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Predicting Behaviors of Residents by Modeling Preceding Action Transition from Trajectories

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The smooth provision of support to residents by information display systems or robots will essentially require that their behaviors be appropriately grasped and that predictions be made that allow some margin for preparations. In this paper, we offer new perspectives by proposing a novel method to predict residents' behaviors. The proposed method mainly consists of the following two phases: (1) to grasp the chains of residents' potential actions from their trajectories, and then, (2) to identify the rules of association between residents' behaviors, subject behavior to support and their last actions. In order to verify the performance of the proposed method in predicting residents' behaviors, we have conducted experiments using two residents' trajectories that have been tracked for around one year.

Keywords: Behavior Modeling, Event Mining, Time-Series Association Rule

1. Introduction

It is vitally important to have appropriate knowledge or understanding of residents' behaviors if one wants to support them with information display systems or robots. Since the provision of support takes considerable time to prepare, it is essential to grasp residents' ongoing behaviors to predict their intended behaviors. The prediction of targeted behaviors will ensure smooth provision of higher-quality support services.

In order to grasp residents' behaviors at home using a variety of sensors, it would be better to install such sensors in the residential environments rather than imposing wearable sensors, because the former requires no electric charges and poses little burden on users. There are numerous research studies available on intelligent sensor network systems for use in the house [1, 6–9]. Those systems consisting of a large number and variety of sensors, though able to record residents' behaviors in detail, are so large in scale that it is not practicable to deploy such a large-scale system in the existing residential environments.

In the above-mentioned context, we have constructed a system to measure and estimate residents' locations with multiple laser range finders (LRFs) deployed in the residential environments [10]. Using the system, we have individually tracked trajectories of two residents' behaviors for around one year without placing any special restraints or burden on their way of life.

Use of trajectories as a means to predict people's behaviors [4, 13, 16] focuses more on short-term predictions as to where they are going to be headed from their present locations and in that sense it is more suited to mobile robots or simplified displays of information. On the other hand, robots to support people in their residence should be more focused on providing aids or substitutes for residents' behaviors, such as preparations for going out or cooking, and should require much longer-term predictions because preparations to provide such aids or substitutes take a longer time.

What will residents' trajectories tell us? Our daily life may be considered as chains of multiple activities in the residential environments; for example, we wash our face, take in a newspaper, and prepare breakfast in the period of time between getting out of bed and taking breakfast. In addition, each of these multi-layered activities may be described as a chain of much more deeply layered activities; for example, taking in a newspaper consists of the following actions: move to the door entrance, pick up a newspaper, and return from the entrance. Such multi-layered and chained activities are so heavily associated with the residents' locations in the house that they often stay at their respective locations to do such activities. For the sake of better comprehension of the discussions described in this paper, activities like eating and sleeping that globally define residents' daily life are defined as "behaviors" and small individual activities that compose each behavior, as "actions." Table 1 gives a combination of general locations in the house and residents' behaviors; of course, more than one behavior may be performed at a particular location and any behavior may be performed at more locations than one particular location; nevertheless, locations where residents usually stay in the house seem to provide important clues to grasping their behaviors. On the other hand, when residents do not stay in the house, we may assume that they must be on the move or it must be immediately before or after they are about to move in the house. In other words, if we divide residents' trajectories into the moving and staying parts, we will be able to grasp a flow of their behaviors by mining their trajectories to discover their transitions between the moving and the staying parts.

The following factors are supposed to trigger residents' behaviors in the house: (1) time elapsed from the last performance of the behavior; (2) current time; (3) last actions. Take eating for example, people will feel hungry eight hours after the last meal; people who usually eat at twelve o'clock will feel like eating around twelve o'clock; people spend some time to prepare for each meal. Among these three factors that work compositely rather than individually, we consider the third factor (last actions), which involves closely following resident's behaviors that vary from hour to hour, the most important for providing support, because there is too large a difference in duration of time between the former two factors. On the other hand, predictions of residents' behaviors derived from their last actions should take into full account the diversities of actions, time lags between the predictions and the actual occurrence of behaviors subject to support, and the seasonal variations.

Table 1. Pair Examples of Locations and Behaviors

Location in a House	Corresponding Behaviors
Dining Table	Eating, Reading Books
Kitchen	Cooking
Bed	Sleeping
Bathroom	Taking a Bath
Washstand	Washing Hands or Face
Entrance	Going out, Coming Home

In this paper, on the basis of the above-mentioned perspectives, we propose a new method to predict residents' behaviors from their trajectories. The proposed method mainly consists of the following two phases: (1) to grasp the chains of residents' potential actions from data on their trajectories; (2) and then to predict residents' behaviors by identifying rules of association between residents' behaviors subject to support and their last actions.

2. Capture of Trajectories

2.1. System to Measure Trajectories

To obtain an environment where we could capture residents' trajectories, we use an experimental house, about 9.5 [m] in length and about 4.9 [m] in width as indicated in the center of Fig. 1, equipped with a system to measure residents' trajectories [10]. Residents' locations are measured with LRF modules shown at top left in Fig. 1. The LRF modules, made of a combination of URG-LX04 manufactured by Hokuyo Denki and Armadillo220 manufactured by Artmark Techno, have the following specifications: maximum measuring distance: 5.6 [m]; angles

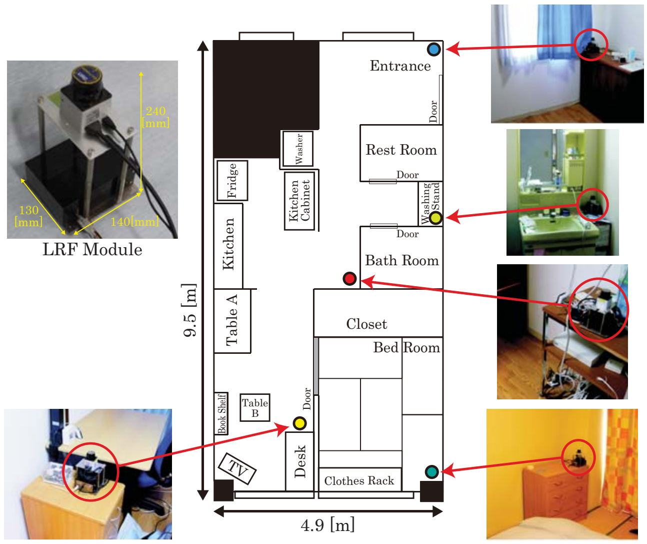


Fig. 1. Layout of LRF modules and experimental house

in measuring range: 240 [deg]; angular resolution capacity: about 0.36 [deg]; measuring cycle: 10 [Hz]. These modules are installed at the height of a resident's waist in the positions indicated in Fig. 1 after being manually calibrated on the sensor outputs. The modules are connected to a wired LAN to process captured sensor data and integrate processed results.

2.2. Computation of Trajectories

At the preprocessing stage, areas such as desktops where people are not supposed to exist are given as grid maps at the time of the system's initial installation (Fig. 2-A). After that, data captured from LRFs are first subjected to background subtraction processing for each distance to convert them into a coordinate system of the room, so that captured data should have points removed from unpopulated grid maps. Detection and tracking of a resident are made at the following stages: (1) the preprocessing stage to capture from LRF-captured data the points where people may be present; (2) the stage to detect human presence from the captured points; and (3) the stage to track it through particle filters [3]. At the detection stage, points captured at the preprocessing stage are segmented into neighboring points to be applied to circular shapes by the least squares method before we commence human tracking. At the human tracking stage, residents' locations on two-dimensional coordinates, $\boldsymbol{x}_t = (x, y)$, provide the settings of particle filters. As for diffused particles, points on unpopulated grid maps as well as points present on the LRF side in LRF outputs are removed to evaluate remaining particles using the following equation, with d_i denoting distances between particles and observation points $\boldsymbol{y}_{t,1}, \cdots, \boldsymbol{y}_{t,m}$; m denoting the number of observation points determined as present in the foreground; σ representing a dispersion term that is empirically set to 0.25 [m]; R denoting that the distance from the center of the body to the contour of the body is assumed constant or 0.15 [m] at the height of the waist, where measurements are taken in the

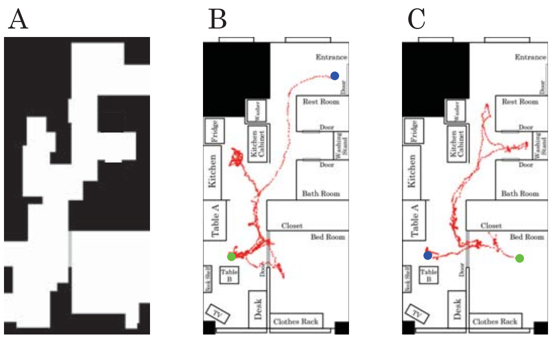


Fig. 2. Grid Map for Calculating Trajectories and Trajectory Examples (A: Grid Map B, C: Trajectory Examples)

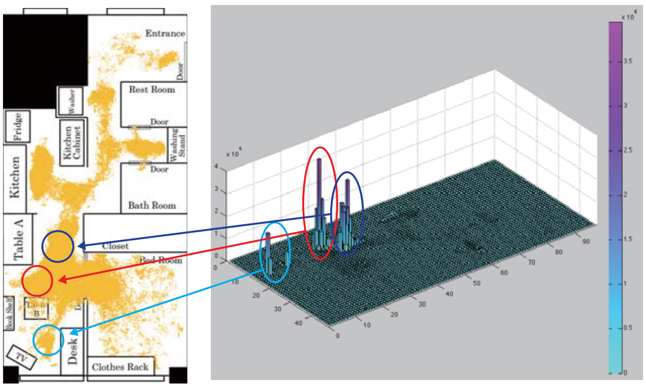
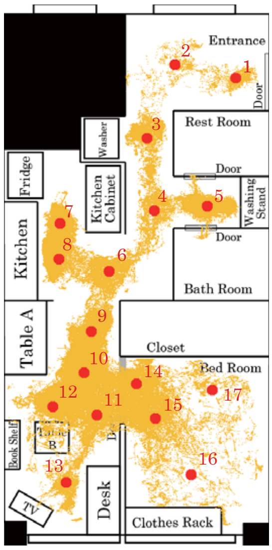


Fig. 3. Stay points around Aug. 2009



Pos.	Corresponding Furniture
1	Entrance
2	Window
3	Washer
4	
5	Washstand, Restroom, Bathroom
6	Cabinet
7	Kitchen, Fridge
8	Kichen
9	Table A
10	Table A, Door
11	Door
12	Table B
13	Desk
14	Door, Closet
15	Door
16	Clothes Rack
17	Bed

Fig. 4. Clustering result of stay points

experimental environment to capture data.

$$p(\boldsymbol{y}_{t,1},\dots,\boldsymbol{y}_{t,m}|\boldsymbol{x}_t)=\prod_{i=1}^{m} exp(\frac{-(d_i-R)^2}{\sigma^2})$$

In the event of a failure in tracking several frames in succession, the system determines that residents have disappeared and returns to the stage to detect residents. A total of 709 frames in the experiments conducted by Noguchi et al. [10] have produced a mean error in captured trajectories of 0.18 [m].

Fig. 2-B and 2-C show examples of actual data on trajectories (great circles in the figures indicate start and end points of the trajectories); Fig. 2-B shows data on the residents' trajectories from the entrance to Table B when they return home; and Fig. 2-C, data on the residents' trajectories from moving away from Table B till going to bed.

3. Grasping Chains of Actions from Stay Points in Trajectories

3.1. Capture of Typical Staying Locations

In this study, in order to classify staying actions by locations, we capture typical staying locations by clustering stay points that exist in the trajectories.

Fig. 3 illustrates stay points as captured from the trajectories dated August 2009, on condition that the resident should move within a range of 0.2 [m] in the space of one second; the plan on the left shows such stay points plotted on a two-dimensional image and the graph on the right, their two-dimensional histogram. The locations circled in the Figure indicate particular locations where many stay points are concentrated; stay points are disproportionately concentrated at particular limited locations, which makes it difficult to extract from the plan on the left the locations that would define residents' daily life, for example, the entrance, in front of the washing machine, and so on. We have therefore clustered the stay points as follows:

1. Divide the house into meshes to count stay points in each mesh.
2. Digitize the counts into 0 or 1 by a certain threshold.
3. Develop a new set of data on the digitized counts on the assumption that they are positioned in the center of respective meshes and cluster them by the k-means method.

Fig. 4 shows the results of clustering the above-mentioned stay points by the k-means method (numbered points indicate cluster centers); it also shows that cluster centers are allocated not only to the location in front of Table A where the resident stays for a considerable length of time but also to other locations where the histogram in Fig. 3 does not recognize the presence of the resident. The relationships between the positions of captured cluster centers and the main items of furniture arranged in the house are given in the list on the right side of Fig. 4, which shows that locations of typical stay points in daily life are affected by the items of furniture and the room arrangement in the house.

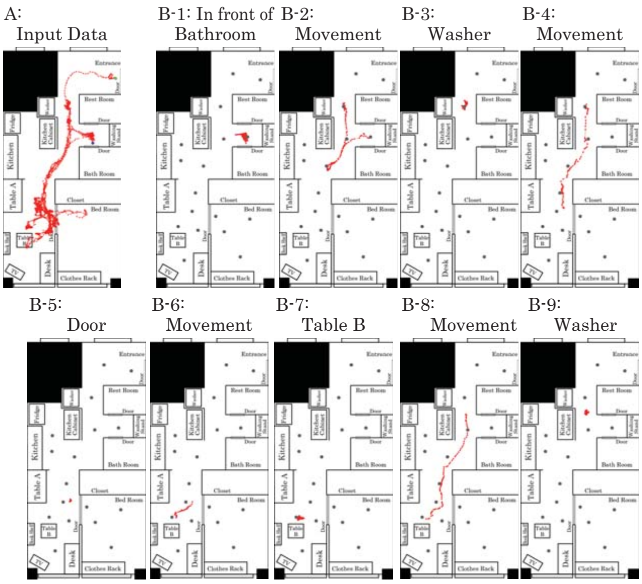


Fig. 5. A: Input data B: The first nine extracted patterns

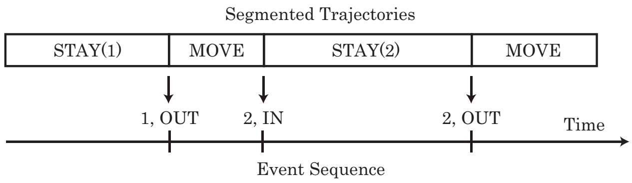


Fig. 6. Transition Event Extraction from Segmented Trajectories

3.2. Grasping Chains of Actions

We extract stay points from the input trajectories to seek the nearest neighbor algorithm whose cluster centers the extracted stay points stay at. Any of the extracted stay points staying at a certain cluster center are defined as a staying action at the said cluster center. The time segment between two staying actions is defined as a moving action. Start and end points of the trajectories should be treated in the same way as stay points, because there is the potentiality that residents may be present even when no trajectories are available. For example, when they are outside the measuring range of LRFs or when they bend down or sleep at locations lower than the measurable height of LRFs, trajectories are cut off and they reemerge in other cases.

Fig. 5 illustrates how the trajectories (Figure A) measured over the period from 15h 17m 57s to 15h 25m 12s on August 4, 2009, can be divided into staying and moving actions by the above-mentioned method (Figures B-1 to B-9); they show a part of staying actions at typical staying locations and moving actions between those staying locations.

4. Algorithm to Predict Behaviors

4.1. Capture of Events Representing Changeovers in Actions

On the basis of the chains of actions captured in Section 3, we capture time-series data on the events that represent changeovers in actions as follows:

- Changeover from a staying action to a moving action is captured as an event that gets out of ID for the cluster center where the staying action belongs to.
- Changeover from a moving action to a staying action is captured as an event that gets into ID for the cluster center where the staying action belongs to.

Fig. 6 illustrates the outline of how to capture the events representing changeovers in actions. Events that are useful for predictions are derived from the above-mentioned captured events.

4.2. Extraction of Pre-Features to Predict Behaviors by Time-Series Association Rules

For the convenience of the subsequent discussions, we define the terms used to describe event mining as follows; as for episodes, we use serial episodes from among the various definitions available [5].

Definition 1: Window: A certain segment on the temporal axis is defined as window $W(t_{start}, t_{end})$.

Definition 2: Episode: A partial series of events in a window is defined as episode $E = [e_1, e_2, \dots, e_n]$. On the other hand, the fact that window W is made up of episode $E = [e_1, e_2, \dots, e_n]$ means that events $E_{window} = [e_{w1}, e_{w2}, \dots, e_{wm}]$ contain integer arrays $\{\phi(1)...\phi(n)\}$ where $1 \leq \phi(1) < ... < \phi(i) < ... < \phi(n) \leq m$ and that $e_{w\phi(i)} = e_i$ is satisfied for any $i = 1, 2, \dots, n$

Definition 3: Minimal Occurrence: When episode E is satisfied in a certain segment on the temporal axis $mo = [t_s, t_e]$ and episode E is not satisfied in other partial segments on mo, then such mo is defined as a minimal occurrence of E.

In this study, we apply time-series association rules [2] established by Harms et al. to predict behaviors and pre-behavior features with some time lags between them as well as different lengths of duration in their occurrence. Specifically, as illustrated in Fig. 7, if an antecedent episode is satisfied in a certain window, then follows a time lag and another predicted event is satisfied in another window (called prediction time range). Its confidence is represented by the probability that the rule can be established when an antecedent episode is satisfied, and is as follows:

$$Confidence(Rule(A,e)) = \frac{freq(Rule(A,e))}{freq(A)}$$

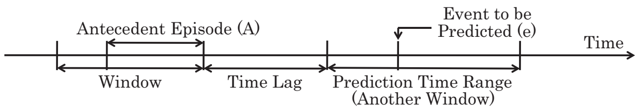


Fig. 7. Time-series association rule

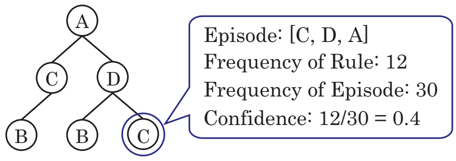


Fig. 8. Episode tree

where, $freq(X)$ denotes the occurrence frequencies of X in time-series data. In this study, we use minimum occurrence frequencies to calculate occurrences. On the basis of the above-mentioned time-series association rules, we conduct learning for the time-series association rules by defining the start of a behavior in the supervised learning period as an event to be predicted.

4.3. Speeding-Up of Identifying Rules

In the special circumstance where there are very few events to predict from among generally huge amounts of data on time-series events, identifying the association rules needs to be done more efficiently than simplistically learning rules, because the latter makes the calculations too protracted for the direct use of generally accepted methods such as depth-first search [12, 15] and breadth-first search [14]. We therefore attempt to speed up learning by using the features of predicted events, namely, that they represent episodes of single events and that they are few and known in the period of supervised learning.

The conditions of the time-series association rules for the establishment of predicted events may be considered satisfied if there is an antecedent episode within a time window in such a way that the last event occurs in the time segment between 0 and time earlier by the prediction time range when viewed at the time of the predicted event minus time lag. In this way, the last event in the antecedent episode can easily be captured. In addition, a relatively small number of predicted events in the whole data of events allow us to significantly reduce the scanning of unnecessary event data if we first calculate the number of established rules and then calculate the total number of established episodes among captured candidate antecedent episodes.

In this study, we conduct learning as in Alg. 1 using tree structure data with nodes of events that compose antecedent episodes (Fig. 8). With each node containing data on the number of established rules and the total number of established episodes, the 4th to 7th lines in Alg. 1 are used to expand from the last candidate events in antecedent episodes, as captured from predicted events in the negative direction on the temporal axis, as well as to calculate the number of established rules (right-side numerator in Eq. (1)); the 9th to 12th lines are used to calculate the total number of established episodes in each node of expanded antecedent episodes (right-side denominator in Eq. (1)). Actually, we have installed DFS-MO algorithm [11], a depth-first search method that recursively contracts the database by buffering the minimal occurrence of parent nodes as well as efficiently calculates all child nodes by one scanning.

Alg. 1 Main Algorithm

Input: $S_{all} \leftarrow$ all events
Input: $S_{last} \leftarrow$ candidate last events of antecedent episodes
1 **begin**
2 initialize $EpisodeTree$
3 $MOList \leftarrow MOs$ of each 1_event episodes in S_{last}
4 **while** $MOList \neq$ null **do**
5 $MO \leftarrow$ remove head item of $MOList$
6 $expand\_Tree(EpisodeTree, MO)$
7 **end while**
8 $MOList \leftarrow MOs$ of each 1_event episodes in S_{all}
9 **while** $MOList \neq$ null **do**
10 $MO \leftarrow$ remove head item of $MOList$
11 $expand\_MO(EpisodeTree, MO)$
12 **end while**
13 get all rules from $EpisodeTree$
14 **end**

4.4. Predictions from Learning Results

Predictions are made with the time-series association rules captured in Section 4.2 as follows:

1 Capture events in the window from current time.

2 Capture established antecedent episodes.

3 In case of any antecedent episodes that exceed the threshold of confidence in the rule, predictions are made in accordance with the rule.

For example, with the threshold of confidence in the rules set at 0.5, predictions will be made if events in the window are [A, B, C, D] for the antecedent episodes of [A, C, D] within a learned rule after a rule is learned whose confidence is 0.6.

5. Experiments

5.1. Predictive Experiments and Their Results

We have carried out experiments with two subjects who live in the same house for different lengths of time (hereinafter referred to as Subject A and Subject B) to predict the start of the following behaviors subject to support by robots: going out; eating; sleeping; taking a bath. As for Subject A, only the start of his going out and his sleeping is predicted because there is a lack of reference material due to the time he is living in the house, whereas for Subject B, the start of all four behaviors is predicted. We have used Subject A's trajectories for 12 months and Subject B's trajectories for 9 months (3 months for eating when its reference is available). We have used the following parameters: not more than 20 cm per second as a staying condition; 17 classes for the clustering (Section 3.1); parameters for the time-series association rule (Section 4.2): 60 seconds in the time window; 30 seconds in the time lag; 120 seconds in the prediction time range. Those parameters are used to allow for predictions of behaviors in 30 to 150 seconds. We have applied the learning results of the past thirty eating behaviors and fifty behaviors for others.

We now define accuracy, precision, and specificity as criteria on which to evaluate predictions. In Table 2, proper duration for making a prediction refers to the period of 30 to 150 seconds for each behavior within the parameters of the experiments. Accuracy, precision, and specificity are calculated from the following equations with values given in the table.

$$Accuracy = \frac{TP}{TP+TN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Specificity = \frac{FN}{FP+FN}$$

Prediction performance should be evaluated by units of behaviors; while accuracy is evaluated by units of behaviors, precision and specificity are calculated in frames (1 fps) for all behaviors because FP and FN in the table cannot be expressed by units of behaviors.

Table 2. Values Used for Evaluating Prediction

		Proper duration for making a prediction	
		True	False
Predictive Output	Positive	TP	FP
	Negative	TN	FN

Table 3. Accuracy and Precision at Specificity 0.99

	Going out (A)	Going out (B)	Eating (B)
Acc.	**0.93**	**0.84**	**0.63**
Pre.	0.12	0.06	0.06
	Sleeping (A)	Sleeping (B)	Taking a bath (B)
Acc.	0.42	**0.81**	**0.97**
Pre.	0.03	0.05	0.06

Table 3 highlights the accuracies and precisions in predictions of behaviors at a specificity of 0.99. A specificity of 0.99 indicates that predictions are output once in a hundred at a time when normally predictions should not be made. While accuracy is generally high except for Subject A's sleeping, precision is generally low. Fig. 9 shows an example of successful predictions for Subject A's go-

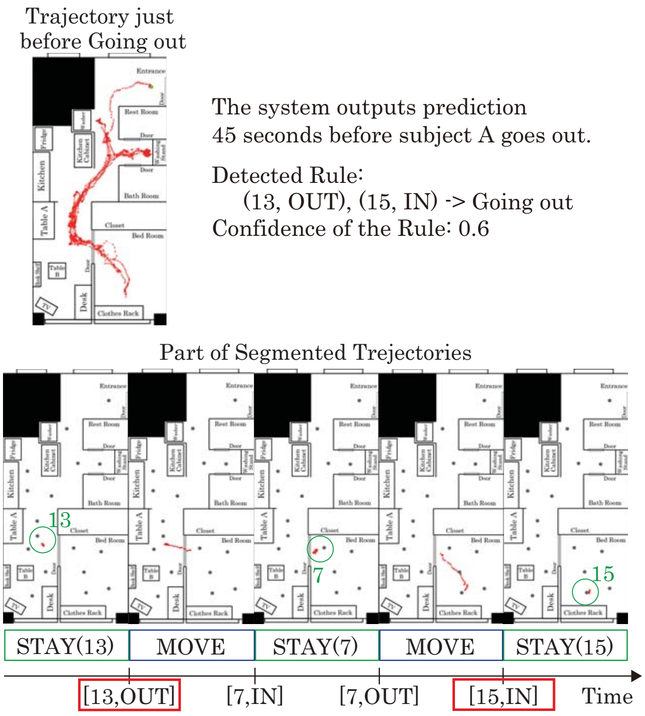


Fig. 9. Example of succeeded prediction

ing out on the morning of October 19, 2009; the numbers indicated in the Figure are the ones allocated at the actual clustering; events are captured in time-series and predictions are made 45 seconds before Subject A goes out. In another successful example of predictions, the system predicts and identifies the rule of Subject B's taking a bath with a confidence of 0.43, 78 seconds before Subject B takes a bath: (moves away from the vicinity of the kitchen rack → moves away from the vicinity of the washing machine → stays in front of the wash basin) → takes a bath. Predictions of behaviors in almost all cases are made based on plural events or more than two events in particular, because behaviors at certain locations are not always uniquely determined as described in the Section 1. For example, for Subject A's sleeping behavior, the system has failed to detect a highly confident rule, because Subject A stays at Table B immediately before going to bed, which the system can detect as a single event of moving away from Table B. This proves the low accuracy rates for Subject A's sleeping behavior. On the other hand, the proposed method can predict with high rates of accuracy such behaviors as those that involve preparatory moving actions immediately before the intended behaviors.

Table 4 and 5 give the maximum and mean time for learning supervised behaviors and the maximum and mean time for making predictions from events in the windows for each frame, as measured in the experiments to predict behaviors. The CPU used for calculations in the experiments is Intel Core i7-620M (2.66 GHz, 2-core, 4 threads), out of which 4 threads are used for learning and 1 thread for making of predictions. In respect of learning time, all behaviors are learned within 15 seconds; for

Table 4. Max and mean time for finding rules [s]

	Going out (A)	Going out (B)	Eating (B)
Max	4.8	10.3	10.0
Mean	1.1	3.4	4.4
	Sleeping (A)	Sleeping (B)	Sleeping (B)
Max	0.7	10.3	6.3
Mean	0.4	3.9	3.9

Table 5. Max and mean time for processing each frame [ms]

	Going out (A)	Going out (B)	Eating (B)
Max	45.0	41.0	33.0
Mean	3.0	3.0	0.9
	Sleeping (A)	Sleeping (B)	Taking a bath (B)
Max	20.0	40.0	30.0
Mean	2.0	2.7	2.5

Table 6. Existence Rate of Predictive Output at Specificity 0.99

	Going out (A)	Going out (B)	Eating (B)
30-600 [s]	0.26	0.18	0.16
30-150 [s]	0.12	0.06	0.06
	Sleeping (A)	Sleeping (B)	Taking a bath (B)
30-600 [s]	0.05	0.08	0.09
30-150 [s]	0.03	0.05	0.06

example, the calculation time for going out and sleeping behaviors seems quite reasonable, given that such behaviors are usually calculated when the proposed system has adequate allowance. In respect of the time for processing frames, the maximum time for any behaviors is 50 ms or less per frame, which indicates in turn that the proposed system with prediction outputs at around 1 fps would still allow for some calculation time even after making plural predictions at less frequencies. In other words, an online system would be quite possible in terms of calculation time.

5.2. Consideration of Precision

Table 6 shows a comparison between existing rates of predictive outputs (precision) at 30 to 600 seconds and at 30 to 150 seconds before behaviors. The table clearly shows how learning results obtained in such a short period of time as two minutes per behavior are distributed in the range of 10 minutes. Table 7 compares the precision of predictive outputs between the proposed system and the random noise (system capable of absolutely random predictive outputs). The table clearly shows that the proposed system outputs predictions with sufficiently large amounts of information. This proves it is significantly useful in terms of precision in predicting human behaviors in daily life from their trajectories.

Table 7. Precision Ratio of This System to Random Noise

	Going out (A)	Going out (B)	Eating (B)
$x:1$	53	46	64
	Sleeping (A)	Sleeping (B)	Taking a bath (B)
$x:1$	14	39	49

5.3. Variations in Performance of Learning Rules with Seasonal Variations in Behaviors

As described in the Section 1, actions immediately before each behavior vary with seasons, probably affecting prediction results in some way.

Fig. 10 illustrates typical staying locations (17 classes) of Subject A as captured each month of the year. While typical staying locations in individual months vary from the neighborhood of the entrance to the bedroom, depending on the lengths of time and frequencies of the behaviors in particular months, there are no large variations in staying locations throughout the year. This seems to indicate that chains of behaviors do not vary that much with seasonal variations.

Table 8 illustrates the experimental results of predicting behaviors on the learning results of the first 50 behaviors (experimental parameters in Section 5.1 are applied). Please note that we have omitted experiments for the eating behavior that is less frequently attempted. We see generally little difference in values between Table 3 and 8. This seems to indicate that among actions immediately before behaviors, key actions are not much affected by seasonal variations.

Table 8. Prediction Performance with Rules from First 50 Behaviors

	Going out (A)	Going out (B)	
Acc.	**0.88**	**0.90**	
Pre.	0.11	0.06	
	Sleeping (A)	Sleeping (B)	Taking a bath (B)
Acc.	0.51	**0.83**	**0.97**
Pre.	0.03	0.05	0.05

6. Conclusion

In this study, we have proposed a new method to predict residents' behaviors from actions that probably involve potential stays in trajectories on the basis of accumulated data on their trajectories in the house. The proposed method is largely divided into two phases: (1) to grasp the chains of residents' potential actions from their trajectories, and then, (2) to identify the rules of association between residents' behaviors, subject to support and their last actions.

In the experiments to verify the performance of the proposed method, we have applied two subjects' trajectories that have been recorded in the period of around one year,

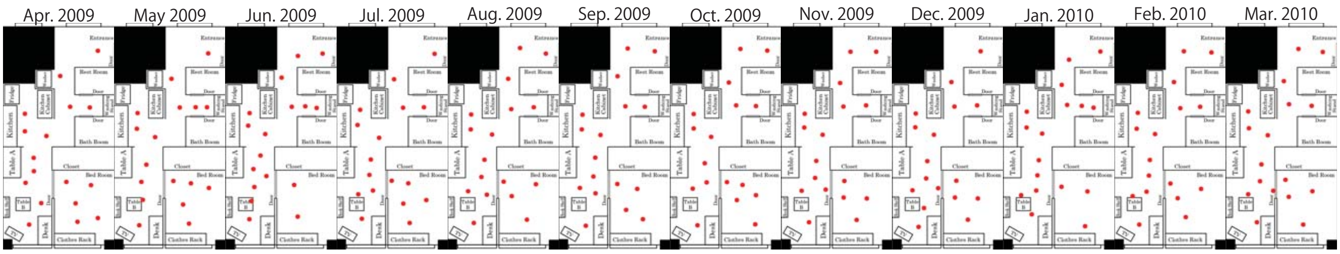


Fig. 10. Differences of Typical Locations of Staying

to find that the proposed method can predict a majority of behaviors including going out with accuracies of 0.8 or more. Despite the generally low precision in prediction outputs of individual behaviors, the proposed method is found around forty times better in precision than random prediction outputs on almost all behaviors, proving the practicability of the proposed method from a precision point of view.

The proposed method seems most suited for predictions of behaviors that involve some preparatory trajectories. On the other hand, the proposed method seems unable to predict with high accuracy behaviors that do not involve any preparations or that take place several hours after preparations. Since seasonal variations are found to have no significant impacts on the precision of predictions, we may determine that there are no significant variations in the core part of people's preparations immediately prior to behaviors.

The proposed method could be further improved in terms of the precision of predictions by addressing the following three specific issues in the future: (1) Instead of the empirical estimation of system parameters as done in this study, there could be a more appropriate and efficient estimation of system parameters to construct a prediction system so that the proposed method can be better utilized. (2) Windows and durations of time could be used as information for predictions; since windows and durations of time themselves are information sources as described in the Section 1 and since actions immediately prior to the behaviors that we have chosen to predict in this study may also vary with windows and time, the introduction of such information to the prediction method could lead to improvements in the precision of predictions. (3) There should be sequential updating of rules: not only the information obtained in the learning period but also the evaluations of the prediction results should be incorporated into the updating of rules as well as into the thresholds of confidence of prediction outputs, which could result in less failures in predictions.

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