can enjoy services. An intelligent space obtains user position information, user behavior information, information of environment around a user, and so on by a sensor network. The intelligent space can infer user context by using these information and provide services according to user context. Because the environment is active and a user can be passive in the intelligent space, everyone can enjoy services. Some of them provide services at home. The Aware Home[1] aims to provide services in a variety of scenes, such as support of finding objects a user lost and support of taking a medicine. Perkowitz et al. support user's cooking by utilizing recipes got from the internet[2]. Isoda et al. remind a user of the state that had been reached before an interruption of his work when he came back to his work after the interruption[3]. Aoki et al. support solitary old people by detecting their irregular state[4,5]. There are also lots of other researches which aim to infer user context for providing appropriate services[6,7,8,9] These respectively focus on different scenes in daily life.

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We focus on scenes in which user's mode significantly changes. In such scenes, an intelligent space can effectively provide services to a user. In daily life, user's mode significantly changes in scenes of going out, coming home, getting up, and going to bed. There are respectively different services to be provided and the timing to be done it on each scene. Our research aims to provide appropriate activity support services according to user intention by detecting user behavior in these scenes with a behavioral pattern extracted from history of objects a user touched in the intelligent space. For example, suppose a user behavior of going out is detected. At that time, a service to warn that a gas valve is open and to close it automatically can be provided. Also a service to notify a user that he does not have something important to go out can be provided. These services improve user amenity, and bring the user relief and safety by preventing danger in advance. These can be provided to a user effectively in user mode shift such as going out, going to bed, and so on. If a user is notified that he does not have his important item after he has gone out of his room, it requires extra time and energy to go back to his room for getting the item. Services should be proactively provided by detecting behavior of his going out before he has gone out. We aim to provide services proactively before user's mode has changed.

To detect user behavior, a behavioral pattern is created by extracting characteristics of behavior of individual user from past behavior logs which are collected as samples in advance per every scene to be detected. User behavior is detected by matching current user behavior log with a behavioral pattern of each scene. For example, a behavior of a user's preparing to go out is different from a behavior of other user's preparing to go out. For providing appropriate services, it is important to recognize user behavior fastly and precisely with a personalized behavioral pattern adapted to individual user. A user is frustrated with inappropriate services provided by mistaken recognition in an intelligent space. In addition, if it costs long time to collect sample behavior logs, services can not start being provided to a user at an early point. Considering practical use, a behavioral pattern must be created with small number of sample behavior logs which can be collected in short duration. If a behavioral pattern is created in short duration, then it is possible to start providing services early. Existing research recognizes user behavior by measuring user motion such as gesture and movement history. This method is efficient to recognize behavior precisely. However, because the method uses probabilistic model such as Hidden Markov Model(HMM), it needs a lot of sample behavior logs to create a behavioral pattern. It can not be applied to a problem of this paper.

This paper proposes a method to detect user behavior in a scene in which user's mode changes. Most people often behave in a set order before his mode shift for not making omission of things to do. The order shows personal characteristics significantly. The proposed method pays attention to not user motion but target objects of user operation. The method records kind of objects which a user touched in order of time as behavior log and creates a behavioral pattern by extracting characteristic habits of the user from small number of behavior logs collected in short duration.

This method can

- individualize user behavior with order of objects a user touches in every scene in which user's mode changes, and
- start providing services to a user by creating a personal adapted behavioral pattern in short duration, and
- detect user behavior without being affected by rare order of user's action.

In this paper, An experiment collected behavior logs of 8 experimental subjects in scenes of going out, coming home, getting up and going to bed. The experiment created a behavioral pattern of each scene only with 5 behavior logs which can be collected in a week in actual life, and then tried detecting user behavior.

## 2 Providing Service According to Behavior in Home

### 2.1 Behavior Detection in User Mode Shift

An intelligent space can provide various ubiquitous services to support user activity. We aim to provide services proactively according to user behavior by grasping user intention with the behavior. A user behaves with a variety of intention in a variety of scenes of daily life. However, he does not need services in the all scenes. In general, it is desirable for him to be provided services in special scenes in which his mode significantly changes. For example, suppose a user goes out without closing a gas valve. If he notices the fact after he has gone out of his house, he must waste time and energy to go back to his house to close the gas valve. In such a scene, an intelligent space can improve his amenity by warning that a gas valve is open before he has gone out and closing it automatically. It also means an intelligent space can bring relief and safety to him by preventing danger in advance. There are some scenes in which user's mode significantly changes in daily life. They are scenes of going out, coming home, getting up and going to bed. To provide effective services to a user proactively, we must detect user behavior in these scenes before his mode has changed.

There are respectively different services to be provided and the timing to be done it on each scene. In scenes of going out and going to bed, above mentioned important and urgent services which are able to give relief and safety to a user by preventing danger in advance can be provided. There are definite deadlines to effectively provide services to a user in these scenes. Services in a scene of going out must be provided before a user has gone out through the entrance door. Services in a scene of going to bed should be provided before he has lain down and has slept on the bed. A reminder service is envisioned in a scene of coming home. It reminds a user of things to do in home after his coming home. Similarly, in a scene of getting up, it is envisioned a reminder service reminds him of one day schedule and things to complete by he goes out. For example, a service to inform of urgent message which must be immediately provided after a user comes home should be provided even in a case he only simply comes into his house for a moment. This can be realized only by using a sensor which detects open/close of the entrance door. On the other hand, it is wrong to judge that he came home when he came back into his house to get an umbrella. It is wrong also to judge that he got up when he stood up to go to the toilet in the middle of his sleep. A reminder service based on these wrong judgement makes him uncomfortable. User behavior in these scenes must be precisely detected for providing services. In scenes of coming home and getting up, because services such as a reminder service do not have high urgency, there is no definite deadline to provide services. Nevertheless, services can support him more effectively without making him uncomfortable by providing services before his mode has changed. Consequently, it is adequate to provide services before his mode has changed after a series of regular actions when he comes home or when he gets up. A user often tends to forget something to do in a scene when his mode changes. It is effective to provide assistive services in such a scene. To realize providing advance services effectively, user behavior needs to be detected before his mode has changed.

### 2.2 Behavioral Pattern

A lot of existing researches recognize user behavior by matching user behavior log with a behavioral pattern. A behavioral pattern is a pattern of characteristic behavior of a user in special scenes. Behavior log is behavior data obtained from observed user behavior. Behavior log is categorized into two kinds. One is a sample behavior log which is used to create a behavioral pattern as sample. The other is a match-target behavior log which is matched with a behavioral pattern to recognize behavior. In advance, specific amount of sample behavior logs are collected in a special scene and a behavioral pattern is created with them. After that, user behavior is recognized by matching a match-target behavior log with the behavioral pattern. A few researches obtain values of floor pressure sensors and open/close sensors as behavior log[3,7,8,10]. In addition, some researches use more varieties of sensors such as infra-red sensors, video cameras, and so on[6,9]. Values of these data are affected by not only a user but also other people and environmental objects. However, it is desirable that behavior log shows individual personal behavior in detail for precise detection of user behavior.

### 2.3 Problem for Practical Behavior Detection

To detect user behavior precisely, a behavioral pattern must be personalized. Perkowitz et al. aim to provide services according to user behavior with a mannered behavioral pattern such as how to cook, which is automatically extracted from the web[2]. Because this method does not adapt a behavioral pattern to individual, it can not realize providing services according to individual intention.

Considering a practical use, an individual behavioral pattern must be created in short duration to provide services early without giving a user stress in an intelligent space. In existing researches, there are effective methods to recognize user behavior. They use a behavioral pattern created with probabilistic model such as HMM[1,4,5,11,12,13]. These methods regard user behavior as a series of state transition. They judge whether a match-target behavior log meets a behavioral pattern from the result of repeating multiplication of probability according to state transition. Because a behavioral pattern is created with sample behavior logs by a stochastic method, the probability is high while a user behaves in order he frequently behaves. On the other hand, the probability gets low when he behaves in order he rarely behaves. This method can perform reliable behavior recognition based on probabilistic theory. However, because user behavior forms a complex order structure in which regularity and irregularity are mixed, a stochastic method needs a lot of sample behavior logs to create a behavioral pattern which can represent such a complex behavior in daily life. It can not perform reliable probabilistic statistics with small number of sample behavior logs. A behavioral pattern is created in every scene to be recognized. Therefore, a lot of sample behavior logs of each scene must be collected. Suppose a behavioral pattern of a scene a user goes out. Only about 30 sample behavior logs can be collected in a month. Moreover, also behavior logs other than a scene of going out must be collected. Probabilistic statistics are performed by combining these many behavior logs. Consequently, existing methods using probabilistic model need long time till it starts providing services to a user. These method is not adequate to realization of ubiquitous environment under the present circumstances.

In addition, existing methods can not recognize user behavior containing rare actions exceptionally because probability gets low as a result of probabilistic calculation. Even if a few rare actions are contained in user behavior, the behavior is usual for himself. If he can not be provided services which are normally provided, he is dissatisfied. Exceptional rare actions are often weaved into actual user behavior in daily life. Even if user behavior contains rare actions, it must be recognized precisely and appropriate services must be provided for the user.

A problem to solve in this paper is how to create an effective behavioral pattern with collected behavior logs in each scene. A behavioral pattern must satisfy following conditions.

- It is personalized and created in short duration.
- It can recognize behavior containing rare actions.

## 3 Behavior Detection in Intelligent Space

### 3.1 Habitual Behavior of Individual User

We are developing the "Tagged World" as an intelligent space to provide services proactively according to user behavior by detecting user behavior in a scene in which user's mode changes. For example, when a user goes out, the intelligent space warns him that a gas valve is open. In another example, the intelligent space calls an elevator to his living floor in a condominium. These services can prevent danger in advance and improve user amenity. In the Tagged World, the RFID tags are embedded in various objects of living space such as a wallet, a cell phone and a doorknob. Because a unique tag-ID is individually stored in a

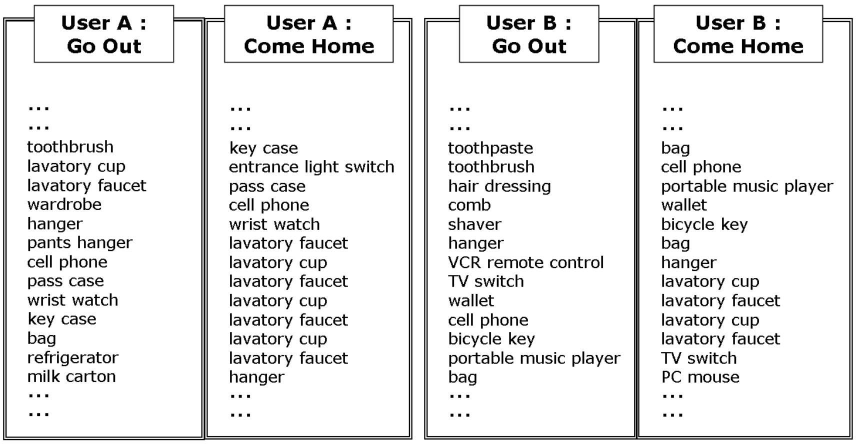


**Fig. 1.** Examples of behavior log

tag, every object can be identified by the tag-ID. A user equips a finger-ring-type RFID reader. The user touches various objects in living space in daily life. When the user touches objects, the RFID reader reads tag-IDs of the objects. Then, a time series of tag-IDs and time stamps which indicate access time are recorded as a behavior log of the user.

A user has some habitual actions in a scene his mode changes. This means the user habitually touches same objects every time in the scene. When a user goes out, for example, there can be habitual actions such as having a wallet, wearing a wristwatch, going to the toilet and having a cell phone. At the same time, accesses to a wallet, a wristwatch, a doorknob of the toilet and a cell phone are recorded as a behavior log in the Tagged World. A time series of stored tag-IDs shows targets of user operation. It details what kind of objects a user uses. It is a behavior log which shows his personal behavior. Some go to the toilet but others do not. Kind and the order of these habitual actions vary with individual user. Thus each scene to provide services to user is characterized by kind of objects and the order of objects which a user touches. These characters indicate his habit. Objects a user touches indicate his intention and his behavior. Their logs are adequate to be used as individual sample behavior logs.

Our research conducted a questionnaire survey. In the questionnaire, answerers recorded kind of objects they touched and the order of objects they touched in 4 scenes of going out, coming home, getting up, and going to bed every day in detail. After that, we had answerers replicate their behaviors in 4 scenes in an experimental space constructed as the Tagged World. Fig. 1 shows examples of behavior logs of two users in scenes of going out and coming home. These are factly collected in the Tagged World. A behavior log is a time series of tag-IDs and time stamps in our research, but this paper shows a time series of objects a user touches as a behavior log for an easy-to-understand explanation. For example, in a scene of going out, habitual actions of user A are different from those of user B as shown in Fig. 1. By looking at the log, it is inferred that user A brushed his teeth, changed his clothes, picked up portable commodities, and brought out a milk carton from a refrigerator. It is inferred that user B brushed his teeth, set his hair, operated a VCR and then picked up portable commodities. These behavior logs show that kind of touched objects and the order of them are individually different among users even in a same scene.

### 3.2 Kind and Order of Touched Objects

The proposed method detects user behavior by paying attention to touching to target objects of user operation. The number of objects a user touches in a scene in which his mode significantly changes is more than the number of objects he touches in other scenes. In scenes such as watching a TV, having a meal and reading a book, a user touches a small number of objects, or he touches a small number of limited kind of objects. Compared to these scenes, it is obvious that more objects are touched in scenes in which user's mode significantly changes. Thus, it is contemplated that user behavior in his mode shift can be detected by paying attention to target objects of his operation. To detect user behavior, a behavior log is checked with following two points.

1. kind of objects which a user touched
2. order of objects which a user touched

Let us consider a case checking only with kind of objects[15]. Suppose to detect a behavior in a scene of going out. There are differences between the objects touched for going out and the objects touched for cooking or for eating meals. It can be guessed that the behavior of going out has been done with high probability just by evaluating kind of objects. But the behavior can not be identified only with kind of objects, because the objects touched for going out are similar to the objects touched for coming home. In our prior experiment, more than 80% of behavior of going out was precisely detected with a behavioral pattern of going out, which is created by paying attention only to kind of objects. But at the same time, more than 50% of behavior of coming home was mistakenly detected.

Therefore, our method evaluates the behavior log in more detail, paying attention to also the order of touched objects. As shown in Fig. 1, in a scene of coming home, it is inferred that user A put some portable commodities, gargled in the lavatory, and hanged up his clothes. It is inferred that user B put some portable commodities, hanged up his clothes, and gargled in the lavatory. Compared to each user's scene of going out, it is found that in a different scene a user touches different kind of objects or touches same objects in different order. The objects touched for going out are similar to the objects touched for coming home, but the order of them are different. Not a behavior of coming home but only a behavior of going out is detected by checking order. The proposed method evaluates the order of not only successive two objects but also non-successive two objects in a behavior log. In actual user behavior, there is a case which a user finds the door locked after he turned the doorknob to go out through the entrance door. At that time, he turns the doorknob again to go out after he unlocks the door.

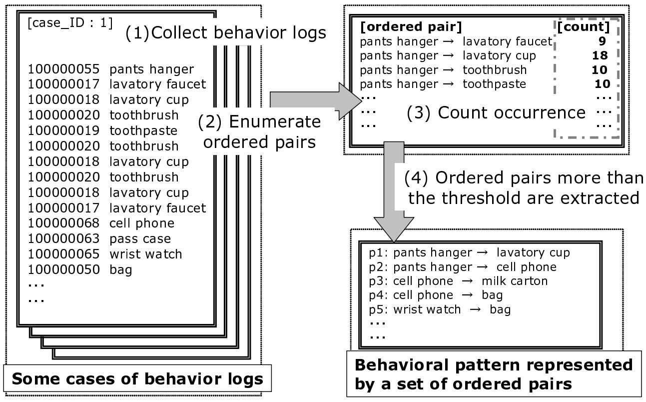


**Fig. 2.** How to create a behavioral pattern

Such an action is rare for him. By focusing on discrete order, the method can flexibly recognize behavior containing such a rare action.

### 3.3 Behavior Detection Based on Discrete Ordered Pairs

With sample behavior logs which are histories of objects a user touched, the proposed method creates a behavioral pattern represented by a set of ordered pairs which show the order relation of his access to objects. Using a behavioral pattern in a scene of going out as an example, this paper describes how to create a behavioral pattern with Fig. 2. Generally, existing methods based on probabilistic model such as HMM[4,11] create a behavioral pattern which is high detection performance with both behavior logs in a scene of going out and them of in scenes other than a scene of going out as sample behavior logs. Consider our problems that a behavioral pattern must be created only with a small number of sample behavior logs. Even behavior logs of going out can not be collected a lot. We can not expect to collect behavior logs of other scenes which are proper to make detection performance high. Therefore, a behavioral pattern must be created only with behavior logs of going out. A behavioral pattern is created in a following flow.

1. collect sample behavior logs
2. enumerate ordered pairs in the behavior logs
3. extract ordered pairs which count of occurrence is more than the threshold

First, behavior logs of $w$ cases are collected as sample behavior logs. The time length $t_l$ of a sample behavior log is fixed. If $m$ objects are sequentially touched in a behavior log $l$, then $l$ is represented as a conjunction $\{o_1, o_2, \ldots, o_i, \ldots, o_m\}$, where, $o_{i-1} \neq o_i (1 < i \leq m)$. Second, all ordered pairs between two objects are enumerated from all of collected sample behavior logs. If an object $o_j$ is touched after an object $o_i$ is touched, then an ordered pair $p$ is represented as $\{o_i \rightarrow o_j\}$, which includes a case of $o_i = o_j$. For example, ordered pairs enumerated from a behavior log $\{o_1, o_2, o_3\}$ are $p_1 : \{o_1 \rightarrow o_2\} p_2 : \{o_1 \rightarrow o_3\} p_3 : \{o_2 \rightarrow o_3\}$. Next, the occurrence of all ordered pairs is counted up as occurrence count. It means not the number of times that each ordered pair occurred in a sample behavior log, but the number of sample behavior logs that each ordered pair occurred in $w$ sample behavior logs. Finally, the ordered pairs where ratio of occurrence count to $w$ is more than a given extraction threshold $e$ % are extracted as a behavioral pattern. This method does not consider the time distance between two objects. In actual user behavior, most actions may not be performed in fixed time relation. Even if the time distance is close, it does not always indicate characteristics of user behavior. Because characteristic ordered pairs may be missed by extracting ordered pairs with limited time distance, this method daringly does not consider the time distance.

The Tagged World matches a current behavior log of time length $t_l$, which is obtained from user behavior online, with a created behavioral pattern $\pi$. If more than a given detection threshold $d$ % of ordered pairs composing the behavioral pattern $\pi$ exist in the current behavior log, user behavior of going out is detected.

### 3.4 Characteristic of the Proposed Method

The HMM used in the existing methods calculates output probability of an observed symbol sequence by the product of transition probabilities between two successive states and symbol output probability on each state. Thus, if a rare symbol occurs in an observed symbol sequence, the output probability is low. In actual user behavior, there is a case a user finds the door locked after he turned the doorknob to go out through the entrance door. Then he unlocks the door and turns the doorknob again. Because a rare action occurs in a part of the behavior in such a case, the HMM may not be able to detect the user goes out. The proposed method in this paper detects user behavior with paying attention to only occurrence count of ordered pairs which represent characteristic order of actions. The ordered pairs of low occurrence probability are excluded when a behavioral pattern is created. This method can detect user behavior even in a case rare actions occur in the behavior by separating order check from a probabilistic model daringly.

Like the proposed method, Mori et al.[7,8] do not use a probabilistic state transition model such as HMM. They detect user behavior proactively with behavioral patterns created based on characteristics both kind of "events" which happen from several seconds to dozens of seconds before a prediction target behavior and the order of them. Their method defines events as changes of two kinds of sensor. One is a pressure sensor which is set in floor, a chair, a bed, and so on, which are used to detect position of a user. The other is open/close sensor which is set in a refrigerator, chest of drawers, and so on. A sample behavior log is time series of events which happened during several seconds. Their method creates a lot of behavioral patterns by extracting all of possible patterns of order of events from some sample behavior logs. When matching with the behavioral patterns, if time series of events which perfectly meet any of behavioral patterns happen then it is inferred that a prediction target behavior will happen soon. Because all of possible behavioral patterns are extracted, if only behavioral patterns which bring out high prediction performance can be selected from the behavioral patterns, their method can realize precise behavior detection. However, as a matter of fact, it is not easy to select only good behavioral patterns by estimating prediction performance of each behavioral pattern now because there are only a small number of sample behavior logs. Compared with this, our method attempts precise behavior detection by taking the following strategy.

- It creates one behavioral pattern to avoid comparing quality among patterns.
- It represents a variety of behavioral patterns potentially by making a pattern be a set of ordered pairs which means many judgement factors for prediction.
- It extracts more characteristics of user behavior from behavior logs not for dozens of seconds but dozens of minutes as judgement factors.
- It makes every behavior distinct by focusing on history of objects a user touched, which significantly indicates characteristics of his behavior.

Because our method focuses on contact to objects as event, a lot of events occur in a sample behavior log. In addition, it is assumed that length of a sample behavior log is dozens of minutes. This means our method regards several habitual actions as characteristics of user behavior, such as “brush teeth”, “go to the toilet” and “pick up a pass case and a key from a drawer” before a user goes out. It can regard also the order of these actions as characteristics, such as “he picks up a pass case and a key from a drawer after he brushes his teeth”. If a behavioral pattern is created from sample behavior logs of dozens of seconds, it will increase the chance to mistakenly detect scenes other than going out, because it may regard only one action as characteristic. Our method prevents this mistaken detection by differentiating one behavior and others, using several habitual actions. Inevitably, the number of occurrence of events in our method is more than that of a method in paper[7,8]. Consequently it is impractical to consider all of possible behavioral patterns extracted from sample behavior logs, because there can be vast amounts of possible behavioral patterns. For the reason, our method detects user behavior by partial meeting a behavioral pattern which potentially considers lots of behavioral patterns. Finally, history of user position, open/close information of refrigerator, and so on are used in existing method. They indicate user behavior, however, history of touched objects in our method shows more significant characteristics of user behavior.

## 4 Performance Evaluation

### 4.1 Experiment

This paper conducted an experiment to verify whether the proposed method can correctly detect user behavior with a behavioral pattern created only with 5 sample behavior logs which can be collected in a week, with 8 experimental subjects. This experiment set the extraction threshold to 80% and set the time length $t_l$ of a behavior log to 10 minutes.

We collected behavior logs of all experimental subjects for this experiment. They are used as sample behavior logs and match-target behavior logs. Before the experiment, we conducted a questionnaire survey for 2 weeks with 8 subjects. In the questionnaire, subjects recorded complete detail about kind of objects they touched and the order of objects they touched in 4 scenes of going out, coming home, getting up, and going to bed every day. In a scene of going out, subjects recorded for 10 minutes before they touched a doorknob of the entrance door to go out. In a scene of going to bed, subjects recorded for 10 minutes before they had lain down on their bed. In a scene of coming home, subjects recorded for 10 minutes after they touched a doorknob of the entrance door when they came back to their home. In a scene of getting up, subjects recorded for 10 minutes after they got out of their bed when they got up. With the result of questionnaire, we confirmed that many people respectively touch different objects or touch objects in different order in different scenes. We constructed the Tagged World in an experimental space which models actual house. Of course, the experimental space has living, kitchen, entrance, and so on. Also real household goods such as kitchen gas stove, kitchen sink, and electric appliances are set in the space. Experimental subjects can live same as in their own home. We collected behavior logs of actual objects which 8 subjects touch in 4 scenes respectively in the experimental space. Similar to the questionnaire, the time length of a behavior log is ten minutes. They are stored in a database. 70 behavior logs were collected per a subject. In some of collected behavior logs, there are unusual rare actions. For example, a user finds the entrance door locked after he turned the doorknob and unlocks the door. In another example, a user takes an umbrella in rainy day.

Next, we calculated true-positive rate(TPR) and true-negative rate(TNR) per experimental subject by repeatedly creating a behavioral pattern and matching behavior logs with the pattern, using behavior logs in the database. TPR shows the rate which behavior logs in a specific scene is correctly detected with a behavioral pattern of the specific scene. TNR shows the rate which behavior logs in scenes other than a specific scene is correctly neglected with a behavioral pattern of the specific scene. The experiment calculates TPR and TNR by following flow. Matching with a behavioral pattern is executed with all settings of the detection threshold $d$ from 1% to 100%. Here, true case means behavior logs in a scene to be created a behavioral pattern and false case means behavior logs in scenes other than the scene of true case.

1. It selects 5 true cases and creates a behavioral pattern from them.
2. It selects other 1 true case and matches it with the behavioral pattern.
3. It matches all of false cases with the behavioral pattern.
4. It repeats 100 times from step 1 to step 3, with a new behavioral pattern which is created by selecting new combination of 5 true cases every time.

In daily life, a user touches less number and less kinds of objects in scenes other than scenes in which his mode significantly changes. In addition, he touches

**Table 1.** Result of "Go Out"

| subject | TPR(%) | TNR(%)* |
|---|---|---|
| A | 94 | 96.02 |
| B | 98 | 85.44 |
| C | 78 | 83.20 |
| D | 95 | 98.00 |
| E | 99 | 98.96 |
| F | 96 | 97.00 |
| G | 100 | 96.36 |
| H | 98 | 95.18 |
| average* | 94.75 | 93.77 |

**Table 2.** Result of "Come Home"

| subject | TPR(%) | TNR(%)* |
|---|---|---|
| A | 89 | 95.93 |
| B | 99 | 98.12 |
| C | 81 | 83.37 |
| D | 98 | 78.40 |
| E | 93 | 99.60 |
| F | 99 | 100.00 |
| G | 100 | 96.80 |
| H | 100 | 98.27 |
| average* | 94.88 | 94.34 |

different kinds of objects. Considering characteristics of our method, it can distinguish between these scenes. Actually, we conducted a preparatory experiment to demonstrate it. The experiment matched behavior logs of three scenes which are cooking, taking meals and after taking a bath with a behavioral pattern of going out. In the result, any of behavior logs were not detected mistakenly. The proportion of the number of ordered pairs existing both in each behavior log and in a behavioral pattern of going out to the number of ordered pairs composing the behavioral pattern of going out is up to 7%. It is less percentage in most cases. Therefore, these scenes have no chance to be detected by a behavioral pattern of going out. With this result in mind, an experiment of this paper uses behavior logs of scenes of user mode change other than true cases as false cases. It means this experiment evaluate detection performance of our method with severer constraint.

Because this experiment assumes that a small number of behavior logs collected in short duration can be used, a behavioral pattern is created only with true cases. To evaluate detection performance, it is contemplated that we use recall and precision which are used to evaluate retrieval performance. However, this experiment daringly sets only scenes which can be mistakenly detected as false cases without recognizing scenes which can be easily distinguished. Therefore, it does not evaluate with precision. It evaluates with TPR and TNR as recall. Both are desired to be high. The deadline to provide services in a scene of going out is the time a user touches an entrance doorknob to go out. Similarly, in a scene of coming home, the deadline is ten minutes after he touches an entrance doorknob when he comes home. In a scene of getting up, the deadline is ten minutes after he leaves his bed when he gets up. In a scene of going to bed, the deadline is the time he lies down on his bed to sleep. In the experiment, his behavior in each scene must be correctly detected in ten minutes which is length of a match-target behavior log.

### 4.2 Behavior Detection Performance

From Table 1 to Table 4, four tables show TPR and TNR per a scene. In Tables, values of TNR and average are rounded off in the third decimal place

**Table 3.** Result of "Get Up"

| subject | TPR(%) | TNR(%)* |
|---|---|---|
| A | 73 | 99.12 |
| B | 90 | 96.78 |
| C | 63 | 84.35 |
| D | 100 | 99.22 |
| E | 64 | 87.32 |
| F | 97 | 99.68 |
| G | 100 | 74.33 |
| H | 56 | 83.60 |
| average* | 80.38 | 90.55 |

**Table 4.** Result of "Go To Bed"

| subject | TPR(%) | TNR(%)* |
|---|---|---|
| A | 62 | 85.34 |
| B | 91 | 71.84 |
| C | 95 | 96.92 |
| D | 78 | 94.66 |
| E | 28 | 91.24 |
| F | 95 | 99.14 |
| G | 98 | 99.32 |
| H | 58 | 100.00 |
| average* | 75.63 | 92.31 |

(singed by "*"). A suitable detection threshold is different according to behavior. The experiment calculated suitable detection threshold of each behavior and used it for evaluation. First, TPR and TNR are averaged per experimental subject. Next, the averaged values of all experimental subjects are averaged. Finally, the detection threshold which the value is highest is adopted for evaluation. The detection threshold of each behavior is followed. Going out : 33%, Coming home: 31%, Getting up : 47%, Going to bed : 63%.

As shown in Table 1 and Table 2, more than 90% of behaviors of going out and coming home are correctly detected. Table 3 and Table 4 show about getting up and going to bed. Although part of TPR shows low rates, others result in high rates. These results prove that our method can bring out high detection performance. It means that our method extracted enough characteristics of user behavior to detect from a limited number of sample behavior logs by focusing on habitually touched objects which significantly indicate characteristics of user behavior. Generally, people lives their daily life by a week which is a standard period. Considering two conditions which are to have to create a behavioral pattern in possible short duration and to use an enough variety of behavior logs which are appropriate for sample behavior logs, to collect sample behavior logs and to start providing services to a user within one week are a standard. As a result of the experiment, our method can create an effective behavioral pattern only with five sample behavior logs which can be enough collected within one week. This means that our method is more practical than existing methods which need a lot of sample behavior logs because it can create a personalized behavioral pattern in short duration and start providing services.

### 4.3 Discussion

Analyzing experimental result and considering characteristics of the method, we discuss causes which our method does not detect some true cases or which our method mistakenly detects false cases. The causes are followed.

1. Some users have few habitual actions

   There is a case which a behavioral pattern is composed of only few ordered pairs because few habitual actions are occurred in sample behavior logs. In such a case, if those limited ordered pairs just happen also in a false case then our method may detect the false case mistakenly. Also, if those limited ordered pairs do not accidentally occur in a true case, then our method does not detect the true case correctly.

2. Some users have common habitual actions among different scenes

   If a user has same actions in same order of them in different scenes, behavioral patterns of the scenes may have same ordered pairs. If same objects are touched in different scenes, most of users touch them in different order. As a result, their behavioral patterns have more ordered pairs which are occurred only in one scene than ordered pairs which are occurred in different scenes in common. But because some users touch same objects in same order in different scenes, for example when going out and when getting up, their behavioral pattern has same ordered pairs in these scenes. It makes recognition accuracy of their behavior worse. In more negative consideration, even if a user touches same objects in different order in different scenes, our method may perform mistaken detection when he behaves in unusual order.
3. Thresholds are not suitable for a user

   In this paper, our method set fixed values to an extraction threshold and a detection threshold. However, our analyzation tells suitable thresholds vary among users. Because there are not a lot of sample behavior logs, the setting of thresholds is a delicate problem. If an extraction threshold is too high, our method may not be able to extract enough proper ordered pairs as characteristics of user behavior. If it is too low, a behavioral pattern may include many improper ordered pairs. A proper detection threshold varies among users and behaviors. In our experiment, a proper detection threshold was 30% for some users, and it was 50% or 60% for other users. We must develop a method to set an ideal detection threshold for each user.
4. Infrequently users have greatly unusual actions

   Our method detects user behavior based on habitual behavior of each user. Even if a behavioral pattern enough represents characteristics of user habit, it can not detect user behavior in a case which he behaves with greatly unusual actions. Suppose a user hurries up before he goes out. If he omits only a part of his habitual actions, our method can correctly detect his going out. But if he omits most of his habitual actions, our method may not be able to do that.

We must solve these problems in the future. The first and second problems may be solved by adding information other than touched objects into behavior logs. It makes us collect more characteristics of user behavior by combining our method with these information. The existing methods check open/close of refrigerator and drawers, ON/OFF of switches and electric appliances, position of a user, objects around a user, and so on as information[3,7,8,10]. We think these are useful as supplementary information. In this paper, we embedded passive-type RFID tags to objects because it is not realistic to supply electric power to many small objects such as a wallet and a pass case. However, some objects such as an alarm clock, electric appliances and walls of room are already supplied electric power now. We can practically set active device such as a small wireless communication device in these objects. Such devices will give us effective information to improve detection performance. The second problem relates to a constraint that sample behavior logs must be collected in short duration. If sample behavior logs can be collected in long duration, not only more behavior logs as true cases but also proper behavior logs as false cases may be collected. With many false cases and many true cases, we can create more precise behavioral pattern by extracting characteristics which are shown not in false cases and but only in true cases. But we can use only true cases in a constraint of a problem to solve in this paper. Therefore we can extract only "characteristics which are shown in true cases very much" in actual. Our method attempts to overcome its weakness by differentiating user behavior of each scene with information of touched objects which are extremely characteristic of every scene in which user's mode significantly changes. However, some cases detected user behavior mistakenly in the experiment because behavioral patterns of different scenes such as going out and getting up include some same ordered pairs. To solve this problem, it is important to improve an initial behavioral pattren. In addition, after a behavioral pattern mistakenly detected a false case, we need a method to refine the behavioral pattern with the false case to keep the mistake from recurring in a long-term perspective.

Because our research aims to provide services to users, we have a considerable problem of the timing to provide services to users after detection of their behavior. Suppose our method detects that a user goes out when he is brushing his teeth in the lavatory. It is not the best to warn him that a window of his room is open immediately after that. Because he may intend to close the window after his brushing. Instead it will be comfortable for him to warn him immediately before he put his shoes on in the entrance. Too early providing services makes him uncomfortable. In the future, we must develop a method to determine the timing to provide services, using position information of a user.

## 5 Conclusion

This paper proposed a detection method of user behavior with a behavioral pattern which is created in practical short duration. A behavioral pattern is created with sample behavior logs which are time series of objects a user touches in the Tagged World. An experiment have proved our method can detect user behavior with a behavioral pattern created using only 5 sample behavior logs which can be collected even in a week. In the future, we will consider how to set suitable threshold for individual user.

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