Hibikino-Musashi@Home
2019 Team Description Paper

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Abstract. Our team, Hibikino-Musashi@Home (HMA), was founded in
2010. It is based in the Kitakyushu Science and Research Park, Japan.
Since 2010, we have participated in the RoboCup@Home Japan Open
competition open platform league annually. We also participated in the
RoboCup 2017 Nagoya as an open platform league and domestic standard
platform league teams, and in the RoboCup 2018 Montreal as a domestic
standard platform league team. Currently, we have 23 members from
seven different laboratories based in Kyushu Institute of Technol-ogy.
This paper aims to introduce the activities that are performed by our
team and the technologies that we use.

1 Introduction

Our team, Hibikino-Musashi@Home (HMA) was founded in 2010 and it has
been competing in the RoboCup@Home Japan Open competition open platform
league (OPL) annually since then. Our team is developing a home-service robot,
and we intend to demonstrate our robot in this event to present our research
outcomes.

In RoboCup 2017 Nagoya, we participated in OPL and domestic standard
platform league (DSPL), and in the RoboCup 2018 Montreal, we participated
in DSPL. In both these competitions, we employed a TOYOTA HSR robot and
were awarded the first prize in DSPL[1].

This paper describes the technologies used by us. Especially, this paper out-
lines an object recognition system that uses deep learning [2], speech recognition
system, sound localization system, and a brain-inspired amygdala model, which
was originally proposed by us and is installed in our HSR.

2 System overview

Figure 1 presents an overview of our HSR system. We has used an HSR since
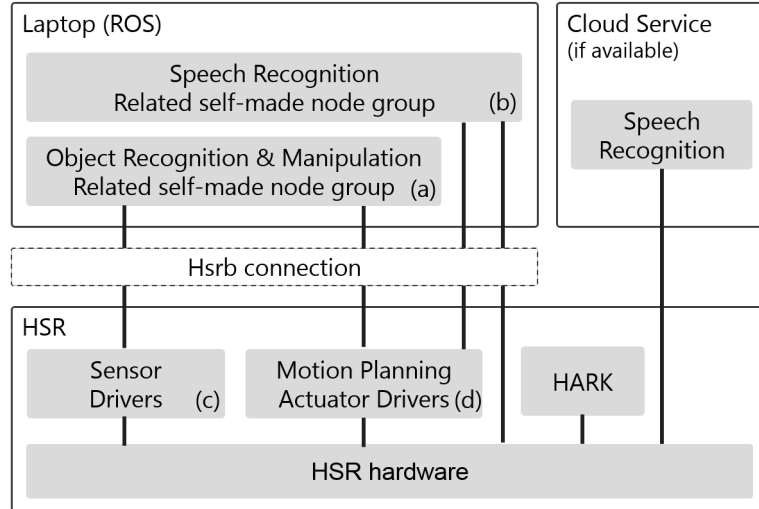2016. In this section, we will introduce the specifications of our HSR.

Fig. 1. Block diagram overview of our HSR system.

2.1   Hardware overview

We participated in RoboCup 2018 Montreal with the HSR. The computational resources built into the HSR were inadequate to support our intelligent systems and were unable to extract the maximum performance from the system. To overcome this limitation, using an Official Standard Laptop for DSPL that can fulfill the computational requirements of our intelligent systems has been permitted since RoboCup 2018 Montreal. One of our team members (Yutaro ISHIDA) contributed a rule definition of the Official Standard Laptop for DSPL discussed in GitHub [3, 4]. We use an ALIENWARE (Intel Core i7-8700K CPU, 32GB RAM and GTX-1080 GPU) as the Official Standard Laptop for DSPL. Consequently, the computer equipped inside the HSR could be used to run basic HSR software, such as its sensor drivers and motion planning and actuator drivers. This increased the operational stability of the HSR.

2.2   Software overview

In this section, we introduce the software installed in our HSR. Figure 1 shows the system installed in our HSR. The system is based on the Robot Operating System [5]. In our HSR system, the laptop computer and a cloud service, only if a network connection is available, are used for system processing. The laptop is connected to a computer through an Hsrb interface. The built-in computer specializes in low-layer systems, such as the HSR's sensor drivers, motion planning, and actuator drivers, as shown in Fig. 1 (c)(d).

3 Object recognition

In this section, we explain the object recognition system (shown in Fig, 1 (a)), which is based on you look only once (YOLO) [6].

To train YOLO, a complex annotation phase is required for annotating labels and bounding boxes of objects. In the RoboCup@Home competition, predefined objects are usually announced during the setup days right before the start of the competition days. Thus, we have limited time to train YOLO in the competition, and the annotation phase impedes the use of the trained YOLO in the competition days.

We propose an autonomous annotation system for YOLO using chroma keys. Figure 2 shows an overview of the proposed system. In the system, two RGB-D cameras are used, and they are identical to the camera implemented on the HSR. These cameras differ in terms of mounting positions and angles: one of the cameras captures an object from a higher position than the other camera. Since two different mounting positions and angles are used, two different images of a given object are captured simultaneously. Using these images for training, YOLO can recognize objects captured from high and low positions. The objects captured by the cameras are placed on a turntable. We capture 200 images of a given object by one camera as the table turns. Thus, we obtain 400 images per object.

Figure 3 shows the processing flow to generate training images for YOLO. To adapt to various lightning conditions, we apply an automatic color equation algorithm [7] to the captured images (Fig. 3 (a)). We use a python library [8] to this end. Then, we remove image backgrounds using chroma keys (Fig. 3 (b)).

For backgrounds of training images, we shoot background images, for example, table and shelf, among others. Moreover, we apply the automatic color equation algorithm to the background images (Fig. 3 (c)). To incorporate the object images into the background images, we define 20-25 object locations on the background images (the number of object locations depends on the background images). Then, by placing the object images on the defined object locations autonomously, training images for YOLO are generated (Fig. 3 (d)). If there
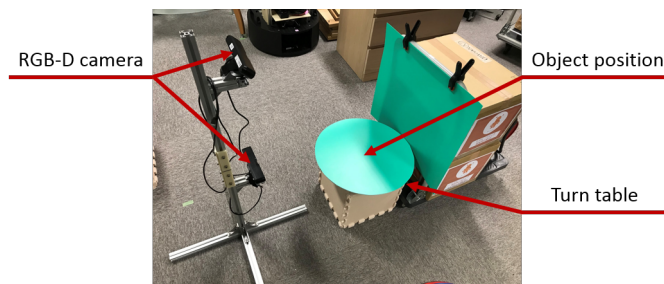

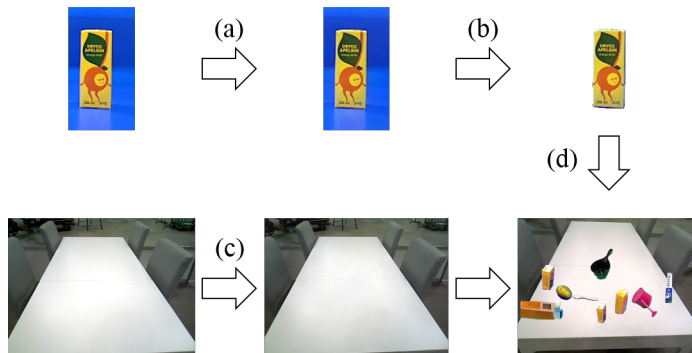**Fig. 2.** Overview of proposed autonomous annotation system for YOLO.

Fig. 3. Processing flow to generate training images for YOLO.

are 91 class objects and 100 background images, 1,237,600 training images are generated. Additionally, annotation data for the training images are generated autonomously because object labels and positions are known.

Image generation requires 30 min (in parallel using six CPU cores), and training of YOLO requires approximately six hours when using the GTX1080 GPU on the Standard Laptop. Even though the generated training data are artificial, recognition of YOLO in actual environments works.

4   Speech recognition and sound localization

The voice recognition/sound source localization system (shown in Fig. 1 (b)) operates as follows:

1. The microphone array captures the voice of the person addressing it and uses a speech recognition engine, Web Speech API on google chrome, to recognize what is being said.
2. The voice of the person addressing the microphone array is captured, and sound source localization is performed according to the MUSIC method using HARK [9], an auditory software package for robots.

5   Brain-inspired amygdala model

In this section, we explain the brain-inspired amygdala model that learns preferences through human-robot interactions.

Two types of knowledge are required by home-service robots: the first is common knowledge pertaining to the world and the second is local knowledge depending on environment. For example, common knowledge is required when a robot is asked to bring "green tea."' In this case, the robot must know what "green tea" is. To obtain common knowledge, deep learning is one of the powerful
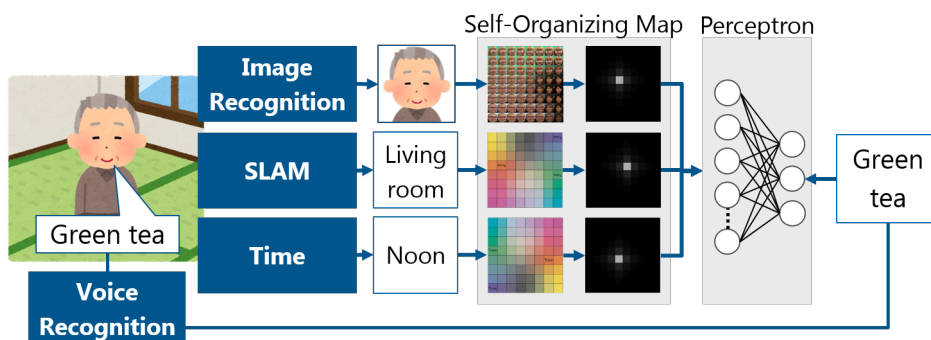
Fig. 4. Brain-inspired amygdala model.

solutions because big data on "green tea" is available. On the contrary, local knowledge is required when a robot is asked to bring "that." In this case, the robot must know what "that" is, and "that" depends on people's preferences. To obtain local knowledge, deep learning is not effective because big data on "that" is unavailable. In the case of humans, we can know someone's preference from our past experiences with that human. Similarly, the robot must obtain such preferences from a few human-robot interactions.

We focus on the amygdala, an area of the human brain. The amygdala causes fear conditioning [10], a type of classical conditioning that has been made popular by Pavlov's dogs. By applying classical conditioning to home-service robots, the robots can be made to obtain local knowledge through a few human-robot interactions, similar to that in Pavlov's experiments with dogs.

Figure 4 shows the proposed amygdala model [11]. The model comprises multiple self-organizing maps (SOMs) [12] and a single perceptron. When a robot is asked to bring an object, the model receives information about the ordered object via voice recognition. At the same time, the model receives information about the face of the person placing the order via image recognition and about their location via SLAM and time. These pieces of information are input into the SOMs. Then, the SOMs classify the information and output the classification results. The classification results are input into the perceptron, and the perceptron learns relation between the classification results and the ordered object. Thereafter, if the robot is asked to bring "that," the model can estimate what the ordering person wants by using information about face, place, and time.

We confirmed experimentally that the model learns preferences through a few human-robot interactions. In the experiment, we defined two situations; A and B. In situation A, face A, place A, and time A are always given, and the ordered object is always object A. In situation B, face A, place B, and time B are always given, and ordered object is always object B. At first, we input situation A into the model as an interaction and repeated the same procedure five times.
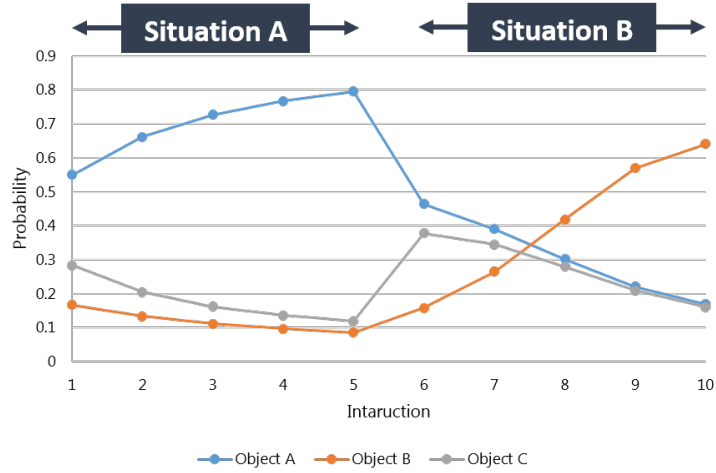
Fig. 5. Learning preferences through human-robot interactions.

Then, we input situation B into the model as an interaction and repeated the same procedure five times.

Figure 5 shows the results of our experiments. The vertical axis in the figure indicates the probability that the model estimates preferences from face, place, and time. During the interaction associated with situation A, the probability of object A increases. On the contrary, during the interaction associated with situation B, the probability of object B become increases and peaks in the eighth interaction. Thus, the model learns preferences from a few human-robot interactions.

6   Competition results

Table 1 shows the results achieved by our team in the recent competitions. We participated in RoboCup and World Robot Challenge for several years, and as a result, our team has won prizes and academic awards.

Especially, we participated in the RoboCup 2018 Montreal using the system described herein. We scored 335 points out of 2125 points. These points were 62 % of the points scored by the top OPL team. We were able to demonstrate the performance of HSR and our technologies. Especially, we won the Procter & Gamble Dishwasher Challenge Award in RoboCup 2018 owing to the object recognition and manipulation used by YOLO. Thanks to these results, we were awarded the first prize in the competition.

Table 1. Results of recent competitions.

Competition	Result
RoboCup Japan Open 2017 Aichi	@Home DSPL 2nd
	@Home OPL 3rd
RoboCup 2017 Nagoya	**@Home DSPL 1st**
	@Home OPL 5th
RoboCup Japan Open 2018 Ogaki	@Home DSPL 2nd
	@Home OPL 1st
	JSAI Award
RoboCup 2018 Montreal	**@Home DSPL 1st**
	P&G Dishwasher Challenge Award
World Robot Challenge 2018	Service Robotics Category
	Partner Robot Challenge Real Space 1st
	METI Minister's Award
	RSJ Special Award

7 Conclusions

In this paper, we summarized available information about our HSR, which we entered into RoboCup 2018 Montreal. The object recognition and voice interaction capabilities that we built into the robot were described as well. Currently, we are developing many different pieces of software for an HSR that will be entered into RoboCup 2019 Sydney.

GitHub

The source codes of our systems and our original dataset are published on GitHub. The URL is as follows:
https://github.com/hibikino-musashi-athome

Acknowledgment

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Robot's Software Description

For our robot we are using the following software:

- OS: Ubuntu 16.04.
- Middleware: ROS Kinetic.
- State management: SMACH (ROS).
- Speech recognition (English):
    - rospeex [13].
    - Web Speech API.
    - Julius.
- Morphological Analysis Dependency Structure Analysis (English): SyntaxNet.
- Speech synthesis (English): Web Speech API.
- Speech recognition (Japanese): Julius.
- Morphological Analysis (Japanese): MeCab.
- Dependency structure analysis (Japanese): CaboCha.
- Speech synthesis (Japanese): Open JTalk.
- Sound location: HARK.
- Object detection: Point cloud library (PCL) and You only look once (YOLO) [6].
- Object recognition: YOLO.
- Human detection / tracking:
    - Depth image + particle filter.
    - OpenPose [14].
- Face detection: Convolutional Neural Network.
- SLAM: hector_slam (ROS).
- Path planning: move_base (ROS).