Team eR@sers[DSPL] (Toyota HSR) 2017 Team Description Paper

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https://sites.google.com/site/erasers2050/home/

Abstract. Team eR@sers has taken part in RoboCup@Home since 2008. 2008 was the first year of the eR@sers. The eR@sers achieved a first place at RoboCup 2008 ,2010 and second place RoboCup 2009, 2012. and its social robot HSR obtained the @Home Innovation Award in 2016. Our team, eR@sers were adopted for RoboCup@Home Standard Platform(HSR) User Teams. We have imploved the ability of robots with various techniques, which are going to be applied to other robot systems or social IT systems. We introduce them and our latest research briefly in this description.

1 Team Summary

1.1 History

The Japanese Robot Team eR@sers(erasers) is the result of a joint effort of four Japanese research groups:

Tamagawa University:the group of the College of Enginerring at Tamagawa University of Tokyo in Japan that is involved in the world championship RoboCup competitions in Four-legged since 2005. At the RoboCup 2006 Bremen , the team, FC Twaves, got the best results(best 16) in the team that participated from Japan. The members at Tamagawa University are interested in a compliant human-machine interaction architecture that is based on the machine intention recognition of the human. This work is motivated by the desire to minimize the need for classical direct human-machine interface and communication.

Waseda University,National Institute of Informatics ,Okayama Prefectural University and National Institute of Information and Communications Technology that are involved in the research of the computational mechanism which enable robots to learn the communication by language and actions through natural interaction with human. Based on the success of the preliminary challenge of the @Home Simulation in RoboCup Japan Open 2013 Tokyo, and the demonstration in the international RoboCup 2013 Eindhoven, the proposal of a new RoboCup @Home Simulation challenge has obtained the recognition of the international RoboCup committee and held the demo challenge in the RoboCup 2015 China in July 2015.

1.2 Focus of research/research interests

We mainly focus on the adaptability to the environmental changes, and on the integration between the sensory-motor data and symbolic representation, utilizing only the neuro-dynamical model.

1.3 Re-usability of the system for other research groups

All developed functions could be packed in ROS modules.

1.4 Applicability of the robot in the real world

Almost all training data would be real data and the system is performed and evaluated in the real environment

1.5 3rd party robot's software

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Ubuntu14.04 + ROS Indigo
Tensorflow 1.0
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2 Innovative technology and scientific contribution

2.1 Learning non-parametric policies as random variable transformations[1]

Learning how to act under uncertainty is a central problem in the field of machine learning. One of major approaches to attack this problem is policy gradient, which explicitly represents the policy and attempts to find the optimal one. Although this makes it straightforward to generate continuous action value, the policy is confined to a particular family of distributions such as normal distributions due to the difficulty of drawing action values from arbitrary probability distributions. To get rid of this limitation, we propose a method to learn non-parametric policy without any concern about generating action values.

Our approach, shown in Fig.1, is to find a transformation from random variable n_t (following a normal distribution for simplicity), whose distribution is known, to one that follows desired distribution. Consider a random variable transformation from n_t to the action value a_t depending on the state value s_t, namely,

$$a_t = f(s_t, n_t; \theta), \tag{1}$$

where θ is the parameter of the function approximator. In this case, the form of the distribution of a_t can vary depending on s_t and θ. In particular, the distribution can be multimodal if the function approximator is sufficiently expressive. Once one find f such that a_t follows desired distribution, samples of the distribution can easily be drawn by calculating f.

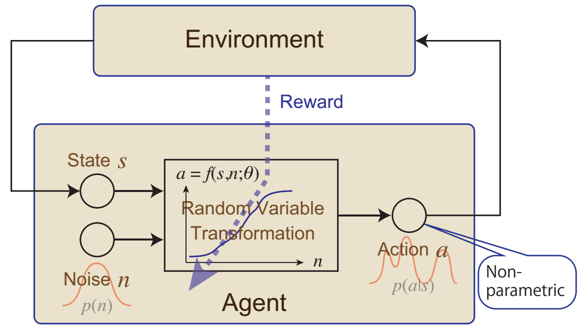

Fig. 1. A schematic illustration of our approach. Action value a is calculated from the state value s and noise n. The function f of them is learned to acquire a desired distribution of a. The optimization is performed with respect not to the value of n but to the distribution of n.

In the field of reinforcement learning, the goal is to maximize the expected reward w.r.t. the stochastic policy. To maximize the expected reward:

$$E = \int R(s_t, a_t) \int \delta(a_t - f(s_t, n_t; \theta)) p(n_t) \mathrm{d}n_t \mathrm{d}a_t, \tag{2}$$

we derived the gradient of E w.r.t. θ, which yields an update rule:

$$\theta \leftarrow \theta + \alpha_t r_t \frac{(f_{nn} - (\log p(n))' f_n) f_\theta - f_n f_{n\theta}}{f_n^2}. \tag{3}$$

Interestingly, the update rule contains the second derivatives. Still, we can easily implement this operation with TensorFlow.

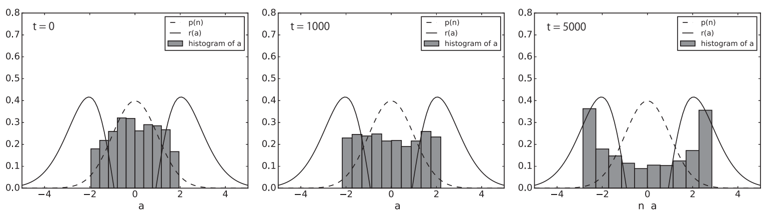

Fig. 2. A numerical experiment. The input noise n was drawn from $N(0,1)$, which is indicated by dashed curves (the horizontal axes are shared by n and a). The histograms show the distribution of $a = f(n)$. The solid curves show the reward function $r = 0.7e^{-(a+1)^2/4} + 0.7e^{-(a-1)^2/4} - 1.5e^{-a^2/2}$.

We trained a fully-connected four-layer neural network, whose input and output are n and a respectively, and whose weight parameters are constrained to be non-negative. The frequency of a around zero decreased to avoid negative reward, whereas that around ± 2 increased pursuing the reward. This shows that a bimodal distribution can be acquired with our algorithm, and also suggests its potential to achieve a variety of distributions depending on the problem. We are currently applying our algorithm to neural networks with state input, to deal with control problems and to achieve social behaviors through learning with our robot.

2.2 Language-motion translation [2],[3]

We will enhance our recurrent neural net model for language-motion translation. The model is based on the sequence-to-sequence model and it is trained with sentences and corresponding motions of robot (**??**). The model enable the robot to handle the ambiguity and synonymy in the sentences, such as logical words "not", "and", and "or".

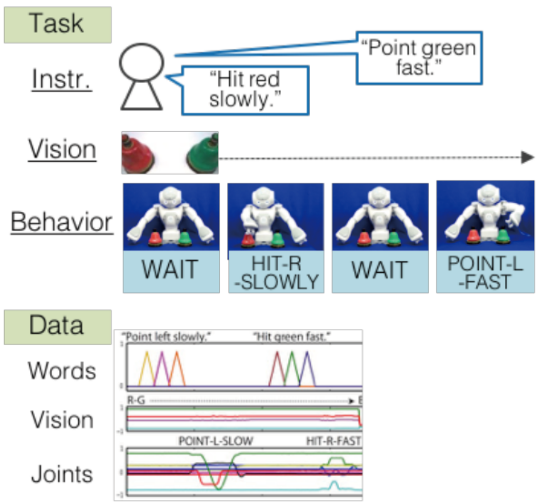

Fig. 3. Translation from a sentence to a motion by RNN

2.3 Object handling [4],[5]

We will enhance our deep learning model for object recognition and motion generation. The model consists of multiple deep auto-encoders with the time sequence input of multi-modal information (4). The model directly control all joints of the robot which handles the object by using raw image and/or sound.

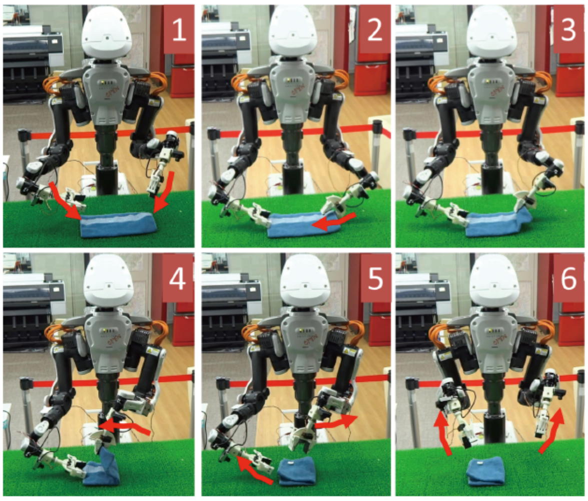

Fig. 4. Cloth folding task based on deep learning model

2.4 RoboCup@Home Simulation[7], [6]

Research on high level human-robot interaction systems that aims skill acquisition, concept learning, modification of dialogue strategy and so on requires large-scaled experience database based on social and embodied interaction experiments. However, if we use real robot systems, costs for development of robots and performing many experiments will be too huge. If we choose virtual robot simulator, limitation arises on embodied interaction between virtual robots and real users. We thus propose an enhanced robot simulator that enables multiuser to connect to central simulation world, and enables users to join the virtual world through immersive user interface. As an example task, we propose an application to RoboCup@Home tasks.

Another function that can be simulated is using natural language and gesture instruction to recognize which object is being referred to by the user. A user might ask the robot to move and/or manipulate an object by saying something like, "Please bring that dish to the dining table" while pointing to the dish. If the pointing and/or speech are vague, the robot should be able to ask appropriate questions to remove the uncertainty. Such dialogue management is a high-level interaction function inherent in high-level HRI.

3 Contribution for RoboCup@Home

Starting from 2006, RoboCup@Home has been the largest international annual competition for autonomous service robots as part of the RoboCup initiative. The challenge consists of a set of benchmark tests to evaluate the robots' abilities and performances in a realistic non-standardized home environment setting.

Fig. 5. Clean-up task

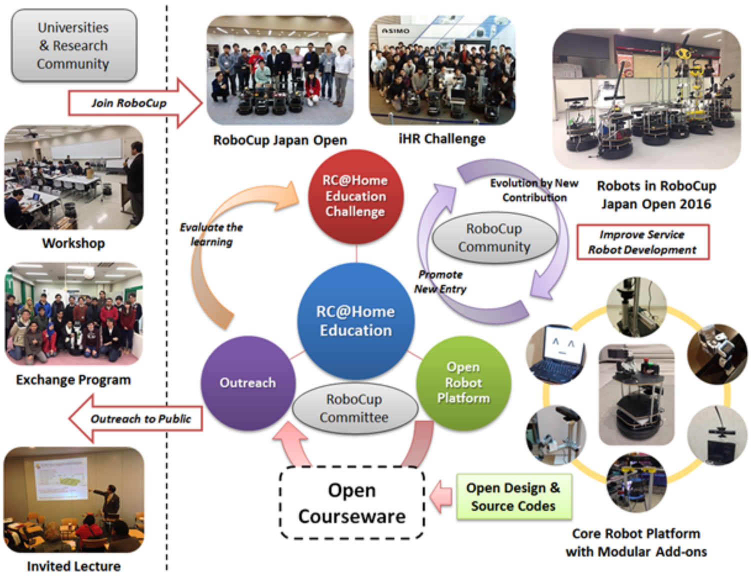

Fig. 6. RoboCup@Home Education initiative to promote service robot development for entry level audience in RoboCup@Home

It has greatly fostered artificial intelligence development in various domains including human-robot interaction, navigation and mapping in dynamic environments, computer vision, object recognition and manipulation, and many more developments on robot intelligence.

However, it is observed that the development curve of the RoboCup@Home teams have a very steep start. The amount of technical knowledge and resources (both manpower and cost) required to start a new team has made the event exclusive to only established research organizations. For instance, in domestic RoboCup Japan Open challenge, the participating teams in RoboCup@Home were merely around 10 teams, which are about the same teams for the past few years. There were actually several new team requests however the development gap was huge for them to even complete the construction of the robots.

For this reason, RoboCup@Home Education initiative (Fig.6) had been started at RoboCup Japan in 2015. RoboCup@Home Education is an educational initiative in RoboCup@Home that promotes educational efforts to boost RoboCup@Home participation and service robot development. Under this initiative, currently there are 3 projects started in Japan:

1. RoboCup@Home Education Challenge at RoboCup Japan Open
2. Development of an educational Open Robot Platform for RoboCup@Home
3. We host RoboCup@Home Education Workshop Roma, Italy,March 15–16,2017 `https://sites.google.com/dis.uniroma1.it/athomeedu-rome2017/home`
4. Outreach programs (domestic workshops, international academic exchanges, etc.)

(For more information, visit `http://www.robocupathomeedu.org/`)

4 The contents of the web site

Our relevant publications, technical reports, as well as videos and pictures ar available in :
Official website:
`https://sites.google.com/site/erasers2050/home/`

Photos and Videos of the robot:
`https://sites.google.com/site/erasers2050/photos-movies/`

5 External computing

We will use "External devices" or " Cloud services " or " Internet API ' s " as listed below

Desktop Computer

- 6th generation Intel Core i7-7700K processor 4.4 GHz
- 32GB RAM DDR4
- Windows 10 Home, Ubuntu14.04LTE

ROSPEEX

ROSPEEX is a cloud-based multilingual communication package for ROS (Robot Operating System). (For more information, visit `http://rospeex.org/top/`)

Microsoft Cognitive Services API

We use Microsoft Cognitive Services API.

(For more information, visit `https://azure.microsoft.com/ja-jp/services/cognitive-services/`)

IBM Watson Developer Cloud

We use IBM Watson Developer Cloud.

(For more information, visit `https://www.ibm.com/jp-ja/marketplace/cognitive-application-development`)

NVIDIA GeForce NOW

(For more information, visit `https://www.nvidia.com/en-us/shield/games/#geforcenow/`)

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