Identification of Personal Actions with Brightness Distribution Sensors to Harmonize Domestic Affairs

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***Abstract*—There are many attempts to recognize actions using sensors in homes. Some of them aim to keep watching on the elderly living alone, while others try to bring ecological life, scheduling domestic actions consuming energy. We need an inexpensive method to make it prevail in the society. In the meantime, recognition results threaten privacy, if outsiders obtain them. Almost all people mind whether they are used in malicious ways. The sensor should prevent the leak of the privacy of users. This work proposes a method to recognize various domestic actions with a single kind of sensors, which is not only inexpensive, but also safe enough to protect the privacy. The method uses brightness distribution sensors presenting a sequence of cells, each of which indicates the brightness of one direction in the view area of the sensor. The method gets local features along with the persons who conduct domestic actions. The method enables to recognize both of domestic actions and the period in which they are conducted. To evaluate the accuracy of the method, 10 men and women have participated in an experiment, where they take various domestic actions in their own ways with 4 brightness distribution sensors installed on the wall of an actual kitchen. As a result, the method has marked high performance on the recognition of “vacuuming”, “cooking”, and “taking a rest”, along with their periods. The method also identifies all examinees who conduct them in high accuracy. It is possible to recognize domestic actions in actual home spaces.**

Keywords*–*Domestic action; Brightness distribution sensor.

I. INTRODUCTION

There are many attempts to recognize actions by robots [1], [2], sensing [3] and constructing Internet of Things (IoT) [4] in homes. Among them, recognition of actions by sensors in homes is expected to bring various benefits [5]. It allows us to keep watching of the elderly living alone, as well as to make domestic action schedules reducing energy consumption. In Japan where the ratio of the elderly is increasing rapidly, it is essential to keep watching of the elderly living alone, in order to find fatal accidents and mental decline due to loneliness. Energy saving is also inevitable for people in Japan lacking petroleum production. Inexpensive sensors would realize to keep watching the elderly, even if there are few persons to take care of the elderly. They would also contribute to using electricity efficiently in daily activities. The recognition of actions of each of family members would lead to accommodate the timing of actions of every member so as to minimize the energy consumption, avoiding degradation of the life quality of whole members.

On the other hand, recording of domestic actions has dangers to reveal the privacy of the family members to outsiders. They mind unexpected troubles caused by improper use of the records. Almost all people hate installing sensors which recognize domestic actions from the viewpoint of the privacy.

We need low cost sensors to recognize domestic actions with privacy protection. Nakajima et.al have developed brightness distribution sensors [6] to detect emergencies for the elderly, protecting their privacy. Using the brightness distribution sensors, this work presents a method to recognize domestic actions. The method identifies domestic actions along with persons who take them. A brightness distribution sensor has a field of vision like a camera. However, instead of a real image of the field, it produces brightness values of the field in one dimension. It protects the privacy because human beings cannot understand the brightness values. Brightness distribution sensors are realized inexpensively, changing lenses of web cameras into rod lenses.

The paper presents the practicability of brightness distribution sensors with the accuracy to recognize each of various daily life actions taken in an actual environment. We have experimented to distinguish 10 persons take various actions in an actual living space. The method has identified both of actors and periods of actions, such as “vacuuming”, “cooking”, and “taking a rest” in high accuracy.

Section 2 presents related works. The proposed method is explained in section 3. Section 4 presents an experiment to verify the effectiveness of the proposed method. In section 5, the paper discusses the experiment results. Section 6 concludes the work.

II. RELATED WORKS

In order to keep watching the elderly, a work presented in [7] has conducted a long term investigation to detect their accidents. Works presented in [8]–[11] utilize ubiquitous sensors to identify domestic actions. The work in [8] recognizes physiological actions, such as sleeping, meal, excreting, and bathing. It detects unusual conditions of the elderly with deviation from usual actions. It costs high for the method presented in [8] to recognize actions, because they use qualified sensors which are specialized to find feature of these actions. The method does not provide ability to generalize actions to be recognized, but recognizes only 4 actions. It also fails to recognize who takes the actions. It does not address the versatility of daily life actions. A visit of a person other than the family members may cause the method to present unexpected outputs. The work explained in [9] is similar to the previous one, because it keeps watching of the elderly, using accelerometers, video cameras, and microphones.

There is also a method to keep watching of the elderly with an integrated platform which manages energy and support for the elderly to live safely and comfortably [10][11].These method watches the elderly using image data, which a third person can understand.

There are methods to detect domestic actions in smart houses [12]–[15]. Family members can accommodate their energy consumption, following a schedule the method proposes. The methods should not present a schedule which is far from usual daily life [16]. Nakamura et al. proposes the method which integrates data by GPS, smart taps, and laser range

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scanners [12]. The method cannot identify who has conducted each of actions, even though it uses several laser range scanners which are expensive. Generally, there are more than family members in a house. The fail of recognition of actors prevents the method to present a schedule acceptable to all members. For example, let us consider a family where a specific person is in charge of house-keeping. If the method cannot recognize actors of actions, it might presents wrong schedule that makes other family members to take care of the house keeping.

There are methods to recognize domestic actions with smart meters which recognize electric power consumption of every electronic appliances[13][14].There is also a method to recognize domestic actions, measuring energy consumption of each appliance [15]. They cannot recognize domestic actions which do not consume electricity. It cannot provide proper services, due to the lack of the generality.

III. Recognition of Domestic Actions and Their Actors

A. Method overview

In the recognition of domestic actions, we should identify actors of the actions, and the periods in which actors take the actions. Various domestic actions must be recognized with a single kind of sensors to reduce the cost. Since actors are identified, we should provide a method to protect their privacy. The proposed method realizes the recognition with sensors which get brightness distribution. The sensors extract the brightness distribution from original images of target objects. Since it prevents the reconstruction of original images, it protects the privacy.

The method calculates a background difference of the brightness distribution acquired at home. It also calculates a spatial difference and a temporal difference. They include a lot of local features of domestic actions. Base on the Bag-of-Features, the method represents each of brightness distribution data the sensors sample at a specific time as a multi-dimensional vector. Clustering all of the brightness distribution data, the method calculates the centroid of each cluster. The centroids are standards to represent features of all brightness distribution data. For each cell in a specific brightness distribution data, the method searches the cluster nearest to the cell. Voting to the cluster, it constructs a histogram for the brightness distribution data. The features of a domestic action of an actor are represented with the histogram. It is considered features vary with actors and kinds of domestic actions. The shape of histograms is similar with each other when a specific actor takes the same kind of domestic actions. The method constructs a classifier to detect domestic actions and their actors from the shape of histograms. Actors take their domestic actions anytime. The method constructs histograms periodically to recognize domestic actions and their actors.

Figure 1 shows the overview of the method to periodically recognize domestic actions and their actors. Taking the average of the brightness vertically, brightness distribution sensors put out brightness distribution data which consist of an array of cells as many as the number of horizontal pixels of original images. The method installs brightness distribution sensors at home. It gets brightness distribution data of a background image at a situation which contains no target person or target object. The method also gets a time series of brightness distribution data at a situation where a specific actor is conducting each domestic action. The method calculates the background difference, subtracting the brightness distribution data at the domestic action from that of the background image. The background difference expresses values which change when the brightness distribution sensor captures persons and objects different from the background image are captured. We address

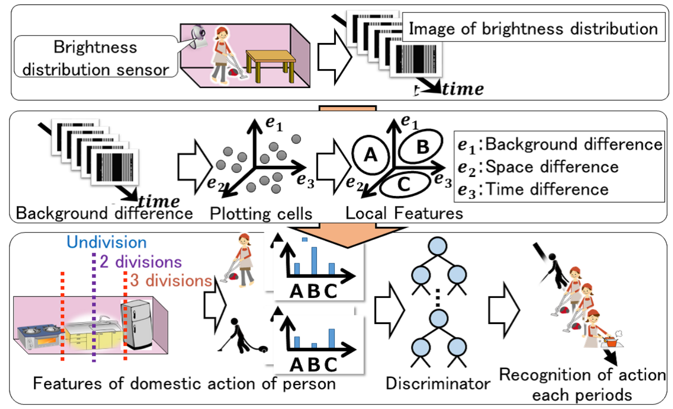

Figure 1. Method overview

three kinds of local elements corresponds to the appearance, the shape, and the motion from the background difference. The appearance is the background difference itself, the difference of the brightness of reflecting light of a target from that of the background. The shape is expressed with the spatial difference of the background difference. It is variation of the brightness of reflecting light affected by the shape of a target. The motion is expressed with the temporal difference of the background difference. The motion is the brightness variation of reflecting light affected by the motion of a target.

The method plots all cells of a time series of brightness distribution data in three dimension space whose axes are three local elements: the background difference, the position difference, and the time difference. The method classifies all cells in the three dimension space into clusters. The centroid of each cluster is the representative value of the cluster. On the basis of the centroids, the method recognizes features of a time series of brightness distribution data. Note that each centroid is also represented with a three dimension vector whose elements are the background difference, the position difference, and the time difference. For example, suppose the background difference and the position difference are 0 while the time difference is 10 in the centroid of a cluster. The cluster represents a feature pattern of motion. The method assigns the vector of each cell to the cluster whose centroid is nearest from the vector. Let us consider chronological brightness distribution data in a domestic action of a specific person. The method constructs a histogram which expresses the number of vectors in a time series of brightness distribution data. The shape of the histograms shows features of the domestic action of the person.

The method also considers where the person takes the action in the viewing field of the brightness distribution sensor. It divides an array of cells from a brightness distribution sensor into two and three parts in each period. It also constructs histograms from the divided cells. The method takes various histograms to construct a discriminator of actions and their actors with the Random Forest. The method gives histograms which are constructed with newly data of chronological brightness distribution into the discriminator. Providing a new time series of brightness distribution data for the discriminator, the method recognizes domestic actions along with their actors.

B. Brightness distribution sensor

The brightness distribution represents how brightness values distribute in an image of a target object. Suppose an image of a target represented with a matrix, like one taken with a Web camera. The brightness distribution is represented with an array of cells, each of which expresses the average

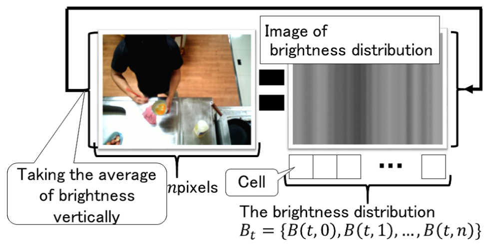

Figure 2. A brightness distribution sensor

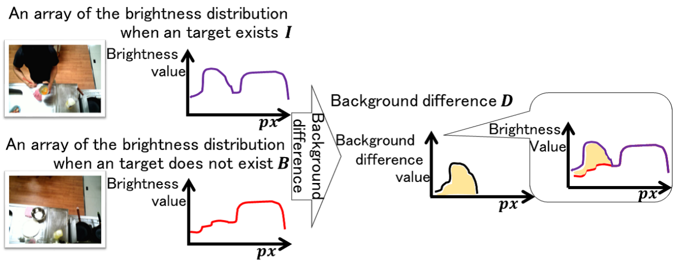

Figure 3. Background difference

of the brightness of the column corresponding to the cell. The result is an array of the brightness which spreads in the row direction. A brightness distribution sensor realizes the calculation optically, condensing vertical brightness with a rod lens [6]. Figure 2 shows information acquired with a brightness distribution sensor. Let n be the number of pixels in the row direction of the sensor. The brightness distribution at time point t, B_t, is formula (1) where $B(t,p)$ is the brightness of the p-th cell.

$$B_t = B(t,0), B(t,1), \cdots, B(t,n) \tag{1}$$

A brightness distribution sensor has three advantages in the recognition of domestic actions. First, a brightness distribution sensor covers a large angle in a room to recognize various domestic actions. It is programmable so as to recognize various actions with brightness features. It reduces the number of sensors required to recognize domestic actions. The sensor has high versatility to recognize domestic actions. Second, a brightness distribution sensor protects privacy. Since the brightness values are averaged optically for every cell, the third person cannot reconstruct an image of an actor taking a specific domestic action. Third, a brightness distribution sensor is inexpensive. We can implement a brightness distribution sensor, exchanging lenses of a web camera into a rod lenses. Utilizing the CMOS sensor of the web camera, we can make an inexpensive brightness distribution sensor.

C. Background difference

Figure 3 shows how to calculate the background difference. Let I and B are an array of the brightness distribution when an target exists, and that when the target does not exist, respectively. The background difference, D, is the difference of I from B. The recognition of domestic actions should not be affected by a background, such as the wall texture in a room. However, brightness distribution data contains both of moving objects and the background. Since background difference D contains no background information, it contributes to more precise recognition of domestic actions. Like the brightness distribution, background difference D is formula (2) where $D(t,p)$ is the background difference value of the p-th cell at time point t.

$$D_t = D(t,0), D(t,1), \cdots, D(t,n) \tag{2}$$

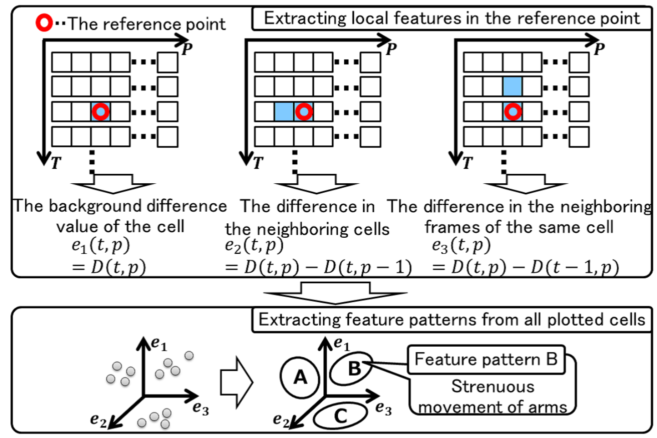

Figure 4. Extracting feature patterns from local elements

D. Extraction of feature patterns with local elements

Figure 4 shows how to extract feature patterns from local elements. Let $D(t,p)$ is the background difference of the p-th cell in the t-th frame of the chronological brightness distribution data recording a specific domestic action. For the cell, the method calculates three local elements: $e_1(t,p)$, $e_2(t,p)$, and $e_3(t,p)$. The first element, $e_1(t,p)$, is the background difference, which is given with (3).

$$e_1(t,p) = D(t,p) \tag{3}$$

It considers only the target, excluding the background, to show the appearance of the target. The second element is obtained with (4).

$$e_2(t,p) = D(t,p) - D(t,p-1) \tag{4}$$

$e_2(t,p)$ is the difference of the background difference value of the cell from the neighbor one. It corresponds to the spatial difference of the background difference value. Since the equation figures out the brightness difference in the neighboring cells, it contributes to recognizing the shadow of a target to show its shape. The third element is calculated with (5).

$$e_3(t,p) = D(t,p) - D(t-1,p) \tag{5}$$

Since $e_3(t,p)$ is the brightness difference in the neighboring frames of the same cell, it is the time difference of the brightness to recognize motion of the target. The method performs clustering vectors consisting of the 3 local elements. It regards the centroid vector of each cluster as a feature pattern. Feature patterns allow us to represent motion of the target in various domestic actions. For example, in vacuuming, many cells would show a feature pattern of strenuous movement of arms. The method classifies all cells in the three dimension space with the k-means.

E. Histograms for location

Figure 5 shows how to calculate histograms which show a feature of domestic actions. For example, an actor proceeds vacuuming along a path the actor determines. The path varies with each actor. In addition, rules to determine paths are qualitative and ambiguous. For example, one actor might have a rule to proceed vacuuming around the table clockwise. We should recognize where each feature pattern appears to distinguish actors. The method divides each frame into two and three parts. Combined with the original one, the method gets in total 6 time series of brightness distribution data. For each cell in the 6 time series, the method finds the nearest cluster. The method constructs histograms for each time series. Histograms constructed from the 6 time series

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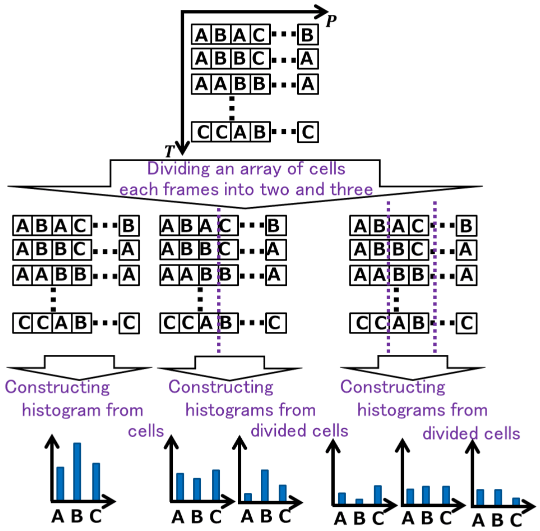

Figure 5. Calculation of histograms

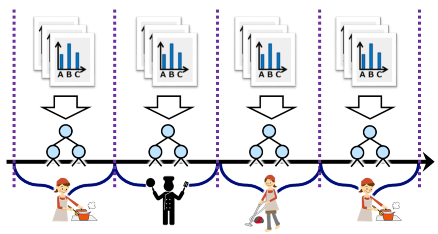

Figure 6. Division of a time series of brightness distribution data

represents features of brightness distribution data. The features include the location where the actor takes the action, such as person X proceeding vacuuming around the table clockwise. Since each actor seems to have his own rule to conduct a specific domestic action, the histograms presents features of domestic actions of a specific actor.

F. *Recognition of time series*

The proposed method divides a whole time series of the brightness distribution data into several parts. To detect when an actor takes a specific action, it is necessary to recognize domestic actions along with their actors in each part. When an action is recognized, it is not preferable for several actions to be taken in a single time series of brightness distribution data. However, since the timing of each domestic action depends on its actor, it is difficult to find the switching of one domestic action to another. A single time series of brightness distribution data can contain several domestic actions. As shown in Figure 6, the method sequentially recognizes domestic actions for every time series of fixed length, without the consideration of switching of domestic actions. Instead of the considering any switching of domestic actions, the method identifies the domestic action conducted for the longest time in a given duration. It regards the domestic action as the one representing the duration. The method constructs histograms sequentially for every duration of a fixed length. It gives the histograms to a discriminator based on the Random Forest. Through the process, the method recognizes domestic actions, their actors, and the periods in which the actors conduct the domestic actions.

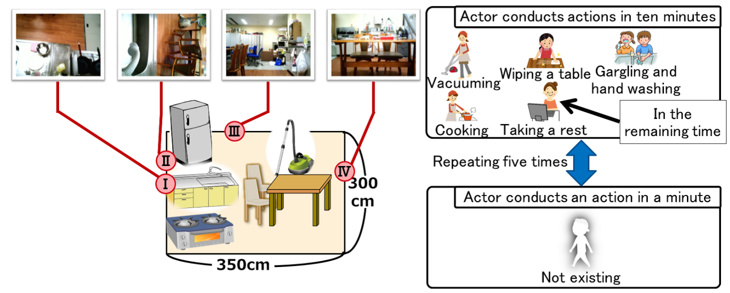

Figure 7. Living space and domestic actions

IV. An Experiment in Living Space

A. *Outline of experiment*

We have evaluated the proposed method to identify the actor, the period, and the kind of domestic action conducted in a living space. We validate identification accuracy of the method. Subjects are ten males and females who are all twenties. Each subject conducts domestic actions one by one in the living space. Figure 7 shows a sketch of a living space with a kitchen on floorings, where domestic actions are taken place in the experiment. We install four brightness distribution sensors so that their visual fields coves whole of the living space. Target domestic actions in the experiment should be ones which frequently happen in any living space. We adopt “vacuuming”, “wiping a table”, “cooking”, “gargling and hand washing”, and “taking a rest” as target domestic actions, in addition to “none”, which means there is nobody. The “vacuuming” action is a domestic action that a subject vacuums the floorings. A subject might vacuum under the tables and chairs, moving them. The “wiping a table” is a domestic action that a subject wipes the table with a wet towel placed on the sink. A subject might wipe under objects on the table, moving the objects. The “cooking” is a domestic action in which a subject takes an egg from the refrigerator, stirs the egg inside a bowl, flies the egg with salad oil with a frying pan, serves it on a plate, and washes all the cooking utensils. The cook utensils in the experiment are a bowl, a chopsticks, and a frying pan. Ingredients in the experiment are eggs and salad oil. The “gargling and hand washing” is a domestic action in which a subject washes his own hands with soap and gargles with water in the sink. The “gargling and hand washing” has a peculiar vertical motion in front of the sink. We install sensor B in the sideway at the sink so that it is rotated by ninety degree from the gravity direction. The “taking a rest” is a domestic action in which a subject spends time freely within the visual field of the brightness distribution sensors. It varies with each subject. The “none” is a state in which no subject stays in visual field. We use a brightness distribution data of the “none” to examine the rate of wrong detection of domestic actions. Every subject conducts the 4 kinds of domestic actions within 10 minutes. If they finish them earlier, they can spend the remaining time with the “taking a rest” action. We do not give subjects more specific directions for each kind of domestic actions. We do not specify the time length and the order of domestic actions. Brightness distribution data vary with each subject. We examine the identification accuracy of domestic actions varying with subjects. After the ten minutes, subjects take a rest for one minute outside the visual fields of the brightness distribution sensors. The rest is treated as a “none” state. Every subject repeats the above five times.

B. *Evaluation method*

We evaluate the ability of the proposed method in terms of identification of kinds and actors of domestic actions. We take a video of all domestic actions. We divide the video data into slots, which of which lasts twenty seconds. We label every slot with a pair of an actor and a domestic action the actor conducts longest in the slot. Since the " none " has no actor, we do not label any " none " slot. The method divides a set of brightness distribution data from the four brightness distribution sensors into periods. Each of the period lasts 20 seconds synchronized with the video data. The method constructs histograms for each period, according to the way explained in section 3. In the experiment, the number of clusters in the k-means method is 25. Because of the synchronization, each period is associated with a pair of histograms and a label. A discriminator is trained, taking histograms and labels as explanatory variables and response variables, respectively. We use the cross validation to verify the discriminator. In the cross validation, one pair of histograms and a label is used as a test data, while the remaining pairs are used as instruction data. We verify the identification ability of actors by the recall, the precision, and the F measure. Let us consider periods where a specific actor takes a specified action. The recall is the rate of the correctly detected periods out of the periods the actor actually takes the action. The precision is the rate of the correctly detected periods out of all detected periods. The F measure is the harmonic mean of the precision and the recall. The identification ability of domestic actions is also evaluated with the recall, the precision, and the F measure.

C. Result of experiment

TABLE I. IDENTIFICATION OF DOMESTIC ACTIONS

	Precision	*Recall*	*F-measure*
not existing	0.782	0.933	0.851
vacuuming	0.743	0.759	0.751
wiping a table	0.605	0.267	0.371
cooking	0.854	0.943	0.897
gargling and hand washing	0.855	0.355	0.461
taking a rest	0.806	0.709	0.754

Table I shows the result of the identification of domestic actions. Domestic actions with the high accuracy are the " vacuuming ", the " cooking ", and the " taking a rest " action, as well as the " none " state. On the contrary, the bad accuracy is found for the " wiping a table " and the " gargling and hand washing " actions.

TABLE II. THE RESULT OF IDENTIFICATION OF ACTORS.

	Precision	*Recall*	*F-measure*
actor A	0.770	0.765	0.768
actor B	0.824	0.801	0.813
actor C	0.781	0.791	0.786
actor D	0.877	0.839	0.857
actor E	0.894	0.900	0.897
actor F	0.785	0.780	0.783
actor G	0.852	0.789	0.819
actor H	0.758	0.763	0.760
actor I	0.726	0.558	0.631
actor J	0.793	0.793	0.793

The result of identification of actors is presented in Table II. The accuracy is fairly high for every actor. The results indicate the proposed method recognizes an actor and the period when the actor conducts the " vacuuming " , the " cooking " , and the " taking a rest " actions in the experiment.

The 6 kinds of domestic actions are divided into 2 groups: the " high accuracy " group and the " low accuracy " group in order to examine what conditions cause misidentification. The " high accuracy " group contains actions identified with high accuracy, while the " low accuracy " one consists of actions with low identification accuracy. As shown in Table1, the " high accuracy " group includes the " vacuuming ", the " cooking ", and the " taking a rest " actions, along with the " none " state.

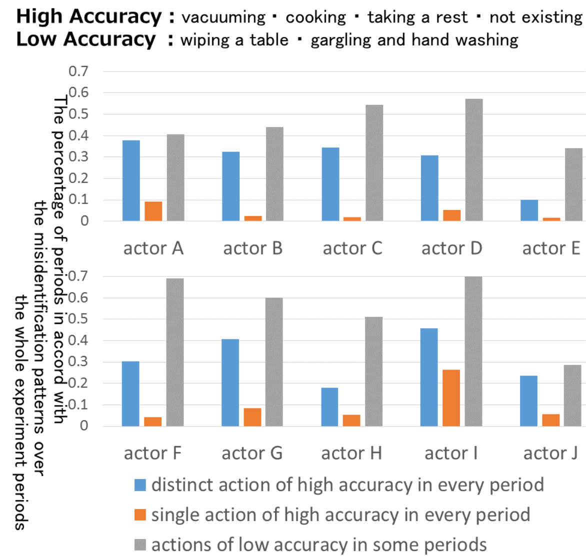

Figure 8. Comparison of misidentification patterns

The " wiping a table " and the " gargling and hand washing " are listed in the " low accuracy " group.

Some actions are identified with high accuracy, while others with low accuracy. Even if the actions of good accuracy take place, the recognition accuracy might get lower in periods where domestic actions switch or periods whose adjacent periods contain domestic actions of low accuracy. We examine how misidentified periods affect the identification ability of the method. We consider the following three patterns for sequential three periods, to see their effects on misidentification.

1) An actor conducts distinct domestic actions of high accuracy in each of the period, which is labeled with " distinct action of high accuracy in every period " .
2) An actor conducts a single domestic action of high accuracy in all of the three periods, which is labeled with " single action of high accuracy in every period ".
3) An actor conducts domestic actions of low accuracy in any of the three periods, which is labeled with " actions of low accuracy in some periods " .

We examine how many times these patterns appear in misidentified periods. We consider what condition makes the method misidentify frequently.

The three patterns are labeled in Figure 8. Neither of the first and the second contains domestic action of low accuracy. In the first and the third pattern, domestic actions are switched. The Figure 8 shows the percentages of periods in accord with the misidentification patterns over the whole experiment periods for every actor. As the result, common to all actors, the patterns are arranged as " actions of low accuracy in some periods ", " distinct action of high accuracy in every period ", and " single action of high accuracy in every period " , in the descending order of their frequency.

V. DISCUSSION

First, we address reasons for the low accuracy for some actions. The " wiping a table " and the " gargling and hand washing " actions are shorter than other domestic actions in their length. In addition to that, hands move in front of a body in the actions ". The method fails to extract feature of hands by the background difference. Since those action resemble with each other, the method fails to identify them.

On the contrary, we have expected low accuracy while actors are “taking a rest”, because they can take any action during the period. However, the time prepared for the experiment is so short that actors cannot afford to enjoy their own free behavior when they finish all specified actions. They take similar behavior while “taking a rest”. The method gets an unexpected high accuracy to identify the “taking a rest” actions, even though there is no constraint for their behavior.

For all actors, the method gets the low accuracy of identification in the period where actions are switched or actions of low accuracy are taken place in adjacent periods. Note that we aim to identify the length of a specific domestic action, which contributes to monitoring the elderly and scheduling actions to save energy. To accomplish the aim, the misidentification in the switching of domestic actions brings less harmful impacts than that during a single domestic action. If we consider only domestic actions of high accuracy, we can expect more proper recognition of their period.

VI. Conclusion

In this paper, we propose the identification method of domestic actions, along with their actors, and period. The method recognizes domestic actions with brightness distribution sensors. The recognition repeated in a fixed period allows to identify actors conducting domestic actions independent from the timing the actors take the domestic actions.

The method identifies actors and the period of the “vacuuming”, the “cooking”, the “taking a rest” actions in high accuracy, in an experiment. The method contributes to watching of the elderly and effective usage of electricity.

We are going to verify the effectiveness of the method with other kinds of domestic actions.

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