A Behavioral Pattern Adapted to Individual for Providing Ubiquitous Service in Intelligent Space

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Abstract: We aim to provide ubiquitous services proactively in a ubiquitous environment according to user intention. User behavior must be precisely recognized for providing appropriate services for individual user. This paper proposes a user behavior detection method with a personalized behavioral pattern in an intelligent space which identify objects a user touches. They are adapted to individual user. The proposed method focuses on some special scenes in which user's mode significantly changes, such as a scene of going out. In such scenes, user can be provided services most effectively. The method can detect user behavior precisely with a behavioral pattern created by focusing on discrete order of objects a user touches. It separates the order check from a probabilistic model. Because a behavioral pattern can be adapted to individual user in a short time, the method can start providing services to user early. Experiments have proved that our method detects more than 90% of user behavior correctly with a behavioral pattern which is created in a practical short time with less than 10 sample behavior logs.

Key–Words: ubiquitous, rapid adaptation, personalization, intelligent space, RFID

1 Introduction

A variety of services can be used with information device such as a cell phone and an information appliance in a ubiquitous environment. However, users who are unfamiliar with information devices including elderly people can not enough benefit from services because they must operate information devices actively to do it.

An intelligent space is researched as an environment in which anyone can benefit from services without special operations. User behavior data is acquired by a variety of sensors in an intelligent space. A user does not have to operate information devices actively. An intelligent space can automatically provide services according to user behavior[1, 2, 3, 4, 5, 6, 7].

We are developing an intelligent space which can identify objects a user touches. We aim to provide appropriate lifestyle support services according to user intention by detecting user behavior 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 some scenes such as going out, going to bed, and so on. In such scenes, user's mode significantly changes. We aim to provide services proactively before user's mode has changed. 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.

A user is frustrated with inappropriate services provided by mistaken recognition in an intelligent space. 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. It is important to recognize user behavior fastly and precisely with a personalized behavioral pattern adapted to individual user. Past behavior logs must be collected as samples in advance to recognize user behavior. With past behavior logs, individual behavioral pattern is created in each scene such as going out, going to bed and so on. A behavioral pattern represents characteristics of user behavior. User behavior is detected by matching actual user behavior with a behavioral pattern of each scene. 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 rapidly adapt to individual user with small number of sample behavior logs in a short time.

Existing research recognizes user behavior with measuring user motion such as gesture and movement history. This method is efficient to recognize behavior precisely. However, because the method uses probabilistic model, it needs a lot of sample behavior logs to create a behavioral pattern. It can not apply a problem of this paper.

This paper proposes a personal adapted detection method of user behavior in a scene in which user's mode changes, to provide ubiquitous services at effective timing to a user. Taking specific scenes into account, the proposed 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 a short time, and
- detect user behavior without being affected by rare order of user's action.

This method pays attention to not user motion but target objects of user operation. The method records kind of object which a user touched and the order of them as behavior log and creates a behavioral pattern by extracting characteristic habits of the user from small number of behavior logs in a short time. Experiments have proved the proposed method can precisely detect more than 90% of user behavior with a behavioral pattern which is adapted to individual with less than 10 sample behavior logs.

2 Providing Ubiquitous Service

2.1 Providing Service According to Behavior

An intelligent space can provide various ubiquitous services to support user activity. We aims to provide services proactively according to user behavior by grasping user intention with user 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 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 user mode has changed.

There are methods to recognize user behavior with motion capture or video picture[6, 8, 9]. These methods aim to recognize small unit of behavior such as standing up and sitting down. Because these methods do not recognize more large unit of behavior such as going out and going to bed, they can not detect such a user behavior before his mode has changed. There is a method classifying user activity every time with behavior data obtained by floor pressure sensor[10]. Because the method does not specify user behavior on-line, it can not provide services according to user behavior.

2.2 Behavior Log and 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.

In a few researches[3, 4], values of floor pressure sensor and open-close sensor are obtained as behavior log. Values of these data are affected by not only a user but also other people and environmental objects. However, to detect user behavior before user's mode has changed significantly, behavior log should show individual behavior in detail.

2.3 Practical Behavioral Pattern

In existing researches, there are effective methods to recognize user behavior. They use a behavioral pattern created with probabilistic model such as Hidden Markov Model(HMM)[1, 2, 5, 11]. 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, behavior logs except a scene of going out must be collected. Probabilistic statistics are performed by combining these 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. Considering a practical use, to provide services early without giving a user stress in an intelligent space, individual behavioral pattern must be created in a short time. In addition, existing methods can not recognize user behavior containing rare actions exceptionally because probability gets low as a result of probabilistic calculation. 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.

There is a research to provide services according to user behavior with a behavioral pattern which is automatically extracted from the web[12]. Because this research does not adapt a behavioral pattern to individual, it can not realize provision of services according to individual intention. To recognize user behavior precisely, a behavioral pattern must be personalized.

To create a behavioral pattern with behavior logs collected in special scenes, it is necessary to understand correctly in what scene each behavior log was collected. For that purpose, data mining technique[13] may be able to mine only behavior logs in special scenes to create a behavioral pattern. However, if behavior logs are automatically mined then there will be mistakenly mined behavior logs in them. This means it is difficult to create a behavioral pattern which can lead to high-precision recognition only with data mining technique. It has a problem for practical use. Because our research focuses on special scenes in which user's mode changes, it is supposed that a user can specify behavior logs in each special scene. A problem to solve in this paper is not how to mine behavior logs but how to create an effective behavioral pattern with collected behavior logs in each special scene. A behavioral pattern must satisfy following conditions.

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

3 Tagged World

3.1 Individual Habit Represented by Objects

Our research is 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 a living space such as a wallet, a cell phone and a doorknob. Because a unique tag-ID is individually stored in a tag, every object can be identified by the tag-ID. A user equips a portable computer in which an RFID reader is embedded. The user touches various objects in living space in daily life. When the user accesses 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. In the Tagged World, the time series is stored in the portable computer as a behavior log of the user.

A user has some habitual actions in a scene in which his mode changes. This means the user habitually accesses same objects every time in the scene. When a person 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 tag-IDs stored in our research 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. The kind and the order of these habitual actions vary with individual user. Thus each scene to provide services to

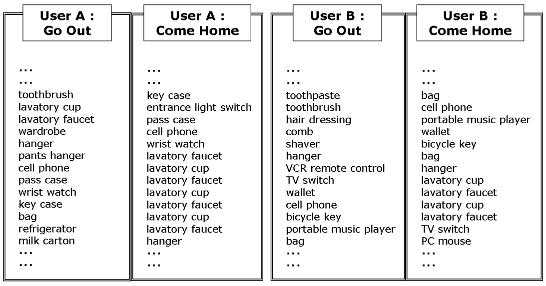

Figure 1: Examples of behavior log

user is characterized by the kind of objects and the order of objects which a user accesses. These characters indicate user's habit. A part of behavior logs is shown in Figure 1. 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 accesses as a behavior log for an easy-to-understand explanation.

The proposed method collects some behavior logs in every special scene in advance. After that, user habit is extracted from behavior logs and a behavioral pattern is created. User behavior is detected by matching a behavior log which is obtained according to actual user behavior with the behavioral pattern on a portable computer a user equips. Because the portable computer works as an assistant of a user in the Tagged World, our research names it the pocket assistant.

3.2 Two Phase Detection of User Behavior

The proposed method detects user behavior by paying attention to touching to target objects of user operation. To detect user behavior, a behavior log is checked with following two points.

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

The first phase considers only the kind of objects[14]. 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 and eating meals. It can be guessed that the behavior of going out has been done with high probability just by evaluating the kind of objects. But the behavior can not be identified only in the first phase, because the objects touched for going out are similar to the objects touched for coming home. Our prior experiment showed, with a behavioral pattern of going out which is created by paying attention to only the kind of objects, more than 80% of behavior of going out was detected. But at the same time it was shown that more than 50% of behavior of coming home was mistakenly detected.

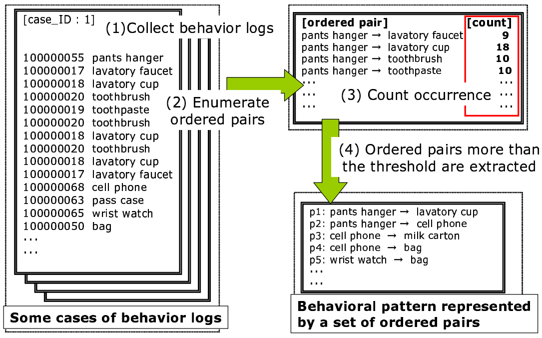

Figure 2: How to create a behavioral pattern

The second phase evaluates the behavior log in more detail, paying attention to the order of accessed objects. The objects touched for going out are similar to the objects touched for coming home, but the order of them are different. Only 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 turns the doorknob to go out through the entrance door. At that time, he turns the doorknob again to go out. By focusing on discrete order, the method can flexibly recognize behavior containing such rare actions.

4 Detection Based on Discrete Order

4.1 Behavioral Pattern by Ordered Pair Set

The proposed method creates a behavioral pattern in a special scene in advance to detect user behavior by checking order of objects a user touched. This method can create a behavioral pattern adapted to individual user habit in a short time with personal behavior logs. A behavioral pattern is represented by a set of ordered pair of two objects. Citing a example of behavioral pattern of going out, Figure 2 illustrates a flow to create a behavioral pattern. A behavioral pattern is created in the follwing flow.

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

First, behavior logs of w cases are collected as sample cases. In this paper, the number of sample cases used to create a behavioral pattern is called as the window size. Since behavior logs of plural cases are collected, the touched objects vary with each behavior log. If m objects are sequentially accessed in a behavior log l, then l is represented as a conjunction $\{o_1, o_2, \dots, o_i, \dots, o_m\}$, where, $o_{i-1} \neq o_i (1 < i \leq m)$. Second, all ordered pairs between two objects are enumerated from collected behavior logs. If an object o_j is accessed after an object o_i is accessed, then a ordered pair p is represented as $\{o_i \rightarrow o_j\}$, which includes a case of $o_i = o_j$. Not only the ordered pairs which are composed of successive two objects in a behavior log but also the ordered pairs which are composed of non-successive two objects accessed in a behavior log are enumerated. For example, the ordered pairs enumerated from a behavior log $\{o_1, o_2, o_3\}$ are $p_1 : \{o_1 \rightarrow o_2\}$, $p_2 : \{o_1 \rightarrow o_3\}$ and $p_3 : \{o_2 \rightarrow o_3\}$. The ordered pair is enumerated from all of collected sample behavior logs.

Next, the occurrence of all ordered pairs is counted up. The occurrence count means not the number of times that an ordered pair occurred in a sample case, but the number of sample cases that an ordered pair occurred in w sample cases. Finally, the ordered pairs where occurrence count is more than an extraction threshold e are extracted as a behavioral pattern. The behavioral pattern π represented by a set of extracted n ordered pairs is defined as follows.

$$\pi = \{p_1, p_2, ..., p_n\}, \;\; occur(p_i) > e,$$

where $occur(p_i)$ is the occurrence count of an ordered pair p_i in w sample cases.

When ordered pairs are extracted, the time distance between two objects can be considered. However, 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, the proposed method daringly does not consider the time distance.

The existing researches using HMM create a behavioral pattern with considering a transition probability only between two states which are successive in terms of the time. However, in actual user actions, the order of actions often changes in a short term viewpoint. Furthermore, it is clear that the order of actions has a regular order with a long term viewpoint. The behavioral pattern of existing methods using HMM can not represent such a complex behavior in which regular order and irregular order are weaved. In addition, existing methods need a lot of sample cases to perform highly-reliable probability statistics. They must collect behavior logs in scenes not to recognize as well as a scene to recognize. Consequently, they need long time to create a behavioral pattern.

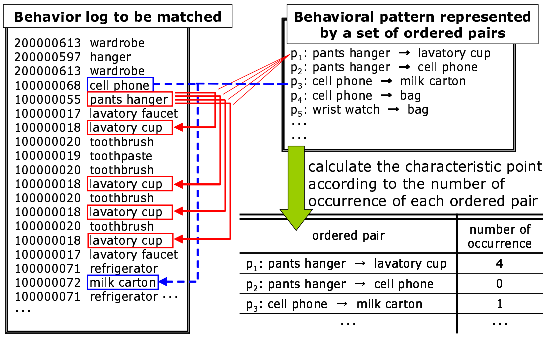

Figure 3: How to match a behavioral pattern with behavior log

To provide effective services to a user, the proposed method focuses on special scenes in which user's mode changes. Because behavior logs in each scene respectively have different ordered pairs, each scene can be enough characterized only with behavior logs in one scene. This method flexibly represents complex user behavior with a behavioral pattern created with considering not only successive two objects but also non-successive two objects. Because it is concise representation focusing only on characteristic order between two objects, a behavioral pattern adapted to individual user can be created in a practical short time.

4.2 Matching with Ordered Pair Set

The proposed method compares behavior logs obtained from actual user behavior with a behavioral pattern to detect a specific behavior. This paper refers to the degree how much a behavior log meets a behavioral pattern as a characteristic point.

Figure 3 illustrates a proposed matching method. Suppose a box in top right corner of the figure shows a match target behavioral pattern and a box in the left side of the figure shows a behavior log obtained from an actual behavior during a given time period. First, the proposed method counts up the number of occurrence that each ordered pair in the behavioral pattern occurs in the behavior log. In Figure 3, ordered pair p_1 : {pants hanger $\rightarrow$ lavatory cup} occurs four times in the behavior log. In the same way, p_2 : {pants hanger $\rightarrow$ cell phone} does not occur and p_3 : {cell phone $\rightarrow$ milk carton} occurs once in the behavior log. Next, the characteristic point is calculated according to the number of occurrence counted before. The characteristic point CP of a behavioral pattern $\pi : \{p_1, p_2, ..., p_n\}$ is calculated as follows.

$$CP = \sum_{i=1}^{n} calcAddedPoint(occur(p_i)).$$

Here,

$$calcAddedPoint(k) = \sum_{i=1}^{k} point(i).$$

The proposed method adds different value to the characteristic point in each occurrence when an ordered pair occurs more than twice. A function $point(k)$ returns value which is added to the characteristic point at the kth occurrence of the ordered pair. For example, if an ordered pair occurs three times in a behavior log, then added value to the characteristic point is calculated as $calcAddedPoint(3) = point(1) + point(2) + point(3)$. The added value does not depend on the kind of objects in an ordered pair. As a result of matching with a behavioral pattern, the behavior is regarded to be detected if the characteristic point CP is more than a detection threshold given in advance.

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 turns 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 characteristic order of actions. The ordered pairs which occurrence probability is low are excluded at the creation of a behavioral pattern. This method can detect user behavior even in a case rare actions occur in the behavior by not using probabilistic model daringly.

5 Performance Evaluation

5.1 Experiments

Two experiments have been conducted to verify whether the proposed method can create a behavioral pattern adapted to individual user in a practical short time and detect user behavior precisely, with 15 experimental subjects in an experimental space which models actual Japanese houses. This paper defines logs of target behaviors of detection as true cases, on the other hand, defines logs of behaviors similar to the target behaviors as false cases. In the experiment, behavior logs of going out were collected as true cases and behavior logs of coming home were mainly collected as false cases. A behavior of coming home may be mistakenly detected as a behavior of going out because accessed objects in a behavior of coming home are very similar to ones in a behavior of going out. In addition, also other behavior logs were collected as false cases, which may be mistakenly detected as a behavior of going out because they have similar movement route or similar actions to the behavior of going out. 20 true cases and 10 false cases were collected per an experimental 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.

Table 1: Value of characteristic point added according to occurrence count of an ordered pair

	point(1)	point(2)	point(3)	point(4)
alg-0	16	16	16	16
alg-3	16	0	0	0
alg-11	16	8	4	2

Totally 300 true cases and 150 false cases were collected. This experiment set a extraction threshold e to 0.66 times of number of sample cases w. The time length of both a sample behavior log and a match target behavior log are set to 10 minutes. All results of experiments are average of 15 experimental subjects.

5.2 Evaluation of Detection Method

The first experiment evaluates characteristic point summation algorithm and detection threshold setting on matching with a behavioral pattern. 12 characteristic summation algorithms are compared. Table 1 shows values added to the characteristic point according to occurrence of an ordered pair about principal 3 of 12 algorithms. The function $point(k)$ shows a value added to the characteristic point at the kth occurrence of an ordered pair. Each algorithm has the different value of $point(k)$ to weigh the occurrence count of an ordered pair as a characteristic of a behavior. With each algorithm, different values are added when an ordered pair occurs more than twice. For example, because the algorithm-3 does not regard the occurrence count as a characteristic, the characteristic point is added only at the first occurrence per an ordered pair. Any of 12 algorithms does not add a value to the characteristic point after the ordered pair occurs more than 5 times.

The detection threshold on the matching is calculated with characteristic points obtained by matching a behavioral pattern in the past. The first experiment compares following settings of detection threshold.

1. **Avg*90% to Avg*10%** After Avg, the average value, of past characteristic points is calculated,

values from the 90% to 10% are adopted as detection threshold.

2. Avg$-\sigma$, Avg-2σ After Avg and the standard deviation σ of past characteristic points are calculated, Avg -σ and Avg -2σ are adopted as detection threshold.

3. Mid Of MinMax After the minimum value is selected from past characteristic points of true cases and the maximum value is selected from past characteristic points of false cases, the mean value of those two values is adopted as a detection threshold.

4. Mid of Avg After the average value of past characteristic points of true cases and the average value of past characteristic points of false cases are calculated, the mean value of those two values is adopted as detection threshold.

5. Mid of Avg$-\sigma$, Mid of Avg-2σ With the average value M and the standard deviation σ which are obtained from past characteristic points of true cases, $M - \sigma$ and $M - 2\sigma$ are calculated. With the average value m and the standard deviation σ which are obtained from past characteristic points of false cases, $m + \sigma$ and $m + 2\sigma$ are calculated. The mean value of $M - \sigma$ and $m + \sigma$, the mean value of $M - 2\sigma$ and $m + 2\sigma$ are respectively set as a detection threshold.

Above 1 and 2 set a detection threshold only by the characteristic points obtained from true cases. 3, 4 and 5 set a detection threshold by the combination of characteristic points obtained from both true cases and false cases.

About each experimental subject, the first experiment uses 10 true cases selected randomly from 20 true cases and 10 false cases, to create a behavioral pattern which the window size is set to 5 and to match with it. The experiment compares classification accuracy of true cases and false cases in all combinations of characteristic point summation algorithms and detection threshold settings. The result showed a combination of algorithm-3 and Avg*50% leads the highest accuracy. The algorithm-3 doesn't add the characteristic point even if an ordered pair occurs more than twice. Other algorithms add the characteristic point if an ordered pair occurs more than twice. They cause unevenness of the characteristic point of true cases. In consequence, the detection threshold becomes not stable and the classification accuracy becomes low. Because the algorithm-3 doesn't cause unevenness of the characteristic point, it gets high classification accuracy. The first experiment considered that more effective detection threshold may be set by combining true cases and false cases. However, as a result, such settings led almost the same or lower classification accuracy. Values of the characteristic points obtained by false cases are unevenness. If the characteristic point obtained by false cases is not optimal, then it will lead lower classification accuracy than only by true cases.

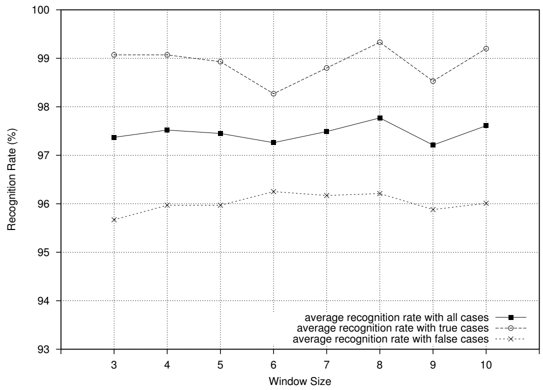

Figure 4: Correlation between window size and recognition rate

Table 2: Recognition rate of "going out" behavior

going out	Recognition Rate (%)	
w = 4	True Cases	False Cases
Subject A	100.00	100.00
Subject B	100.00	92.60
Subject C	100.00	97.40
Subject D	98.00	99.80
Subject E	100.00	90.00
Subject F	100.00	94.20
Subject G	98.00	90.80
Subject H	100.00	100.00
Subject I	100.00	100.00
Subject J	100.00	98.20
Subject K	96.00	100.00
Subject L	100.00	90.00
Subject M	94.00	90.20
Subject N	100.00	96.40
Subject O	100.00	100.00
Average	99.07	95.97

5.3 Recognition with Adapted Pattern

The second experiment evaluates the preciseness of the proposed method with the recognition rate of user behavior. It continuously repeats creating a behavioral pattern and matching with it to verify the method can correctly detect true cases and neglect false cases. The paper discusses a difference of performance with the change of the window size. It indicates the speed of

Table 3: Recognition rate of "coming home" behavior

coming home	Recognition Rate (%)	
w = 4	True Cases	False Cases
Subject A	96.00	93.70
Subject B	94.00	37.60
Subject C	100.00	100.00
Subject D	98.00	100.00
Subject E	100.00	100.00
Subject F	78.00	100.00
Subject G	80.00	99.80
Subject H	98.00	100.00
Subject I	94.00	94.90
Subject J	98.00	100.00
Subject K	80.00	59.40
Subject L	100.00	100.00
Subject M	84.00	98.88
Subject N	100.00	100.00
Subject O	98.00	100.00
Average	93.20	92.28

adaptation to individual user. To evaluate a performance for unknown behavior logs, the second experiment uses 10 true cases, which are not used in the first experiment, as behavior logs to be matched. The procedure of the experiment is the following.

1. It selects 1 of 5 behavioral patterns created in the first experiment and sets the initial detection threshold using the result of the first experiment
2. It picks 1 case from 10 true cases
3. It matches the picked case and also with 10 false cases with the behavioral pattern
4. It creates a new behavioral pattern by adding a behavior log of matched true case to the window
5. It calculates the recognition rate of true cases and false cases respectively by 10 times repeat of steps from (2) to (4)
6. It evaluates the average recognition rate of true cases and false cases respectively by 5 times repeat of steps from (1) to (5)

These operations are done with the window size 3 to 10 respectively.

Figure 4 shows the recognition rate with each window size and Table 2 shows the recognition rate of each experimental subject. The recognition rate of true cases is more than 98% and that of false cases is more than 95%. The latter means the ratio with which the proposed method neglects false cases. There is almost no difference in the recognition rate according to the window size. The proposed method can recognize user behavior with simple and few parameters by focusing on characteristic orders of the target objects of user operation in true cases. Without combining of true cases and false cases, the method can create an enough characterized behavioral pattern for detecting user behavior in a scene in which user's mode changes. The experiment shows the method can create a behavioral pattern adapted to individual user in a short time with less than 10 sample behavior logs. Comparing with existing methods which needs a lot of sample behavior logs for learning, our method is more practical because it can create a personalized behavioral pattern in a short time.

This paper similarly had an experiment for detecting a behavior of coming home as another example. Table 3 shows the recognition rate of each experimental subject. As a result, the recognition rate of true cases is 93.20% and the recognition rate of false cases is 92.28%. Less objects are touched in a behavior of coming home than in a behavior of going out. It is considered that the recognition rate of coming home is lower than that of going out because the differences of the characteristic point between true cases and false cases in a behavior of coming home are smaller than those in a behavior of going out. Also about a scene of coming home, the proposed method can create a behavioral pattern adapted to individual user in a practical short time.

6 Conclusion

We aim to provide services proactively according to user behavior. This paper proposed a detection method of user behavior with a behavioral pattern which is adapted to individual user and is created in a practical short time. By focusing on some scenes in which user's mode changes and services can be effectively provided, the method enough characterizes user behavior in each scene. In the method, a behavioral pattern can be created in a short time with small number of sample behavior logs which are time series of objects user touches in Tagged World. It can detect user behavior by separating a probabilistic model from an order check even if the behavior contains exceptional rare actions. Experiments have proved our method detects more than 90% of user behavior correctly with a behavioral pattern created with small number of sample behavior logs less than 10.

In the future, we will make the portable computer collaborate closely with the intelligent space by collecting the information of living space. It enables to provide ubiquitous services based on a more detailed situation judgement.

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