# Analysis of Human Behavior to a Communication Robot in an Open Field


Shogo Nabe[12] Takayuki Kanda[1] Kazuo Hiraki[12] Hiroshi Ishiguro[13] Kiyoshi Kogure[1] Norihiro Hagita[1]

[1]ATR Intelligent Robotics Laboratories
2-2-2 Hikaridai Seika-cha Soraku-gun,
Kyoto, Japan
+81-774-95-1492
{nabe, kanda}@atr.jp

[2]Graduate School of Arts and Science,
The University of Tokyo
c/o Dr. K. Hiraki, 3-8-1 Komaba,
Meguro-ku, Tokyo, 153-8902, Japan
khiraki@idea.c.u-tokyo.ac.jp

[3]Osaka University
Suita, Osaka, 565-0871, Japan
ishiguro@ams.eng.osaka-u.ac.jp



## ABSTRACT
This paper investigates human behavior around an interactive robot at a science museum. To develop a communication robot that works in daily environments, it is important to investigate the available information from a robot about people's behavior. Such information will enable the robot to predict people's behavior so that the robot can optimize its interactive behavior. We analyzed visitor behavior toward a simple interactive robot exhibited at a science museum in relation to information from sound level and range sensors. We discovered factors that influence the way people approach, maintain distance, and interact both physically and verbally with the robot. This enabled us to extract meaningful information from the sensory information and apply it to communication robots.



## Categories and Subject Descriptors
H.5.2 [**Information Interface and presentation**]: User Interfaces– *User-centered design, Interaction styles;* I.2.9 [**Artificial Intelligence**]: Robotics

## General Terms
Design, Experimentation, Human Factors.

## Keywords
Field trial, analysis of human behavior, communication robot, psychology


## 1. INTRODUCTION
The development of robots is entering a new stage that focuses on interaction with people in their daily environments. This concept is rapidly emerging: a communication robot who will act as a peer providing communicational as well as mental and physical support. Such interactive tasks are important for robots designed to participate in society. Many robots have already been applied to various fields in daily environments [1-3]. We are particularly interested in open, public environments, such as museums, stations, and department stores, where we expect that in the near future robots may be installed so that people of all ages can interact with them. Such communication robots exhibit great promise in the early stages of development.

Previous works showed effective usage of nonverbal information conveyed through the bodies of both humans and robots for making human-robot interaction as natural as human to human. For instance, robots are capable of joint attention with their arms and head [4-6] , and they also can use emotion to estimate a person's mental state [7,8]. Breazeal et al. demonstrated the importance of a robot's nonverbal behavior in collaborative activities with people [9].

It is, however, difficult to recognize such subtle information in a public space. To develop a communication robot that works in daily environments, it is important to investigate the available information about people's behavior by observing the surrounding situation to predict behavior, instead of sensing subtle information, which is effective in laboratories. An example is shown in our previous work. Nomura et al. analyzed a relationship between questionnaire responses and behavior at a museum where interactive robots were exhibited. They reported that visitors spend more time with the robot when the floor is more crowded [10]; however little was investigated about how to improve robotic communication capability.

We took an interdisciplinary approach involving robotics and human science, which, we believe, is a unique methodological view. Regarding distance, a successful example exists from the work of a psychologist who argued that people at close distances (<45 cm) often have intimate communication [11]. Based on his theory, Tasaki et al. developed an interactive robot that changes its interactive behavior based on distance. For example, it expects tactile interaction at short distances and verbal interaction at medium distances [12]. However, it is rare that knowledge about human behavior allows sensory information to be mapped to predict the behavior of people. For most other sensors, there is no appropriate knowledge from human science, and there are no available sensors in public places to apply theories from human science, which requires more subtle and difficult capabilities, such as recognition of eye-gaze.

This paper reports our approach from a field trial, where we investigated the available information from an interactive robot by analyzing people's behavior toward it in relation to sensory information. We conducted a field trial at a science museum in Osaka, Japan, installing an infrared range finder, a sound level sensor, and a video camera on a simple interactive robot. We categorized the distances from which people have physical interaction, verbal communication, and observations with a robot and revealed the relationships between the surrounding sensors and human interaction with the robot. Our findings imbue sensory

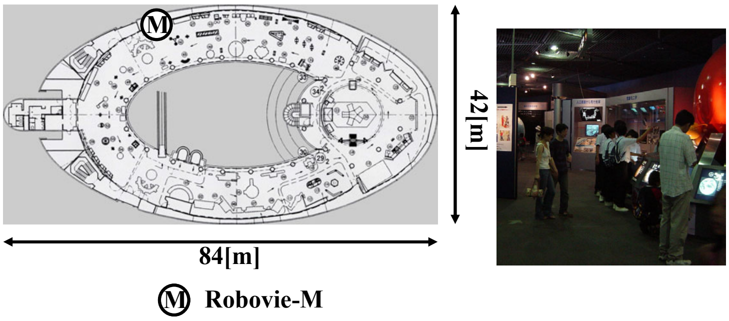



**Figure 1 Overview of the Osaka Science Museum and a Visitor Scene**

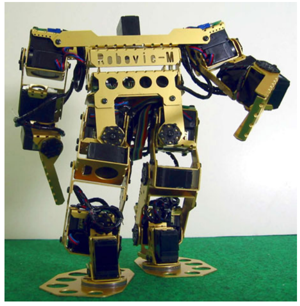



**Figure 2. The Robot Used in the Experiment**

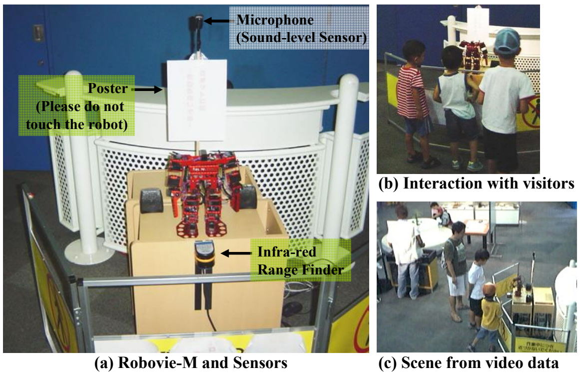



**Figure 3. Scene from the Experiment**

data with meaning and help us develop a communication robot that relies on such information to optimize interactive behavior.

## 2. EXPERIMENTAL SETTING

This section presents an overview of the communication robots, the sensors that gathered information of the environment, and the experimental procedure of this research.

### 2.1 Hardware

Our experiment was held as part of a communication robot exhibition at the Osaka Science Museum, where a ubiquitous sensor network was constructed (Figure 1). This sensor network recorded visitor behavior, and robots used the obtained information to assist visitors viewing museum exhibits and to encourage interest in science and technology. We used some of the sensors involved in this network to conduct our experiment.

#### *2.1.1 Communication robots*

Figure 2 shows "Robovie-M", a small-sized communication robot that stands 29 cm tall. It has 22 Degrees of Freedom (DOF), allowing it to walk, bow, and do handstands [1]. This robot is controlled by a connected PC, which also spoke for the robot, as if the robot were a ventriloquist dummy. Since the robot lacks its own sensors for any input, the connected PC was equipped with an infrared range finder and a virtual sound level sensor (see the next section). These devices enabled it to interact with visitors who approached the robot or made a loud sound.

#### *2.1.2 Sensor Systems*

The experiment included infrared range finders, sound level sensors, digital video cameras, and sound recording devices. Infrared range finders measured distances from 20 to 300 cm and angular ranges from -108 to 108º. Sound level sensors measured the ambient noise of the site, which consisted of a microphone with a computer to the power of the sound signal. Digital video cameras were located on the ceiling to record exhibition scenes. Sound was recorded by a microphone attached to the PC, where it was stored on hard drive. Each sensor was connected to a PC to control the information maintained in a database processed on a central server via Ethernet. Other sensors, such as an RFID tag reader, were involved in the exhibition, although we did not use them in our analysis.

### 2.2 Procedure

We observed visitor interaction with Robovie-M to highlight human behavior toward robots in various situations. In our experiment, we placed a robot on a pedestal and equipped it with an infrared range finder and a sound level sensor. Since the robot was not designed to perform hands-on interaction, we surrounded it with a "do not touch" warning (Figure 3). An experimenter sat beside the robot at a distance of three meters to ensure safety and prevent visitors from touching the robot, when necessary.

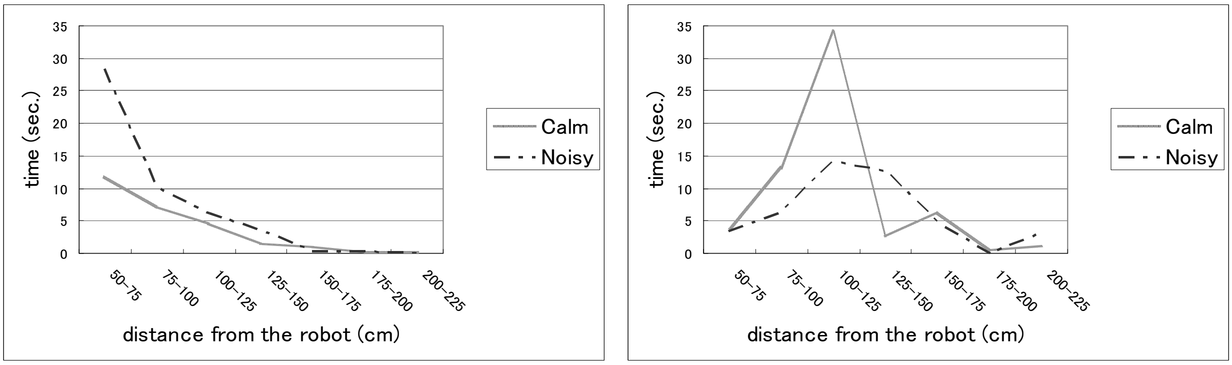
The robot behaved as if displaying physical ability and responded whenever visitors spoke to it. During situations with no visitors, the robot kept performing various exercises to show that it is operating and to draw visitors' attention. When visitors were detected by the infrared range finder, the robot stopped whatever it was doing and started a different exercise that involved speaking and inducing participation from the people. At this time, since the robot assumed that loud sounds, detected by the sound level sensor, were utterances from people in from of him, he responded with: "Thank you for talking to me."

Interaction scenes between this robot and visitors were recorded by digital video camera and sound recorder. The experiment was held on August 18th and 19th, 2005 at the Osaka Science Museum, as shown in Figure 1. This period included the Japanese summer holidays, where many children came to the museum even in weekdays..

## 3. DATA ANALYSIS

From the data gathered from the field trial, we observed visitor and robot interaction scenes and analyzed the effects of the

[1] http://www.vstone.co.jp/e/rt01e.htm




**(a) Children (n=138)** **(b) Adults (n=100)**

**Figure 4. Average Length of Interaction of Visitors**

surrounding situation by coding them. In this section we describe our method and the results of our analysis.

## 3.1 Method

Since various sensor data existed in separate forms (such as video, audio, and sensor information), we applied "Interaction Debugger", an application software developed in our laboratory. This software enables us to simultaneously view the interaction scenes, display various sensor data, and annotate each scene with time records that can be later accessed to make analyses. The details of this software will be reported in [13].

From the interaction scenes, we randomly selected subjects from the visitors and sequentially coded the following information about their interaction with the robots: personal attributes, distance in front of the robot, interaction behavior, and the presence of other people. These codes contain the following information.

**Person attribution**

Here we described subject attributes, which include such details as adult/child or gender. In addition, we gave each subject a unique ID for later identification.

**Distance towards the robot**

In this code, we measured the distances subjects kept from the robot during each moment of their interaction. We recorded the sensor value of the infrared range finder rounded down to the nearest 25 cm (e.g., a sensor value of 92 cm would be coded as "75 cm").

**Interaction behavior**

In this code we described the following human behavior during interactions: interaction start/end, physical contact, and verbal interaction.

interaction start/end: coded when the subject started or ended interaction with the robot.

physical contact: coded when the subject touched the robot or stretched a hand toward the robot[2].

*verbal interaction: coded when the subject made an explicit utterance, which was judged as speech directed at the robot from its meaning.*

**Presence of other people**

In this code we described the presence of other visitors around the robot. Adults and children were coded separately. Additional codes were coded with other codes, such as 'interaction start' and so on..

From this coding we analyzed the effect of the surrounding situation on human behavior in human-robot communication.

## 3.2 Results

In this section we describe the results obtained from our experiment. From observing interaction with Robovie-M, we recognized that the following surrounding situation characteristics efficiently predict human behavior: age, distance, presence of other people, and ambient noise. In addition, we investigated the correspondence between ambient noise and the number of people around the sensor, and revealed that the sensor value of sound level represents the crowdedness of the site to some extent.

238 subjects were analyzed: 143 males and 95 females, 100 adults and 138 children. The average length of interaction with the robot was 40.5 seconds. From the analysis, we obtained the following results:

**Subject age**

Since it has been suggested that differences exist in how adults and children respond to robots [14], we treated these two discretely in our analysis. As a result, we found various differences in behavior that we will describe in the following individual analysis sections.

**Distance**

[2] Though touching was prohibited in the Robovie-M experiments, we coded subjects as touching the robot since children often attempted to touch the robot.

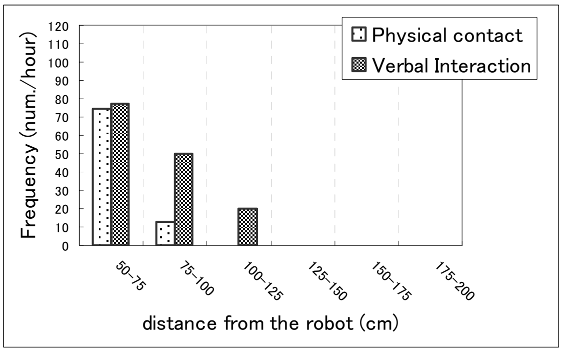



**Figure 5. Interactive Behavior of Children**

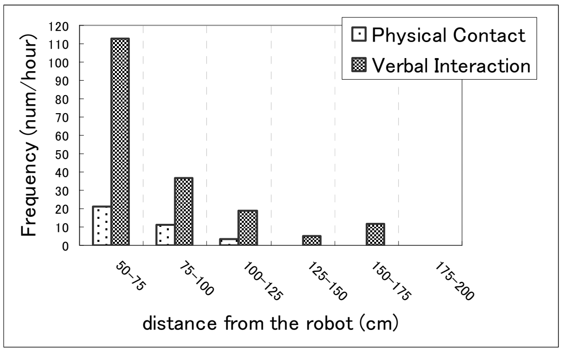



**Figure 6. Interactive Behavior of Adults**

By observing subject interactions with the robot, we discovered that human behavior differed based on distance. We investigated the time subjects spent at each distance from the robot during interaction and counted the number of 'physical contact' and 'verbal interaction' incidents.

Since the robot was closed off, no subject could approach nearer than 50 cm. Children spent the longest time at distances of 50-75 cm, an average of 16.8 seconds, which accounted for 48.7% of their entire interaction. In contrast, adults spent most of their time at distances of 100-125 cm, an average of 20.9 seconds, which accounted for 42.9% of their entire interaction. All but one subjects interacted with the robot closer than 225 cm. The only subject among the 238 subjects interacted further than this distance spent 9.3 seconds out of her whole 27.1 seconds of interaction in distance of 300-325cmm, which we consider not to include in the analyses because of its too small sample size. These results are shown in Figure 4.

During the entire experiment, 'physical contact' was observed 52 times with children and eight times with adults. 92.3% of such actions by children were observed at distances of 50-75 cm, and none were carried out further away than 100 cm. Even though the number was small for adults, all of them were carried out within distance of 125cm (Figure 5). Note the strong suspicion that this behavior's amount was likely affected by the experimental setting, where we prohibited visitors from touching the robot. However, we don't believe that this affected different distances toward this behavior.

'Verbal interaction' was observed 70 times with children and 39 times with adults during the entire experiment. For children, most were observed at distances of 50-75 cm (accounting for 71.4%), and none were carried out further than 125 cm. For adults, most were observed at distances of 50-75 cm (accounting for 41.0%), and none were carried out further than 175 cm. More than 75% of this behavior was carried out within 100 cm for children and 125 cm for adults (Figure 6).

Based on these results, we defined three distance categories for human-robot interaction: '*physical distance*', '*verbal distance*', and '*observation distance*'. We define them as the distances at which each of following behavior or state, 'physical contact', 'verbal interaction', and 'interaction time' would respectively occur. Based of these definitions, we obtained the following distances for our experimental situation: for children; 100 cm, 125 cm, and 225 cm and for adults; 125 cm, 175 cm, 225 cm.

**Presence of other people**

From the coded data of the presence of others, we detected changes in human behavior by investigating how subject distance behavior changes in various situations in the presence of others. We divided the robot situations into four categories to conduct this analysis: where the subject is interacting with the robot alone, in the presence of a child, in the presence of an adult, and in the presence of both a child and an adult.

We found that the distance maintained by subjects from the robot was changed by the presence of others (Figure 7). The children who approached the robot in the presence of an adult had significantly lower rates to come into distance of 75cm ('*physical distance*') during their interaction. The adults who approached the robot when other adults were near had significantly lower rates to come into distance of 200cm (including '*verbal distance*' and '*observation distance*'). However, adults of those who approached the robot when a child is in presence were suggested to have higher rates to come into distance of 75cm (which is included in '*physical distance*').

**Ambient Noise**

The data gathered by the sound level sensor revealed the effect of ambient noise on the interaction time of subjects. For each subject we calculated the average sound level around the robot a minute preceding his/her appearance. Afterwards, we took the top and bottom 25% of subjects from those who had the maximum and minimum sound level values and compared these two groups as 'noisy situation' and 'calm situation.'

Children of 'calm situation' interacted with the robot for 26.2 seconds in average, while those of 'noisy situation' interacted for 49.1 seconds. The results showed that children of 'noisy situations' stayed significantly[3] longer than 'calm situation' children. In contrast, adults of 'calm situation' and 'noisy situation' interacted with the robot for respectively 61.7 and 44.5 seconds, though there was no significant difference of staying time between adults in these two situations, although a difference is suggested in the distance they maintained. 'Noisy situation' adults kept more distance from robots than 'calm situation' adults. (Figure 1)

[3] $p < 0.05$; We applied nonparametric test (Kruskal-Wallis test) to the data.

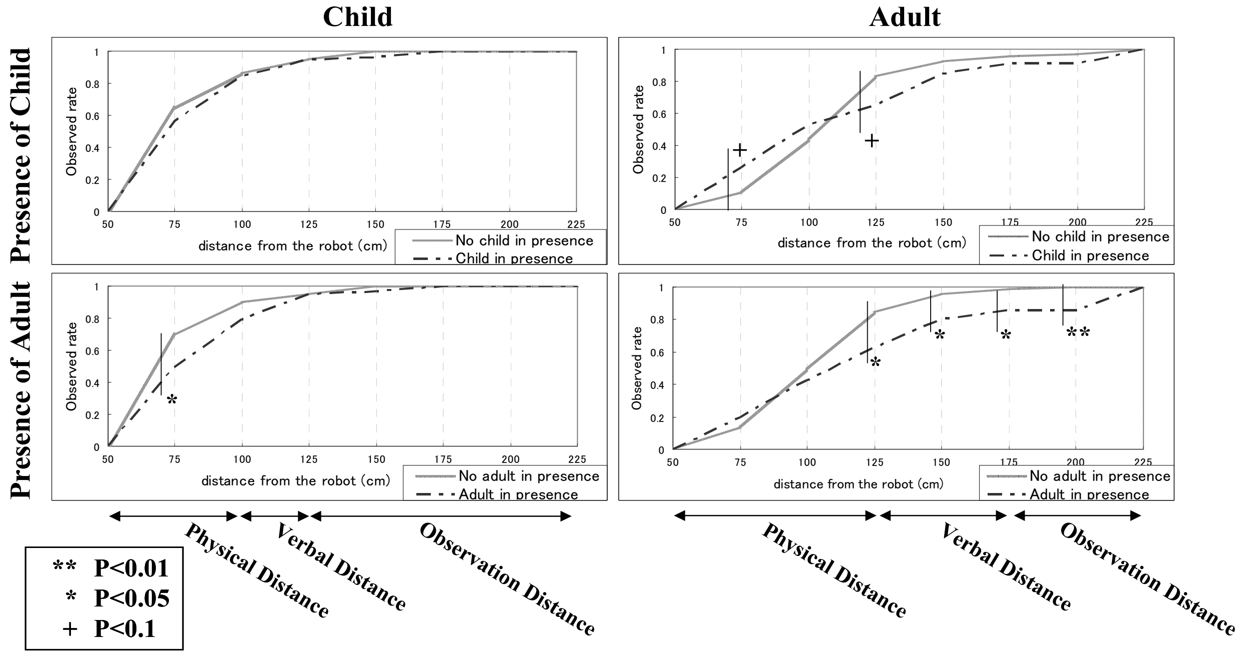



**Figure 7. Subjects' distance towards the robot changing by presence of other people**
**Rate represents how much of the subjects came closer than each distance, while "presence of child/adult" stands for the situation when each subject came to the robot.**
**(E.g. From the graph of Adult-'Presence of Adult', it can be read that roughly 8 out of 10 adults, who came to the robot when there were no other adults around, came closer than 125cm from the robot.)**

### *3.2.1 Ambient Noise and Crowdedness of the Site*

In addition to our analysis above, we investigated the correspondence between ambient noise and crowdedness of the site. There are two research questions here; "To what extent" and "In what range" the ambient noise reflects the crowdedness?

For the first question, we compared the number of people in the site with the sound-level measured by the sensor settled on ceiling. The number of people was counted from three video cameras in every first moment of 10 minutes, during August 27, 28, 30, and 31.

The result revealed correspondence between sensor value of sound-level meter and crowdedness of the site. Since the sound-level is in logarithm scale, we also took the logarithm of the number of the person, and compared the Peason correlation, which resulted in 0.76 (Figure 8). It seems particularly sensitive when there are not so much people around.

For the second question, we compared values of two sound-level meter settled in a distant place (roughly 15m); one was the sensor settled beside Robovie-M, and the other was settled on ceiling to avoid from effected by particular exhibit. We compared the average sound level of every previous minute the subjects mentioned in section *3.2.1* appeared in front of Robovie-M.

From data gathered from interactions of 138 subjects, we found strong correlation (Peason correlation is 0.89) between these two (Figure 9). Thus, the noisiness of the two places is related each other, which may affected by the two possibilities: first, the crowdedness of two places are correlated (if some exhibit is crowded, people often visited to the other exhibits in the museum), and second, a sound caused by a crowded situation of one place affected to the noisiness of the other place.

These two analyses suggest the possibility, that human behavior we compared in different situation of ambient noise (in section *3.2.1*) might have been affected by quite global crowdedness of the site.

# 4. DISCUSSION

## 4.1 Contributions

Our analysis demonstrated the importance of observing people's surrounding situations in human-robot interaction. We observed information from three sources: 'distance,' 'presence of bystanders,' and 'ambient noise.' Especially in short interactions with various people in public spaces, using such information seems promising to help robots achieve natural human-robot communication. Here, we explain the availability of sensors for recognizing the three sources and discuss how a communication robot would improve interaction.

**Distance**

asily observable. Many sensors are designed for this purpose, including ultrasonic, laser range, infrared range, and stereo vision. Our analysis verified the predictability of people's behavior. People at close distances mainly perform tactile interaction while people at farther distances simply observe without active interaction with the robot. This of course, is obvious, as Hall argued for inter-human communication many years ago [11]. For example, since people can only perform tactile interaction within

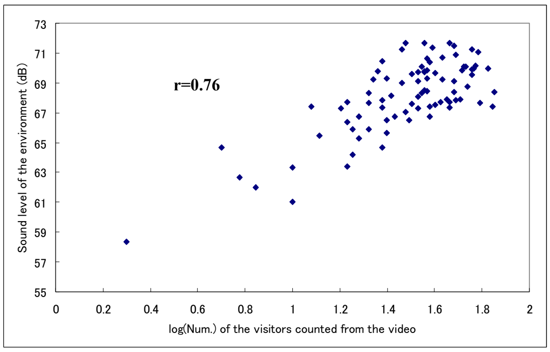



**Figure 8. Relation between sound-level of environment and crowdedness of the museum**

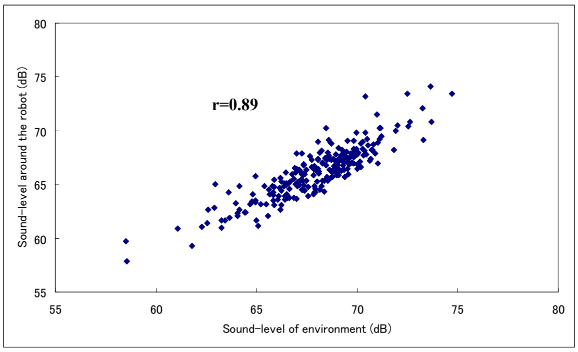



**Figure 9. Sound-level around the robot strongly correlates with that of environment**

a distance limited by their arm length, it only happens at close range.

We categorized human-robot distance based on our analysis because we believe that it is important to give such meaning to sensory information. The categorization helps design robot behavior based on the meanings, although we should probably adjust the thresholds for these categories depending on the types of robots and situations where they will be placed. We defined three distance categories for human-robot interaction: 'physical distance,' 'verbal distance,' and 'observation distance.' For example, we should prepare robot behavior based on such meanings as "waiting for a person who will enter into the verbal distance," instead of implementation as "waiting for a person who will approach within 175 cm of the robot."

Moreover, distance information will increase the intelligent design of robotic behavior. For example, we can anticipate that a person approaching the verbal distance of a robot might be willing to talk with it. Thus, the robot may start to speak to the particular person when he/she approaches the verbal distance, while it may behave as if giving a speech when people are only in the observation distance. When choosing an exhibition target to explain by referring to whether people being interacted with have already heard the explanation, an exhibit/guide robot should consider the people within the observation distance.

**Presence of other people**
Although the presence of other people was observed on video in our analysis, we believe several sensors, such as RFID tags [15] and floor sensors [16] enable us to observe individuals automatically.

Analysis results revealed that the presence of other people affected distance and behavior toward the robot. Adults tended to stay further away when someone was already near the robot. Children tended to stay further away when an adult was already near the robot.

It allows us to design robot behavior that predicts the approaching behavior of people. For instance, a robot may encourage a person at the distance of observation to approach when people have difficulty doing so, such as in the presence of an adult nearby.

**Ambient noise**
We observed ambient noise from a sound level sensor, which consisted of a microphone with a computer that calculated the power of the sound signal. Analysis of ambient noise revealed that children tended to stay longer with the robot when the museum was noisier. We also found that the sound level collected by the sound-level sensor represents the degree of crowdedness of the museum, which suggests that children tended to spend more time with robots when the museum was crowded. This result is consistent to the research Nomura et al. have made in the same science museum before [10].

By using information about ambient noise, a robot may exhibit more variety of behavior to entertain children, who are expected to stay longer when the ambient noise is louder. Alternatively, the robot may slightly subdue its behavior to thin the crowd. Moreover, observation of ambient noise can contribute to sound volume adjustments of the robot's utterances so that surrounding people can always hear what the robot is saying.

We believe that this source demonstrates the powerfulness of our approach. The sensor cost was very low, requiring only a microphone with cheap calculation. Thus, although it appears to correlate with the number of people in the environment, there are many advantages to using ambient noise instead of counting people with expensive sensors.

## 4.2 Other surrounding situation

We focused on people's behavior in short interactions at a first meeting with the robot. As a result, we found three sources of information about people's behavior mentioned above that seem particularly useful at the beginning of interaction, such as low-level behaviors, staying time, and activeness of interaction.

In addition, we believe that there are many other possible sources for people's surrounding situation. One promising sensing technology is wearable sensors, even though using them limits field applications because people need to wear the sensors somewhere around the robot. For instance, obtaining a visitor's history of activity by ubiquitous sensors enables a robot to choose an appropriate exhibits to explain [17]. Katagiri et al. revealed that an infrared tag allows us to identify people's line of sight, which potentially helps us to automatically identify interest in exhibits [18]. Similar information can be retrieved with a RFID tag. As shown in the example, these sources seem particularly helpful after the beginning of interaction about high-level behavior, such as preference and interest.

Individual attributes of people are also important, such as adult or child and group membership [19], although available sensing technologies have not been established yet. As shown in our analysis, children's behavior differed from adults'. Thus, it has potential to provide us with information about individual differences for both low-level and high-level behaviors. Similarly, we believe that it is important to develop a robot's capability of identifying several interacting persons as members of a family or a large group. For example, a child may approach the robot even when an adult is nearby, if that adult is the child's parent.

## 4.3 Limitations

This research is in its early stage; we only investigated the available sensory information with a particular robot in a particular environment. In a science museum, visitors are probably more biased in favor of robots than people in other situations. Robovie-M has a very mechanical appearance, which might also influence people's behavior. Thus, we are not yet sure about the generality of the particular findings concerning the effects of observed information on people's behavior, such as children staying around the robot longer when it was noisy, although we believe that using these three sources (though not limited to three) will be helpful in other situations as well as in the science museum. Future research will conduct field trials in other open environments.

# 5. CONCLUSION

Since interaction is often short with various people in public spaces, we believe that it is important to consider the people's surrounding situation. We conducted a field trial at a science museum where a simple interactive robot was equipped with an infrared range and sound level sensors. We analyzed the changes in people's behavior during their interaction with the robot in relation to the information obtained with these sensors and other factors easily observable with other sensors. As a result, we revealed three observable sources of information that allow us to predict people's behavior: 'distance,' 'presence of bystanders,' and 'ambient noise.' For example, visitors often avoided the robot if there were already an adult near the robot.

# 6. ACKNOWLEDGMENTS

This research was supported by the Ministry of Internal Affairs and Communications of Japan. We wish to thank the staff at the Osaka Science Museum for their cooperation. We also wish to thank the helpful suggestions and cooperation of the following ATR colleagues: Satoshi Koizumi, Masahiro Shiomi, Toshihiko Shibata, Kenta Nohara, Hideaki Terauchi and Yoshimi Kawamura.

# 7. REFERENCES

[1] Fujita, M., AIBO; towards the era of digital creatures, *Int. J. of Robotics Research*, Vol. 20 No. 10, pp. 781-794, 2001.

[2] Shibata, T., Tanie, K., Physical and affective interaction between human and mental commit robot, *Proc, IEEE Int. Conf. on Robotics and Automation*, pp.2572-2577, 2001

[3] Gockley, R., Bruce, A., Forlizzi, J., Michalowski, M., Mundell, A., Rosenthal, S., Sellner, B., Simmons, R., Snipes, K., Schultz, A. C., Wang, J., Designing Robots for Long-Term Social Interaction, *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2005)*, pp. 2199-2204, 2005

[4] Scassellati, B., *Investigating Models of Social Development Using a Humanoid Robot*, Biorobotics, MIT Press, 2000

[5] Nakadai, K., Hidai, K., Mizoguchi, H., Okuno, H. G., Kitano, H., Real-Time Auditory and Visual Multiple-Object Tracking for Robots, *Int. Joint. Conf. on Artificial Intelligence (IJCAI'01)*, pp.1425-1432, 2001

[6] Sugiyama, O., Kanda, T., Imai, M., Ishiguro, H., Hagita, N., Three-Layered Draw-Attention Model for Humanoid Robots with Gestures and Verbal Vues, *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2005)*, pp. 2140-2145, 2005

[7] Kanda, T., Iwase, I., Shiomi, M., Ishiguro, H., A Tension-Moderating Mechanism for Promoting Speech-Based Human-Robot Interaction, *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2005)*, pp. 527-532, 2005

[8] Fujie, S., Ejiri, Y., Matsusaka, Y., Kikuchi, H., Kobayashi, T., Recognition of Para-linguistic Information and its Application to Spoken Dialogue System, *IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU '03)*, pp. 231 - 236, 2003

[9] Breazeal, C., Kidd, C. D., Thormaz, A. L., Hoffman, G., Merlin, M. Effects of Nonverbal Communication on Efficiency and Robustness in Human-Robot Teamwork, *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2005)*, pp. 383-388, 2005

[10] Nomura, T., Tasaki, T., Kanda, T., Shiomi, M., Ishiguro, H., Hagita, N., Questionnaire-Based Research on Opinions of Visitors for Communication Robots at an Exhibition in Japan, *International Conf. on Human-Computer Interaction (Interact 2005)*, 2005 (to appear)

[11] Hall, E. T., Hidden Dimension, *Doubleday Publishing*, ISBN 0385084765, 1996

[12] Tasaki, T., Komatani, K., Ogata, T., Okuno, H. G., Spatially Mapping of Friendliness for Human-Robot Interaction, *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2005)*, pp. 521-526, 2005

[13] Kooijmans, T., Kanda, T., Bartneck, C., Ishiguro, H., Hagita, N., Interaction Debugger: an Approach to Analyze Human-Robot Interaction, *Human-Robot Interaction Conference 2006 (HRI2006)*, (under review)

[14] Trahanias, P., Burgard, W., Argyros, A., Hähnel, D., Baltzakis, H., Pfaff, P., Stachniss, C., TOURBOT and WabFAIR, *IEEE Robotics & Automation Magazine*, Vol. 12, No. 2, June, 2005

[15] Kanda, T., Hirano, T., Eaton, D., Ishiguro, H., Person Identification and Interaction of Social Robots by Using Wireless Tags, *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS2003)*, pp.1657-1664, 2003

[16] Murakita, T., Ikeda, T., Ishiguro, H., Human tracking using floor sensors based on the Markov chain Monte Carlo method. pp. 917–920, 2004

[17] Koide, Y., Kanda, T., Sumi, Y., Kogure, K., Ishiguro, H., An Approach to Integrating an Interactive Guide Robot with Ubiquitous Sensors, *IEEE/RSJ Int. Conf. on Intelligence Robots and Systems (IROS2004)*, pp.2500-2505, 2004

[18] Katagiri, Y., Bono, M., Suzuki, N., Capturing Conversational Participation in Ubiquitous Sensor Environment, *Proceeding of Pervasive 2004 Workshop on Memory and Sharing of Experiences*, 101-106, April, 2004

[19] Kanda, T., Sato, S., Saiwaki, N., Ishiguro, H., Friendly social robot that understands human's friendly relationships, *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2004)*, pp.2215-2222, 2004.