Behavior Labeling Algorithms from Accumulated Sensor Data Matched to Usage of Livelihood Support Application

Kana Oshima, Ryo Urushibata, Akinori Fujii, Hiroshi Noguchi, Masamichi Shimosaka,
Tomomasa Sato, Taketoshi Mori
The University of Tokyo, Tokyo, Japan
{oshima,urushib,fujii,noguchi,simosaka,tomo, tmori}@ics.t.u-tokyo.ac.jp

***Abstract*— This paper presents three behavior labeling algorithms based on supervised learning using accumulated pyroelectric sensor data in the living space. We summarize features of each algorithm to use them in combination matched to usage of the livelihood support application. They are (1)labeling algorithms based on time attribution of "on-off" data, (2)one based on Hidden Markov Models, and (3)one based on switching model around a behavioral change-point. We show the behavior labeling results of three algorithms for one month data under the same conditions. Then we point out features on the basis of these results.**

I. INTRODUCTION

Recently, many researches to give appropriate support to the resident from information obtained from sensors in living space have been extensively studied[1][2]. In addition, the demand for automatically figuring out the life and behavior pattern of the resident by system is increasing because the number of elder people living alone is in upward trend sharply. Then it becomes important to figure out the life pattern on the basis near human's concept. This paper presents behavior labeling algorithms that put on a behavioral label that corresponds to the behavior time to time. For example behavioral labels are "Sleep", "Meal" and so on. And these algorithms use data of pyroelectric sensors that are set up for the house of people living alone. Especially, we show the algorithm based on supervised learning using correct behavior labels made by some means, because we aim at an behavior labeling near human's cognition.

We have been using these kind of method for the livelihood support based on the behavior forecast and the anomaly detection, assuming context awareness or intention understanding as its application. First, it estimates the resident's situation from simple sensors, and figures out the life pattern. Then it performs supporting tasks to the residents and detect anomalies based on them. Our research group studied for the support based on the pattern by arranging many kinds in large quantities of sensors in "Sensing Room". For instance, the researches for information support[3][4] and for the support based on the behavior prediction[5] have reported. Also we have performed some experiments of figuring out the behavior pattern using the pyroelectric sensors, and detecting anomalies based on it[6]. Based on these background researches, the purpose of this research is the behavior labeling using data of pyroelectric sensors that can be easily set up.

About the behavior labeling algorithm, our research group proposed (1)the labeling algorithm based on time attribution of "on-off" data[7], and (2)one based on Hidden Markov Models[8][9]. In addition to these, we propose a new algorithm: (3)one based on switching model around a behavioral change-point. Then we compare and examine all three algorithms. This paper is composed as follows: Section II presents these three algorithms. Section III presents the experiment of the behavior labeling for one month data under the same conditions. Section IV provides experimental results and shows features on these basis, and Section V. summarizes them. Section VI. concludes this paper.

II. BEHAVIOR LABELING ALGORITHMS

In this section we explain three behavior labeling algorithms based on supervised learning as in Fig.1. They are as follows:

1. the behavior labeling algorithm based on time attribution of "on-off" data
2. one based on Hidden Markov Models
3. one based on the switching model around a behavioral change-point

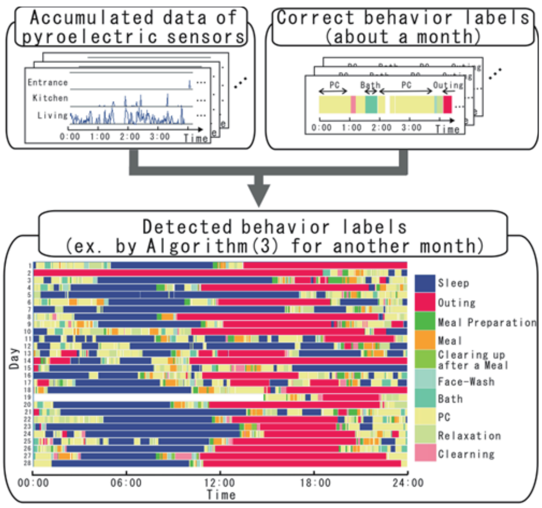

Fig. 1. Overview of Behavior Labeling Based on Supervised Learning

We call the algorithm that puts on a behavior label which corresponds to the behavior at the time every each time

”behavior labeling”. For example it puts on ”Sleep”, ”Meal”, ”Bath”, and so on based on the classification for the living behaviors by standard near person’s concept. For the input, we use the pyroelectric sensor data with the correct behavior labels. The pyroelectric sensor is the one that detects person’s movement by infrared rays. It counts the presence of movement 15 times or less a minute, and outputs the number of counts(from 0 to 15). It has an advantage in respect of the cost and privacy because we can basically use it only by setting it up on the wall one by one in the room. And, the correct labels are made by some means of life records etc.

Three algorithms respectively focus on a different feature of the living behaviors. First, Algorithm(1) aims at the anomaly detection. For figuring out the behavior pattern, it put on a behavior ID to each data segment based on duration and time of segments when there is the person’s reaction. It is based on the idea that the behavior and the room are closely related. Second, Algorithm(2) is focused on the transition of time-series data, and based on Hidden Markov Models(HMMs) which estimate the state transition model in each behavior. Third, Algorithm(3) is focused on features before and after a behavioral change-point where the change from a certain behavior into another behavior is occured. And it puts on behavior labels based on switching model around a behavioral change-poin. Algorithm(2) is focused on the state transition in each data segment. On the other hand, Algorithm(3) is focused on the features of data before and after time when the behavior label is changed. These three algorithms are shown as follows.

A. Algorithm based on Time Attribution of ”on-off” Data

Our research group proposed the algorithm that extracts cluster using Guassian Mixture Model based on time attribution of the segments when there is the person’s reaction in each room, and puts on behavior IDs[7]. This is unsupervised classification. For this research, we extended the method for putting on behavior labels by this algorithm. The relation between the behavior IDs and labels is acquired preliminarily by learning data with the correct behavior labels.

The overview of this algorithm is shown in Fig.2 First we make ”on-off” segments. State ”on” means ”from the start of a behavior to the end of it”. Second ”on” segments in each room are plotted on the plane which axes are time and duration. Then they are divided into the following two clusters.

A The Long-Side Cluster: the cluster that the duration mean value is large, and the time dispersion is small while the duration dispersion is large

B The Long-Length Cluster: the cluster that the duration mean value is small(almost zero), and the time dispersion is large while the duration dispersion is small

Here, the cluster B is represented by one Gaussian Model, and the cluster A is by some Gaussian Models. It is easy to initialize the cluster B, because there are a lot of numbers of plots, and the cluster center is decided well. Meanwhile it is difficult to find the centroid of the cluster A, because the number of plots is little, and they has been distributed. So we initialize only the cluster A by the following process.

Look under the left in Fig.2. The process devides the abridged duration range [0,1] into ten parts, and assign thte point 0,1,2,$\cdots$,9 to each part. Then, the index of each time span, $P(t)$, is defined as the sum of the index of the rectangle where the plot density is higher than a threshold(call this state ”ON”). Then as shown under the right in Fig.2, the process makes some rectangles that consist of the combination of squares, and regards each rectangular area as a cluster area as follows:

1) If $P(t)$ is higher than the one at the next time span by the threshold, the process decides that a cluster should exist at the time span.
2) The process give a cluster to the mass of ”ON” consecutive during the time span
3) If squares near the squares given a cluster are ”ON”, the process regards them as the same cluster.
4) The process repeats the same processing as 3), until the range of the cluster becomes independent.

Then the process respectively represents these rectangles by Gaussian Model. The initial values of mean, covariance, and weight are determined from the centroid, covariance, number of plots in each rectangle.

When a new ”on” segment is created, the process sequentially updates the cluster that reflects the new ”on” segment by the SDEM(Sequential Discounting Expectation and Maximization) alrogithm, and allocates it to the cluster which likelihood is maximum. Finally, the process puts on the same ID to the segment that belongs to the same cluster, and sets a behavior label corresponding to it.

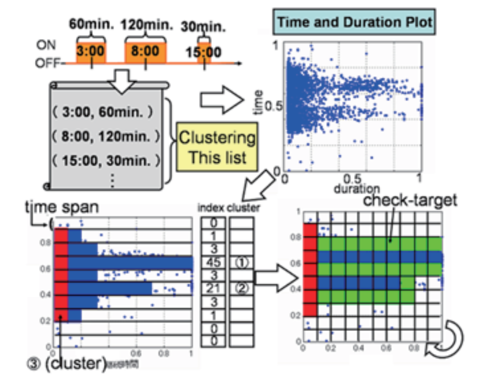

Fig. 2. Algorithm Based on Time Attribution of ”on-off” Data

B. Algorithm based on Hidden Markov Models

Moreover, our research group proposed an algorithm[8][9] which puts on behavior labels to segments of equal length by the clustering of time-series data based on Hidden Markov Models(HMMs) proposed by Smyth[10]. The overview is shown in Fig.3. Extending the method, in this research, it first creates data groups corresponding to each behavior label from the learning data with the correct behavior labels.

Then, it preliminarily make HMM model of each behavior label. Second, it makes segments of same length from data for labeling, and calculates the likelihood of the HMM models to each segment. Finally, it sets the behavior label corresponding to HMM which likelihood is maximum in each segment as an behavior label of the segment.

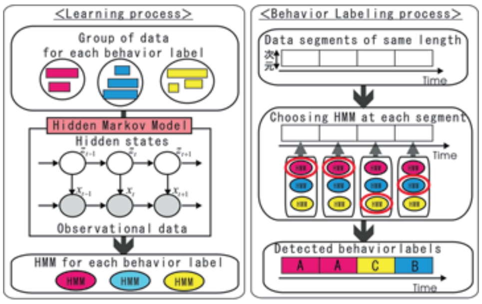

Fig. 3. Algorithm Based on Hidden Markov Models

C. Algorithm based on the Switching Model around a Behavioral Change-Point

We propose a new algorithm that puts on behavior labels from focusing on the features of data before and after a behavioral change-point when the change from a certain behavior into another behavior is occured. The overview is shown in Fig.5. This algorithm refers to the action segmentation algorithm using switching linear dynamics proposed by Segawa et al[11] that is the previous work in human mo-cap recognition. We show the process below.

1) Extracting Segments around a Behavioral Change-Point: The behavioral change-point of each behavior label is defined as the start-point and end-point of the label shown in Fig.5. Then, the process extracts segments of constant length $W_f + W_l$ from data around the start-point and end-point, and makes groups of segments around behavioral change-points. The optimum value of $W_f + W_l$ is derived at the learning stage.

2) Acquiring Switching Models around Behavioral Change-Points: Next, the process models the groups of segments around behavioral change-points for each behavior label by the following switching model of histograms.

Switching Model of Histograms

One switching model of histograms θ is composed of a behavioral change-point τ, histograms of data before it H_f, and those after it H_l.

$$\theta = \{\tau, H_f, H_l\} \tag{1}$$

Then, we think a segment of data around a change-point $X_{1:D,1:W}$. Here D is dimension and W is length of the segment. Histograms H_f, H_l of the switching model $\theta(X_{1:D,1:W})$ is represented by sets of histograms of each dimension of data before and after it.

$$H_f = [h(X_{1,1:\tau}), \cdots, h(X_{D,1:\tau})] \tag{2}$$
$$H_l = [h(X_{1,\tau+1:W}), \cdots, h(X_{D,\tau+1:W})] \tag{3}$$

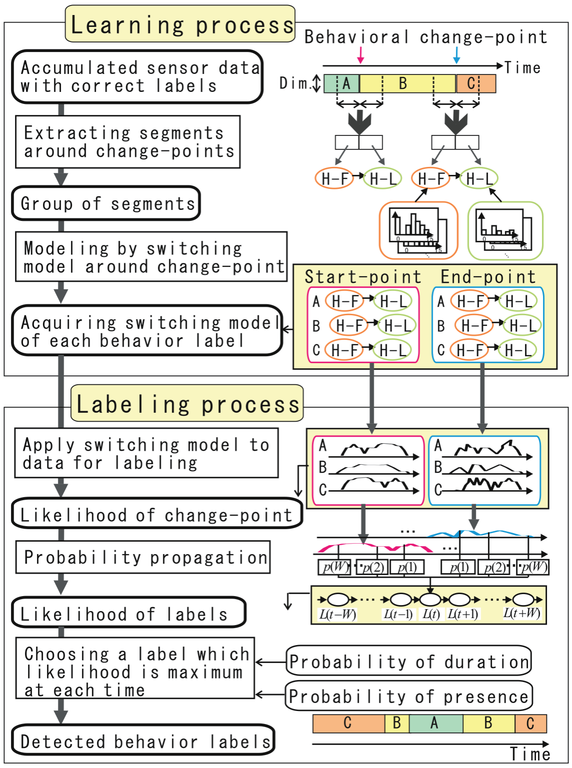

Fig. 4. Algorithm based on the Switching Model around a Behavioral Change-Point

$h(X_d)$ is a histogram by one dimensional data. Here, we set the number of bins $R = 3$, and adopt a histogram consisting of R bins. Because of the characteristic of pyroelectric sensor, one of these is a class of only "0", and $R - 1$ others are classes wherer the remainder data(from 1 to 15) is equally devided in $R - 1$. A behavioral change-point τ is estimated by searching the point where the sum of the likelihood is maximum.

Next, we show how to calculate the likelihood of the switching model of histograms $P(X'|\theta)$. We represent the switching model of data X' as $\theta' = \{\tau', H'_f, H'_l\}$. Then, we define the likelihood $P(X'|\theta)$ using the sum of absolute distances between histograms. Here, $|H_d - H'_d|$ is the distance between histograms.

$$P(X'|\theta) = \exp \sum_d -(|H_{f,d} - H'_{f,d}| + |H_{l,d} - H'_{l,d}|) \tag{4}$$

Acquiring Switching Models on each Changing Standard

The process models each segment around the behavioral change-point by the switching model of histograms, and classifies the group of segments at the behavioral changing standard by clustering. Then, it units the belonging segments of each cluster, and makes the switching model around the behavioral change-point of each cluster.

3) Behavior Labeling based on Switching Model around Behavioral Change-Point: The process calculates the like-

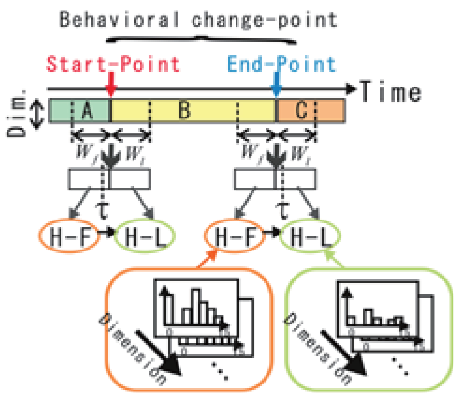

Fig. 5. Modeling with Switching Model of Histograms

lihood of the behavior label using the acquired switching model around the behavioral change-point(start-point and end-point). Finally, it decides a behavior label at each time, considering the duration of the label and the resident's presence in each room.

Calculation of Likelihood of Behavior Labels

The process calculates the likelihood of the switching

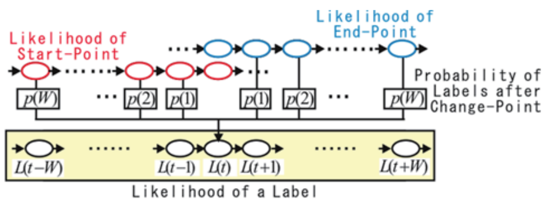

Fig. 6. Probability Propagation

model at each changing standard for each behavior label from a segment $t - W_f - 1 : t + W_l$ of time-series data for labeling. Here, we represent each behavior label as $A^n (1 \leq n \leq N, N$: the number of behaviors), then define the log likelihood of the behavioral change-point for the label $l^n(t)$ as maximum log likelihood at time t. Next, shown in Fig.6, it calculates the likelihood of the behavior label from time-series likelihood of the change-point based on the probability propagation method using the probability of label after change-point. Here, $p(t_c)$ is the probability of the label t_c minutes later after the start-point τ of A^n. The log likelihood of the label $\mathcal{L}^n(t)$ is calculated from the log likelihood of start-point and end point l_s^n, l_e^n as follows:

$$\mathcal{L}^n(t) = \sum_{t_c} \frac{1}{t_c} p(t_c)(l_s^n(t - t_c) + l_e^n(t + t_c)) \tag{5}$$

Behavior Label Determination considering duration and rooms

As show in Fig.7, the process determines that the behavior label at each time is one which log likelihood is maximum. Here, it adds the probability of duration of the label one minute ago T_{t-1} and that of the resident's presence in each room $\mathbf{o}_t$ as conditional probabilities by using Bayes's

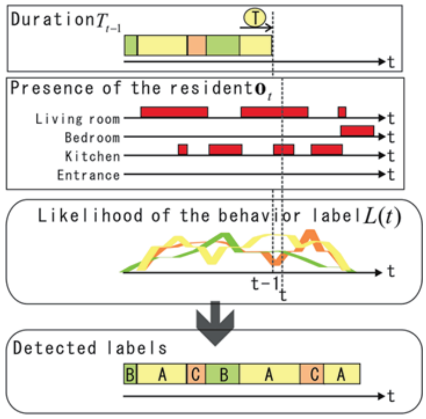

Fig. 7. Putting on Labels Considering Duration and Rooms

theorem.

$$u(t) = \arg\max_n \left(\mathcal{L}^n(t) + \log \frac{P(T_{t-1}|A_n)}{P(T_{t-1})} \frac{P(\mathbf{o}_t|A_n)}{P(\mathbf{o}_t)} \right) \tag{6}$$

III. Experiment

We show the results of these three behavior labeling algorithms for multi-dimensional time-series data. We use the accumulated data of two months of pyroelectric sensor installed on 1LDK apartment house where a man in twenties lives alone. We set one month of the first half for learning, and one of the latter half for evaluation. The installation places of sensors are the entrance, corridor, lavatory, kitchen, living room, and Japanese-style room as Fig.8. Ten behavior labels as follows are setted according to the life of this resident. 1.Sleep, 2.Outing, 3.Meal Preparation, 4.Meal, 5.Clearing off after a Meal, 6.Face-Wash, 7.Bath, 8.PC, 9.Relaxation, 10.Cleaning. However, we excludes "toilet" because it is a too short behavior of less than one minute.

The pyroelectric sensor is the one to detect person's movement by using infrared rays, and it counts the presence of person's movement 15 times or less a minute. Three algorithms label the accumulated data of latter half 28 days(length:28(days)*1440(minutes),dimension:6) from pyroelectric sensors that is output the integral value from 0 to 15 in one minute. Then, we evaluate the results by Recall, Precision and F-measure. F-measure is the harmonic mean of Recall and Precision.

$$F = \frac{2RP}{R + P} \tag{7}$$

We calculate each evaluation value by comparing the correct label to the detected label using the label which number is max in the section of the back and forth of ten minutes at each time. Also, we show the mean value of the result in the manual labeling by the person as an object of comparison. Four persons manually set labels for sensor data on GUI screen, and it took about two hours.

IV. Experimental Result

First, we show an example of labeling results for one day by three algorithms in Fig.9. On the day, the resident took

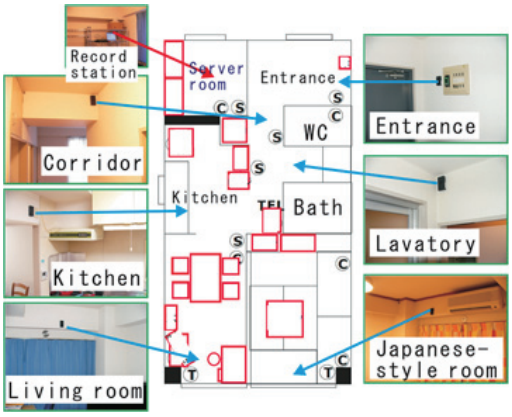

Fig. 8. Installation Environment

"Sleep" in the living room, "Outing" around noon, and spend a lot of time in the living room after returning home.

Second, we show Recall, Precision, and F-measure of three algorithms and manual labeling in Table.I. As seen in Table.I, even if the person manually sets labels, F-measure is About 90 percent from 70 percent. And depending on the behavior, there are some behaviors that are difficult to put on labels correctly. If F-measures of some algorithms are similar percentage, there might be the difference in the recall ratio and the precision ratio. So the features appear to the result in each algorithm. They are brought together as follows.

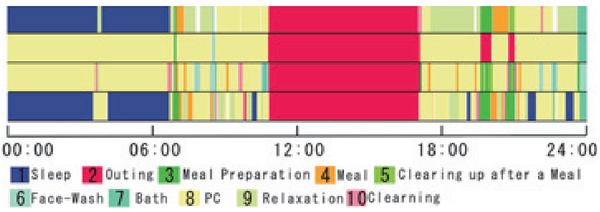

Fig. 9. Result of Behavior Labeling(Top:Ground Truth, Second:GMM, third:HMM, Bottom:Switching Model

A. Algorithm based on Time Attribution of "on-off" Data

This algorithm put eight IDs. These eight IDs corresponded to six behavior labels, so it can not put labels to four kinds of other behaviors.

Advantage

This algorithm is effective against the behaviors that are strongly related to the room. For example, "Face-Wash", "Bath", "Sleep" in the bedroom, "Outing", and so on. This is effective for living behaviors because those important, ex."Sleep", "Outing", "Meal" associated behavior, behaviors in the lavatory of "Face-Wash"and "Bath", are mostly related strongly to the room. The advantage of this is enumerated as follows.

- It can accurately detect the beginning and finish time.: About behaviors that are strongly related to the room, the beggining and finish time of movement to the room often correspond to those of the behavior. So we can know those time at the unit time of the sensor.
- It doesn't detect interrupted labels so much.: Because it puts on ids to "on" segments in each room, an individual label is detected as a mass. So it is few that the label is detected with interruption.
- The reason for the classification is intuitively comprehensible because it classifies the behaviors in each room.
- Even when the kind of behaviors increases, it may be possible to correspond in real time by making a new cluster.
- It can classify corresponding to each home, because it uses the priority of the room based on the room arrangement.
- We can simply expect the recall ratio to rise by divising the method to install the sensors.

Disadvantage

It cannot distinguish the behaviors that have similar duration in the same room. For example, "PC", "Meal", "Sleep" in the living room. So it cannot distinguish "Sleep" excluding in the bedroom from other behaviors among above-mentioned important behaviors. In addition, the recall ratio of "Meal" is low because it cannot distinguish it from other behaviors in the living room. The F-measure ratio of "Meal Preparation" and "Clearing off after a Meal" only in the kitchen is also

TABLE I

EVALUATION(F-MEASURE,RECALL,AND PRECISION)

Label	GMM	HMM	switch	manual
F-measure				
1 Sleep	54.6%	54.4%	90.2%	89.9%
2 Outing	89.0%	64.9%	95.8%	99.2%
3 Meal Preparation	37.5%	37.3%	55.5%	77.3%
4 Meal	70.1%	64.6%	70.0%	86.8%
5 Clearing up after a Meal	-	19.0%	13.4%	58.6%
6 Face-Wash	61.0%	37.6%	64.3%	72.8%
7 Bath	67.3%	35.3%	70.7%	71.7%
8 PC	42.0%	32.8%	52.5%	62.8%
9 Relaxation	-	1.3%	25.8%	19.2%
10 Cleaning	-	4.3%	23.5%	22.9%
Recall				
1 Sleep	38.8%	38.2%	92.8%	88.7%
2 Outing	83.4%	48.1%	97.2%	98.6%
3 Meal Preparation	31.9%	41.5%	70.8%	80.2%
4 Meal	53.9%	66.6%	84.2%	87.3%
5 Clearing up after a Meal	-	32.4%	11.4%	77.4%
6 Face-Wash	49.3%	87.1%	67.3%	72.9%
7 Bath	84.6%	29.4%	73.6%	69.6%
8 PC	93.4%	75.9%	52.1%	74.6%
9 Relaxation	-	0.7%	18.8%	15.7%
10 Cleaning	-	9.7%	27.4%	18.4%
Precision				
1 Sleep	92.1%	94.0%	87.7%	92.0%
2 Outing	95.3%	99.8%	94.4%	99.8%
3 Meal Preparation	45.7%	33.9%	45.6%	75.1%
4 Meal	100%	62.7%	59.9%	86.7%
5 Clearing up after a Meal	-	13.4%	16.4%	47.2%
6 Face-Wash	79.9%	24.0%	61.5%	73.3%
7 Bath	55.9%	44.2%	67.9%	75.9%
8 PC	27.1%	20.9%	52.9%	54.8%
9 Relaxation	-	33.3%	41.0%	30.0%
10 Cleaning	-	2.8%	20.6%	30.3%

low because it cannot appropriately estimate ”on” segments for the adjacent rooms of the kitchen and living room.

B. Algorithm based on Hidden Markov Models

Advantage

This algorithm is effective against the behaviors that take characteristic data transitions. For example, ”Meal”, ”Sleep” in the bedroom, and so on. So it can appropriately put labels for those behaviors because it can estimate the particular state transition from observational data. The advantage of this is enumerated as follows.

- It can consider the data transition in time direction.: HMM is the model to estimate the state which outputs the observational data at each time, and calculate the transition probability from the state before one time. So it can deal with the information of data in time direction.
- It can estimate the invisibility states behind observational data.
- It can absorb exceptional behaviors included the learning data. HMM estimates the state and the transition between states by calculating the argument values, the probability of outputing the observational data from each state and that of the state transition. So it can do modeling absorbing them because a few exceptional behaviors don’t have a big influence on the argument value.
- It can calculate the likelihood of all behaviors every each time.
- It can detect such ”PC” without omission as the behavior that is difficult to make modeling because the variation of its data is wide.
- It doesn’t need the advance knowledge such as the room arrangement, because it is a machine learning based modeling.

Disadvantage

Between behaviors that take a similar data transition, the behavior with a narrower variation is absorbed to that with a wider variation. For example, all ”Sleep” in the living room is detected as ”PC”. Because ”PC” takes wide variation of data from little reaction like ”Sleep” to somewhat large reaction, so the model of ”PC” includes that of ”Sleep”.

C. Algorithm based on the Switching Model around a Behavioral Change-Point

Advantage

This algorithm is effective against the behavior that (a)have some features around the behavioral change-point such as ”Meal”, (b)is strongly related to the room such as ”Bath” and ”Face-Wash”, (c)have characteristic duration such as ”Sleep” and ”Outing”, and (d)have few number of samples such as ”Cleaning”. About (d), the thorough cleaning that was done only once in the evaluation data set for a long time of two hours or less can be detected only by it. The advantage of this is enumerated as follows.

- It can comparatively distinguish between the behaviors that take a similar data transition while acting. For example, between ”Sleep” and ”PC” in the living room, ”Face-Wash” and ”Bath” in the lavatory, and so on.: If the transitions of data for some behaviors are similar, there is a difference between them in the features around behavioral change-points. So it can distinguish them using the features.
- It can correspond to two or more patterns of the behavior changing.: Because it makes models for each changing standard, it can deal with various changings about same behavior.
- It can calculate the likelihood of all behaviors every each time.
- It can detect such as ”Meal Preparation”, ”Meal”, and ”Clearing after a Meal” bringing a series of behaviors together, because it uses the features before and after the behavioral change-point.
- It can correspond the data of irregular living habits.
- We can visually understand how to change behaviors by histograms before and after the behavioral change-point.

Disadvantage

It is difficult to detect appropriately the behavior that has no consecutive features before and after a behavioral change-point. Because it is based on models around the behavioral change-point, it cannot correctly detect the behavior which it cannot appropriately do modeling from the segments around the change-point.

V. Add-up for advantages of three algorithms

We summarize the advantages of these three behavior labeling algorithms. Algorithm(1) works well with the behaviors that are strongly related to the room. For example, ”Face-Wash”, ”Bath”, ”Sleep” in the bedroom, ”Outing”, and so on. And it can accurately detect the beginning and finish time of them. Algorithm(2) is good at the behaviors that take characteristic data transitions. For example, ”Meal”, ”Sleep” in the bedroom, and so on. Algorithm(3) is well suited to against the behavior that have some special features around the behavioral change-point such as ”Meal”, one that is strongly related to the room such as ”Bath” and ”Face-Wash”, one that have characteristic duration such as ”Sleep” and ”Outing”, and one that have few number of samples such as ”Cleaning”. And it can comparatively distinguish between the behaviors that take a similar data transition while acting.

VI. Conclusion

We showed three behavior labeing algorithms as follows: (1)the algorithm based on time attribution of ”on-off” data, (2)one based on Hidden Markov Models, (3)one based on switching model around a behavioral change-point. Then we summarized the features of each algorithm, and confirm that each have an effective behavior. Algorithm (1) is effective against the behavior which is strongly related to the room. Algorithm (2) is effective against that taking a characteristic data transition. Algorithm (3) is effective against that having some characteristics around the behavioral change-point, and it can distinguish between the behaviors that take a similar data transition. When applying these algorithms, it is recommended to collate with features of each algorithm, and combine these, matched to the objective use of the livelihood support application.

REFERENCES

[1] Kidd Cory D., Robert J. Orr, Gregory D. Abowd, Christopher G. Atkeson, Irfan A. Essa, Blair MacIntyre, Elizabeth Mynatt, Thad E. Starner and Wendy Newstetter. The Aware Home: A Living Laboratory for Ubiquitous Computing Research. In Proceedings of the Second International Workshop on Cooperative Buildings, pp. 191–198, 1999.

[2] Taketoshi Mori, Hiroshi Noguchi, Aritoki Takada and Tomomasa Sato. Sensing Room: Distributed Sensor Environment for Measurement of Human Daily Behavior. In 1st International Workshop on Networked Sensing Systems(INSS), pp. 40–43, 2004.

[3] Taketoshi Mori, Noritaka Hayama, Hiroshi Noguchi and Tomomasa Sato. Informational Support in Distributed Sensor Environment Sensing Room. In Proceedings of IEEE International Workshop on Robot and Human Interactive Communication, pp. 353-358, 2004.

[4] Hiroshi Noguchi and Taketoshi Mori and Tomomasa Sato. Attentive Information Support with Massive Embedded Sensors in Room, pp883-pp892, Human-Computer Interaction, Julie A. Jacko, LNCS 4551, Springer, Heidelberg, ISBN:978-3-540-73106-1, 2007.

[5] Taketoshi Mori, Aritoki Takada, Hiroshi Noguchi, Tatsuya Harada and Tomomasa Sato. Behavior Prediction System Based on Environmental Sensor Records. In Proceedings of International Workshop on Networked Sensing Systems, pp. 197-202, 2005.

[6] Taketoshi Mori, Akinori Fujii, Masamichi Shimosaka, Hiroshi Noguchi and Tomomasa Sato:Typical Behavior Patterns Extraction and Anomaly Detection Algorithm Based on Accumulated Home Sensor Data. In FGCN2007 Workshop: International Symposium on Smart Home (SH07), pp. 12-18, 2007.

[7] Taketoshi Mori, Ryo Urushibata, Masamichi Shimosaka, Hiroshi Noguchi and Tomomasa Sato. Anomaly Detection Algorithm based on Life Pattern Extraction from Accumulated Pyroelectric Sensor Data. In Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 2545-2552, 2008.

[8] Taketoshi Mori, Aritoki Takada, Yasuhiko Iwamura and Tomomasa Sato. Automatic Human Life Summarization System in Sensory Living Space. In Proceedings of IEEE International Conference on Systems, Man and Cybernetics(SMC), pp. 1583-1588, 2004.

[9] Akinori Fujii, Taketoshi Mori, Hiroshi Noguchi, Masamichi Shimosaka, Akira Baba and Tomomasa Sato. Behavior Description Algorithm based on Home Sensor Data using Nonlinear Transformations. In Proceedings of 5th International conference on Networked Sensing Systems(INSS), pp. 63-66, 2008.

[10] Padhraic Smyth. Clustering Sequences with Hidden Markov Models. In Advances in Neural Information Processing Systems, pp. 648-655, 1997.

[11] Yushi Segawa, Taketoshi Mori, Masamichi Shimosaka and Tomomasa Sato. Human-like Segmentation of Daily Actions based on Switching Model of Linear Dynamic Systems and Human Body Hierarchy. In Proceedings of ROBOMEC2006, pp. 2A1-D05, 2006.