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[Poster Presentation] Implementation of Recognizing Indoor Activities Using Cloud Service for Machine Learning

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Abstract Online changing point detection of activities is needed to achieve automatically monitoring service for home elderly. In the previous study, we proposed the system that captures activities of the elderly using speech dialog by Virtual Agent based on environmental changes. Specifically, in this paper, we focus on auto activity recognition using machine learning on the proposed system and implement this subsystem using machine learning service on the cloud. Also, we collect sensor data and activity logs and execute machine learning to evaluate Auto Recognition accuracy.

Key words elderly care, home care, machine learning, activity recognition, cloud service

1 Introduction

Nowadays, Japan has been facing a hyper-aging society. In 2025, the total population will decrease to 120 million, while people over the age of 65 will increase to 37 million. Thus, approximately 30% of the population will become the elderly[1]. As the population ages, many facilities of welfare and nursing care suffer from a chronic shortage of workers. As a result, related jobs opening ratio is as high as 2.68 (as of Dec. 2014)[2]. The number of a nursing home is not sufficient for the number of applicants, who are over 524,000 elderly people. The Japanese government starts to encourage *home care* rather than building new facilities. Needless to say, the elderly care will rely more on home, which poses a burden to the family as caregivers. Under these circumstances, the system and the technology, which reduces burdens of elderly care at home, attract great attention.

Among many technologies which are being used to realize care at home studied so far, the *elderly monitoring system* based on ICT is a promising system. As examples of the elderly monitoring system, commercialized systems which detect leaving the bed[3] and which safeguard the elderly's health and well-being using robots[4] are enumerated. Especially these days, many researchers enthusiastically develop the monitoring system which recognizes *activities of daily living (ADL)* using activity recognition technology and notifies caregivers of the elderly's emergency situations. Under activity recognition technology, a lot of data is collected with sensors such as environment sensors, wearable sensors and cameras, and conditions or activities of target elderly person are estimated and recognized. As examples of activity recognition technology, there are technologies that learn and recognize the presence and ADL[5] using camera images, and learn acceleration data collected with wearable sensors or smartphone and recognize user's actions (e.g. walking, working, at rest)[6], and recognize ADL using many environment sensors which are installed widely in a smart home[7]. However, the conventional monitoring system has problems including installation cost and invasiveness, the need of real-time activity recognition and the lack of communication with the elderly.

To cope with these problems, in the previous work, we proposed sensing and care system which captures the ADL of the elderly based on dialog triggered by environment changes in a home [8]. The system consists of *environment sensing section* in which sensor box [9] is used, *activity recognition service* which recognizes the elderly's activities and *care service* which cares elderly by dialog using Virtual Agent (VA) based on recognized activities. In this paper, we focus on auto recognition in activity recognition service which estimates the elderly's activities using machine learning.

To make classifiers which recognized activities, first, we preprocess collected data. Next, we use machine learning service on the cloud and we make the classifiers every characteristic environment. In making classifiers, we use the learning algorithm corresponding to multiclass data.

2 Implementation and Evaluation

Auto recognition makes classifiers to automatically recognize activities by machine learning using collected environmental data and activity logs. In this section, we

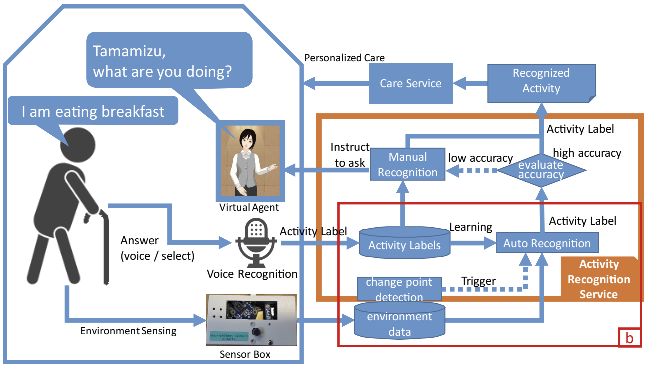

Figure 1: System Architecture

show flow and implementation of machine learning, experiment, and evaluation.

2.1 Data Preprocessing

The following steps show the way to collect and preprocess data to machine learning.

Step1 Data collection
To collect environmental data, we use autonomous sensor box which is developed by our laboratory. We put the sensor box in every location where activities are done that we want to monitor. For example, if we want to monitor activities in the living (e.g. eating, watching TV), we put a sensor box in the living. Also, the system collects activity logs through speech dialogue with VA triggered by environmental changes.

Step2 Unifying expression of activity logs
The system replaces synonyms with the same word because there are synonyms in collected activity logs. For example, the system replaces "come back home" and "return home" with "return home".

Step3 Replicating activity logs
We define duration every activity and the system replicate activity logs based on the duration because the number of activity logs on change point detection is too low to use for machine learning.

Step4 Deleting minor data
The system calculates frequency every activity log and does not use the logs whose number is less than 10 for machine learning because activity logs which are rarely recorded are noise in machine learning.

Step5 Joining data
The system joins environment data and activity logs to make train data. In specifically, the system tags each sensor data at activities as activity labels which have the same location, year, month, date, hour and minute.

Step6 Feature Engineering
The system engineer features of data to improve accuracy of classification. The system adds last 60 environment data from sensor database to the data. Also, the system adds the last activity and the 2nd last activity to the data.

As the result of this preprocessing, the train data has the format shown in Table 1.

Table 1: data format

column name	description	example
location	-	living
year	-	2017
month	-	5
day	-	31
weekday	0 means Sunday	4
hour	-	17
minute	-	29
sound	-	57.472817
motion	-	true
temperature	-	25,77802
humidity	-	57.7684
pressure	-	98.36391
vibration	-	502
light	-	63
sound-1	last sound data	50.159038
⋮	⋮	⋮
light-60	60th last light data	11
activity	-	brushing of teeth
activity-1	last activity	eating
activity-2	2nd last activity	wake up

2.2 Machine Learning and Evaluation

We use machine learning service on the cloud and make classifiers for recognizing activities from processed data shown in Table 1. First, we divide processed data by a location. Next, we also divide data into train data and test data. As train data, we use 70% of the data from the oldest. As test data, we use 30% of the data from the newest. On the learning, we use an ensemble learning algorithm based on decision tree and make classifier which classifies environmental data into a class (activity) based on other columns (year, month, day, weekday, ...). Also, we let the system repeatedly learn as the system changes the hyperparameters randomly within determined range and optimize hyperparameters in terms of the accuracy.

Also, we make a confusion matrix which shows the number of estimated activity every actual activity to evaluate accuracies every classifier. Furthermore, we calculate overall accuracy shown in (1) and average accuracy shown in (2) to evaluate accuracies every location.

$$\text{overall accuracy} = \frac{\sum_i^M n_{i,i}}{\sum_i^M \sum_j^M n_{i,j}} \tag{1}$$

$$\text{average accuracy} = \frac{1}{M} \sum_i^M \frac{n_{i,i}}{\sum_j^M n_{i,j}} \tag{2}$$

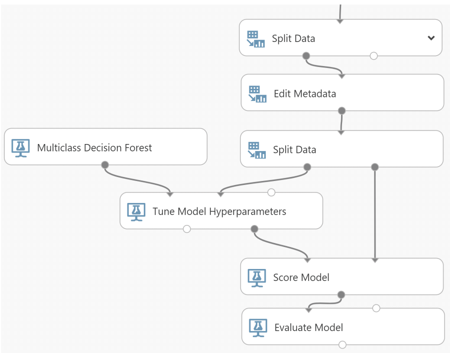

Figure 2: Module Layouts on Microsoft AML

Here, $n_{i,j}$ shows the number that the system estimates the actual activity i as the activity j. Also, M shows the number of types of the activity which can be classified. (1) shows the rate of data estimated correctly in all test data. (2) shows the average of the rate of data estimated correctly every activity in test data.

2.3 Implementation

In this paper, we implemented auto recognition using Microsoft Azure Machine Learning (Microsoft AML). Microsoft AML is one of machine learning service on the cloud. In Microsoft AML, we can select learning algorithm, split data and evaluate trained model by laying out modules and connecting input and output of these modules through a web browser. In this study, we used Multi-class Decision Forest [10] which is one of ensemble learning algorithm base on a decision tree. Also, hyperparameters of Multi-class Decision Forest which we can configure in Microsoft AML are a number of decision trees, maximum depth of the decision trees, a number of random splits per node which is used when building each node of the tree and minimum number of samples per leaf node. We set the range of a number of decision trees as integral values of 1 to 8, the range of maximum depth of the decision trees as integral values of 1 to 32, a number of random splits per node as 1, 128 or 1024 and minimum number of samples per leaf node as 1 or 4. After the system randomly selected hyperparameters from these ranges and learned 20 times, we used hyperparameters which were used in the best classifier. Fig. 2 shows the module layouts on Microsoft AML. In Fig. 2, the first module receives processed data shown in Table 1 as the input.

2.4 Experiment

To evaluate classification accuracies of auto recognition, we conducted the experiment in which we installed sensor boxes in an actual house, collected sensor data and activity logs and executed auto recognition. We installed sensor boxed at the living, washroom, roomA and entrance in the home where two elderly people were living. In this experiment, auto recognition targeted at one of two elderly people. The system collected activity logs by speech dialog with VA based on changing points, but the system notified the subject of results of change point detection and let the subject record activities on the ground of experiment environment. We collected 615 activity logs in 37 days. We replaced synonyms with unified expression because there are synonyms in the collected data. Also, as the result of preprocessing shown in 2.1, we collected these activities that are "smart-phone", "PC", "wake up", "wash dishes", "read news-paper", "eating" in the living, "in the toilet", "hand-wash, gargle", "wash feet", "brushing of teeth", "measure weight, blood pressure", "bathe" in washroom, "PC", "open shutter", "smart-phone" in roomA and "outgo", "bed", "return home" in entrance. We set the duration of "measure weight, blood pressure" as 10 minutes, the duration of "eating" as 5 minutes, the duration of "bathe" as 30 minutes and the duration of other activities as 1 minutes. As the result, the number of preprocessed data in the living was 1123, the number of the data in washroom was 5270, the number of the data in roomA was 409 and the number of the data in entrance was 1112.

Fig. 3 shows the result of evaluating classifiers that were made from collected activity logs and sensor data. In Fig. 3, the left label shows actual activities and the above label shows activities that were estimated by classifiers. Also, the number in cells shows the rate that the system estimated the activity of the left label as the activity of the above label and empty cells show 0.0%. Furthermore, Table 2 shows the result of calculating overall accuracy and average accuracy.

According to Table 2, we consider that high-accuracy classifiers have been made in roomA and entrance because overall accuracy and average accuracy is higher than other classifiers. However, overall accuracy and average accuracy of the classifier in washroom was lower and average accuracy of the classifier in the living was lower. Therefore we consider that the system cannot have made high-accuracy classifiers in washroom and the living. As the reason that accuracies of classifiers in washroom and the living are lower, we consider the volume of types of activity, the activity that does not have effects on environment and that is independent with time of day and sequence of activities, time lag between recording activity logs and doing activities and the problem of installation position of sensor boxes. To cope with these problems, we consider the improvement of accuracy of change point detection, adjusting installation position of sensor boxes and changing granularity of expression of activity that users should record.

3 Conclusion

In this paper, we implemented auto activity recognition using machine learning service on the cloud. First, we showed the way to make classifier to recognize activities using environmental data and activity logs. Next, we

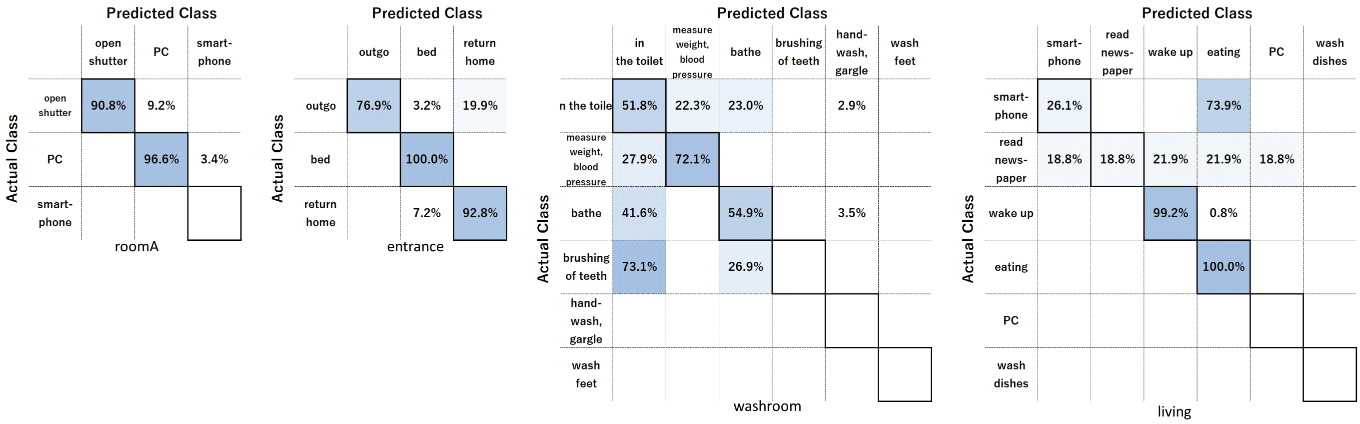

Figure 3: Result of Evaluating Classifiers

Table 2: Accuracy of Classifiers Made per Locations

location	overall accuracy	average accuracy
roomA	93.50%	93.66%
entrance	85.33%	89.88%
washroom	58.57%	44.71%
living	86.94%	61.00%

used Microsoft AML, which is one of machine learning services on the cloud, and we implemented the process to learn activities. Also, we collected data from the actual home environment and evaluated the accuracy of classifiers.

As the future works, we consider to collect activity logs more accurately and to improve the accuracy of classifiers by devising the method of representing activity logs. Also, we consider to let many people use the proposed system and evaluate versatility and utility of the system.

Acknowledgements

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