Figuring Out Conscientious Degree from Brightness Distribution in IADL

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***Abstract*—Because of the rapid increase of the elderly, the lack of helpers to take care of the elderly has become a serious problem in Japan.. A way should be found to enable the elderly to be independent as long as possible. The paper refers to the motivation to keep the quality of life high as living willingness. The elderly with living willingness would keep their living environments comfortable. On the contrary, the elderly losing their living willingness are likely to make disorder in their house keeping, such as lazy cleaning and skipping of dish washing. The detection of the disorder of their daily activities makes it possible to find the decline of their living willingness early, because the disorder implies their physical and mental health get worse. Instrumental Activities of Daily Living (IADL) plays an important role to find the disorder. The activities are conducted to improve the quality of life. The laziness of the elderly in IADL implies they are losing their motivation to improve the quality of life. The paper proposes a method to recognize IADL, preserving the privacy of the elderly. It also figures out conscientious degree the elderly take IADL. The method uses the brightness distribution sensor. It provides a classifier of IADL from the brightness distribution. In an experiment for the elderly, the f-measure with which the method has recognized activities of cleaning, cooking, and washing are 0.975, 0.912, and 0.927, respectively. The experiment shows 0.599 in Nagelkerke R^2, which indicates how well the method figures out conscientious degree in the activities. It reveals the method is precise enough to measure the decline of the elderly in the living willingness.**

Keywords–Elderly; Daily Living; Privacy; Brightness; Sensor;

I. INTRODUCTION

Japan is suffering from a rapid progress of declining birth rate and increasing an aging population. As a result, it is worried that Japan will be short of nursing care staff by 2025. It is highly required to take measures to improve the self-supporting degree of each of the elderly, which means how an elderly person can spend his or her daily life independently [1]. Especially, it is essential to prevent the elderly from running into a condition where they require long-term and constant care in daily activities. To achieve the goal, it plays a vital role to find symptoms of the decline of their health condition from their daily activities. We should pay special attentions to the elderly living alone, because it is difficult to find symptoms of their decline. As one of the symptoms of the decline, the elderly tend to lose their motivation to keep high quality of their life. The paper refers to the motivation to keep the quality of life high as a “living willingness.” The decrement in the living willingness of the elderly appears in their daily life. It is verified that the elderly could be in unhealthy condition physically and mentally when a living rhythm changes into disordered manner. Moreover, a lazy lifestyle negatively affects the self-supporting degree and the health of the elderly [2].

If we could notice that one’s lifestyle is becoming disordered manner, various measures can be taken to recover their living willingness. Lawton [3] has pointed out the Instrumental Activities of Daily Living (IADL) are effective to judge the self-supporting degree of the elderly. IADL are not essential to keep our life. However, if we carry out them, we can improve the quality of our life. Examples of IADL include cleaning and washing. Let us consider to measure the degree of carrying out IADL in terms of not only the frequency of the execution, but also the conscientiousness in the execution. If the degree of a specific elder person is high, we can estimate he or she is willing to enjoy daily life. On the contrary, an elderly person whose degree is getting worse is worried to lose the living willingness. The degree of carrying out IADL is considered to imply symptoms of the decline of the elderly. It is expected that we can find the elderly who have just started losing their living willingness. Furthermore, it is also expected to provide some measures to recover their living willingness. There are many works that apply IADL to detect the changes of the elderly such as abnormality in health conditions [4][5]. They examine the frequency and the execution time in each IADL action. This paper proposes to use IADL as an index of the living willingness of the elderly. It examines the conscientious degree of IADL in addition to the frequency and the execution time. It is thought that the elderly who carry out IADL less conscientiously is going to stop IADL actions eventually. The examination of the conscientious degree of IADL will contribute to the detection of the declines of the elderly in the earlier stage with higher accuracy.

This paper focuses on cleaning actions among the IADL actions. First, cleaning action is identified with the machine learning and extracted from many living daily activities. The conscientious degree of a cleaning action is figured out from the characteristics of the action during the cleaning period. This paper proposes a model to identify the conscientious degree. The method uses the brightness distribution sensors [6] to collect movement logs in order to protect the privacy of the elderly. The brightness distribution acquired by the sensors brings information significant enough for a machine to discern living activities, while it makes no meanings for humans to perceive what the elderly are doing.

This study figures out the conscientious degree with the difference of the body trunk movement of the person carrying

 ISBN: 978-1-61208-426-8

out of the living activities. The method can discover symptoms of the decline in the early stage, using both of the execution degree and the conscientious degree.

The remainings of the paper are organized in the following way. Section II describes the related works. Section III explains the method to discern the living activity, using brightness distribution sensors. It also states how to figure out the conscientious degree of discerned cleaning actions. Section IV illustrates the process of an experiment to evaluate the proposed method along with its result, followed by discussion of the result in Section V. Section VI concludes this paper.

II. RELATED WORKS

There is a method to automatically recognize activities of the elderly in daily life with cameras set up in their house [7]. The camera acquires a lot of information unrelated to activities of them from their daily life. Since the method pays little attention to the privacy of the elderly, it causes the elderly to be stressed. It is not preferable to set up a camera in a house. A method to recognize living activities with a Kinect sensor [8] also has the problem in the viewpoints of the privacy protection, because it acquires a lot of irrelevant information as well as the camera. Techniques to recognize actions at home protecting the privacy are proposed with acceleration sensors [3], infrared sensors [9], and laser range finders [10]. Acceleration sensors measure the movement of persons who wear them in their body. They cannot acquire any data unless they are worn. Some of the elderly feel resistance to wear them, while others forget to wear them. The amount of data infrared sensors acquire is small and its accuracy is poor. It is difficult to figure out living willingness with the sensors due to the poor accuracy. Though they can be applied to the detection of emergency such as accidents and spasms, it costs high to set up many of them in various places to overcome their poor accuracy. Laser range finders implement data acquisition in a wide range. However, it is unrealistic to install many of the sensors to detect actions, because they are expensive sensors.

III. FIGURING OUT CONSCIENTIOUS DEGREE FROM BRIGHTNESS DISTRIBUTION

A. Brightness Distribution Sensor

The method uses brightness distribution sensors [6] to protect privacy of the elderly. Figure 1 shows the difference of the acquired data between a Web camera and a brightness distribution sensor. The brightness distribution sensor acquires only the brightness value in the horizontal dimension. It recognizes a person, utilizing the fact a brightness value changes largely at the position where the person moves. Two brightness distribution sensors are settled so that the center lines of the data acquisition areas of each sensor should cross almost orthogonally. The volume of information of the sensors is less than that of cameras because they acquire only brightness. Privacy is threatened with malaise of the acquired information by outsiders. Even if outsiders get the brightness information showing activities of a specific person, they do not understand what the person does. Brightness distribution sensors can be set up inexpensively, because we can covert commercial web cameras into brightness distribution sensors, exchanging their lenses into rod lenses. A lot of sensors are not required because they acquire as wide range data as the web cameras. The sensors save space, because a small sensor covers a wide rage.

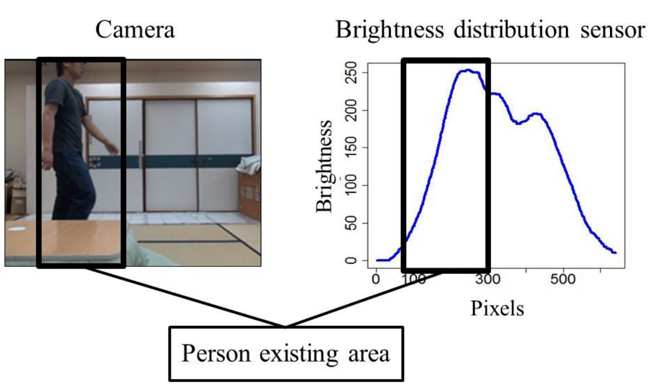

Figure 1. Difference between Web camera and brightness distribution sensor.

B. Activity Classification from Local Features

The method uses the Bag-of-Features method [11] to extract a peculiar feature from the brightness data of each living activity. Each pixel of figures has various properties. First, the Bag-of-Features method clusters pixels of figures into several groups, based on the properties. It figures out the histogram of each figure, counting points in every cluster. The distinguishes images with the features in the shape of the histogram. The proposed method calculates the three local features for each pixel, consisting of background difference values, pixel difference values, and frame difference values. Three local features are the main elements that can be taken from the brightness data. The background difference values are picked up from the difference of the target image from an image containing no living activity. The pixel difference values and the frame difference values are derived from special difference and temporal difference of the background difference value. These local features compose a three dimensional space. Let a brightness value be $b(f,p)$, where p and f denotes the pixel number and the frame number, respectively. Let us denote the background difference value, the pixel difference value, and the frame difference value with $B_s(f,p)$, $P_s(f,p)$, and $F_s(f,p)$, respectively. Three local features can be expressed in (1)-(3), when the number of the frame showing the background is assumed to be 0.

$$B_s(f,p) = b(f,p) - b(0,p) \tag{1}$$

$$P_s(f,p) = B_s(f,p) - B_s(f,p-1) \tag{2}$$

$$F_s(f,p) = B_s(f,p) - B_s(f-1,p) \tag{3}$$

The background difference value is a feature corresponds to the existence of a person. The pixel difference value expresses the edge of position where a person exists. The frame difference value shows the movement of a person. Pixels represented with the three values are plotted in the three dimensional space. All points are clustered using k-means++ [11]. The histogram indicating the number of points included in each cluster is constructed to show the distribution of points for each image. The histogram does not provide any location information, which is important to identify living activities. For instance, the information is important when we want to distinguish living activities in which a person moves around the entire room like cleaning from living activities executed at specific locations like washing. The method reflects the location information dividing the image into parts equal in

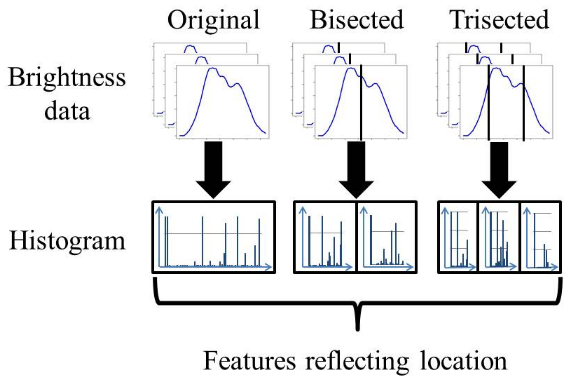

Figure 2. Constructing histogram from division brightness data.

their width. A histogram is constructed from each of them [12]. Figure 2 depicts the outline when the division is applied to the original brightness data. The original brightness data corresponding to the whole of the acquisition area are bisected and trisected in the proposed method. Eventually, six histograms are constructed from a single sensor. The method acquires 12 histograms from one living activity because it uses two sensors. Due to the division of brightness data, features representing person movement appears in all of the six histograms in living activity where a person moves around the entire room like cleaning, while those features appears in specific histograms in case of washing in which a person stays in a specific location. The proposed method constructs a model to identify features of each living activity with the Random Forest method [13]. The model calculates which living activity has been executed, given features in an actual living activity.

C. Figuring Out Conscientious Degree from Flow Line

The proposed solution pays attention to the conscientious degree in the living activity to find a smaller change in the living willingness. Each living activity has its own index to represent its conscientious degree. The method figures out the conscientious degree of each living activity where the person would move around in the room. Among various kinds of living activities, it focuses on cleaning, because it is an essential activity to improve the quality of the life. It pays an attention on the body trunk, which is the most important part for human beings in various living activities.

First, the method presumes the location of the body trunk of a target person from the brightness value in each sensor. Since the brightness value greatly changes at the position the person exists within the range of the sensor, the location of the body trunk is estimated at the position where the change of the brightness value is largest, that is, the position with the maximum background difference value. The position of the body trunk, T, is given by (4).

$$T = \underset{0 \leq p \leq 639}{\arg\max} |B_s(f, p)| \qquad (4)$$

Next, the flow line of the body trunk is constructed, arranging the position of the body trunk all over the frames in the time series order. The proposed method figure out the conscientious degree of the living activities where a person moves around in the room like cleaning. Using the Hidden Markov Model (HMM) [14], the method derives a state change diagram to consider staying and movement of the person in a flow line. The example of the state change diagram the HMM converts from flow lines is shown in Figure 3. The graph of a flow line in the figure indicates the position of the body trunk in the course of the time, assuming the horizontal axis and the vertical axis are the time line and the pixel number, respectively. The state change diagram implies the flow line in the figure roughly has three states. The change of the mean and the variance expresses a significant state change. The change of the mean means the body trunk moves to another position, while that of the variance corresponds to the change in the width of operation of the body trunk. The conscientious degree of the living activity is figured out from the two kinds of state changes. The transition probability is used to examine the relevance among states. The transition probability to a different state is considered to represent the movement order and the work procedure in the living activity, because it is influenced by the position of the body trunk and the change in the width of operation. It is not considered as the feature of each person, because it varies easily with the order and the combination of living activities. The proposed method values the transition probability from one state to the same state, which is referred to as the self transition probability. When the person stays in a specific point, the self transition probability is considered to indicate the location and the time period of the stay, because it gets little influence from the position of body trunk and the change in the width of operation.

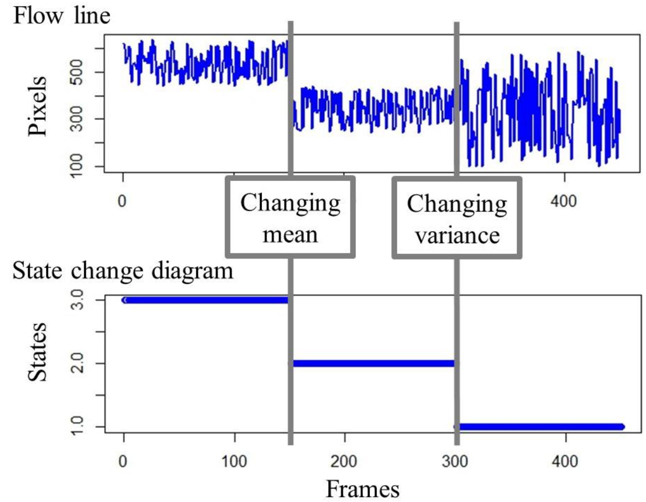

Figure 3. State change diagram converts from flow lines.

Regarding the self transition probability as the feature of the living activity of each person, the proposed method calculates the self transition probability of each state from the two state change diagrams associated with the two sensors. A model is constructed to figure out the conscientious degree of a specific cleaning activity where the person move around the room. The model assumes the self transition probability in each state is the explanatory variable while the conscientious degree is the objective variable. The model uses the logistic regression [15], because the objective variable is a qualitative variable. The combination that minimizes the Akaike Information Criteria (AIC) [15] is selected from two or more explanatory variables, to construct a model which predicts the conscientious degree of the living activity.

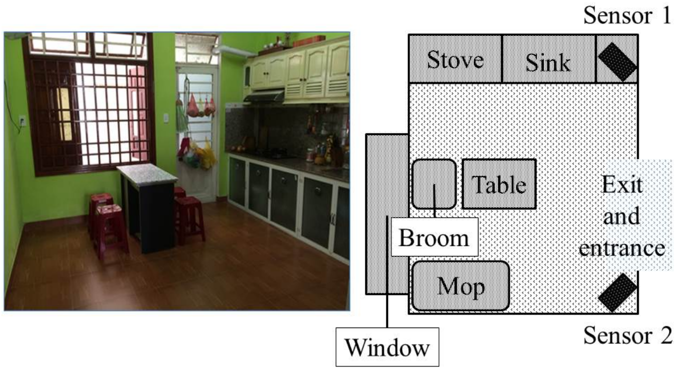

Figure 4. Experimental environment.

IV. EXPERIMENT

A. Purpose and Process

We have verified living activities can be identified with the brightness distribution with an experiment. Using the data collected in the experiment, we examine whether the conscientious degree is able to be estimated from the difference of the body trunk. Figure 4 shows the experimental environment, which is an actual dining-and-kitchen space. The photograph in the left side shows the view taken from the exit and entrance of the floor plan in the right side. The movable space of the experimental environment is a 3 meter square. To decrease the blind spot, a brightness distribution sensors is installed at each of the 2 corners of the space. Each of them is mounted at a point of 80 centimeters in height. Subjects of the experiment are 20 elderly people consist of 8 men and 12 women whose ages range from 60 to 70 years old. In the experiment, subjects conduct three living activities: cleaning, cooking, and washing, according to the standard of IADL. In the cleaning, each of them wipes the entire floor with a mop, after sweeping with a broom. In the cooking, each of them breaks an egg into a bowl to mix with favorite seasonings. The subject flies it and dishes it up. The washing makes each of them keep washing tablewares at the sink. Each of the subjects repeats every living activity 3 times, each of which is finished within 3 minutes. A whole experiment for one subject is organized within 60 minutes so as to prevent the conscientious degree of the activities from varying with their tiredness. The number of times and the length of the activity time is determined in consideration of the load of the subjects.

B. Evaluation

With the Bag-of-Features method, we detect living activities from features in the brightness distribution values sampled in the experiment. We have determined to classify the brightness distribution values into 25 groups after the examination of all combinations. We have used the 20 fold cross validation so that all 20 experiment participants may become test data to evaluate the generalization performance. The algorithms used for the detection are the Random Forest [13], the Naive Bayes classifier [16], and the linear Support Vector Machines [17]. These algorithms are suitable for the detection of living activities because they are known to provide high performance under a lot of objective variables. The performance of the proposed method is evaluated by the f-measure, which is the harmonic average of the precision and the recall. The precision is an index that shows the accuracy of the result because it is the ratio of target actions in actions detected by the method. Recall is an index that shows the coverage of the result because it is the ratio of detected target actions in target actions to be detected by the method. We should take a good balance of the precision and the recall. Even if the precision is high, we are not sure how many target actions to be detected are covered by the detected actions. The f-measure presents the balance of the precision and the recall.

We have paid a special attention to the cleaning to know the conscientious degree of each subject, because it is one major instance of IADL a lot of people take in daily life. It is thought that the cleaning is effective to judge the conscientious degree for almost all persons. In the experiment, cleaning of each subject is recorded with as a video movie to ask people watching it on the conscientious degree of the subject as a questionnaire. The questionnaire asks 15 twenties consisting of 12 males and 3 females to evaluate the conscientious degree of the cleaning of each subject with 5 ranks. Based on the rounded average of their evaluation, we regard the elderly ranked at 4 or more as highly conscientious, while ones ranked 2 or less as poorly conscientious. We have also examine common features for subjects of high conscientious degree and ones of low conscientious degree, to find a criterion to distinguish subjects with the conscientious degree. Focusing on the movement of subjects in the experiment space, we apply the HMM to find the criterion. The HMM decides the state transition in the time series with the Viterbi algorithm after presuming parameters concerning to the state with the Baum-Welch algorithm [14]. Applying the Baum-Welch algorithm to all subject flow line, states are identified in the flow lines representing the movement of subjects. The transition of identified states in each flow line is figured out with the Viterbi algorithm to each flow line of all participants. In the HMM, when we assume too few states, we cannot see any difference among subjects, because each subject stays in specific states too long. On the contrary, too many states make subjects stay in every state too short. In both case, we cannot find any difference among subjects. After trials for all combinations, we have determined 5 is the best number of states to find difference in each subject. If many subjects of high conscientious degree stay in a specific state, the state indicates the feature of the high conscientious degree. The proposed method examines the self transition probability of each state. To predict whether each subject is conscientious or not, it builds a Logistic regression model whose explanatory variables are the self transition probability. It selects combinations of two or more explanatory variables which minimize AIC. The combination of the explanatory variables provides the laergest influence on estimation of the conscientious degree. We calculate Nagelkerke R^2 [18], which shows the degree of fit of the model made by Logistic regression. Nagelkerke R^2 takes the value between 0 and 1. The more it approaches to 1, the better the degree of fit of the model.

C. Result

Table I shows the f-measure values in the detection using the three Supervised learning algorithm. As the table shows, Random Forest is superior to the others. In all kinds of the living activities, the f-measure values exceeds 90 percent when Random Forest is used. The conscientious degree is high in 6 subjects and low in 3 subjects from the result of the question-

TABLE I. F-MEASURE VALUES IN THE DETECTION USING THE THREE SUPERVISED LEARNING ALGORITHM.

	Cleaning	Cooking	Washing
Random Forest	0.975	0.912	0.927
Naive Bayes classifier	0.830	0.793	0.705
Linear Support Vector Machines	0.942	0.897	0.874

TABLE II. CRITERIA OF THE CONSCIENTIOUS DEGREE IN THE QUESTIONNAIRE.

	Number of cases
Fineness in movement of hands	10
How to put force	8
Area within the range of action	7
Fineness in movement of body trunk	7
Repetition degree within the area of action	4
Length of time	3
How to wash mop	3
Presence of periodicity	1
Good quality of posture	1
Dustpan after sweeping with broom	1
Whether the cleaned place is seen or not	1

naire to 15 twenties. Table II shows the summary of the result in the criteria of the conscientious degree in the questionnaire. The table indicates the fineness of movement of hands and the body trunk are adopted as the criterion a lot of people. The conscientious degree decreases when the movement is too large. It justifies the proposed method uses the self transition probability to figuring out the conscientious degree, because the amount of movement influences on the staying time of each point. 5 states are derived, applying the HMM to the movement of each subject. The brightness distribution sensors used in the experiment represent the position of the body trunk with the angle ranging from 0 to 639, where 0 corresponds to the left side while 639 to the right side. Table III shows the mean and the variance of the position in each state for Sensor 1 and Sensor 2. We build several Logistic regression models to calculate the conscientious degree, specifying various combination of the self transition probability in states as explanatory variables. Among the models, the AIC gets minimum for the one in which we specify only the self transition probability of State 4 of Sensor 2 as an explanatory variable. It means the conscientious degree is best discriminated when subjects stay in State 4 of Sensor 2. The model figures out the conscientious degree, Pr_i, with

$$Pr_i = \frac{1}{1 + \exp(107.4 - 113.4 s_i)} \qquad (5)$$

where s_i is the explanatory variable. The fitting degree of the model is fairly good because Nagelkerke R^2 is 0.599. For each of subjects with the high and the low conscientious degree, Figure 5 shows the difference of the self transition probability of each state derived from Sensor 1, when the subject stay in State 4 of Sensor 2. In figure, a horizontal axis shows the IDs of the status of Sensor 1. The vertical axis shows the average probability of the subject staying in each state for both of the high and the low conscientious degree. In State 1 and State 5, there is a big difference of the average probability between subjects of the high and the low conscientious degree. Suppose a subject stays in State 4 of Sensor 2. From Table III, the subject staying State 1 derived from Sensor 1 should be located around B in Figure 5, while the location of the subject staying State 5 of Sensor 1 should be around A. These results

TABLE III. MEAN AND VARIANCE OF THE POSITION IN EACH STATE FOR SENSOR 1 AND SENSOR 2.

	Sensor 1		Sensor 2	
	Mean	Variance	Mean	Variance
State 1	231	540	120	672
State 2	303	406	174	140
State 3	366	281	222	294
State 4	444	792	337	1507
State 5	551	1845	489	3777

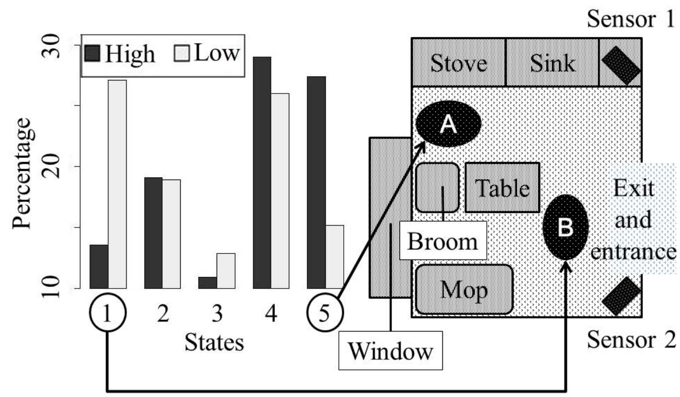

Figure 5. Difference of the self transition probability of each state derived from Sensor 1, when the subject stay in State 4 of Sensor 2.

imply subjects with the high conscientious degree are likely to stay around A, while ones with the low conscientious degree often stay around B. It can be said that the conscientious degree is judged high for subjects cleaning corner spots emphatically, while that of subjects staying in spacious parts is regarded low. The conscientious degree is understood from the length of the staying time in specific locations.

V. DISCUSSION

From the f-measure, it is thought that Random Forest is the best machine learning algorithm to be applied to detect living activities. The f-measure with Random Forest has reached over 90 percent for any examined activities. The method measures the living willingness from the transition of the execution degree calculated from actual living activities for the long term. For instance, suppose the elderly have engaged in specific activities regularly. It is thought that their living willingness decreases, if they get lazy for the activities for some time. The laziness is expected to be found without loss, because the detection accuracy exceeds 90 percent. The proposed method is practical enough. Among the examined activities, the cleaning is detected with the highest f-measure, 0.975. The cooking and the washing are inferior to the others, because the location of the subjects is similar in the activities. Since people cook or wash tablewares in the location far from the sensors, it is difficult for the sensors to recognize small movement of hands and arms in the activities. The activities might fail to match with pre-acquired features of any activity. It is necessary to select better sensor positions to make them recognize the small movement in the cooking and the washing.

In the model to discriminate the conscientious degree, we found State 4 of Sensor 2 has the best self transition probability. In the questionnaire, the conscientious degree of the cleaning is low when the movement of body trunk is too large. There are a lot of answers which value the width of

 ISBN: 978-1-61208-426-8

the movement area to judge the conscientious degree. It is thought the high conscientious degree is related to the staying time in the corner of the room. In the mean time, the time length of the cleaning is not mentioned as a criterion to judge the conscientious degree. It does not work as a criterion because we have specified the time length of each activity in the experiment, which makes the difference among subjects small. Nagelkerke R^2 of the model is 0.599. We can expect the improvement of its value, if we can add factors which are picked up as the criteria, but not incorporated in explanatory variables of the model. For example, we can incorporate the force subjects put during the cleaning, as shown in the second line of Table II, if we can sense it. It has been revealed subjects with the high conscientious degree differ from those of the low conscientious degree in terms of the location they stay. Subjects with the high conscientious degree stay longer in the corner of the room, because they clean the room carefully. On the contrary, subjects low in the conscientious degree stay longer in a spacious part of the room. It implies we can figure out the conscientious degree from the location subjects stay longer.

The proposed method assumes to learn the floor plan of the room beforehand. Even in the case the floor plan is changed, the method is applicable without trouble, if we specify the floor plan to the algorithm.

VI. Conclusion

The paper has proposed to detect living activities with brightness distribution sensors. It has also presented a method to figure out the conscientious degree of the detected activities. An experiment to evaluate the method reveals it can detect cleaning, cooking, and washing with 0.975, 0.912, and 0.927 in the f-measure, respectively. The method implies the conscientious degree can be figured out from the location of cleaning people. Our future work is to apply the method to more kinds of living activities in various places, to expand the coverage of the method.

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