Behavior Description Algorithm based on Home Sensor data using Nonlinear Transformations

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***Abstract*— This paper presents a behavior description algorithm from time-series data in daily life using home sensor. In previous work, we proposed the method of time-series data clustering based on HMM (Hidden Markov Model). This method separates time-series data in segments of equal short length, and gives behavior labels for every segments. But change points of behaviors are not clear and it is difficult to detect short length behavior. In this paper, we propose a new behavior description algorithm by introducing SST (Singular Spectrum Transformation), a nonlinear transformation used for change-point detection, and apply it to our previous method. As an experiment, we apply it for the data in daily life acquired from our experimental environment "Sensing Room", in which there are various sensors such as pressure sensors or electric power sensors, and show the result of behavior labeling compared with HMM algorithm.**

I. INTRODUCTION

The research on so-called "Intelligent spaces" becomes more active along with technological development in recent years. Such environment grasps persons' behaviors by sensors in that and assists or supports persons' behaviors and warn people based on it.

Our research group proposed "Sensing Room", the experimental environment in which sensors are arranged. It has aimed to support people in the room using time-series data. They are acquired with pressure sensors, switch sensors etc. , and accumulated in the server.

When the environment supports our behaviors, we think the problem of "Annotation", that is, labeling of persons' behavior patterns. It is very important to grasp humans' behavior correctly in the respect of the application like anomaly detection from typical behaviors or support based on behavior prediction.

Of course, it is the best to introduce cameras and catch humans' behaviors visually to recognize humans' behaviors. However, it is unreal to understand those using cameras in a private space such as room environment. Moreover, we cannot use cameras in the problems of noise removal or occlusions that the present image processing technology cannot resolve.

In this paper, we propose the algorithm of behavior labeling based on time-series data more accurately by applying the algorithm using SST (Singular Spectrum Transformation) proposed by Ide et al.[1],[2] to our previous time-series data clustering method using HMM (Hidden Markov Model)[3].

II. SENSING ROOM -THE EXPERIMENTAL ENVIRONMENT

Our research group utilize "Sensing Room"[4] as the experimental environment in which the daily behaviors are accumulated. This environment has one room assumed to live alone, and there are much furniture (bed, television, game, PC, desk, table, chair, sofa, refrigerator, microwave oven, drawers, citchen cabinet, component stereo, toaster, table lamp and shoebox) and sinks in the room, so we can live in the room like daily life.

We show the overview of Sensing Room in Fig.1 and the modules in Sensing Room in Fig.2.

Fig. 1. Overview of Sensing Room

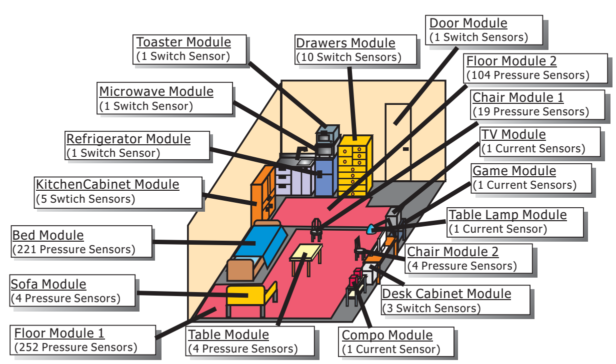

Fig. 2. Modules of Sensing Room

Pressure sensors are attached on the floor, the bed, the chairs, and the table, and pressure values are recorded as time-series data. There are switch sensors on the Refrigerator, the microwave, the drawers, the kitchen cabinet, and the door, and values of 1 or 0 are recorded according to opening and shutting. Electric power sensors are attached to the TV, the game, and the component, and values of electric power are recorded.

Data acquired by these sensors are accumulated in the server in the Sensing Room, and we can access to the data if necessary.

III. Time-Series Data Clustering using HMM

As described first, it is very important that an environment recognize our behaviors in daily life automatically. Our group proposed the method of behavior labeling in daily behavior data[3] that refers to time-series data clustering using HMM proposed by Smyth[5]. Recently, we proposed the algorithms of typical behavior extraction and anomaly detection based on massive quantities of data[6].

There are some reasons to introduce HMM for behavior labeling. One is that this method has a large degree of freedom to the time direction. Some lengths of behaviors are short and others are long, so it is difficult to decide a strict model that represent all behaviors.

Another originates the randomness of behaviors. It is difficult to provide the strict model that defines how a person moves. HMM is defined by probability and made allowing some noises, so it is very useful for our research group and we use it.

In the following, we explain our previous algorithm using HMM. The previous clustering method divides time-series data in segments of equal length, and at the same time, HMM is made from the whole time-series data. We compare the HMM with each data segment using Forward-Algorithm and calculate likelihood vector. These likelihood vectors distributed to the each behavior label using k-means method.

The problem of our previous method is that the labeling of behavior is not necessarily accurate. Fig.3 shows 4 patterns of such non-accurate examples.

First pattern is that change-points are correct but labels are wrong (pattern (a)). This is chiefly because of the clustering using k-means method. This happens because one behavior cluster is absorbed to another big cluster.

Second pattern is that labels are correct but change-points are wrong (pattern (b)). This is because of the accuracy of segments division. It is also because the change of behaviors that changes in a short time are active and it is hard to decide change-point.

In addition, there is a problem that a same label is divided into two or more labels (pattern (c)). It is because a behavior divided by the noise of data or long-term changes.

Finally, there is a problem of the change point disappearance (pattern (d)). It is because a degree of change is too small, and the system cannot distinct change-points, so some behaviors are thought to be same label.

To resolve these problems, we introduce the change-point detection method using SST (Singular Spectrum Transformation). We explain the details in the next chapter.

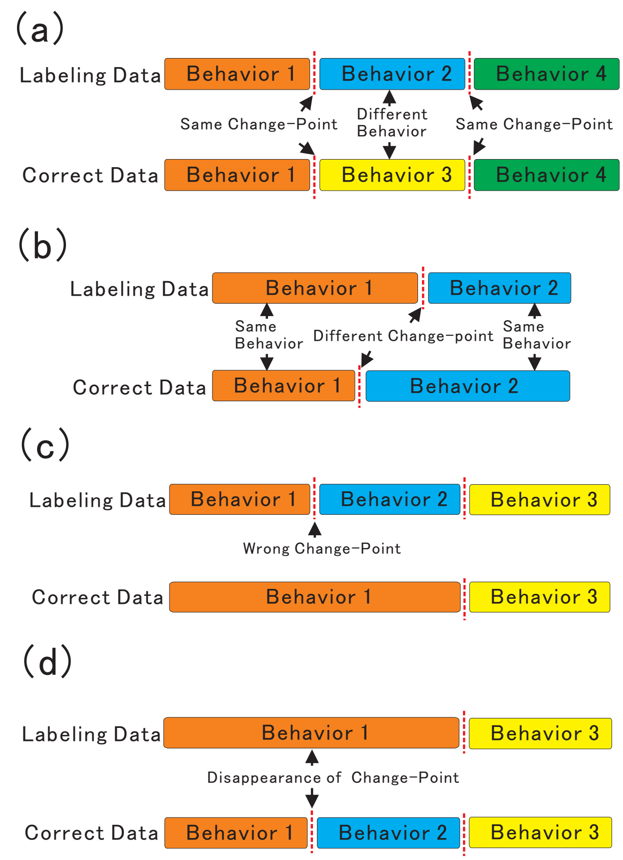

Fig. 3. Examples of Wrong Annotation ((a):Change-Point:same, Label:differnt, (b):Change-Point:differnt, Label:same, (c):Wrong Change-Point, (d):Disappearance of Change-Point)

IV. Change-Point detection using SST (Singular Spectrum Transformation)

A. *Change-point detection algorithm*

In the field of the feature extraction, SSA (Singular Spectrum Analysis) is generally used well. This method extracts pattern features based on making Hankel matrix for time-series data and SVD(Singular Value decomposition).

Moskvina et al. utilize this algorithm for change-point detection[7], and Ide et al. apply this to dynamic time-series data (discrete, continuous, noisy etc.). They proposed the method of knowledge discovery[1], and the method of speeding up change-point detection[2].

In this paper, we aim at more precise labeling of time-series data using SST compared with our previous method referring to the algorithm Ide et al. proposed([1],[2]).

B. *Outline of SST*

Based on the principle of the framework of Ide et al., we constructed a new behavior change detection method.

The overview of this method is shown in Fig.4.

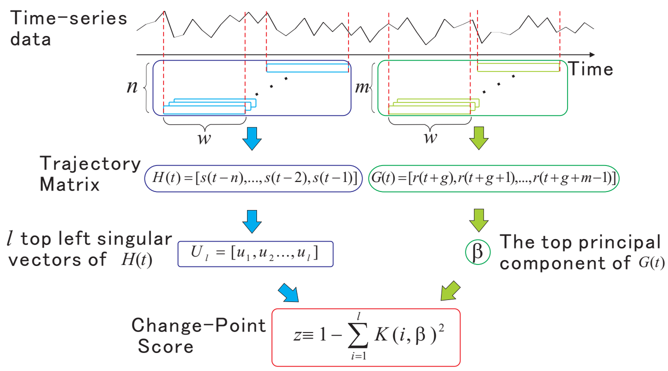

Fig. 4. Overview of SST

Firstly, for the time-series behavior sensor data x , we think $T = x(1), x(2), \cdots, x(t), \cdots$, and a subsequence of length w as $x(t-w), \cdots, x(t-2), x(t-1)$ from T. We represent a row vector as

$$s(t-1) = (x(t-w), \cdots, x(t-1))^T \tag{1}$$

We arrange these vectors and make Hankel matrix as

$$H(t) = [s(t-n), \cdots, s(t-2), s(t-1)] \tag{2}$$

This matrix is called as "Trajectory Matrix" in here. Trajectory matrix express various patterns from time $t-1$ to $t-w-n+1$.

To extract a past typical pattern from a trajectory matrix, Ide et al. express typical pattern as a singular vector of trajectory matrix $H(t)$ by assuming it as linear combinations of $s(t_j)$. As a result, we find l top singular vectors and make matrix as

$$U_l = [u_1, u_2, \cdots, u_l] \tag{3}$$

Moreover, a present pattern is extracted as well as a past typical pattern. We take out m vectors of length w in neighborhood of time t and represent matrix as

$$G(t) = [r(t+g), r(t+g+1), \cdots, r(t+g+m-1)] \tag{4}$$

And we calculate top principal singular vector of $G(t)$ and represent it as $\beta(t)$. The normalized projection of test vector $\beta(t)$ onto the hyper plane made from U_l is represented as

$$\alpha(t) \equiv \frac{U_l^T \beta(t)}{||U_l^T \beta(t)||} \tag{5}$$

So we can define the change-point score as

$$Z(t) \equiv 1 - \alpha(t)^T \beta(t) \tag{6}$$

It is limited to the range from 0 to 1. It is large when present pattern is different from the past patterns and small when it is similar to the past patterns.

As Ide defined[2], in this paper, we think the change-point score as

$$z \equiv 1 - \sum_{i=1}^{r} K(i, \mu)^2 \tag{7}$$

One strong point of this method is that it is very robust, so we can introduce the method for complex time-series data. Moreover, it is possible to change the specification according to the usage, because we can decide the parameter of typical patterns.

C. Application of HMM

We apply HMM after time-series data are converted into the time-series change-point score using SST. Firstly, we decide the threshold of change-point score according to all score and adopt scores that are bigger than the threshold as change points. In these change-points, scores that are originated from "Movement" are removed, and we make HMM for each data segment that is separated by other change-points.

Fig.5 is the concept of proposed algorithm in this paper. We call this algorithm as "SST-HMM algorithm". We explain in detail in the next section.

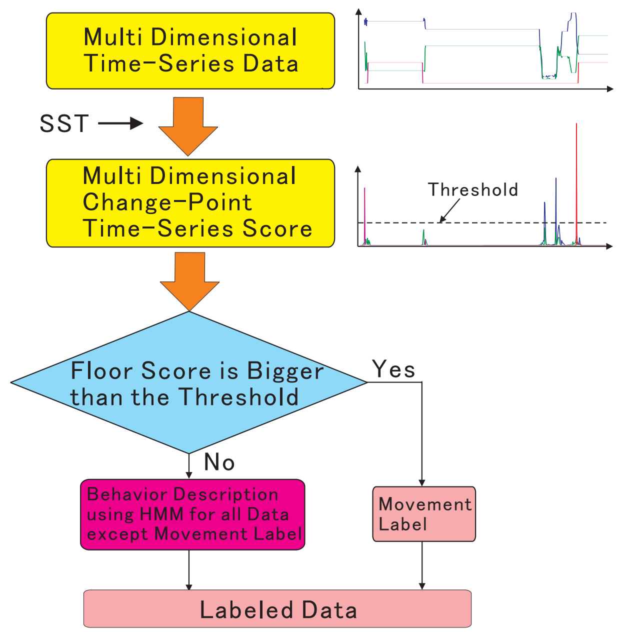

Fig. 5. Concept of SST-HMM algorithm

V. EXPERIMENT

In this section, we describe the experiment setup that SST-HMM algorithm is applied to the multi-dimensional time-series data.

Firstly, time-series data acquired in daily life based on Sensing Room as we described. In this experiment, we use Floor Module, Bed Module, Sofa Module, Television Module, Game Module and Door Module. The subject of this experiment is a man in his twenties, and as a restriction of the behavior, he was imposed to take meals indoors. Moreover, there is an alarm on the wardrobe in the room that rings at random. This alarm doesn't stop until a subject shakes for tens of seconds, and we imposed him that he must stops the alarm when it rings.

The subject lived in the room from 5:00PM to 1:00PM of the next day in the restriction, and the data of 18hours in total from 6:00PM to 0:00PM of the next day was adopted as experimental data. We recorded the behaviors in ten seconds as correct behavior data.

The data form obtained with the sensors in the Sensing Room is as TableI.

TABLE I
THE DETAIL OF SENSORS IN THE SENSING ROOM

Sensor Module	Sensor	Number of Sensors
Floor Sensor Module1	Pressure Sensor	252
Floor Sensor Module2	Pressure Sensor	104
Sofa Module	Pressure Sensor	4
Bed Module	Pressure Sensor	16
Table Module	Pressure Sensor	4
TV Module	Electric Power Sensor	1
Game Module	Electric Power Sensor	1
Door Module	Switch Sensor	1

The sensors of bed, sofa, TV, game are processed from pressure values or electric power values to binary data. It is important for these sensors to judge that a behavior happen or not (bed sensor judges a person sleeps or gets up, for example) and it is not important minute change of sensor value. So we calculate the average for each sensor, and change a datum to 1 if the value is bigger than the average and to 0 if the value is smaller than the average.

SST is applied to the data of seven dimensions, and we detect change-points using SST. Noises and minute changes are included in change-point score data. They should not be counted as change-points, so we take the average of the score and sift these change-point score data. If a change-point score is bigger than the average, it is counted as change-point.

”Movement” label is special among other change points of behaviors, because other behaviors are these of staying in one place (”Out of the room” label is also thought to stay in outside) but sensor values of ”Movement” label changes fluidly, so it is difficult to represent ”Movement” label for the various data patterns.

Then, we pull out the change-points that originate in the floor sensor as ”Movement” label among the all change-points of behaviors. And other change-points are thought to be these of behaviors except ”Movement”. We introduce our previous labeling method using HMM for the data segments divided according to the change-points, and decide all behavior labels combined labels decided from HMM algorithm with ”Movement” label.

VI. EXPERIMENTAL RESULTS

A. Behavior labeling using HMM algorithm

In the following, we show the result of behavior labeling using our previous HMM algorithm.

There are three parameters we should decide for the HMM clustering algorithm. One is the state number of HMM, and the length of each segment, and finally Number of clusters in clustering. Firstly, we think number of clusters in clustering. As the behaviors in the room, we think 9 behaviors, ”Sleep”, ”PC(Works at the desk)”, ”TV”, ”Game”, ”Works at the table”, ”Rest at the sofa”, ”Facial or Hand Washing”, ”Stop Warning” and ”Out of the room” shown in Fig.6. And there are ”Movement” between behaviors, so number of clusters are decided 10. According to the number of clusters, state number is fixed to 10. Moreover, minimum time of a behavior is thought to be 10 seconds, so data are separated into 6480 segments, and the length of each segment is 10 seconds.

The result of behavior labeling using previous HMM algorithm in Fig.7. And Fig.8 is the result of correct data of daily life. In each Figure, the behavior of 1 is ”Sleep”, 2 is ”PC (Works at the desk)”, 3 is ”Watching TV”, 4 is ”Playing game”, 5 is ”Works at the table”, 6 is ”Rest at the Sofa”, 7 is ”Movement in the room”, 8 is ”Facial or hand washing”, 9 is ”Stop Warning” and 10 is ”Out of the room”.

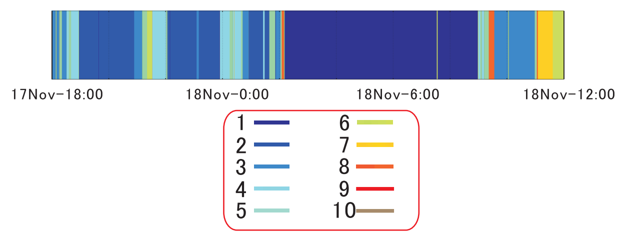

Fig. 7. The result of behavior labeling using HMM algorithm

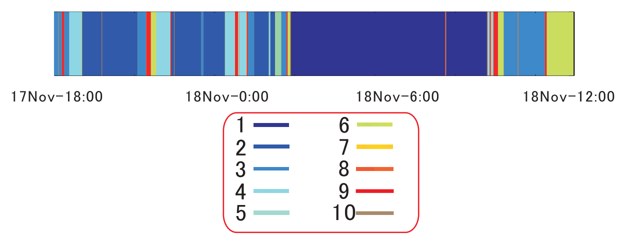

Fig. 8. Correct data of daily life

In this paper, F-measure is used to evaluate whether each behavior correspond to correct answer. It is calculated based on Recall R and Precision P, and it is shown as below.

$$F = \frac{2RP}{(R+P)} \tag{8}$$

$$Recall = \frac{t_p}{t_p + f_n} \tag{9}$$

$$Precision = \frac{t_p}{t_p + f_p} \tag{10}$$

Parameters t_p, f_p, f_n is defined as Fig.9.

The result of F-measure is shown in TableII.

The F-measures of behaviors that continue for a long time (Sleep, TV, Rest at the sofa) are comparatively high. The sensor values of these behaviors hardly change when behaviors continue, so the results become well. On the other hand, the F-measure of the behaviors that happens a little are low or 0. As described first, these behaviors are misidentified to other behavior cluster and misunderstood because of the wrong change-points.

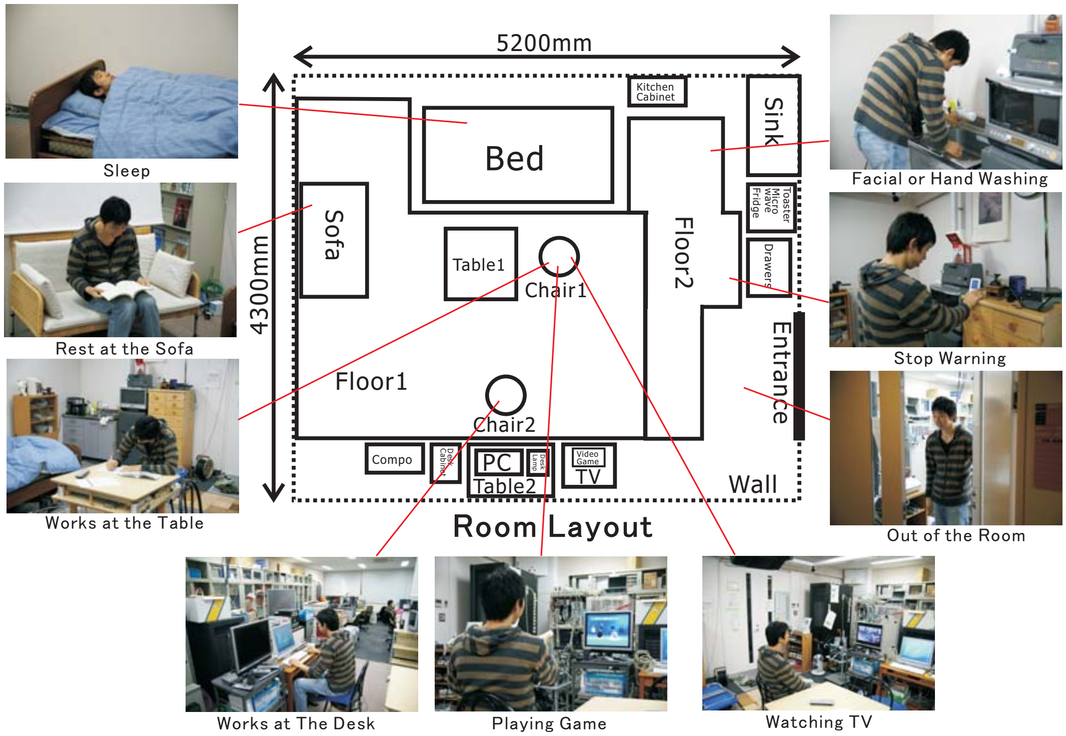

Fig. 6. Behaviors in the room

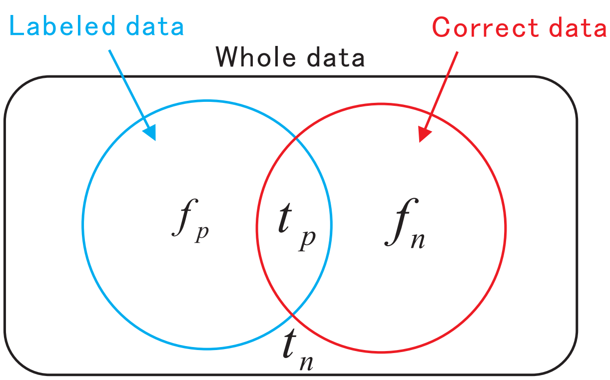

Fig. 9. The explanation of F-measure parameters

TABLE II

THE RESULT OF F-MEASURE USING HMM ALGORITHM

Label	Recall	Precision	F-Measure
1 Sleep	99.9%	99.8%	99.2%
2 PC(Works at the desk)	77.8%	100.0%	87.5%
3 TV	99.8%	96.82%	98.2%
4 Game	0.0%	0.0%	0.0%
5 Works(at the table)	55.9%	99.6%	71.6%
6 Rest(at the sofa)	99.5%	98.7%	99.1%
7 Movement in the room	29.2%	7.1%	11.4%
8 Facial or Hand Washing	0.0%	0.0%	0.0%
9 Stop Warning	0.0%	0.0%	0.0%
10 Out of the room	98.0%	74.9%	84.9%

B. Behavior labeling using SST-HMM algorithm

The result of Behavior labeling using SST-HMM algorithm is shown as below.

By compared this figure with correct data(Fig.8), almost all data are recognized correctly.

Next, the results of introducing SST-HMM algorithm are shown.

Fig.10 is the result of change-point detection using SST.

The score changes like this figure for each time. As described in Fig.5, the label concerning "Movement" is removed from this score, and the labeling using HMM is introduced for other data segments.

Fig.11 is the result of behavior labeling using SST-HMM algorithm.

Table.III shows the result of F-measure using SST-HMM algorithm. In this table, the labels of "Game", "Facial or Hand

TABLE III

THE RESULT OF F-MEASURE USING SST-HMM ALGORITHM

Label	Recall	Precision	F-Measure
1 Sleep	99.9%	100.0%	99.9%
2 PC(Works at the desk)	78.4%	91.3%	84.3%
3 TV	99.6%	70.5%	82.6%
4 Game	100.0%	97.4%	98.6%
5 Works(at the table)	85.9%	19.7%	32.1%
6 Rest(at the sofa)	74.4%	99.7%	85.2%
7 Movement in the room	72.3%	58.0%	64.3%
8 Facial or Hand Washing	42.8%	100.0%	60.0%
9 Stop Warning	62.9%	94.4%	75.5%
10 Out of the room	98.0%	99.2%	98.8%

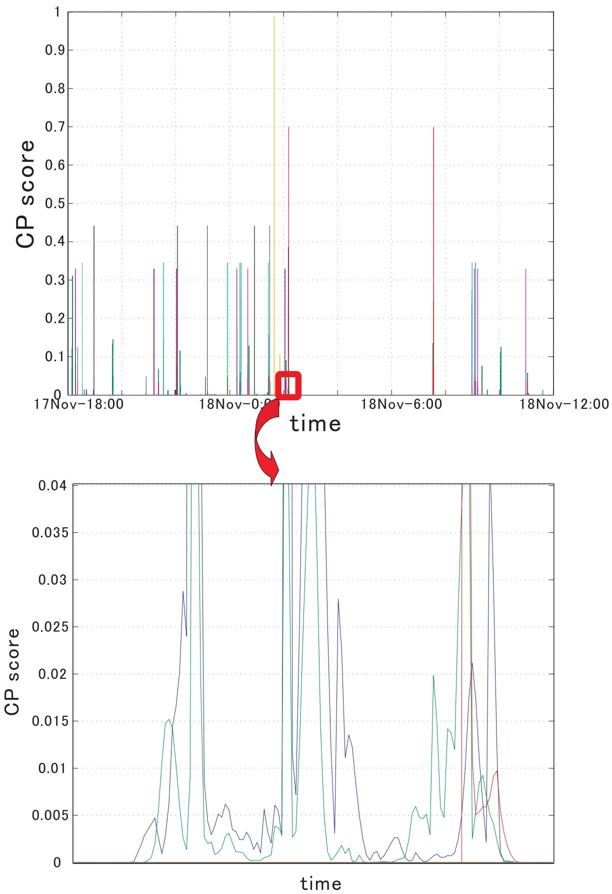

Fig. 10. CP score using SST

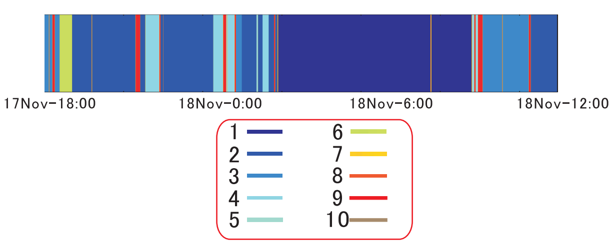

Fig. 11. The result of behavior labeling using SST-HMM algorithm

Washing", and "Stop Warning" that are not recognized are correctly recognized. And F-measure of "Movement" label that is not high when using previous method is high, so this shows it is useful making change-point detection and behavior labeling.

On the other hand, there are labels these F-measures are lower than these using our previous method, especially the label of "Works at the table". "Works at the desk" and "Works at the table" are only decided using floor sensor, and the positions of chairs where these works happen are near compared with other positions, so it is thought that "Works at the table" label is misidentified to the label of "Works at the desk".

One method to improve this is to introduce another sensor that is used in this experiment. We think to enable the understanding of more detailed behaviors. And it is also a problem in accuracy of clustering. It is not a flexible design to decide the number of clusters in clustering in advance. We thought it is more preferable to be able to introduce the clustering method that changes the number of clusters according to applications or the model of behaviors.

VII. Conclusion

In this paper, to resolve the problems of change-point gap, disappearance, wrong labeling in our previous method, we introduced the change-point detection algorithm using SST, and enabled more precise change-point detection and the behavior labeling using it.

As the future tasks, it is not necessarily useful in the purpose of detection of change-points using k-means method our research group has used. That is, when more behaviors are thought by clustering than these in this experiment, number of clusters is not sufficient and the system leads inevitably wrong labels or detect wrong change-point. If the system can detect correct change-point, it is possible to make an algorithm that learns behaviors by preserving the behavior between the change points beforehand as a template or removing outliers when a new label comes and registering the behavior as a new template.

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