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Family Members Identification with Brightness Distribution Sensors to Self-sustaining of Power as Personal Actions

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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. *Copyright © 2015 IFSA Publishing, S. L.*

Keywords: Brightness distribution sensor, Domestic action, Recognition of personal actions, Energy saving, Living space.

1. 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 for a family members 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 be combined with home power generation and electric vehicle as a battery 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 a mixture of 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.

2. 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]. The method derive a schedule from domestic actions are detected, home power generation, and electric vehicle as a battery. Family members can accommodate their energy consumption in self-sustaining of power, following the schedule. 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 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 electronics [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.

3. Recognition of Actions and Actors

3.1. 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.

Fig. 1 shows the overview of the method to periodically recognize domestic actions and their actors.

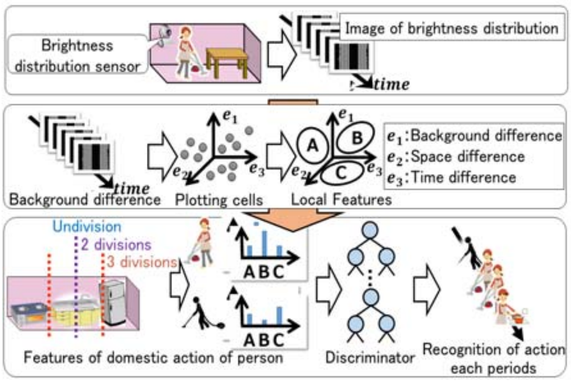

Fig. 1. Method overview.

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 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 inputs histograms which are constructed newly chronological brightness distribution data into the discriminator. Providing a new time series of brightness distribution data for the discriminator, the method recognizes domestic actions along with their actors.

3.2. 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 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 lense [6]. Fig. 2 shows information acquired with a brightness distribution sensor.

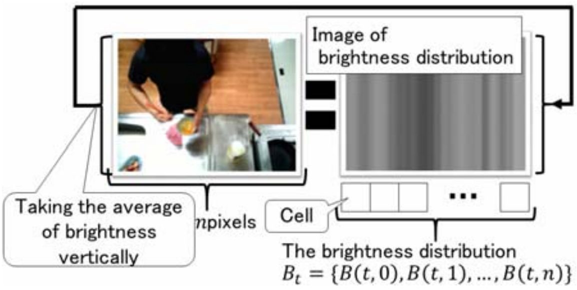

Fig. 2. A brightness distribution sensor.

Let *n* the number of pixels in the row direction of the sensor. The brightness distribution at time point *t*, *Bt*, is

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

where *B(t,p)* is the brightness of the *p*-th cell.

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.

3.3. Background Difference

Fig. 3 shows how to calculate the background difference. Let *I* and *B* are an array of the brightness distribution when a 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 represented with an array

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

where *D(t,p)* is the background difference value of the *p*-th cell at time point *t*.

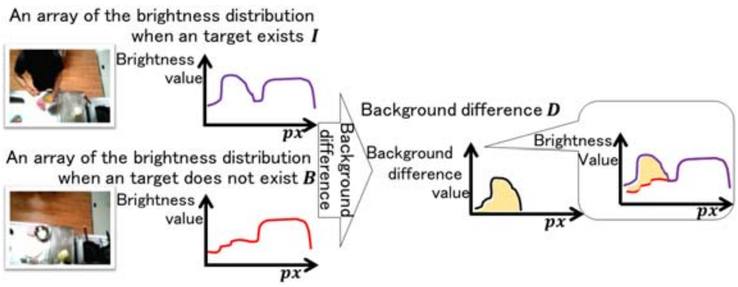

Fig. 3. A background difference.

3.4. Extraction of Feature Patterns with Local Elements

Fig. 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.

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

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

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

$e_2(t,p)$ 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

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

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.

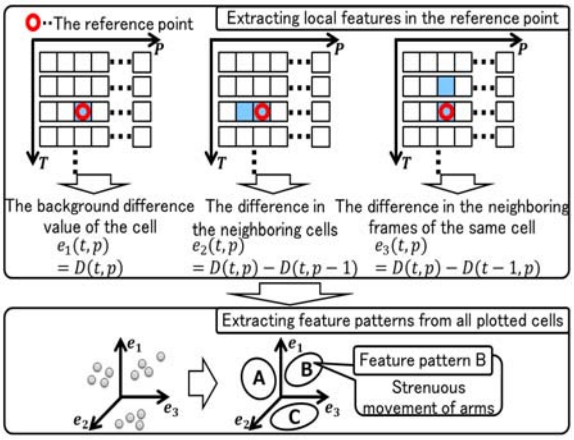

Fig. 4. Extracting feature patterns from local elements.

3.5. Histograms for Location

Fig. 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 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.

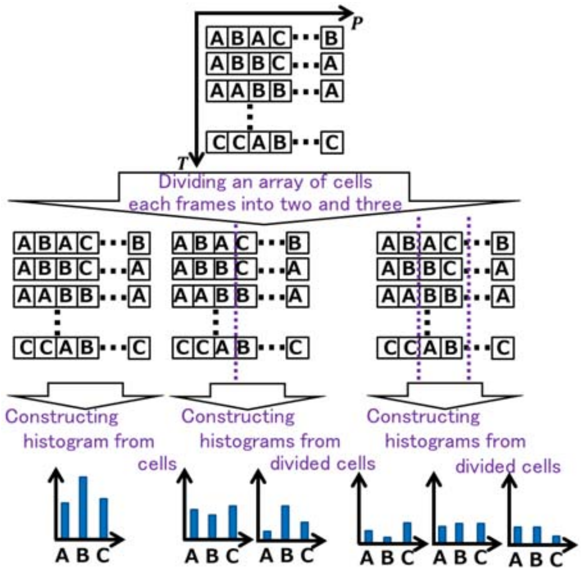

Fig. 5. Calculation of histograms.

3.6. 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 Fig. 6, the method sequentially recognizes domestic actions for every time series of fixed length, without the consideration of switching of domestic actions.

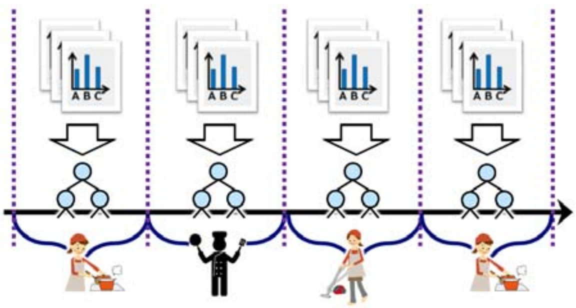

Fig. 6. Division of a time series of brightness distribution data.

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.

4. An Experiment in Living Space

4.1. A Summary of Experiment

We need a system to recognize that who, when, and what domestic action conducts in a living space. We experiment by the method to identify that who, when, and what domestic action conducts in a living space. We validate identification accuracy of the method. Actors are ten men and women who are twenties. Actors conduct domestic actions one by one in a living space in which view angle of brightness distribution sensor. Fig. 7 shows a sketch of a living space in which a kitchen on flooring and domestic actions in the experiment.

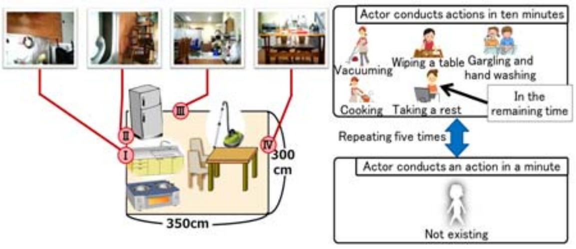

Fig. 7. A sketch of a living space and Domestic actions in the experiment.

We install four brightness distribution sensors in order to view a living space in which a kitchen on flooring. Domestic actions which appear frequently in living space are suitable domestic actions in the experiment. Domestic actions in the experiment are "vacuuming", "wiping a table", "cooking", "gargling and hand washing", "taking a rest", and "not exist". The "vacuuming" is a domestic action which an actor vacuum a flooring in view angle. We consider an actor vacuums under a tables and a chairs by moving a tables and a chairs. The "wiping a table" is a domestic action which an actor moistens a dish towel which is placed dresser by a sink, and wipes a table. We consider an actor wipe under objects which is on the table by moving objects. The "cooking" is a domestic action which an actor takes an egg from a refrigerator, stirs the egg by bowl, heats the egg and a salad oil by a frying pan, serves on a plate, and washes cook utensils. Cook utensils in the experiment are a bowl, chopsticks, and a frying pan. Ingredients in the experiment are eggs and a salad oil. The "gargling and hand washing" is a domestic action which an actor washes own hands with soap and gargles with water in the sink. The "gargling and hand washing" makes a peculiar feature to gravity direction in the sink. We install a sensor B in the sink so that the sensor B is sideway as ninety degree rotation from gravity direction. The "taking a rest" is a domestic action which an actor spends time freely in view angle of the brightness distribution sensor as not setting a rule of conducting specific action. The "taking arrest" has a feature which various contents of domestic actions. The "not existing" is a state which an actor is not in view angle. We use a brightness distribution data of the "not existing" to verify identification accuracy of domestic actions. Actors conduct the "vacuuming", the "cooking", the "gargling and hand washing", and the "wiping a table" within ten minutes. After conducting four domestic actions, Actors conduct "taking a rest" in time left of ten minutes. We do not give actors directions for these domestic actions specifically. We do not also give actors directions for a length of time and an order of domestic actions. Brightness distribution data is various in the experiment. We verify identification accuracy of brightness distribution data in the experiment. After ten minute, actors take a rest for a minute outside view angle of brightness distribution sensors. The "not existing" is state which actors take a rest. Actors repeat above rule five times.

4.2. Evaluation Method

We evaluate domestic actions and actors in the experiment. We explain how to get response variables in a supervised learning. We take a video of domestic actions of each actor for make response variables by brightness distribution sensor. We divide the video every twenty seconds. We label a domestic action on the period in which an actor conduct the domestic action such as the longest conducting the domestic action in twenty seconds. The "not existing" is the only which brightness distribution data is constant by everyone. We do not label the "not existing" on the period. We explain how to get explanatory variables in the supervised learning. The method divides one dimension brightness distribution data by four brightness distribution sensors every twenty seconds. The method uses one dimension brightness distribution data. It gets histograms which show features of domestic actions. In the experiment, the cluster number is twenty five in the k-means method. The method divided one dimension brightness distribution data every twenty seconds in the experiment. A discriminator learns histograms as explanatory variables and labels as response variables in a period. We use the cross validation to verify the discriminator. The cross validation extracts histograms of a period as test data and histograms of other period is training data in chronological background difference data. The cross validation repeats assigning test data so that all period is test data once. We verify identification ability to actors by the recall, the precision, and the F measure in the period. The recall is a fraction of a response to an actor by the method in the same actor who has conducted. The precision is a fraction of the actor who has conducted in the response to the same actor by the method. The F measure is harmonic mean of the precision and the recall. As with verifying identification ability to actors, we verify identification ability to domestic actions by a recall, a precision, and the F measure in the period. The recall is a fraction of a response to a domestic action by the method in the same domestic action which has been conducted. The precision is a fraction of the domestic action which has been conducted in the response to the same domestic action by the method. A highly trusted method gets high values of the recall, the precision, and the F measure of actors and domestic actions. The Random Forest cannot identify domestic actions which is not conducted long time by actors. We verify the sum of periods of each of domestic actions. Even though the recognition of the period of good accuracy of identification of domestic actions, the recognition accuracy is lower in the period which is a switching a domestic action and adjacent periods are a conducting a bad accuracy identification domestic action. We examine that assigning the period affects identification ability of the method. We consider three misidentification patterns about three periods which are sequential. Pattern 1: an actor conducts good accuracy domestic actions which occur two or three times in three periods. Pattern 2: an actor conducts a single kind good accuracy domestic action which occurs once in three periods. Pattern 3: an actor conducts bad accuracy domestic actions in any period. In Pattern 1 and Pattern 3, the period is timing of switching a domestic action. In Pattern 1 and Pattern 2, an actor conducts only good accuracy domestic action(s) in three periods. We verify how many these misidentification patterns have the period which is center of three periods. We consider that what period the method misidentifies frequently. We cannot trust a bad accuracy untrusted domestic action and a period by the method. We exclude the period in which an actor conducts a bad accuracy domestic action.

4.3. Result of Experiment

The Table 1 shows the result of identification of domestic actions. Good accuracy domestic actions are the “not existing”, the “vacuuming”, the “cooking”, and the “taking a rest”. Bad accuracy domestic actions are the “wiping a table” and “gargling and hand washing”.

The Table 2 shows the result of identification of actors. Every identification accuracy of actors are good. The method recognizes an actor and the period in which the actor conducts the “vacuuming”, the “cooking”, and “taking a rest” in the experiment.

We classify six domestic actions into “High Accuracy ones” and “Low Accuracy ones” in order to verify identification ability affected by periods.

Table 1. The result of 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

As shown in Table 1, the high accuracy group consists of “vacuuming”, “cooking”, “taking a rest”, and “not existing”. The low accuracy group is composed of “wiping a table” and “gargling and hand washing”. We classify every periods into three misidentification patterns which consists of three sequential periods. The first pattern is three sequential different high accuracy actions in Fig. 8.

Table 2. 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

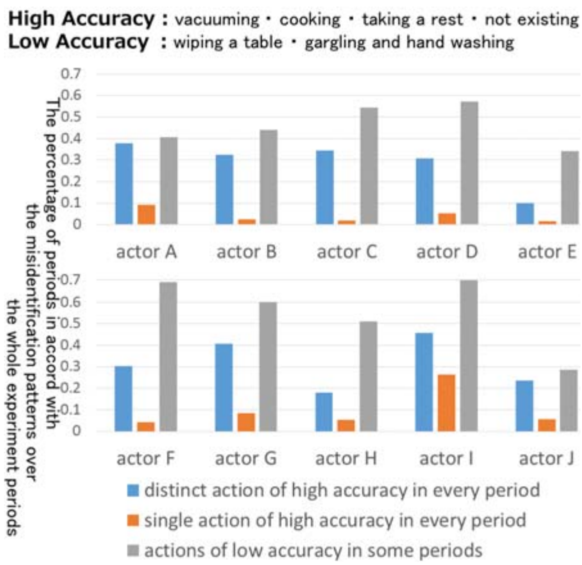

Fig. 8. Percentages of misidentification patterns as a period in every actors.

In the second pattern, a single high accuracy action takes place in the three sequential periods**.** In the third pattern, low accuracy action takes place in any one of three sequential periods. The first and the third pattern correspond to switching of domestic actions. In the first and the second pattern, there is no period where an actor conducts a low accuracy action. Fig. 8 shows percentages of misidentification for every actor. In all actors, the misidentification occurs in the same way; the highest misidentification in one low accuracy action in three sequential periods, the second highest misidentification in the switching of high accuracy actions, and the lowest in successive periods of a single high accuracy action.

5. Discussion

The length of the period of the “wiping a table” and the “gargling and hand washing” is shorter than other domestic actions. Therefore, the number of samples of these domestic actions is less as shown Table 3. Hands move in front of a body in “wiping a table” and the “gargling and hand washing”. The method fails to extract feature of hands by the background difference. The method fails to identify these domestic actions. Actors cannot afford to spend own free time in the “taking a rest”. The method tends to get unique feature of actors in the “taking a rest”. The method gets an unexpected high accuracy of identification of the “taking a rest” in which there is no rule. In domestic actions of a high accuracy identification, the method gets a low accuracy of identification of periods in which the period is switching of domestic actions and adjacent periods of the period are low accuracy domestic actions. The misidentification of the switching domestic action is more little negatively affected than the misidentification of the conducting domestic action in the recognition of the length of time of the period. The method is more trustable than the result in the recognition of periods which have domestic actions of high accuracy identification.

6. Conclusions

In this paper, we propose an identification method of domestic actions, actors, and periods. The method recognizes various domestic actions with brightness distribution sensors. The brightness distribution sensor is inexpensive and protects privacy of actors by brightness distribution data which the third person cannot reconstruct an original image.

We experiment to utility of the method with demonstration which the method detect domestic actions by ten actors in daily life. The method identifies actors and periods of the “vacuuming”, “cooking”, “taking a rest” in a high accuracy. The method contributes to watching elderly persons and state leveling of electric power consumption.

We will verify utility of the method with more various domestic actions. After that, we will improve the method to be state leveling of electric supply, accommodating controlled power consumption of each home.

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