

An Affective Guide Robot in a Shopping Mall

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ABSTRACT

To explore possible robot tasks in daily life, we developed a guide robot for a shopping mall and conducted a field trial with it. The robot was designed to interact naturally with customers and to affectively provide shopping information. It was also designed to repeatedly interact with people to build a rapport; since a shopping mall is a place people repeatedly visit, it provides the chance to explicitly design a robot for multiple interactions. For this capability, we used RFID tags for person identification. The robot was semi-autonomous, partially controlled by a human operator, to cope with the difficulty of speech recognition in a real environment and to handle unexpected situations.

A field trial was conducted at a shopping mall for 25 days to observe how the robot performed this task and how people interacted with it. The robot interacted with approximately 100 groups of customers each day. We invited customers to sign up for RFID tags and those who participated answered questionnaires. The results revealed that 63 out of 235 people in fact went shopping based on the information provided by the robot. The experimental results suggest promising potential for robots working in shopping malls.

Categories and Subject Descriptors

H.5.2 [Information Interfaces and Presentation]: User Interfaces-Interaction styles

General Terms

Design, Human Factors

Keywords

Communication robots, service robots, field trial

1. INTRODUCTION

Recent progress in robotics has enabled us to start developing humanoid robots that interact with people and support their daily activities. We believe that humanoid robots will be suitable for communicating with humans. Previous studies have demonstrated the merits of the physical presence of robots for providing information [1, 2]. Moreover, their human-like bodies enable them to perform natural gaze motion [3] and deictic gestures [4].

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HRI-09, March 11- 13, 2009, La Jolla, California, USA.

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Fig. 1 Robot guiding a customer with deictic representation

These features of humanoid robots might allow them to perform such communicative tasks in human society as route guidance and to explain exhibits. Since we are not yet sure what the communicative tasks of robots will be like, many researchers have started to conduct field trials to explore possible tasks. Such explorations are one important research activity, since HRI remains a very young field where few real social robots are working in daily environments. Field trials enable us to envision the future scenes of human-robot interaction and their accompanying problems that must be solved so that robots can be accepted in daily life.

Previous studies have revealed that social robots can be used as museum guides [5, 6], as receptionist for assisting visitors [26], as peer-tutors in schools [7], in the context of mental-care for elderly people [8], in autism therapy [9, 10], and child-care [11]. In contrast, our study focuses on an information-providing task in daily environments at a shopping mall. Compared with schools and museums, a shopping mall is a public environment open to ordinary people who are often busy, who are not seeking a tool to “kill” time, and who do not have special interest in robotics technology: the environment is challenging. This paper aims to answer the following questions:

- Can a robot function in an information-providing task in an open public environment, such as a shopping mall?
- Can a robot influence people’s daily activities, such as shopping?
- Can a robot elicit spontaneous repeated interaction?

In the paper, we report a number of technical challenges for a robot in a shopping mall. One notable feature is using a human operator to cope with difficulties in real environments. This is quite often used in Human-Computer Interaction (HCI) and HRI for prototyping, known as Wizard of Oz (WOZ) [12, 13]. In addition, since our vision is to use a human operator for more than making a prototype, we believe that a robot could start working in daily environments with human operators with a technique that minimizes the task load of operators, such as one with which one operator can control four robots [14].

2. DESIGN

There are two aspects of design related to HRI: one is the appearance that considers impressions and expectations [15, 16]. Another

er aspect concerns behavior design, e.g., a scenario design for assisted play [17] and design patterns of interactive behaviors [4].

These two aspects are of course mutually related; however, in this study we focused on the latter direction to establish how we can design a robot's interactive behavior for a shopping mall. Here, we introduce how we designed the robot's roles, how we realized them in the system framework, and how we considered them while creating the robot's interactive behaviors. We believe that this provides a chance to start considering the design process of such a social robot that works in the real world.

2.1 Contemplating robot roles

What kind of robots do people want in their daily lives? According to a Japanese government report [18], a majority of respondents believe that providing information at such public spaces as stations and shopping malls is one desired task of robots¹. People also want physical tasks, such as toting luggage. Thus, we decided to explore an information-providing task for a robot in a public space as a guide robot at a mall with many shops nearby.

The next question addresses the roles of a guide robot in a mall. Many other facilities, such as maps and large screens, provide information. In contrast, a robot has unique features based on its physical existence, its interactivity, and its capability for personal communication. We defined the three roles based on this consideration.

Role 1: Guiding

The size of shopping malls continues to become larger and larger. Sometimes people get lost in a mall and ask for directions. Even though a mall has maps, many people still prefer to ask for help. Some information is not shown on a map; thus, people ask "where can I buy an umbrella?" or "where can I print a digital camera?" (the author was actually asked this strange question in a mall, which seems to suggest the needs of humans' support for the robot). Here, a route guidance service is needed.

In contrast to a map or other facilities, a robot has unique features: a physical existence, it is co-located with people, and it is equipped with human-like body properties. Thus, as shown in Fig. 1, a robot can naturally explain a route like humans by pointing to it, looking in the same direction as the person is looking, and using such reference terms as "this way."

Role 2: Building Rapport

From the customer view, since a robot is one representative of the mall, it needs to be friendly so that customers feel comfortable. In addition, since a mall is a place that people repeatedly visit, a robot needs to naturally repeat interaction with the same person; thus, a function that builds rapport with each customer is useful. The importance of building rapport has been studied in HCI in the context of affective computing [19].

Moreover, one future scenario in this direction is a function of customer relationship management. Previously, this was done by

¹ This might be relatively high in Japan rather than other countries: 76.2% of the respondents think it is good to have robots at a transportation facility such as a station and 87.5% of them think at the place guidance is a good task for robots; 64.2% of the respondents think it is good to have robots at a commercial place, such as a shopping mall, and 87.9% of them think at the place guidance is a good task for robots.

humans: for example, in a small shop, the shopkeeper remembers the "regulars" and molds communication to each individual. For example, he/she might be particularly cordial to the good customers who often frequent the shop. Recently, since the number of customers is too unwieldy to manage, information systems have assumed this role in part, such as the mileage services of airplane companies, the point systems of credit cards, and online shopping services such as Amazon. However, these information systems do not provide natural personalized communication as humans do; in contrast, we believe that in the future a robot might be able to provide natural communication and personalized service for individual customers and develop relationships or a rapport with them.

Role 3: Advertisements

From the mall's point of view, advertising is one important device or facility they need. For instance, posters and signs are placed everywhere in malls. Recently, information technologies are being used for such purposes as well. Fig. 2 shows a large screen (about 5 m by 2.5 m) for providing shopping information to customers, placed in the shopping mall where we conducted our field trial. The screen shows such shop information as places in the mall, product features of the shops, etc.

We believe that a robot can also be a powerful tool for this purpose. Since a robot's presence is novel, it can attract people's attention and redirect their interest to the information it provides [20]. In addition, it can provide information to people in a way people talk together; for example, it can mention shops and products from its first-person view (See 2.3.4).



Fig. 2 Shopping mall and its large information screen

2.2 System Design

The robot's role is limited by its recognition and action capabilities, which are largely limited by its hardware and infrastructure. Thus, first, we should consider system design (hardware and infrastructure). In HRI, we need to explore a promising combination of hardware and infrastructure. Some researchers are studying a stand-alone robot that has all sensing, decision making, and acting capabilities. In contrast, some researchers are focusing on a combination of robots, ubiquitous sensors, and humans. We have chosen the latter strategy, known as a "network robot system" [21], in which a robot's sensing is supported by ubiquitous sensors and its decision processes by a human operator.

From a user view, the central component is a robot that provides information in a natural way with its speaking capability as well as its body properties for making gestures. Thus, regardless whether it is a stand-alone or a networked robot system, users can concentrate on the robot in front of them.

In contrast to the user view, in a network robot system, most of the intelligent processing is done apart from the robot. Sensing is mainly done by ubiquitous sensors. There are three important sensing elements in our system: *position estimation*, *person identification*, and *speech recognition*. For *position estimation*, we used floor sensors that accurately and simultaneously identify the

positions of multiple people. This could also be done with other techniques, such as a distance sensor. For *person identification*, we employed a passive-type Radio Frequency Identification (RFID) tag that always provides accurate identification. Such tags require intentional user contact with a RFID reader; since passive-type RFIDs have been widely adopted for train tickets in Japan, we consider this unproblematic.

We used a human operator for *speech recognition* and *decision making*. For this way of providing information, instability and awkwardness would cause critical disappointment, and the quality of current speech recognition technology remains far from useful. For instance, a speech recognition system prepared for noisy environment, which performs 92.5% word accuracy in 75 dBA noise [22], resulted in only 21.3% accuracy in a real environment [23]. This reflects the natural way of daily utterances, the changes of voice volume among people and/or within the same person, and the unpredictability of noise in a real environment. Thus, since a speech recognition program causes many recognition errors, the robots have to ask for elucidation too often.

2.3 Behavior Design

2.3.1 General Design

We set two basic policies for designing the robot's interaction. First, it takes the communication initiative and introduces itself as a guide robot. It asks about places and then provides information in response to user requests. Thus, customers clearly understand that the robot is engaged in route guidance.

Second, its way of utterance and other behaviors are prepared in an affective manner [19], not in a reactive manner. The robot engages in human-like greetings, report its "experience" with products in shops and tries to establish a relationship (or rapport) [24] with the individuals. This is very different from master-slave type communication where a robot prompts a user to provide a command.

2.3.2 Guiding behavior

There are two types of behaviors prepared for guiding: *route guidance* and *recommendation*. The former is a behavior in which the robot explains a route to a destination with utterances and gestures, as shown in Fig. 1. The robot points in the first direction and says "please go that way" with an appropriate reference term chosen by an attention-drawing model [25]. It continues the explanation, saying: "After that, you will see the shop on your right." Since the robot knows all of the mall's shops and facilities (toilets, exits, parking, etc.), it can explain 134 destinations.

In addition, for situations where a user hasn't decided where to go, we designed *recommendation* behaviors in which the robot suggests restaurants and shops. For example, when a user asks, "where is a good restaurant?" the robot starts a dialogue by asking a few questions, such as "What kind of food would you like?" and chooses a restaurant to recommend.

2.3.3 Building rapport behavior

For persons wearing RFID tags, the robot starts to build rapport through a dialogue that consists of the following three policies.

Self disclosure: The importance of self-disclosure for humans to be friendly has long been studied. Bickmore and Picard used this strategy for relational agents for building relationships with users

[24]. Gockley *et al.* made a receptionist robot that tells new stories and successfully attracted people to interact with it [26]. In our previous study, which was successful, our robot disclosed a secret [28]. In this study, we follow the same strategy: letting the robot perform self-disclosure. For example, the robot mentions its favorite food, "I like *Takoyaki*," and its experiences, such as, "this is my second day working in this mall."

Explicit indication of person being identified: Since we found that people appreciated having their names used by robots in our previous studies [11], we continued this strategy. The robot greets a person by the name under which he/she registered, such as "Hello, Mr. Yamada." In addition, it uses a history of previous dialogue to inform that the robot remembers the person. For example, on day one, if the robot asked "do you like ice cream?" and if the person answered "yes," the robot says "ok, I'll remember that;" on day two, the robot says, "I remember that you said you like ice cream, so today, I'm going to tell you my favorite flavor of ice cream."

Change of friendliness in behaviors: For a person who repeatedly visits, the robot gradually changes its behavior to show a more and more friendly attitude. For example, on day one, it says "I'm a little nervous talking with you for first time;" but on day three it says, "I think we are friends" to show its warm attitude toward the person.

2.3.4 Behavior for advertisements

The robot is also intended to provide advertisements about shops and products in a manner that resembles *word of mouth*. When the robot starts a conversation with a customer, it starts with a greeting and then engages in *word of mouth* behavior as a form of casual chat. It affectively reports its pretended experiences about products in shops. For example, the robot might say, "yesterday, I ate a crêpe in the food court. It was nice and very moist. I was surprised!" "The beef stew *omurice* at Bombardier Jr. was good and spicy. The egg was really soft, too, which was also very good." We implemented five topics per day and changed the topics every day so that daily shoppers didn't get bored with this behavior.

3. SYSTEM CONFIGURATION

Figure 3 shows an overview of the system configuration. The robot identifies a person with an RFID tag reader and continues to track his/her position with floor sensors. As a WOZ method, speech recognition is conducted by a human operator. This information is sent to a behavior selector, which chooses an interactive behavior based on pre-implemented rules called Episode Rules and the history of previous dialogues with this person.

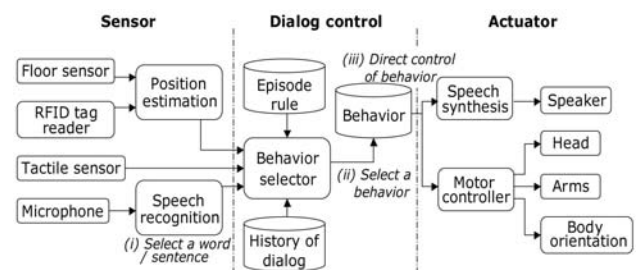


Fig. 3 System configuration

In the figure, italic text represents operator role

3.1 Autonomous system

3.1.1 Robovie

“Robovie” is an interactive humanoid robot characterized by its human-like physical expressions and its various sensors (Fig. 1). We used humanoid robots because a human-like body is useful for naturally capturing and holding the attention of humans [11]. It is 120 cm high, 40 cm wide, and has tactile sensor elements embedded in the soft skin that covers its body.



Fig. 4 RFID tag and reader

3.1.2 Person identification

We invited customers at the field trial to register for an RFID tag for person identification. The left side of Fig. 4 shows a passive-type RFID tag embedded in a cellular phone strap. The accessory is 4 cm high. The RFID tag’s reader is attached to the robot’s chest. Since a passive-type RFID system requires contact distance for reading, users were instructed to place the tag on the tag reader for identification and to interact with the robot (Fig. 4, right).

3.1.3 Position estimation

We installed 16 floor sensor units around the robot that covered a 2 x 2 m area (Fig. 6). Each sensor unit is 50 x 50 cm with 25 on-off pressure switches. The floor sensors have a sampling frequency of 5 Hz. To estimate people’s positions, we used a Markov Chain Monte Carlo method and a bipedal model [27]. This method provided robust estimation of positions without occlusion; the average position error was 21 cm. Thus, it was useful for situations where a person closely interacted with the robot.

Episode rules describe the transition rules among the *situated modules*. 1015 episode rules were implemented. An overview of the interaction flow is summarized in Figure 5. When the robot detects a person, it greets that person. If the person touches his/her RFID tag, the robot starts the flow in the first branch of Fig. 5. It calls the person’s name, provides shopping information of the day, chats about the person’s preferences, and offers route guidance. If the person does not have an RFID tag, it engages in simpler interaction providing shopping information and route guidance.

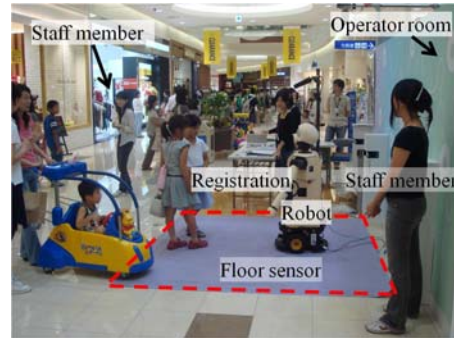


Fig. 6 Field trial environment

3.1.5 Non-verbal behaviors

In addition to the interactive behaviors implemented as *situated modules*, the robot is also designed to sustain interaction non-verbally. The robot orients its body direction to the interacting person whose x-y position is detected with the floor sensor (explained in 3.1.3). Moreover, we implemented gaze behavior. The robot looks at a face of interacting person; for this purpose, we inputted person’s height information in the robot associated with ids of RFID tags, so that the robot is able to orient its gazing direction to the face. During guiding behavior, it points and looks at the direction (Fig. 1) for shared attention.

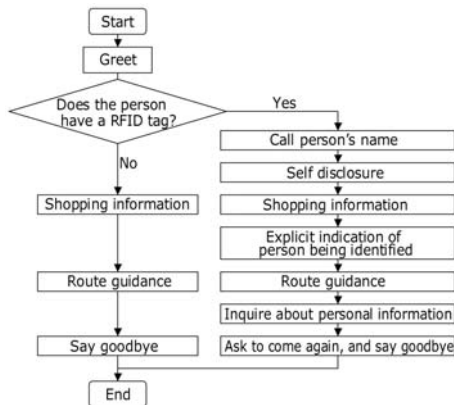


Fig. 5 Flow of robot’s dialogue

3.1.4 Behavior and episode rules

Interactive behavior is implemented with *situated modules* (“behavior” in this paper) and *episode rules* [28]. Each situated module controls the robot’s utterances, gestures, and non-verbal behaviors in reaction to a person’s action. For example, when it offers to shake hands by saying, “let’s shake hands,” it waits for input from a tactile sensor to react to the person’s handshake. Each behavior usually lasts about five to fifteen seconds. 1759 behaviors were implemented based on our design policies.

3.2 Operator’s roles

The robot system is designed to operate without an operator; however, since speech recognition often fails in a noisy environment, there are many unexpected situations in dialogues where the robot cannot correctly respond to requests. Thus, in this study, we used the WOZ method with a human operator to supplement these weaknesses of autonomous robots. The detailed roles are described in the following subsections.

We made an important principle for the operator. In principle, we asked the operator to minimize the amount of operations. This principle is for studying the potential of robot autonomy. Except for substituting speech recognition, the operator only helped the robot when the operation was truly needed. For example, even if a user interrupted the flow and asked, “how old are you?” (a frequently asked question), the operator did not operate the robot. If the user continued to repeat the question without showing signs of stopping, the operator selected the robot’s behavior, or even typed its utterance to answer.

3.2.1 Substitute of speech recognition

When a robot performs a behavior in which it asks a user a question, the teleoperation system prompts the operator to choose the words from the list expected for this situation. For example, when the robot asks, “I can give you the route. Where would you like to go?” the teleoperation system shows a list of places. When the

robot asks “Do you like ice cream?” it shows a simple choice of “yes,” “no,” and “no response” to the operator. Here, the operator behaves in the same way as speech recognition software. After the operator chooses the words, the robot autonomously continues the dialogue with the user.

3.2.2 Supervisor of behavior selector

There are significant degrees of uncertainty about user behavior toward the robot. Sometimes people asked about unexpected things even though the robot has a behavior to answer the question; here, the problem is the lack of episode rules. For example, although the robot has behaviors to guide and explain all of the shoe stores, it was confused when a user asked about a “shop for children’s shoes,” which was not in the speech recognition dictionary. For such situations, the operator selects the next behavior for the robot. After this operation, developers updated the word dictionaries for speech recognition and the episode rules based on the operation histories so that the robot can autonomously select its next behavior in the future.

3.2.3 Knowledge provider

With current technology, only humans can provide knowledge to the robot. Developers input knowledge in advance as a form of behavior. But this in-advance-effort is limited to what the developers can expect; in reality, much unexpected knowledge is needed. For example, although the robot has behaviors for all restaurants, when asked about a Japanese-food restaurant, the robot couldn’t say something like, “there are two Japanese-food restaurants: a *sushi* restaurant and a *soba* restaurant. Which do you prefer?” For such a case, the operator directly typed the sentence so that the robot could respond. Later, developers added the appropriate behaviors for the situation.

3.3 Conversational fillers

The operator roles include decision making so the operator needs a few seconds to manage the robot if the question is complex or difficult. However, since users might feel uncomfortable during slow responses or long pauses, robot response time is critical. To solve such problems, we implemented a *conversational filler* to buy time [29]. When the operator needs a few seconds, he/she executes a *conversational filler* behavior to notify listeners that the robot is going to respond soon.

4. FIELD TRIAL

4.1 Procedure

A field trial was conducted at a large, recently built shopping mall consisting of three floors for shopping and one for parking with approximately 150 stores and a large supermarket. The robot was placed in a main corridor of the mall weekday afternoons from 1 to 5 for five weeks (from July 23rd to August 31st, 2007, except for a busy week in the middle of August). This schedule was decided based on an agreement with the mall management to avoid busy times to prevent situations where too many people might crowd around the robot.

The robot was open to all visitors. Those who signed up for the field trial (participants) received a passive-type RFID embedded in a cell phone strap (Fig. 4). We recruited these participants by two methods: (1) a flyer distributed to residents around the mall, and (2) on-site sign up during the first three weeks while our staff

approached visitors who seemed interested in the robot. The participants filled out consent forms when they enrolled and questionnaires after the field trial. They were not paid, but they were allowed to keep their RFID tags.²

4.2 Results

4.2.1 Overall transition of interactions

Figure 7 shows the number of interactions the robot engaged in. Here, one interaction represents an interaction that continued with the visitor until the robot said goodbye. Fig. 8 shows the interaction scenes (supplement video file contains other scenes of interaction). During the first three weeks our staff invited visitors for registration and interaction with the robot. From the fourth week onwards, our staff stood near the robot for safety. There was an average of 105.7 interactions each day. As the graph shows, the number of interacting persons did not differ over the five-week period. Multiple persons interacted with the robot (an average of 1.9 persons per interaction).

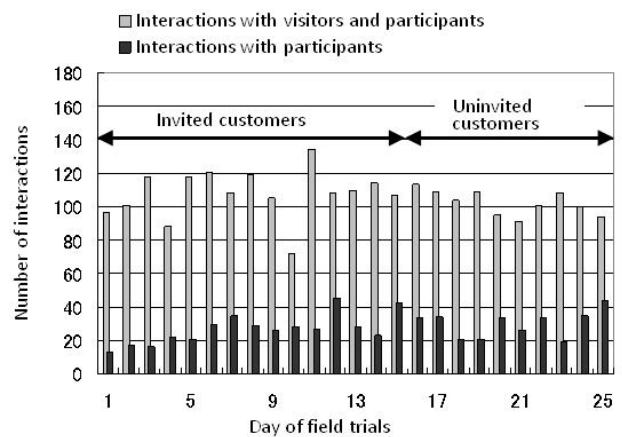


Fig. 7 Daily visitors and participants



Fig. 8 Interaction scenes

(See attached video for other scenes of interaction)

332 participants signed up for the field trial and received RFID tags; 37 participants did not interact with the robot at all, 170 participants visited once, 75 participants visited twice, 38 visited three times, and 26 visited four times; the remaining 23 participants visited from five to 18 times. On average, each participant interacted 2.1 times with the robot, indicating that they did not repeat interaction very much. One obvious shortage was the trial duration; since every day many non-participant visitors waited in line to interact with the robot, some participants reported that they hesitated to interact with the robot because it was too crowded. Fig. 7 shows the number of participants who interacted each day, with an average of 28.0 persons per day.

² The experimental protocol was reviewed and approved by our institutional review board.

4.2.2 Perception of participants

When the field trial finished, we mailed questionnaires to 332 participants and received 235 answers. All items were on a 1-to-7 point scale where 7 represents the most positive, 4 represents neutral, and 1 represents the most negative.

Impression of robot

The questionnaire included items about “Intention of use” (studied in [30]), “(the degree of) Interest,” “Familiarity,” and “Intelligence,” which resulted in respective scores of 5.0, 4.9, 4.9, and 5.1 (S.D.s. were 1.3, 1.4, 1.4, and 1.4). Many positive, free-answer form comments described the robot as cute and friendly.

Route guidance

The questionnaire answers about the adequacy of route guidance resulted in an average of 5.3 points (S.D. was 1.3). In a free-description form, the following comments were made:

- The robot correctly answered when I asked about a particular shop.
- I’m surprised that its route guidance was so detailed.
- Its route guidance was appropriate and very easy to understand.
- The robot was useful for questions that I hesitated to ask because they seemed too simple.

Providing information

The questionnaire answers about the usefulness and interest in the information resulted in an average of 4.6 and 4.7 points (S.D.s. were 1.4 and 1.3). Moreover, 99 out of 235 participants reported that they visited a shop mentioned by the robot, and 63 participants bought something based on the information provided by the robot. We particularly asked about reasons in a free-description form and received the following comments:

- The robot recommended a kind of ice cream that I hadn’t eaten before, so I wanted to try it.
- The movie mentioned by the robot sounded interesting.
- Since Robovie repeatedly mentioned crepes, my child wanted to eat one.

These results suggest that the robot’s information-providing function affected them, increased their interest in particular shops and products, and even encouraged them to actually buy products.

Building rapport

The questionnaire answers about degree of perceived familiarization resulted in a 4.6 point on average (S.D. was 1.5). In the free-description form, comments included:

- Since it said my name, I felt the robot was very friendly.
- The robot was good since it seemed as if it gradually get familiar with me.
- I’m surprised that the robot has such a good memory (People in US also perceive that robots have are good at memorization [31]).
- My child often said “let’s go to the robot’s place,” and this made visiting the mall more fun.
- The robot was very friendly. I went with my five-year-old daughter to interact with the robot; on the last day, she almost cried because it was so sad to say goodbye. She remembers it as an enjoyable event: at home, she imitates the robot’s behavior and draws pictures of it.

4.2.3 Comparison with an information display

We asked participants how often they were influenced by information displays in the same mall (Fig. 2). In the questionnaires,

participants were asked to answer the following: “Usefulness of information provided by display/robot,” “Interest in shops mentioned by display/robot,” “Visiting frequency triggered by display/robot,” and “Shopping frequency triggered by display/robot.” The order of the questionnaires about the display and robot was counterbalanced.

Figure 9 shows the comparison result. There were significant differences ($F(1,229) = 40.96, 69.52, 36, 19, \text{ and } 7.66, p < .01$ for all four items). Thus, for the participants, the robot provided more useful information and elicited more shopping.

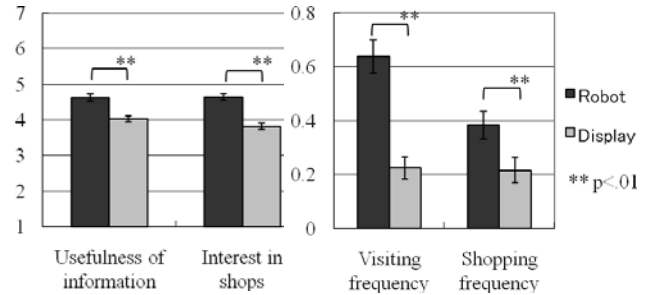


Fig. 9 Comparison of robot and a display

Note that this is not like laboratory experiments with precise control. Thus, the comparisons have the following unbalanced factors. Yet we believe the comparisons are still useful to understand the phenomena caused by the robot.

Duration of comparison: For the robot, we asked about their experience during the field trial. For the display, to include its possible novelty effect (it could be novel to them, as it is very large) we asked them to answer their experience regarding the four months of the duration (from the opening of the mall until the end of the field trial).

Way of providing information: The display shows information about a shop by highlighting information. The target shop is switched about once a minute. Note that since this display is in a commercial-based service, we assume that it is well prepared.

Participant interest: The participants might be more interested in the robot than the other mall visitors, since we suspect that participation in the field trial reflected interest in the robot. However, this is a limitation of our study as a field trial, which needed spontaneous participation; for example, they had to register for the RFID tags.

4.2.4 Integrated analysis

Structural equation modeling (SEM)

We analyzed the relationships among impression, perceived usefulness, and the affect on shopping behavior using structural equation modeling (SEM), which is a relatively new statistical analysis for revealing the relationships behind observed data. Its process resembles factor analysis to reveal latent variables and regression analysis to associate variables to produce a graphical model of causal-result relation. Since SEM is an established technique with many textbooks such as [32, 33], we leave further explanation of this technique to these textbooks. The following paragraphs report how we applied this technique to our data.

For the modeling, our hypothesis is that their interaction experiences with the robot (observed as impression and day of visit)

affected their shopping behavior as an advertisement effect. We made a model that included the latent variables of advertisement and interest effects as possible consequences. We added the latent variables of the impressions of the robot and established rapport (relationships) with it as well as the experience of shopping as possible causal factors.

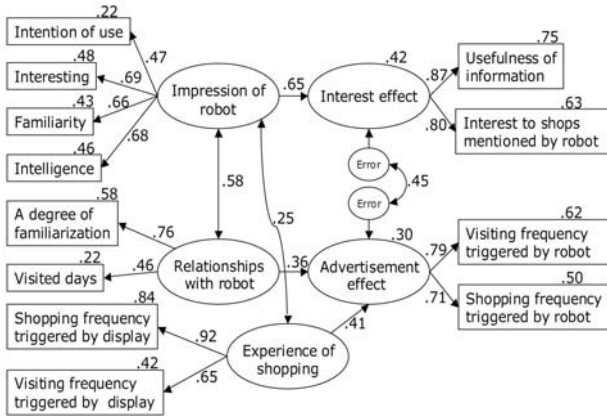


Fig. 10 Retrieved model about observed variables

Analysis Result

Figure 10 shows the best-fit model produced by SEM. In the figure, for readability we didn't draw error variables that are only associated with one variable. The variables in the squares are the observed variables (such as the questionnaire items), and those in the circles are the latent variables retrieved by the analysis (named by us). The numbers around the arrows (path) are the values of the path coefficients, similar to coefficients in regression analysis. The numbers on the variables show the coefficient of determination, R^2 . Thus, 30% of the "Advertisement effect" is explained by the factors of "Relationships with robot" and "Experience of shopping," and 42% of the "Interest effect" is explained by the factor of "Impression of robot."

Regarding the model's validity, this analysis result shows good fitness in the appropriateness indicators of $GFI=.957$, $AGFI=.931$, $CFI=.987$, and $RMSEA=.028$. (According to [32], the desired range of the indicators should be as follows: $GFI, AGFI \geq .90$, $CFI \geq .95$, and $RMSEA \leq .05$). Each path coefficient is significant at a significance level of 1%.

In SEM analysis, there is an indicator, AIC, for the best-fitness of this model. The model with the minimum AIC value is considered the best among the models with the same variables. The analysis result of Fig. 10 has a minimum AIC value of 115.9. For example, a model with one extra path from "Impression of robot" to "Advertisement effect" results in an AIC value of 116.9, so this path itself is not significant (coefficient = $-.10$, $p=.36$). This suggests that "Advertisement effect" is not directly affected by "Impression of robot."

Interpretation

The interpretation of this modeling result is quite interesting. The model suggests that the participants who positively evaluated the impression of the robot tended to be positive about the interest effect (coefficient = $.65$); however, the advertisement effect is not associated with the impression of the robot, but with the relationships with it (coefficient = $.36$). Thus, the factor of the relationships with the robot explains 13% of the deviation of the adver-

tisement effect. Although this ratio might not be so high, we believe that it is interestingly high for such shopping behavior, since shopping behavior largely depends on people's various situations (financial, interests, time, occasion, etc). It implies that development of relationships with the robot would increase the advertisement effect. Although to increase the relationships, impression could be important.

5. DISCUSSION

5.1 Degree of operator involvement

Since this study was conducted with operators, it is useful to show how often the robot was under their control. Fig. 11 shows the number of operations. As described in Section 3.2, one operator role was to "Substitute speech recognition," which we expect to be automated in the future. The operator did this two or three times per dialogue.

In contrast, the result shows that the operator's load for the remaining two roles, "Supervisor of behavior selector" and "Knowledge provider," gradually decreased. This result is promising, because these two roles will be difficult to do autonomously. After day 10, 254.2 "Substitute of speech recognition," 1.7 "Knowledge provider," and 13.4 "Supervisor of behavior selector" operations were conducted per day.

During the field trial, we continued to implement the interactive behaviors to supplement the missing knowledge that the operators needed to operate. On average, we added 0.2 interactive behaviors to reduce the "Knowledge provider" task and 3.4 rules for transition among behaviors to reduce the "Supervisor of behavior selector" task per day. This result shows one promising case of robot development that operates in a real field under the supervision of human operators.

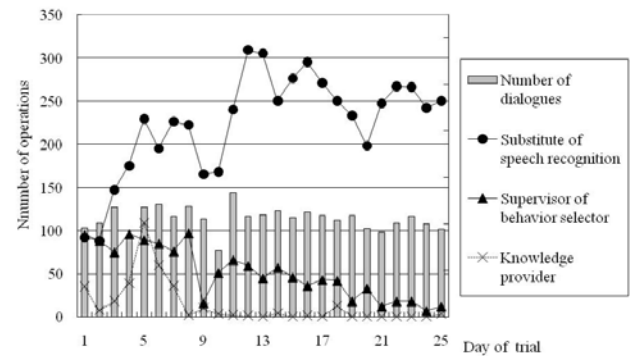


Fig. 11 Number of operations by operator

6. CONCLUSION

We developed a robot that was designed to provide information such as route guidance and other shopping information for a shopping mall. A five-week field trial was conducted in a shopping mall. We recruited and registered participants for RFID tags and gave them questionnaires after the field trial. Analysis results indicate that they accepted the robot with positive impressions and were influenced by the information provided by it. The comparison shows that the robot more successfully invited visitors for shopping than an information-presenting display. Integrated analysis revealed the importance of establishing relationships between

customers and the robot for larger advertisement effects on shopping behavior. The robot performed well in the information-providing task using gestures and natural language and successfully influenced people's daily shopping activities. In contrast, the study failed to show whether the robot could elicit spontaneous repeated interactions; a limited number of participants visited repeatedly. This aspect should be explored more in future studies.

7. ACKNOWLEDGMENTS

We wish to thank the administrative staff at the Takanohara AEON for their cooperation. We wish to thank Dr. Akimoto, Dr. Miyashita, Dr. Sakamoto, Mr. Glas, Mr. Tajika, Mr. Nohara, Mr. Izawa, and Mr. Yoshii for their help. This research was supported by the Ministry of Internal Affairs and Communications of Japan.

8. REFERENCES

- [1] Kidd, C. and Breazeal, C., Effect of a Robot on User Perceptions, *IROS'04*, pp. 3559-3564, 2004.
- [2] Powers, A. *et al.*, Comparing a Computer Agent with a Humanoid Robot, *HRI2007*, pp.145-152, 2007.
- [3] Mutlu, B. *et al.*, A Storytelling Robot: Modeling and Evaluation of Human-like Gaze Behavior, *IEEE Int. Conf. on Humanoid Robots (Humanoids2006)*, pp. 518-523, 2006.
- [4] Kahn, P. H. Jr., *et al.*, Design Patterns for Sociality in Human Robot Interaction, *HRI2008*, pp. 97-104, 2008.
- [5] Burgard, W. *et al.*, The interactive museum tour-guide robot, *Proc. of National Conference on Artificial Intelligence*, pp. 11-18, 1998.
- [6] Siegwart, R. *et al.*, Robox at Expo.02: A Large Scale Installation of Personal Robots, *Robotics and Autonomous Systems*, 42(3), pp. 203-222, 2003.
- [7] Kanda, T. *et al.*, Interactive Robots as Social Partners and Peer Tutors for Children: A Field Trial, *Human Computer Interaction*, 19(1-2), pp. 61-84, 2004.
- [8] Wada, K. *et al.*, Effects of robot-assisted activity for elderly people and nurses at a day service center, *Proceedings of the IEEE*, 92(11), pp. 1780-1788, 2004.
- [9] Dautenhahn, K. *et al.*, A quantitative technique for analysing robot-human interactions, *IROS'02*, pp.1132-1138, 2002.
- [10] Kozima, H., Nakagawa C., and Yasuda, Y., Interactive robots for communication-care: A case-study in autism therapy, *Ro-Man 2005*, pp. 341-346, 2005.
- [11] Tanaka, F. *et al.*, Socialization between toddlers and robots at an early childhood education center, *Proc. of the National Academy of Sciences of the USA*, 104(46), pp. 17954-17958, 2007.
- [12] Dahlback, D. *et al.*, Wizard of Oz studies - why and how, *Knowledge based systems*, 6(4), pp. 258-266, 1993.
- [13] Green A. *et al.* Applying the Wizard-of-Oz Framework to Cooperative Service Discovery and Configuration, *Ro-Man 2004*, 2004.
- [14] Glas, D. F. *et al.*, Simultaneous Teleoperation of Multiple Social Robots, *HRI2008*, pp.311-318, 2008.
- [15] Dario, P., Guglielmelli, E., and Laschi, C., Humanoids and personal robots: Design and experiments, *Journal of Robotic Systems*, 18 (12), pp. 673 – 690, 2001.
- [16] Goetz, J., Kiesler, S., and Powers, A., Matching robot appearance and behaviors to tasks to improve human robot cooperation, *Ro-Man 2003*, pp. 55-60, 2003.
- [17] Robins, B., Ferrari, E., and Dautenhahn, K., Developing Scenarios for Robot Assisted Play, *Ro-Man2008*, pp. 180-186, 2008.
- [18] Research study for the scope of the strategy map of robotics technology, 2005. (Available at <http://www.nedo.go.jp/database/index.html>, with index code 100007875) (in Japanese)
- [19] Picard, R. W., *Affective Computing*, 1997.
- [20] Kanda, T. *et al.*, Who will be the customer?: A social robot that anticipates people's behavior from their trajectories, *UbiComp2008*, 2008.
- [21] Sanfeliu, A., Hagita, N., and Saffiotti, A., Special Issue: Network Robot Systems, *Robotics and Autonomous Systems*, 2008.
- [22] Ishi, C. T. *et al.*, Robust speech recognition system for communication robots in real environments, *IEEE Int. Conf. on Humanoid Robots*, pp. 340-345, 2006.
- [23] Shiomi, M. *et al.*, A Semi-autonomous Communication Robot -A Field Trial at a Train Station -, *HRI2008*, pp.303-310, 2008.
- [24] Bickmore, T. W. and Picard, R. W., Establishing and maintaining long-term human-computer relationships, *ACM Transactions on Computer-Human Interaction*, Vol. 12, No. 2, pp. 293–327,2005.
- [25] Sugiyama, O. *et al.*, Humanlike conversation with gestures and verbal cues based on a three-layer attention-drawing model, *Connection science*, 18(4), pp. 379-402, 2006.
- [26] Gockley, R., Forlizzi, J., and Simmons, R., Interactions with a Moody Robot, *HRI2006*, pp. 186-193, 2006.
- [27] Murakita, T. *et al.*, Human Tracking using Floor Sensors based on the Markov Chain Monte Carlo Method, *Proc. Int. Conf. Pattern Recognition (ICPR04)*, pp. 917-920, 2004.
- [28] Kanda, T. *et al.*, A two-month Field Trial in an Elementary School for Long-term Human-robot Interaction, *IEEE Transactions on Robotics*, 23(5), pp. 962-971, 2007.
- [29] Shiwa, T., Kanda, T., Imai, M., Ishiguro, H., and Hagita, N., How Quickly Should Communication Robots Respond? *HRI2008*, 2008.
- [30] Heerink, M., Kröse, B., Wielinga, B., and Evers, V., Enjoyment Intention to Use and Actual Use of a Conversational Robot by Elderly People, *HRI2008*, pp. 113-119, 2008.
- [31] Takayama, L., Ju, W., and Nass, C., Beyond Dirty, Dangerous and Dull: What Everyday People Think Robots Should Do, *HRI 2008*, pp. 25-32, 2008.
- [32] Toyoda, H., *Structural Equation Modeling*, Tokyo Tosho, 2007. (in Japanese)
- [33] Kaplan, D. W., *Structural Equation Modeling: Foundations and Extensions*, Sage Publications, 2000