ID: 66

Proceedings of the International Workshop
on Modern Science and Technology
Kitami, Japan/September 2010

Method for Social Behavior Acquisition by Robots Using Feedback from the Environment and Users

Keisuke Takagi, Rafal Rzepka, Kenji Araki

Graduate School of Information Science and Technology, Hokkaido University
{eyu.8055, kabura, araki}@media.eng.hokudai.ac.jp

Abstract: As robots start living with people, they need to be outfitted with the ability to act socially. However, because of situational dependence of a real environment, it is difficult to be solved by programming the rules manually. Therefore, we propose an algorithm where robots learn social behavior using feedback from the real world environment and users' evaluation of positive or negative feedback achieved while performing a task within the environment. Environmental information is *Time* and *Place* of users' evaluation. They are used as a training set for SVM (support vector machine). With our experiment, we confirmed that it is possible to presume the users' evaluation from information on *Time* and *Place* with high accuracy. We also discovered cases where the evaluation between users differs at the same *Time* and *Place*. We propose a solution for such cases and describe it as a task to be undertaken in near future.

Key words: robotics, social robots, multiuser environment

1. Introduction

This study provides a method for acquiring social behavior by robots using feedback from the environmental information and users' evaluation. Thanks to recent advances in robotics, robots start to work at households, offices, etc. When robots live with people, they will need to be outfitted with the ability to act socially.

As the related research of social robots, there is work on recognition of friendly relationship by a robot among humans by simultaneously identifying each person in the interacting group [1]. In other research, the psychological experiment was performed on the interaction between humans and robots [2]. Another paper describes that robots can create or change relations between human users [3].

In this paper, we suggest that social robots should want people to feel better. For example, it is preferable that a robot cleans a dirty floor. On the other hand, it is not preferable when it cleans a room where a baby is sleeping.

However, because of complex situation dependence of a real environment, it is difficult to solve this problem only by a method of manually programming the rules beforehand. Therefore, we propose an algorithm where a robot learns social behavior using the real world environment information and feedback from users' evaluation of positive or negative feedback achieved while performing a task in the environment. Our method allows a robot to achieve social behavior corresponding to each environment. Environment information in this stage is *Time* and *Place* of users' evaluation. These data are collected by using RFID (Radio Frequency IDentification). They are used as a training set for SVM (support vector machine) [4]. As a result, it becomes possible to correctly presume the users' evaluation from information on *Time* and *Place*.

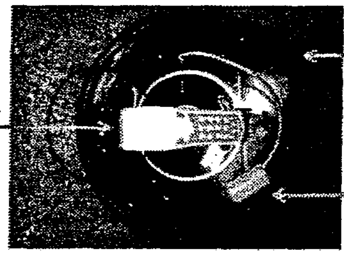

Fig. 1. Roomba, Rootooth, RFID Reader

2. Methods

2.1 Hardware

Fig. 1 shows the robot and devices used in our experiment.

Robot: We use Roomba *which is an autonomous robotic* vacuum cleaner created by iRobot Corporation[1]. Roomba is controlled by serial commands. They are sent by using Rootooth module which gives Roomba wireless Bluetooth capabilities.

RFID: RFID exchanges information from the tags by wireless communication within a short distance. We use passive tags and the reading distance is 30cm. A tag ID and an input of the reader's buttons are sent to a server via wireless. The reader is placed and fixed on Roomba.

2.2 Placement of the RFID tags

Fig. 2 shows the top view of our Language Media Laboratory of Graduate School of Information Science

1 http://www.irobot.com/

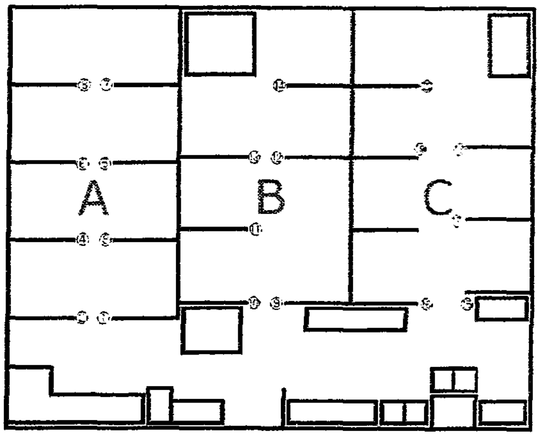

Fig. 2. Experiment environment

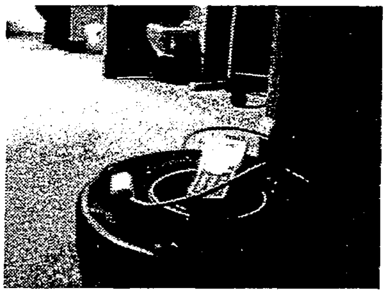

Fig. 3. Reading place tag

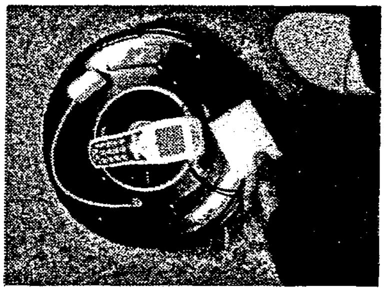

Fig. 4. Personal ID reading action

and Technology main building, Hokkaido University at where we performed our experiment. RFID tags are placed at the points of circled numbers in Fig.2. Tags are divided into three groups of A, B, and C in Fig.2. A reading from one of the tags in a group gives a rough estimation of Roomba's position. In addition, we distributed cards to the experiment participants who are 10 graduate students, members of the laboratory. RFID tags are placed on the back of the cards so it becomes possible to recognize an individual user when he or she brings the ID close to the reader.

2.3 Collection of environmental information

Roomba is ordered to start cleaning. Fig. 3 shows that RFID reader mounted on the robot reads a tag when Roomba approaches it. Current *Time* and *Place* ID are registered in the Situations DB like Table 1. Subjects

Table 1. Situations DB

Time	Place ID
16:24:58	e004010002f9e84e
16:25:14	e004010002f9e84e
16:26:46	e004010002f9e9b8

Table 2. Evaluation DB

Time	User ID	Evaluation
16:25:02	e004010002f9e9b9	positive
16:25:18	e004010002f9e764	negative
16:26:44	e004010002f9e6e7	positive

Table 3. Presumption of a users' evaluation

Time	Place	User	Presumed Evaluation
12:20:05	A	User1	positive
15:14:32	A	User2	negative
17:47:16	B	User3	positive

evaluate Roomba's behavior when they want to. They put card close to the reader like Fig. 4 and Roomba stops at the location of this action. Then they push button on reader for positive or negative evaluation about Roomba's behavior. Current *Time*, User ID and Evaluation value are registered in the Evaluation DB like Table 2. After that, Roomba resumes cleaning.

2.4 Presuming the users' evaluation

Training set is made from collected data composed from *Time*, *Place*, User and Evaluation. We use Weka[2] to create classification models and classify data. The training set is used for SVM. We choose this method because we obtained higher accuracy than from other classification methods. Thereby, it becomes possible to presume the users' evaluation from information on *Time* and *Place* like Table 3.

3. Results

The experimental period was set for 4 days from 25 - 27 January and 1 February 2010. We divided the training set into the following Data of all days, Data of the same day of the week. Tables 4 and 5 show each result by using LOOCV (leave-one-out cross-validation) [5].

Data of all days: Evaluation was performed 75 times. Table 4 shows that choice of all features achieved the highest F-measure. Weighted mean which considers the difference in the number of evaluation was 0.81.

Data of the same day of the week: Evaluation was performed 42 times. Again, Table 5 shows that the choice of all features achieved the highest F-measure. Weighted mean was 0.90. It was 0.09 higher than results of data of all days.

2 http://www.cs.waikato.ac.nz/ml/weka/

Table 4. Data of all days

feature		accuracy	precision	recall	F-measure
Time	positive	0.64	0.69	0.71	0.70
	negative		0.57	0.55	0.56
User	positive	0.75	0.77	0.82	0.79
	negative		0.71	0.65	0.68
Place	positive	0.64	0.67	0.77	0.72
	negative		0.58	0.45	0.51
Time User	positive	0.75	0.78	0.80	0.79
	negative		0.70	0.68	0.69
Time Place	positive	0.73	0.80	0.73	0.76
	negative		0.66	0.74	0.70
User Place	positive	0.75	0.77	0.82	0.79
	negative		0.71	0.65	0.68
all features	positive	0.81	0.83	0.86	0.84
	negative		0.79	0.74	0.77
	weighted mean		0.81	0.81	0.81

Table 5. Data of the same day of the week

feature		accuracy	precision	recall	F-measure
Time	positive	0.62	0.73	0.73	0.73
	negative		0.33	0.33	0.33
User	positive	0.86	0.90	0.90	0.90
	negative		0.75	0.75	0.75
Place	positive	0.79	0.89	0.80	0.84
	negative		0.60	0.75	0.67
Time User	positive	0.88	0.90	0.93	0.92
	negative		0.82	0.75	0.78
Time Place	positive	0.71	0.80	0.80	0.80
	negative		0.50	0.50	0.50
User Place	positive	0.86	0.90	0.90	0.90
	negative		0.75	0.75	0.75
all features	positive	0.90	0.91	0.97	0.94
	negative		0.90	0.75	0.82
	weighted mean		0.90	0.91	0.90

4. Discussion

First, we discuss the effect of features. Choice of all features became the highest F-measure. According to this result, it is confirmed that all features set is effective.

Second, we discuss the reason why results from data of the same day of the week were higher than results from data of all days. In a laboratory environment, users' schedule is similar every week and similar data can be obtained by considering a day of the week. This is the reason why the F-measure increased.

Finally, we discuss about conflicts during user evaluation. During the experiment, there were the cases where users' evaluation conflicted like Table 6. Such situations may affect the existing human relationships within a society [3]. To address this situation, we assume that a robot should convince people or compromise in its behavior. As a method, it is possible to generate a message including elements that can persuade conflicting people and a robot could response to the users trying to explain the reason behind its decision. Some kind of persuasive factor might be preferable. For example, factors as majority rule, a difference in social position, or a reason for urgency could be considered. In addition, it is possible that social positions could be learned from observing the success and failure rate of and reasons exchange between users. If the success rate of the persuasion increases according to a particular user, it can be said that the person has a high position in the given society.

Table 6. Conflict with user evaluation

Time	Place	User	Evaluation
12:41:09	3	User6	positive
12:41:28	3	User5	negative
12:42:11	3	User8	positive

5. Conclusion and Future Work

This paper describes a method for automatic acquisition of social behavior by a robot using environment information and users' feedback. Environment information and users' evaluation are collected from Roomba vacuum cleaner robot and RFID. The data are used for the training set for SVM. By using LOOCV, we achieved an average of F-measure of 0.90 point at most. With this experiment, we confirmed that it is possible to presume users' evaluation with high accuracy. We also discovered cases where the evaluation between users differs at the same time and place. We propose a solution for such cases.

As the future work, we plan to add the method of inputting environmental and preferential information through the text input from users. In addition, it is necessary to apply the presumed evaluation to the behavior of Roomba. Besides, we plan to implement a method for solving users' conflicts by persuasion.

References

[1] T. Kanda, H. Ishiguro & T. Ishida, Psychological Evaluation on Interactions between People and Robot, Journal of the Robotics Society of Japan, 19(3), 2001, 362-371.

[2] T. Kanda & H. Ishiguro, Reading Human Relationships from an Interactive Humanoid Robot, Transactions of Information Processing Society of Japan, 45(8), 2004, 2098-2104.

[3] D. Sakamoto & T. Ono, Sociality of Robot: Robots Construct or Collapse the Human Relations, IPSJ SIG Notes. ICS, 2005, 15-20.

[4] C. Cortes & V. Vapnik, Support-Vector Networks, Machine Learning, 20(3), 1995, 273-297.

[5] Kohavi, R., A study of cross-validation and bootstrap for accuracy estimation and model selection, Proceedings of Fourteenth International Joint Conference on Artificial Intelligence, IJCAI, Montreal, CA, 1995, 1137–1143.