



Proceedings

HRI 2011 Workshop on Expectations in intuitive human-robot interaction

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Programme

9.30-10.00	Opening by the organisers / Introduction of participants
10.00-10.30	Oliver Damm, Karoline Dreier, Frank Hegel, Martina Hielscher-Fastabend Petra Jaecks, Prisca Stenneken, and Britta Wrede: Communicating emotions in robotics: Towards a model of emotional alignment
10.30-11.00	Wilma Alice Bainbridge, Shunichi Nozawa, Ryohei Ueda, Yohei Kakiuchi, Kotaro Nagahama, Kei Okada, and Masayuki Inaba: Understanding Expectations of a Robot's Identity Through Multi-User Interactions
11.00-11.30	Morning break
11.30-11.45	Poster spotlight Marta Díaz, Neus Nuño, Joan Sàez-Pons, Diego Pardo, Cecilio Angulo, Amara Andrés: Building up child-robot relationship. From initial attraction towards social engagement Guido Schillaci and Verena V. Hafner: Prerequisites for Intuitive Interaction - on the example of Humanoid Motor Babbling Laurel Riek, Andra Adams, and Peter Robinson: Exposure to Cinematic Depictions of Robots and Attitudes Towards Them
11.45-12.15	Takanori Komatsu, Rie Kurosawa, and Seiji Yamada.: How does Difference between Users' Expectations and Perceptions about a Robotic Agent (Adaptation Gap) Affect Their Behaviors
12.15-13.00	Discussion
13.00-14.00	Lunch
14.00-14.30	Astrid Weiss, Nicole Mirnig, and Florian Förster: What Users Expect of a Proactive Navigation Robot
14.30-15.00	Guillaume Doisy and Joachim Meyer: Expectations regarding the interaction with a learning robotic system
15.00-16.00	David Hanson: Zeno
16.00-16.30	Afternoon break
16.30-18.00	Wrapping-up discussion round, coming up with a 1-2 page white-paper

Location: Building BC, room BC01

Communicating emotions in robotics: Towards a model of emotional alignment

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ABSTRACT

The expectations of emotional displays play an important role in human-human and human-robot interaction in order to achieve a constructive interaction. However, as we argue in this position paper, current state-of-the-art social robotic models of emotion still neglect the communicational aspects of emotions. Based on different psychological models of emotion, we argue that an intra-personal account of emotion is not sufficient. Rather, we need inter-personal accounts of emotion that go beyond the assumption that a communicative agent simply displays her internal affective state and takes situational aspects into account that influence the emotional display.

Keywords

Social Robotic, Emotions, Emotional Alignment, human-robot interaction, role of expectations in intuitive HRI, expectations of the robot

1. INTRODUCTION

According to Watzlawick's statement with regard to aspects of pragmatic communication that "one cannot not communicate" [38] it we postulate that this holds also true for (1) human- robot interactions (HRI) and (2) for emotionality



Figure 1: The bielefeld anthropomorphic robot head "Flobi".

which leads, in short, to our basic assumption that in HRI one cannot be not emotional. This entails that the mutual emotional signals may or may not be appropriate or aligned and may thus add to or hamper the success of an interaction. In extension to the communicational account of alignment as postulated by Pickering & Garrod [27] we understand an interaction as emotionally aligned, if both interaction partners have the same interpretation of situational affective information and thus, form congruent implicit expectations.

Misalignment may occur if expectations with respect to the quality and reference of an emotional signal are violated. It is well known from interactions with e.g. brain-damaged patients that such expectation violations lead to severe communication problems [24]. Similar effects have been observed in experimental human-robot interactions [9] which lead to the development of the humanoid robot head Flobi (cf. 1). According to the common practice the head is designed to express the basic emotions proposed by Ekman [8] and is able to display these in a well readable manner [14].

In psychological research, we find a large number of theoretical models to differentiate between several aspects of emotions and emotion processing (overview in [20]). Psychologists distinguish for instance between theories about internal intrapersonal feelings on one side and theories about the emotions expressed in interpersonal interactions on the other side. Due to the fact that a speaker can not know what the interaction partner feels, we assume that the most crucial issue concerning expectations in human-robot interaction is to display the expected emotion. In analogy to Pickering & Garrod we assume that these expectations are formed on all levels of emotion processing and also concern the existence of a similar processing system in the interaction partner.

We argue that people expect an emotional display that they often express themselves in their real-life interactions and based on this this expectations establish a model of the robot's social interaction capacities. The communication of emotions encourages people to have an implicit mental model of the human-robot interaction. This is supported by [15] who found that people sympathize more strongly with a robot if it communicates emotions. Additionally, their results show that uniquely human traits are attributed to the robot if it shows emotional displays.

However, computational models of the communicative aspects of emotions are still not existent in social robotics. Common state-of-the-art implementations of emotional models in social robotics focus on internal processes of how an emotion may be computed (such as e.g. the OCC model for emotion synthesis proposed by Ortony, Clore, & Collins [26]) and simply display the computed model. But in human-human interaction it is observed that people do not display their emotional states (feelings). Rather what people show mainly depends on the emotional context. For instance, Kraut and Johnston analysed the behavior of 350 bowlers directly after a successful roll. In contrast to earlier research, they found that the bowlers did not smile directly after the roll, that is the successful event presumably evoking an internal feeling, but only when they turned back to their friends. The authors interpret that as an indicator for a weaker and more erratic association of smiling with happiness than with social interaction [21].

Motivated by the importance of the communicational context of emotional displays we present in this paper first steps towards a pragmatic model of emotional alignment between

humans and robots as a basis for a computational model that is able to produce emotional signals that are more in line with people's implicit expectations about the robot's expression of emotion.

After a summary of previous research in Section II, we address the consequences we draw from these considerations for artificial robotic systems in Section III. In Section IV we discuss first results regarding our model of emotional alignment between humans and robots. Finally, in Section V, we present a conclusion and recommendations for prospective research based on our proposed model of emotional alignment.

2. RELATED WORK

Alignment theory postulates different levels of alignment which correspond to the linguistic processing levels. Accordingly, we postulate emotional alignment levels that correspond to emotional processing levels, namely automatic, schematic and conceptual. Here, we will focus on the schematic level where the social functions of emotions play a major role. Social functions of emotions are distinguished on four types of analysis [20]: (a) individual (intrapersonal), (b) dyadic (interpersonal, between two persons), (c) group (a set of individuals who directly interact), and (d) cultural (within a large group that shares beliefs, norms, cultural models). Currently the implementation of emotions in social robotic systems is focused on the intrapersonal aspect only. We argue, that an acceptable emotional robotic model needs to take at least the interpersonal aspect into account as well. Depending on the robot application, or situational context, group of even cultural aspects of the functions of emotions need to be also considered in future research.

During the last decades several researchers tried to explain the expression and effects of emotions by proposing different models. Here we focus on the intra- and interpersonal models in order to distinguish between interaction relevant and non-relevant models.

2.1 Intrapersonal Models

Several researchers postulate numerous models about the intrapersonal aspect. Some of these models are based on biological approaches, like the James-Lange-Theory ([19]) or the two-factor theory of emotion [30]. Other cognitive theories were proposed by Scherer [31], Ortony, Clore & Collins [26] or Lazarus [22]. Latter theories argue in order for an emotion to occur some kind of cognitive activity is necessary. Currently, the cognitive or appraisal theories are widely accepted and constitute the dominating concept for emotion modeling in social robots. These theories assume a close connection between the displayed emotion (mostly via facial expression) and the experiencing of emotion.

2.2 Interpersonal Models

In contrast to intrapersonal models, the interpersonal models presume that the expression of emotions is mainly related to their social function. Fridlund [11] assumes that,

the direct expression of an emotion is not necessarily a social benefit. Sometimes the direct expression of an emotion could also be a disadvantage, e.g. showing fear to an opponent might motivate him to attack his victim because he believes to get an easy take.

According to the intrapersonal models of emotions, the bowlers in Kraut and Johnston's study [21] should smile whenever they are happy, e.g. they make a good roll. But Kraut and Johnston showed that the bowlers smile significantly more often when looking at their teammates. These findings are supported by results from a study by Fridlund [10] where subjects had to watch a comic movie in four different conditions that varied with respect to their degree of sociality, with the least social situation consisting of just one test subject watching the movie alone up to the most social situation where the subject was watching the film with a friend. Fridlund found that the presence of a friend increases the rate of smiling without any impact on subjective experience.

2.3 Robotic Systems

Since the expression of emotions play such an important role in human interaction, it seems to be helpful to make robots more social by adding emotional displays. The most important reason for adding emotional models to robots is, of course, the possibility to interact in a natural way [5]. But, there has also been work on the role of robotic decision making, e. g. by Sloman and Croucher who argue that robots should have emotions in order to prioritize their decision making process [32]. Yet, this latter kind of approaches does not take communicational functions of emotions into account.

In the following section we list three examples of social robotic systems equipped with an intrapersonal model of emotions. To our knowledge, all social robots that are equipped with an emotion model, focus on internal processes of emotion computation but do not communicative information into account.

The robot Kismet (cf. 2(a)) by Breazeal [3], for example, is designed to engage people in natural and expressive face-to-face interaction. Kismets motivational system is divided into three parts with needs for social interaction, for stimulation and for resting. Every stimulus Kismet receives is separated into its causes and finally appraised based on the intensity and relevance of the stimulus, the intrinsic pleasantness and the goal directness. These four computed values determine a position for the stimulus in the three-dimensional space of valence, arousal and stance. Due to this three-dimensional space an emotion is selected and forwarded to the motor system of Kismet.

Another approach is Velásquez' pet robot Yuppy [36](fig. 2(b)) with an emotion-based control. All emotions expressed by Yuppy are generated by a system, which takes several so-called *Natural Releasers* into account, e.g. interactions with the environment or people. However, although the environment does influence the internally computed "emotion" of the system, there is no communicational context taken into account when determining the displayed expression. Again,

it is the computed emotion that is directly displayed

The Robot Feelix (fig. 2(c)) proposed by Cañamero [4] is an LEGO based 70-cm-tall humanoid. The robot is able to show his emotional state by several facial expressions. Namely these expressions are neutral, anger, sadness, fear, happiness and surprise. To realize their emotional system Cañamero adopted the generic model postulated by Tomkins [35] and complemented it with two more principles. So the implemented theory consists of five variants of a single principle: the increase and decrease of stimulation, high and low stimulation and a moderately high stimulation level. In the application, the level of stimulation determines the facial emotion expressed by Feelix.

Each of the presented robotic systems is able to express its own emotional state, depending on observations, desires or internal drives. These models enable the robots to adapt emotions on a very basic level. However, they are not capable of taking communicational aspects into account. The following section illustrates our intended shift of focus to a more adaptive model of emotions in robotic systems.

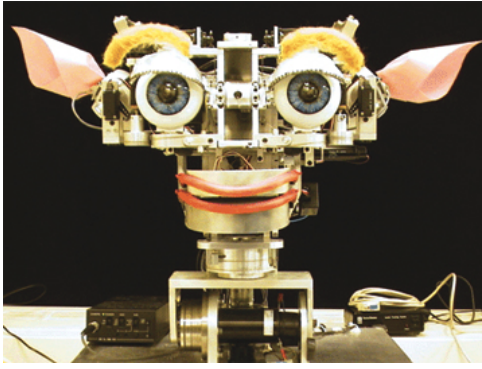
3. CONSEQUENCES FOR ROBOTIC SYSTEMS

Just like the models presented in the previous section many emotion models in robotics focus on the intrapersonal aspects of emotions. Concerning intrapersonal analysis, researchers generally focus on the change of intra-individual components of emotion. The individual organism is the system with respect to which the function of emotions is interpreted. That is, after calculating a feeling, the robot shows as a result the calculated feeling via a facial expression. Therefore, many people in the robotics community believe that displaying emotions means to decide whether the robot is happy or sad, angry or upset, and then display the appropriate face, usually an exaggerated parody of a human person in those states ([25], S.179f.).

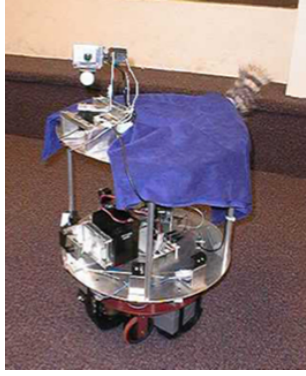
We argue against this approach, as it is not in line with empirical findings from research on emotion in communication [21]. Usually people do not display their actual feelings, as this could be an evolutionary disadvantage (e.g. [11]). When implementing an artificial model of emotions in order to improve the robot's communicative capabilities, we need to focus on the interpersonal aspects of emotion. Regarding interpersonal analysis, researchers focus on how emotions organize the interactions of individuals in meaningful relationships. The interacting dyad is the system with respect to which the consequences of behaviours are interpreted.

In order to achieve a better understanding of the emotional alignment occurring and interacting on different modalities and different processing levels, aspects of (1) congruency and intact or impaired emotion processing on the one hand and (2) schema-driven emotional reactions and attributions of emotional references and questions of audience design in humans and robots, on the other, should be involved.

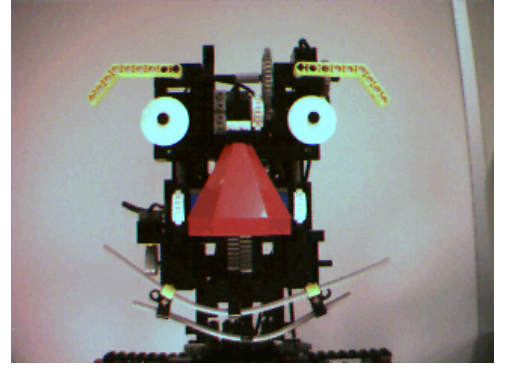
4. LAYER-MODEL OF EMOTIONAL ALIGNMENT



(a) Kismet by Breazeal



(b) Yuppy by Velásquez



(c) Felix by Cañamero

Figure 2: The sociable robot Kismet, the emotional pet robot Yuppy and the Felix humanoid.

As outlined above we assume that emotional alignment in communication resorts to processes at least at three different levels of complexity that we refer to as automatic alignment, schematic alignment and contextual integration and conceptual alignment with conscious and self-conscious representations. Based on these levels we are able to take interaction into account and can thus capture interpersonal emotional processes.

- automatic adaptation
- schematic adaptation and contextual integration
- conceptual adaptation with conscious and self-conscious representations

4.1 Level 1: Automatic Emotional Alignment

Sometimes people automatically display emotional expressions without reflecting the situation cognitively. This automatic emotional alignment has often been described in terms of mimicry or priming.

Mimicry is a nonverbal response frequently occurring in social interactions where people mimic expressions like smiling at another's delight or showing pain at his injury [1]. Specifically, motor mimicry is a form of mirroring the other person's behaviour. This happens, for instance, when a mother who is spoon-feeding her baby can be observed to open her mouth parallel to the baby opening its mouth [2].

Also within an emotional interaction in robotics it has been found that a mimicking anthropomorphic robot affects people's evaluations of robots [16]. Participants were taking part in an interaction scenario during which they read passages of a fairytale to the robot. They did so with lively emotional expression. The experiment realized two conditions to manipulate BARTHOC Jr.'s [?] reactions to speech with emotional content. Specifically, BARTHOC Jr. either mimicked the emotional content of speech or displayed neutral nonverbal signs of confirmation in response. After the interaction, participants evaluated the situational fit of the robot's reaction, the robot's ability to recognize the emotions conveyed by the participants and the degree of human likeness with regard to the robot's reaction.

4.2 Level 2: Schematic Emotional Alignment

On this level we assume emotional contagion to be one relevant factor in schematic emotional alignment in communication. It is often based on complex affective representations resulting from intermodal binding [28] and from combining perception and production components as well as aspects of the situational context. Originally, emotional contagion is described by focusing on different aspects, e.g. mimicry, biofeedback and contagion as possible underlying related mechanisms [13]. Concerning our model of emotional alignment, the most important characteristic of this second level (schematic emotional alignment) is its integrative capacity to allocate information from different emotionally relevant communication channels (c.f. [12]). Spontaneous alignment to different partners and contexts will rely on binding of information, which may also connect antagonistic patterns as recognized anger/threat and elicited fear/flight.

4.3 Level 3: Conceptual Emotional Alignment

As an addition to the communicative alignment model by Pickering & Garrod, we assume a type of alignment, which may not be spontaneous and automatic. So the third level is the conceptual emotional Alignment, which is often described in terms of Empathy in interaction. The term "Empathy" can be seen as the ability to imagine how another person is thinking and feeling and to share these feelings ([29]). Conceptual emotional alignment is based on conscious processing and integrates knowledge about oneself and the relevance of the situation for the own person [33]; [34]. Furthermore it calls, as well as schematic emotional Alignment, for emotion learning and grounds on explicit emotion recognition (e.g. [6]). As an example the concept of a cognitive emotional alignment plays an important role in a therapist-patient or doctor-patient interaction, where the expert recognizes the patient's emotion expressions and reacts consciously and (verbal or nonverbal) empathically. This case has a high relevance for human-robot interaction, because of the fact, that robots will be employed for healthcare in nursing homes or working therapeutically (e.g [37]).

These three levels may represent an evolutionary as well as a functional hierarchy, as Leventhal and Scherer [23] suggested. But we found these different representations to work quite autonomously in healthy subjects as well as in aphasic patients [18]. This observed independence is in accordance

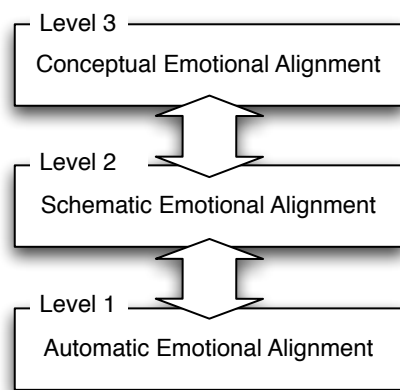


Figure 3: Layers of emotional alignment

with experimental results by Hess and Blairy [17] as well as in psychiatric groups where the phenomenon is known as the empathy's paradox (cf. [7]).

5. CONCLUSIONS

We argue that the display of emotions in both, humans as well as robots, feed into the expectations of the interaction partner. This means that in certain situations we have specific expectations about the affective reaction of our interlocutor. If this expectation is violated this will affect our evaluation of the interaction partner and thus influence our further behaviour which may become more or less constructive.

In order for a robot to meet our expectations about emotional reactions we have argued that it needs a layered model of emotional processing and representation. In contrast to current state-of-the-art social robots and agents this entails more than an intrapersonal account of emotional display, according to which the robot simply shows its computed "emotion". We argue that also an interpersonal account needs to be taken that respects contextually influenced rules of emotional reactions.

6. ACKNOWLEDGEMENTS

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7. ADDITIONAL AUTHORS

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Understanding Expectations of a Robot's Identity Through Multi-User Interactions

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ABSTRACT

We conducted two experiments looking at how to read user expectations of a robot's identity within multi-user environments. Multi-user environments are unpredictable and fast-paced, which can become a challenge for roboticists to interpret. However, they also present a rich landscape of data, and we propose methodologies to retrieve user reactions to the robot through sensor data. We also emphasize the necessity of using the results from these methodologies to define a robot's identity based on user expectations. In Experiment 1, we found that sensor data taken from a handshake with the robot can be used to find differences in the views of different demographic groups towards interaction with our robot. In Experiment 2, we expand the subject pool and reaffirm the usefulness of sensor data in multi-user environments, while also using questionnaire data to create an identity for our robot.

I.2.9 [Robotics]: Operator interfaces – *methods to research user expectations and intuitive interaction, multi-user environments, robot identity, biofeedback*

1. INTRODUCTION

Humanoid robots are almost ready for the real world - many are safe, durable, and able to perform complex interactions with humans, objects, and environments. However, there are two important issues that have rarely been addressed within human-robot interaction (HRI) research. First, as robots make their entrance into the real world, they will need to be able to handle environments filled with multiple users. Second, robot's identities and personalities have often been designed based on roboticists' intuitions rather than based on the user's expectations. This study proposes new ideas on methodology for examining user impressions on human-robot interactions within a multi-user setting. We also propose molding a robot's identity based on user expectations of a robot.

Recent HRI research has just begun to focus on placing robots within ecologically valid multi-user environments rather than the traditional one-on-one interaction model [1, 2]. Many of these works focus on the engineering obstacles in having a robot interact smoothly with multiple people, and have not yet explored ways of measuring human reactions to the robot. It is especially tricky to extract data from multi-user environments because users have brief, unscripted actions with the robot. Often it is even

impossible to gather surveys from subjects, forcing researchers to rely on other measures. However, these multi-user environments are rich untapped sources of information, because they can provide large amounts of data from several subjects in an ecologically valid setting without any lengthy training of the subjects.

While much of current HRI research looks at subjects' feelings on an interaction, few studies ask the user to define the robot's identity based on their interaction. Roboticists often pre-create a robot's identity before an interaction, assigning it a name, gender, voice, etc. However, it is important that a robot's identity be suited to match the expectations of the general public, rather than the assumptions of an engineer. Expectations of a robot's identity can vary greatly based on a user's age, gender, or culture. We propose measuring users' reactions to a robot to determine how to best create a robot to match user expectations. We also examine how expectations of robot identities differ across these demographic groups. Previous studies have shown that the collection of questionnaire data alone often ignores other signs of a human's feelings towards a robot [3], so we employ both sensor data and questionnaire data to fully assess a user's reactions to a robot within a multi-user setting.



Figure 1. An example of the interaction

The HRP-2 is shown here during Experiment 2, shaking hands with a participant while under observation by the experimenter.

These two main goals - creating natural interactions within multi-user environments, and designing methods to define robotic identities based on user expectation - are very lofty goals that will continue to be themes of HRI research in the years to come. The current study aims to serve as a pilot study for new methodological ideas at how to answer these questions, and as a starting point for discussion.

2. GENERAL METHOD

2.1 Overview

We performed two studies to examine expectations and reactions to a robot's identity within a multi-user setting. Experiment 1 took place at an alumni reunion of our laboratory, and assessed the usefulness of sensor data for understanding human reactions to our robot within this multi-user environment. For Experiment 2, we expanded the model of Experiment 1 and asked people across the University of Tokyo Hongo campus to interact with the robot. For Experiment 2, we examined sensor data as well as questionnaire data. The results of Experiment 2 inspired us to also perform a brief survey across campus to investigate how to match expectations of a robot's voice to its appearance.

2.2 Methods

For both studies, the robot followed the same pattern of behavior. It searched for a human face, and after finding a face for five consecutive frames, it initiated a randomly chosen action: a bow, a handshake, a wave, or inaction. During the interaction, the robot's head followed faces that it found, appearing to create eye contact with the subject, and it continued following the faces during its greeting action. Refer to Figure 1 for an example from Experiment 2 of the handshake gesture.

Data were taken from many different sources. We chose measures that could be easily taken by the robot within a limited amount of time, and that seemed relevant to interpreting human emotion. Our main focus for sensor data was during handshakes with the robot, as there is plenty of data that can be taken just from the contact of the human's hand with the robot's hand. Sensor data included the user's directional forces on the robot's arm (Newtons), tactile measurements from the robot's hand (a unitless analog measure), temperature data measured from the robot's index and middle fingers (Celsius), and the distance to the subject's face taken from its cameras and face recognition software (millimeters). Sensor and video data resulted in about 1 GB of data per minute, and thus several thousand lines of data were collected from each subject. Biographical data for the subject were hand-coded by the experimenter and included the user's gender, country of origin, age group, familiarity with the laboratory and department, and vocal reactions to the robot. Opinion data were taken through a questionnaire to the subjects for Experiment 2.

Data were then analyzed for significance across groups using statistical analysis tests including the Independent Samples T-test, Analysis of Variance (ANOVA), and Pearson's Correlation. For the purposes of these two experiments, data were separated into groups for analysis (such as handshake data versus non-handshake data) rather than separated by subject, in order to capture the wide range of information within each interaction. Groups for analysis were determined by divisions within the biographical data (age, gender, nationality, laboratory familiarity) and by binary measures

taken during the interaction (such as negative reaction versus positive reaction). Sensor data were compared between groups using all pieces of data that either had a face tracking measurement or were a part of the handshake behavior.

2.3 The Robot: HRP-2

The robot we used for our experiments is the HRP-2, a bipedal humanoid robot developed by Kawada Industries through funding from the Japanese Ministry of Economy, Trade and Industry [4]. It is 154 cm tall, weighs 58 kg, and has 30 degrees of freedom. The joints in its hands and arms are flexible so that they accommodate to forces from the user. This results in a safe and natural interaction with the robot, and actions such as a handshake with the robot are comfortable for the user. For both experiments, the HRP-2 was connected only to a power source, and supported itself using auto-balancing in its legs.

The HRP-2 that we used for each experiment is modified for the laboratory (The HRP2JSK), including stereovision, a head with seven degrees of freedom, and multiple movable fingers [5]. It was controlled using code written in Euslisp [6] with a ROS architecture [7]. For this experiment, we mainly collected data from sensors already built into the robot, such as the force and tactile sensors. All joints in the HRP-2 are equipped with force sensors, and there are tactile sensors on both hands. We also modified the hand of the HRP-2 to include temperature sensors in its index and middle fingers (points that made the most contact with a human hand during a handshake). Within this paper, the data from these sensors will be hereafter referred to as *temp0* (index finger) and *temp1* (middle finger). The tactile sensors used to measure tactile forces on the hand will be referred to in this paper as *tactile0* and *tactile1*.

3. EXPERIMENT 1

3.1 Methods

The HRP-2 greeted alumni who came to visit the laboratory as a part of an alumni day. As participants walked into our laboratory, the HRP-2 stood at the door and initiated a greeting as described in the Overall Methods. Participants were all previous members of our laboratory and so had experience with robots. Current members of our laboratory also interacted with the robot. In total, 27 people interacted with the robot (24 male, 3 female) over a period of one hour. Seven were current members of the laboratory, while twenty were alumni. Interactions were very brief, and did not last longer than a few minutes per subject. Sensor data were collected several times a second. After selecting data with only handshake or face tracking measurements, subject data ranged from 118 to 1520 data pieces per subject, with an average number of 437 (SD = 372).

3.2 Methods

To confirm the validity of our data analysis techniques, we compared the sensor data between when the robot was involved in a handshake behavior versus non-contact behaviors. As expected, temperature (*temp0*: $t(7150) = 30.21$, $p < 0.001$; *temp1*: $t(7150) = 26.26$, $p < 0.001$) and tactile data from tactile 1 ($t(7150) = 33.44$, $p < 0.001$) were higher, distance to the subject's face was closer during the handshake ($t(1061) = 3.21$, $p < 0.001$), and forces on the arm were higher except for in the x direction ($p < 0.001$). We then compared other group divisions on the same measurements for while they were engaged in a handshake with the robot, as this

was the only time they were actively touching the robot. Group divisions were decided based on biographical information we could collect without a survey (gender and relationship to the laboratory) and vocalizations of the subjects during the interaction. All subjects in this experiment were Japanese, so we did not look at the effects of culture. Males measured higher for force against the arm in all directions of x, y, z, roll, pitch, and yaw (for all, $p < 0.001$). This likely reflects a gender difference in strength. Females had higher hand temperatures ($temp0$: $t(11127) = 16.25$, $p < 0.001$; $temp1$: $t(11127) = 3.26$, $p < 0.001$), lower tactile measurements ($tactile0$: $t(11127) = 10.14$, $p < 0.001$; $tactile1$: $t(11127) = 10.25$, $p < 0.001$), and closer faces ($t(881) = 4.80$, $p < 0.001$). Alumni of the laboratory showed a similar trend versus current lab members; higher temperatures ($temp0$: $t(11808) = 16.65$, $p < 0.001$; $temp1$: $t(11808) = 14.07$, $p < 0.001$), lower tactile measurements ($tactile0$: $t(11808) = 26.74$, $p < 0.001$; $tactile1$: $t(11808) = 4.93$, $p < 0.001$), and a closer face distance ($t(1471) = 1.246$, $p < 0.001$). We reviewed video of the experiment and coded subjects who made positive remarks (such as, “cool”) versus negative remarks (“scary”), excluding current members of the laboratory. Four subjects made positive remarks, while three made negative remarks. Subjects who made negative remarks versus those who made positive remarks had similar data patterns to the other group divisions, with again higher temperatures ($temp0$: $t(3060) = 12.02$, $p < 0.001$; $temp1$: $t(3060) = 17.22$), lower tactile measurements ($tactile0$: $t(3060) = 15.86$, $p < 0.001$; $tactile1$: $t(3060) = 4.68$, $p < 0.001$), and closer face distances ($t(293) = 2.31$, $p < 0.001$). Refer to Table 1 for a comparison of the average measurements for each group.

Table 1. Sensor Data for Experiment 1.

Average temperature and tactile measurements for different groups are shown, with higher means between group divisions bolded.

Group	Temp 0	Temp 1	Tact 0	Tact 1	Face Dist
All subjects	25.8	24.8	8.8	15.7	1413.8
Handshake	27.4	26.4	22.2	83.9	1337.1
No handshake	25.5	24.4	19.9	7.2	1417.2
Female	27.0	25.5	9.4	34.1	781.2
Male	26.2	25.4	16.6	51.9	1442.5
Alumni	26.7	25.7	12.1	47.0	1447.1
Current members	26.0	25.1	26.5	53.7	1521.0
Negative	26.2	25.5	7.1	57.9	1387.6
Positive	25.4	24.2	9.9	70.6	1514.4

3.3 Discussion

The similar pattern in sensor data (higher temperature, lower tactile measurements, and closer face distance) for women, old (versus current) members of the laboratory, and people expressing negative comments reflects a likely similar reaction to the robot. This pattern especially stands out, because while a handshake

(versus no interaction with the robot) will result in both higher temperature and tactile measurements, these groups show an opposite pattern of high temperature but low tactile measurements. We hypothesize this pattern could reflect violations of expectation of the robot for the subject. The violation of expectation could be negative, such as stress, or it could be positive, such as excitement. Higher finger and hand temperatures have been correlated with stress and arousal in psychology research [8]. Lower tactile measurements could indicate a reluctance to touch the robot or a difference in handshake style. The differences in face distance could indicate several possible emotions, and further research is necessary. Previous research has found that subjects who feel more negatively about a robot are more willing to invade its personal space [3]. However, this close distance to the robot could also indicate close examination of the robot based on curiosity, or even a comfort with the robot. All of these ideas are at most speculative, but the fact that there are significant differences in sensor data across demographic groups demonstrates the potential usefulness of this methodology. Further study is required to determine the relationship between these biological measures and feelings towards a robot, but these results show an interesting pattern ripe for future investigation, and that a robot's sensor data can be useful even in quick, multi-user interactions to extract differences between demographic groups.

4. EXPERIMENT 2

4.1 Methods

In order to reaffirm the effectiveness of our methodology, we conducted a second, similar experiment, but on a larger-scale. Specifically, we aimed for a longer experiment time, a larger subject pool, and working with people who had never met a robot before. We placed the HRP-2 outside in the University of Tokyo Hongo campus for three hours, during the University's Homecoming event for alumni in all departments visiting the campus. People who walked by the robot were asked to briefly “meet” the robot as a part of a demonstration for the laboratory. As subjects came closer, the robot then tracked the subject's face and initiated a greeting with the subject, as described above in the Overall Methods. During Experiment 1, some people remarked that they wanted to speak with the robot, so we had the robot speak a simple greeting when it initiated its handshake and wave gestures. The robot greeted people in Japanese, using an average male speech generation voice [9], and said the Japanese equivalent of, “Nice to meet you, my name is HRP-2”. In total, 70 people interacted with the robot (49 male, 21 female). Participants came from all parts of the school and were of all ages, with an average age of 25 years. Unlike Experiment 1, Experiment 2 included both Japanese and foreign subjects. Seven were from Western countries, while sixty-three were from East Asia.

After interacting with the robot, subjects were asked to fill out a one-page questionnaire. The questionnaire was divided into three parts: 1) *biological information* - the subject's gender, age group, and if they had interacted with a robot before, 2) *adjectives about the interaction* - cool, natural, scary, fast, interesting, and cute, 3) *descriptors of the robot* - human versus robotic, masculine versus feminine, childish versus adult, Japanese versus foreign, and how much the voice matched the robot. Subjects rated the adjectives on a scale of 1 (low) to 10 (high). Fifty-five people filled out the

questionnaire (33 male, 13 female, 9 no response). Fifteen had interacted with a robot before, while forty had not.

4.2 Results

There were slight differences in the sensor data taken from Experiment 2 versus Experiment 1. We coded extra information including whether subjects reciprocated the robot's actions when waved or bowed to. Due to last-minute difficulties with the motors in our robot's hand, we had to switch to a different HRP-2 that did not have its face distance measurement actively working. The tactile sensors were also differently calibrated from the HRP-2 in Experiment 1, so the range for the data is much higher and narrower (239 - 242), still as an analog unitless value. The narrow range of the data made us question the accuracy of the tactile data, but they had a strong correlation with temperature as expected from Experiment 1 (*tactile0 to temp0*: $r = 0.98$, $p < 0.001$; *tactile0 to temp1*: $r = 0.97$, $p < 0.001$; *tactile1 to temp0*: $r = 0.98$, $p < 0.001$; *tactile1 to temp1*: $r = 0.97$, $p < 0.001$), so we believe the sensors were functioning well. The robot's appearance was the same as the robot used in Experiment 1.

We looked at similar groupings to Experiment 1 and found some interesting similarities and differences in the results. A summary of the results between groups can be seen in Table 2. A comparison of lab members who interacted with the robot to people freshly meeting the robot showed a similar pattern to Experiment 1. People new to the robot had higher temperatures (*temp0*: $t(50510) = 31.86$, $p < 0.001$; *temp1*: $t(50510) = 31.15$, $p < 0.001$) and put lower force ($p < 0.001$ for all directions except for y and yaw) on the robot, but unlike Experiment 1, had a higher tactile measurement than lab members (*tactile0*: $t(50510) = 28.34$, $p < 0.001$; *tactile1*: $t(50510) = 28.54$, $p < 0.001$). Gender differences were opposite of Experiment 1; females had lower temperature (*temp0*: $t(50510) = 1.61$, $p < 0.001$; *temp1*: $t(50510) = 2.23$, $p < 0.001$), higher tactile measurements (*tactile0*: $t(50510) = 4.67$, $p < 0.001$; *tactile1*: $t(50510) = 4.57$, $p < 0.001$), and higher force on the arm ($p < 0.001$ in all directions) than males. Females also more frequently reciprocated the robot's waves and bows compared to males ($\chi^2(2, 70) = 13.66$, $p < 0.001$). We also looked at a possible effect of culture on sensor data. East Asian subjects had higher temperatures (*temp0*: $t(49096) = 5.94$, $p < 0.001$; *temp1*: $t(49096) = 5.40$, $p < 0.001$) and lower tactile measurements (*tactile0*: $t(49096) = 3.12$, $p < 0.001$; *tactile1*: $t(49046) = 3.09$, $p < 0.001$), compared to Western subjects.

Subjects' average responses on the questionnaire items are shown in Table 3. We examined correlations of biographical data to the survey results. Age group was closely correlated to several questions in the survey. People in older age groups tended to rate the robot higher for being feminine ($r = -0.33$, $p < 0.05$), but lower for being cool ($r = -0.45$, $p < 0.005$), interesting ($r = -0.41$, $p < 0.005$), cute ($r = -0.34$, $p < 0.05$), and having its voice match its appearance ($r = -0.39$, $p < 0.01$). We also examined correlations between questionnaire answers. Some correlations validated assumptions about how subjects would respond; subjects who found the robot masculine also said the man's voice matched the robot ($r = 0.34$, $p < 0.05$), subjects who found the robot natural said it was more human-like ($r = 0.35$, $p < 0.01$), and there was a direct positive correlation amongst the qualities of cute, cool, and interesting ($p < 0.01$ for each comparison). There was also a significant correlation between subjects who found the robot foreign and those who found it scary ($r = 0.43$, $p < 0.001$),

possibly reflecting interesting cultural perceptions of a robot. We did not find any significant differences in opinion data based on gender or previous experience with robots.

Table 2. Sensor Data for Experiment 2.

Average temperature and tactile measurements for different groups are shown, with higher means between group divisions bolded.

Group	Temp 0	Temp 1	Tact 0	Tact 1
All subjects	20.0	20.3	239.88	240.80
Female	21.4	21.7	240.02	240.93
Male	21.6	21.9	239.64	240.57
General Subject	21.9	22.3	240.05	240.98
Lab member	16.2	16.7	236.03	236.92
East Asian	21.6	22.0	239.71	240.63
Western	20.8	21.2	240.06	240.98

Table 3. Questionnaire results.

Numbers indicate average scores given by subjects on a scale of 1 (low) to 10 (high). Averages are bolded together with the term they were closer to. The questionnaire was delivered in Japanese, and so there may be slight differences in nuance of the English translations used in this paper.

Word	Average	Opposite
Cool	7.57	Uncool
Natural	5.47	Unnatural
Scary	4.48	Not scary
Fast	4.62	Slow
Interesting	8.30	Boring

Word	Average	Opposite
Cute	6.43	Not cute
Voice matches	6.82	Doesn't match
Human-like	4.43	Machine-like
Masculine	8.20	Feminine
Childish	3.44	Adult

4.3 Follow-up Survey

The results of Experiment 2 prompted us to do a brief survey across campus to determine which computer-generated voice (from AquesTalk's library [9]) best matched the robot's appearance. This survey allowed us to choose a voice for the robot for future interaction experiments that would best match expectations of the robot. We asked 76 people (54 male, 22 female, average age 27.6 years) across campus to see a picture of the robot and then choose one of five different voices (two female, two male, and one very machine-like male robotic voice) for the robot. The survey was written in visual programming language Lazarus [10], and conducted on a multi-touch Windows 7 tablet computer. We used only a picture for this survey rather than video or interaction with the robot, to get a large number of opinions from across campus. Female subjects most frequently chose the second female voice (59.1%) while male subjects most frequently

chose the robotic male voice (27.8%) but were more evenly distributed in their choices. People who chose the female voice said it was soft, approachable, and easy to interact with. People who chose the robotic voice said it matched best because it was most stereotypically robotic. These opinion differences reflect very opposite differences in expectations for the robot – for it to be comfortable for interactions with humans, or for it to be as robot-like as possible. It will be interesting to investigate in future studies what factors cause different perspectives on the role a robot's identity should fill. Despite the differences in trend between gender, overall, the most popular voice was the female voice (31.6%), and this voice will be used for future human-robot interaction studies with our HRP-2. We will also try testing how perceptions of the robot's voice change when interacting with the real robot versus selecting a voice based on solely a picture.

4.4 Discussion

The sensor data from this experiment present several interesting possible interpretations. First of all, the opposite trend in the data based on gender stands out. This difference could come from a number of factors – potential differences in the subject pool (the female engineer alumni of Experiment 1 versus the general female population of Experiment 2), differences in the robot (the added voice), or perhaps differences in the experiment presentation (for Experiment 1, every alumnus met the robot, while for Experiment 2, only people who actively approached the robot became subjects). However, there is still the similar pattern of a higher temperature, lower tactile, and lower force in one gender between both experiments. As women in Experiment 2 were much more likely to reciprocate a robot's gestures than men, it seems possible that the women in this experiment felt more comfortable with the robot. However, further investigation into gender differences in expectations and feelings towards robots will be necessary.

One other interesting pattern is the higher temperature and lower tactile data of East Asian subjects versus Western subjects. This could reflect a possible cultural difference in comfort with interactions with robots, or a cultural difference in hand-shaking, as it is a much more common greeting in the West.

We also found a difference in the tactile results from Experiment 1 and 2 for members of the lab versus non-members. However, we believe the difference may not be particularly interesting, as many lab members in Experiment 2 used handshakes with the robot to test its function, and were thus not "fully involved" handshakes, unlike with Experiment 1.

These interpretations, however, are again only explorative and it is impossible to make conclusions about gender or cultural perceptions of robots based on only these results. However, the results of Experiment 2 demonstrate that even within a different setting, we can still find significant differences in sensor data between demographic groups.

Based on the questionnaire and follow-up survey results, we can paint a clear picture of the identity people assign to the robot. To the average subject, the robot was viewed as a masculine, foreign, adult. However, ideas of the robot's identity changed across subject demographics (especially age), and reflect differing expectations in how a robot should appear. There is also the interesting discrepancy of subjects finding the robot masculine and saying that the robot's voice matches, but selecting a feminine voice in the follow-up survey. This perhaps points to a need for a

robot to be dynamic, and able to adjust its identity to match its user's expectations, as they may differ strongly based on subject.

5. GENERAL DISCUSSION

This study accomplished two main tasks that will be important to the future design of human-robot interactions. First, we proposed a methodology for retrieving emotion data from subjects when interacting with a robot. We found that using sensor data based upon measures from a person – their hand temperature, the directional forces of their hand, their face distance – can provide a quick look into people's unconscious reactions towards a robot. While the current study only begins to get at possible differences in robot perceptions, we hope to refine this methodology to further explore potential demographic differences and how they relate to psychological phenomena in future work. We also hope to expand the data we collect to include other information typically used in psychological studies, such as skin conductance, voice data, and tactile measurements across the entire robot's body. Combining the sensor data taken during these quick interactions with questionnaire and behavioral data can create a comprehensive image of a user's feelings and expectations for a robot, and in the future robots could learn to dynamically adjust to these signals in order to meet a user's expectations.

The second main contribution of our study is demonstrating one potential method for robots to collect data quickly within unconstrained multi-user environments. Using sensor data allowed our robots to collect thousands of samples of data from individuals in only minutes of time. From reviewing the robot's camera data, it is easy to separate out individuals' data and collect basic biographical information (such as gender) without having to have an experimenter actively collect data on-site or distribute surveys. While these two experiments were focused solely on the collection and analysis of these sensor data, this methodological approach could be used during any human-robot interaction. For example, a quick handshake before and after public demonstrations of a robot could be used to collect user opinion data quickly, and to allow the robot to adjust to its users' expectations. The ability to take data quickly allows researchers to collect HRI reaction data in fast-paced, complicated, multi-user settings, as demonstrated in Experiments 1 and 2.

Our study also found some potentially interesting demographic differences in expectations towards robots that would be interesting starting points for future investigation. There appears to be a gender difference in attitudes towards robots, but it is still difficult to tease apart the direction of this gender difference. One previous study found that males viewed robots as more human-like, while females viewed robots as more machine-like and unsocial [11]. However, we found some hints in Experiment 2 that females may feel more comfortable with robots. We also found potential differences in expectation for a robot's role and gender from our follow-up survey to Experiment 2. These results are still very preliminary, and further study will be necessary to examine gender differences in robot expectations. We also found other demographic differences that are ripe for future investigation. Some HRI research has proposed cultural differences in views towards robotics between the West and the East [12], and our results from Experiment 2 also present a possible difference in comfort with a robot. The questionnaire results from Experiment 2 also uncover a possible age difference in expectations of robots; while younger people expect robots to

be exciting and modern, older people may be less concerned with the "cool factor" of a robot.

Overall, these results present a glimpse into possible methods to investigate expectations and reactions to robots within natural, multi-user environments, and we propose using these results to shape a robot's identity. This is only the first step in investigating effective methods for adapting robots to match human expectations within a natural multi-user environment, and this will be an interesting field for discovery in future research.

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Building up child-robot relationship

From initial attraction towards social engagement

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ABSTRACT

To explore social bonds' emergence with robots, a field study with 49 sixth grade scholars (aged 11-12 years) and 4 different robots was carried out at an elementary school. A subsequent laboratory experiment with 4 of the participants was completed in order to explore social engagement. At school, children's preferences, expectations on functionality and communication, and interaction behavior were studied. In the lab, recognition, partner's selection, and dyadic interaction were explored. Both at school and in the lab, data from videotaped direct observation, questionnaires and interviews were gathered. The results showed that different robots' appearance and performance elicit in children distinctive perceptions and interactive behavior and affect social processes (e. g., role attribution and attachment). The preliminary results will help in the design of robot-based programs for hospitalized children to improve quality of life¹

Categories and Subject Descriptors

J.4 [Computer applications]: Social and behavioral sciences---Psychology.

General Terms

Human factors, design.

Keywords

Social Assistive Robots; long-term interaction; interdependence theory; role attribution.

1. INTRODUCTION

Social robots, defined as platforms capable to engage people in natural social exchange, have already been proposed as supplementary tools for rehabilitation [1], autism therapy [2] [3] treatment adherence and compliance, and for entertainment, enjoyment and comfort [4] [5] [6]. These studies show very promising results with children. To fulfill therapeutic goals, robot's effectiveness depends strongly on its ability to elicit long-term engagement in children.

A severe disease is a serious event that dramatically affects children and their family's lives. Hospitalized children are confronted with stressful conditions including physical pain and fear. Social support becomes almost limited to hospital staff and relatives, who often are affected themselves by feelings of sorrow and concern. Therefore, another therapeutic-related application of social robots is to help children to cope with the harmful consequences of illness and long-term hospitalization. In this context, we identify two different therapeutic interventions that may be provided by Social Assistive Robots: rehabilitation monitoring and companionship, corresponding with two different social situations. In the case of rehabilitation the relationship between coach and pupil is goal-oriented and focused on the task. In the context of companionship the relationship is needs-oriented for leveraging feelings of isolation and stress. Both roles –coach and companion- require context-specific social competences to engage children in long-term interaction. Beyond novelty effect, robots have to remain compelling over a long period of time to achieve the therapeutic goals. Provided that robots have different social affordances (e. g., facial expression) and interaction capabilities (e. g., conversational skills) we assume that they are not equally suitable to take a specific role and to engage with specific target users. Matching between role demands and robot competences is a central criterion for believable and effective social robots design [7] [8]. To address this challenge, interdependence theory offers a useful situation-based understanding of interaction [9].

This work – whose results are shown partially- explore social bonds' emergence between children and robots applying models and techniques from social psychology. The aim of the present work is to observe and understand the interactive behavior between (non-patient) children and social robots in order to design further in field research involving hospitalized children. Our main assumptions are that (i) social situated specific skills and behavior

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¹ This work is partly supported by Grant TSI-020301-2009-27 (ACROSS project), by the Spanish Government and the FEDER funds.

are required to assume effectively social roles in coaching or companion interaction, and (ii) salient robots' features as appearance (i.e. lifelikeness, baby or adult likeness) act as social cues that elicit prosocial behavior in children. Based on observable features, perception is a complex subjective process of *making sense* mediated by cultural and contextual factors [10]. This paper describes a study developed in two phases. The first one took place at an elementary school where a workshop with 4 different robots (under the supervision of teachers) was carried out. The second phase took place two months later in a behavior research lab at the University. It consisted on a series of play sessions for evaluating some features of long-term engagement. The present study will focus on PLEO and NAO results since they are the most employed robots for coaching and companionship purposes as it is shown in the next section.

2. DESIGNING ROBOT'S SOCIABILITY

Health related social robots are supposed to take long-term assistive and companionship roles in children's everyday lives. Therefore, the essential challenge is to develop robots that keep children engaged over time after the initial novelty effect has worn off.

2.1 Robots for coaching

Pupil-Coach Interdependence: This relationship is based on the social bond (i.e. affective involvement), task, and goals. Obtaining patient collaboration is an essential issue in therapy and requires an agreement about the relevance and usefulness of tasks and goals. To fulfill the therapy's goals, the coach must provide ongoing supervision, encouragement, feedback, counseling, and support. Furthermore, to enhance children agreement and compliance is necessary to create an affective bond. Rehabilitation is usually hard and motivation must come from an affective bond of trust and intimacy (*alliance*) between pupil and coach. The coach must be responsive to pupil needs and emotions in an empathic way and find an acceptable balance between goals commitment and concern for pupil's wellbeing.

Required social skills: For task monitoring it is required an engaging communication and contingent feedback. For empathic rapport is necessary affective communication and awareness of child's psychological and physical state [11].

Selecting a coach-robot. A humanoid robot elicits a more consistent role attributed to authority, competence, expertise, and reliability. We selected the humanoid robot Nao. Nao (see Figure 1) is a state-of-the-art human-like robot platform produced by Aldebaran². Endowed with 25 degrees of freedom for great mobility it features embedded software allowing text to speech, sound localization, visual pattern and colour shape detection, obstacle detection and visual communication through different LEDs. Nao has been used successfully in different European projects within different contexts due to its communicative and motor skills. The KSERA³ project aims to obtain a successful, effective interaction between humans and robots to guarantee acceptance and adoption of service robotics technologies,

although it focuses on elderly. In the French project ROMEO⁴, Nao was used as a comprehensive assistant for persons suffering from loss of autonomy. In Feelix Growing⁵ project, Nao has been used to mimic the emotional skills of one-year-old child and it was capable of forming bonds with people who treat it kindly. The robot is able to use the expressive and behavioral cues that babies learn to interact with others. In these studies Nao has shown to be highly skillful for social multimodal interaction with elderly people and children. Moreover, Nao has all the robots' skills identified in [11] for successful coaching: eye-contact, look-at behaviors, head, arm and hand gestures, speech and speech recognition. In addition, Nao's articulated anatomy and movement accuracy allows for direct imitation by children, especially applicable in motor rehabilitation cases. Considering these results, Nao has been the robotic platform selected to play the role of coach in the in field study.

2.2 Pet-robots for companionship

Recently, pet-like robots have been introduced to reproduce the social-emotional benefits associated with the interaction and the emotional bond between children and companion animals such as entertainment, relief, support and enjoyment [2]. This social bond is supposed to provide therapy relevant effects to hospitalized children in the way real pets do. However, animal-assisted activities, that have been proven to be effective for pediatric purposes [1], are not possible in hospital environment.

Owner-Pet Interdependence: The relationship between master and pet is based on hierarchy and attachment. We assume that a sort of master-pet bond may emerge between a child and a pet robot with social skills according to these two dimensions. Hierarchy means that children have an obvious higher status that could be enhanced if the robot-pet has a baby appearance [12]. The social situation defined by the master/pet interdependence, will naturally produce engaging activities (i.e. teaching new skills, learning to understand, care giving, playing together) and expressions of affection and concern.

Required social skills: In this context, the robot, besides considerations of appearance, life-like, and baby-like features, must be able to deploy (or acquire) social skills for effective communication (i.e. orientation, attention, responsiveness), for hierarchy submission (i.e. recognition, obedience), and to express and generate attachment (i.e. affective expressiveness).

Selecting a pet-robot. For the companionship role we used the robot Pleo, a robot platform that fulfils the above stated requirements of appealing baby-likeness, expressiveness, and an array of different behavior and mood modes. Pleo is a commercial entertainment robot developed by UGOBE⁶ equipped with different tactile sensors beneath its skin, ground sensors in the feet, speakers and microphones. Among its features, it presents a set of creature-like personalities and develops internal drives like hunger or sleep, and several mood modes: happy, extremely scared, curious. Pleo has been tested in several research works [13], [14], [15]. These studies focus on the effect of Pleo in a long-term interaction, especially with children. In this sense, [16] conducted a long-term study with six families, which were given a Pleo for a minimum of two months and a maximum of ten.

² www.aldebaran-robotics.com

³ ksera.ieis.tuel.nl

⁴ www.projectromeo.com

⁵ www.feelix-growing.org

⁶ www.pleoworld.com

Similarly, [17] carried out a study based on the opinions of a blog users about Pleo. The main results are related to initial engagement due to the novelty effect, the care behaviors and the long-term disappointment effect. Even so, the majority of studies identified the development of a social bond with the robot.



Figure 1. The robots Nao, Aibo, Pleo and Spykee

3. FIELD STUDY AT ELEMENTARY SCHOOL

To explore the factors influencing bond emergence between children and social robots, a preliminary study with no patient children was carried out in an elementary school. The main objective was to understand which robot's features regarding appearance and behavior were more salient to children and contributed most to create the first impression. Specifically, children interaction with different kind of robots and eventual robot-related differences were studied. Children attribution of competences and skills based on appearance and previous knowledge were explored. Children attitude, preferences, and emotional behavior were analyzed.

3.1 Method

3.1.1 Participants

The experience involved 49 sixth grade scholars. The children -29 girls and 20 boys- were aged between 11 and 12 years old.

3.1.2 Setting

The activity was presented as a workshop on robotics prepared together with the sixth grade tutors and displayed as a curricular complementary activity to Sciences lessons. The activity took place at school during ordinary class time and under continuous supervision of teachers.

3.1.3 Robots

The robots presented were a mechanoid functional robot (Spykee), a humanoid platform (Nao), a baby dinosaur robot (Pleo) and a mechanic-like puppy (Aibo). These four robots let us study and understand the role of appearance (e. g., animal vs. humanoid and functional vs. biomorphic) in a first impression situation. However, in this paper we focus on interaction with Nao and Pleo, the two robots selected for therapeutic contexts in our ongoing research.

3.1.4 Activity

Robot choice and group assignment: The four robots in off state were exposed together on a stage and children were encouraged to observe them freely and choose the one they prefer to play with during the workshop (Fig. 2). Children were not allowed to touch them and no further explanation was given. Children were assigned to one of the four workshops according to the expressed preference. The workshops took place simultaneously in two classrooms, the gymnasium and in the hall.

Self-presentation: The robots were activated and performed non-interactive behavior, i. e., pre-defined routines. Self-presentation behaviors were deliberately designed in order to show and suggest an engaging but realistic robot motor and interaction skills and competences. Nao's self-presentation started with a short introduction, speaking loud, waving hands, and showing its arms, legs and head mobility. It continued displaying its colored LEDs eyes in an entertaining way followed by playing a song and dancing accordingly. It ended the presentation with a Tai Chi dance, where Nao exhibited great balance and mobility skills. Pleo's skills were shown through some examples of human robot interaction. Firstly, it wakes-up by touching its contact sensors, next it goes sleep again by rubbing its back. Again wake-up, it became angry hanging it by the queue. Walking was shown when standing on a desk a head movements were performed while it was embraced.

Interactive behavior: Children were encouraged to play with the robots in a semi-oriented way. Conductors proposed interactive activities, answered children's questions and asked them about perceptions and expectations in an informal way. Conductors also monitored children to prevent robots damage, and even explored robots functionality boundaries under children request.

3.1.5 Techniques

Direct observation: The whole session was videotaped (still cameras were placed in the 4 settings) and a photographer covered the activity. Additionally, in two of the workshops the sound was digitally recorded.

Questionnaires: Participants answered a post-experience questionnaire to assess satisfaction and perceptions about robots. The questionnaires were composed by yes/no questions (i.e. 'Would you like to have a robot at home?'), multiple choice items (i.e. 'If you had a Nao robot, what would you use it for?: Playing/Helping with homework/Helping with housekeeping/Connecting to the Net/Others'); and open questions (i.e. 'What do you think engineers should improve in Pleo robot?').

Facilitators: Every workshop was conducted by a robotics engineer and an assistant who took notes on observation sheets, supervised the recording and passed the questionnaires.



Figure 2. Robots exhibition for selection



Figure 3. Interactive behavior with Pleo and Nao

2.1 Results

According to the research question and the aim of this paper, further results will only be referred to workshops with Pleo and Nao. Although the whole experience was videorecorded (for future analyses), in this work we focused on initial perceptions and expectations, interactive behavior and utterances observed in the workshops with the robots from a qualitative approach. 33 children selected Nao and Pleo. Pleo was the most selected robot with 18 choices -surprisingly all the children who chose it were girls- followed by Nao (4 girls and 11 boys).

Tables 1 and 2 summarize the results of workshops with Pleo and Nao, respectively.

Table 1. Initial perceptions and behavior with PLEO

	<i>Observed behavior and utterances</i>
Reasons for preference	Nice aspect <i>So cute!</i> Animal likeness Baby likeness
Expectations (before performance)	Love and affect responsiveness Baby likeness behavior Emotional expressiveness Make sounds
Liked most after Self-presentation	Seems a baby How it moves
Interactive behavior	Baby talk Affection giving Taking care activities
Wish it could do/have/be	More life-likeness /Talk /Eat / Grow up Responsiveness/Not so sleepy

Table 2. Initial perceptions and behavior with NAO

	<i>Observed behavior and utterances</i>
Reasons for preference	Seems/is a person Seems an ape Seems more articulated Is the biggest robot
Expectations (before performance)	To walk To grasp things To speak To move hands To dance To do <i>Matrix</i> To follow instructions To sing
Liked most after self-presentation	<i>Thai Chi</i> routines Dancing
Interactive behavior	Spontaneous imitation Admiration Spontaneous Applause Amazement/ <i>Wow!</i> Curiosity about technical issues / <i>That in the head is a USB plug?/ What's for?</i> Exploring Nao's physical , cognitive and social capabilities and constrains/ <i>Is he hearing me now?/Does he see me?</i>
Wish it could do/have/be (From questionnaires)	Hold a conversation Capability to communicate in natural (children's native) language Non verbal communication skill: gaze and intonation/ <i>When looking at people should look in the face.</i> Talk about itself/ <i>Say what he is thinking</i> Improve motor competences/ <i>Play football/hockey and perform moonwalk</i> <i>Assist/ Help with my homework</i>

4. Interaction in the lab: meeting again

A second meeting was designed to explore social bonds emergence. After the school experience, a series of play sessions with Pleo was conducted in the lab. The aim was to observe children behavior when they met Pleo again and explore how the previous contact with the robot in the school affects –it's projected on- subsequent interaction. Specifically, differences and similarities on interactive behavior at laboratory and at school were assessed. Children interaction in a controlled situation under different social conditions (with a facilitator, alone, with a peer, and in a focus group) was explored. Finally, the role adopted by the participants during the interaction with Pleo was explored.

4.1 Method

4.1.1 Participants

At the end of the activity in the school, volunteers' participation for a second activity was requested. The interested children were given a form to be fulfilled, signed and sent back by their parents or tutors in case they consent participation. Eight parents consents were received and finally four children were selected for availability criteria. Three of them had the role of the owner and the fourth girl interacted with them as a part of the lab experience (see below *Playing with Pleo with peers*).

4.1.2 Setting

The experience was carried out in a behavior research lab at the University two months after the school experience. The play session took place in the test room and the group interview in a meeting room.

4.1.3 Robot

Two Pleo robots were employed for the experience. One of them was programmed to exhibit purring and slow smooth movements, and the other one was growling and agitated.

4.1.4 Activity

Choosing a Pleo: The participants were encouraged to choose between two identical Pleo robots that were performing the above mentioned behaviors.

Playing with Pleo in adult presence: The instruction given by the conductor was “*You can stay here with Pleo as long as you want. When you want to give up, just tell me*”.

Playing with Pleo alone: The facilitator leaves the lab and the child stays alone with the robot.

Playing with Pleo with peers: The participant received another classmate in the lab to create a situation that enhances talking about the experience and contrast opinions. The participant was encouraged to talk freely about Pleo to her classmate.

Group Interview: When all the participants finished their laboratory experience, a group interview was made with the four participants, a facilitator, and a robotic engineer. During the interview the Pleo robots were activated on the table.

4.2 Results

The four participants chose the Pleo that exhibited calm behavior to play with. The girls manifested that Pleo reminded them the robot in the school, so they seemed to recognize it as a familiar robot which had been with them before. They wanted to know and asked the facilitator which of the four Pleos in the lab was the one they *have met* at school.

The role they took was consistent with the one adopted in the school, but in this case the difference was that the participant had more time to interact with the robot and she was alone with it during a while. The interactive behaviors observed were petting, lovely hugging, stroking, and baby talk. When the participant played with a peer, she adopted neatly the owner's role interpreting Pleo's behavior and showing understanding of what it likes and likes not (i.e. "It's difficult for him to fall asleep", "It's not hungry now"). Finally, in the group interview, the girls shared their impressions about Pleo and compared it to a real pet companion. They expressed their enjoyment with the robot and agreed with the vision that they could have a closer bond with him similar to the owner-pet relationship.

Table 3 summarizes preliminary results with Pleo in the Lab experience, grouped in five situations: selecting Pleo, in the lab with facilitator, alone with Pleo, with a classmate and group interview.

Table 4. Interactive behavior in the lab

<i>Situation</i>	<i>Observed behavior and opinions</i>
Selecting a Pleo	All the participants chose the 'nice' one, picked it up and took in their arms
In the lab with facilitator	Petting, hugging and feeding behavior
Alone with Pleo in the lab	New activities appeared /Putting him into the doghouse/ Grabbing by the tail / Insisting on feeding
With a classmate	The presence of a peer helps the girl to express her feelings and reinforce her role of owner.
Group Interview Remarks	Similar to real pets Owner feelings Differences/similarities with the one in the school (more active and fun)

5. DISCUSSION

This study shows that robots' salient features as humanoid, mechanic, or animal appearance affect children preferences and are social cues in role attribution. According to appearance and performance children ascribe both functional and social characteristics to robots and interpret their behavior.

Consistent with the literature reviewed, two different interactive behavior patterns emerged in Nao and Pleo workshops. Interacting with Nao, children show spontaneous imitation, admiration and amazement. Nao autonomous behavior (i.e. seeking faces to orient interaction) elicits immediate children attempts to catch its attention and to draw Nao into interaction by waving, saying hello, or approaching to its face. Nao performance

provokes curiosity and willingness to explore and investigate. The expectations about robot capabilities are high (i. e. conversational skills, gait) as a result of its human-like appearance and athletic performance. On the other hand, Pleo generates in children need-oriented affective behavior (e. g., giving affection) and involve in taking care activities. Children expect animal-like behaviors such as 'making sounds' and eating and ascribe Pleo animal characteristics such as internal drives (i.e. sleepiness, anger, hunger), reasoning and intention. In the lab session, children resumed the relationship and reinforced the initial social bond built during previous experience at school. Children asked for *their* baby dinosaur -the one they met at school-, and interpret recognition in Pleo's responses.

6. CONCLUSIONS

Children's perceptions and expectations about robots as social actors affect interactive behavior through role attribution. Robots appearance and primary performance should be carefully designed to elicit role consistent engaging but realistic expectations as a first step in long-term relationship emergence and maintenance.

Considering children suggestions after the interaction experience, some orientations for interface and technical specifications could be proposed. For instance, Pleo should show more life-likeness behaviors (e. g., talk, eat, grow up, sleep) whereas Nao should present more human skills (e. g., verbal and non verbal communication skills, motor competences and assistive tasks).

Understanding of social processes of interdependence and relationship dynamics in specific social situations seems necessary for optimizing matching between robot affordances and context-specific social demands. To achieve this objective is necessary to assess human-robot interaction in terms of role consistency.

Provided that interactive behavior is strongly context dependent, further field studies with target users, i. e., long-term hospitalized children are required to investigate the establishment and maintenance of children-robot companionship in health related scenarios.

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Prerequisites for Intuitive Interaction - on the example of Humanoid Motor Babbling

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Abstract—Motor Babbling has been identified as a self-exploring behaviour adopted by infants and is fundamental for the development of more complex behaviours, self-awareness and social interaction skills. Exploring the possible space of movements and articulations is the first step towards social and intentional behaviours.

We adopt motor babbling for the learning strategies of a humanoid robot that maps its random arm movements with its head movements, determined by the perception of its own body. In this paper, we analyse three random movement strategies and experimentally test on a humanoid robot how they affect the learning speed.

We believe that intuitive human-robot interaction requires physical and dynamic interaction and that creating a body map through learning is a major prerequisite.

I. INTRODUCTION

Researchers in Human-Robot Interaction are interested in developing models inspired by human cognitive processes, in particular such that they result in a natural interaction behaviour. Providing the robot with skills that let the interaction look clever and intuitive ensures a high level of satisfaction for the interacting person.

Cognitive robotics takes its inspiration from developmental studies in humans. Infants incrementally develop cognitive abilities through the interaction with the environment and with persons. Embodied agents, humans, other animals as well as robots, can generate useful sensory stimulations by interacting with the environment. Their actions change the environment and what they perceive from it; on the other hand, what they perceive influences their actions consequently. This is known as sensorimotor coordination[1].

We understand an observed behaviour as we compare a simulated execution of it with a set of motion primitives we have in our memory. But, how much do perceptual abilities require motor skills? In order to imitate a demonstrator, an observer has to recognize the action, but in order to recognize the action the observer must be able to perform the action. This tricky question can be answered if we look at the development as an incremental process: infants learn an ability on top of other abilities already present[1]. Body babbling observed in infants has been classified by Meltzoff and Moore[2] as a mechanism that provides experience for mapping movements to the resulting body configurations.

Such a sensorimotor stage, where infants explore the environment in terms of the physical actions they can perform, inspired several robotics studies. In [3], the role of exploration is to gather evidence to form and test models. In [4], Demirir et al. propose a way for combining knowledge through exploration and knowledge from others, through the creation and use of mirror neuron inspired internal models. Saegusa et al., in [5], consider motor-babbling-based sensorimotor learning as an effective method to autonomously develop an internal model of the own body and the environment using multiple sensorial modalities.

Exploring the possible space of movements and articulations is the first step towards more intentional behaviours, like exploring the world, wherein the agent wants to figure out how its actions change the state of the world. Socially speaking, an agent might be aware of itself, first, to be aware of the other as a being like the self with individual wants and intentions.

In the next section, we discuss the different prerequisites for intuitive interaction and how they could be implemented on a humanoid robot. We then adopt one of the major prerequisites for HRI - motor babbling and learning of a body map - for the learning strategies of a humanoid robot that maps its random arm movements with its head movements, determined by the perception of its own body. We equip the robot with an elementary attentive system for perceiving its own body and for moving its head to focus on it. A self-exploring robot that can optimally adapt to the abilities of its own body in interaction with the environment, itself and others, could give a human the impression that it is intelligent, interested in something it would like to discover, driven by the curiosity of exploring its own movement. We analyse three random movement strategies and experimentally test on a humanoid robot how they affect the learning speed and how much energy they consume. We also implemented a simple algorithm for learning body maps through motor babbling. In the last section, we discuss how the results on motor babbling could influence future research aiming at intuitive human-robot interaction.

II. PREREQUISITES FOR INTUITIVE HUMAN-ROBOT INTERACTION

What do we understand by intuitive interaction? This question is related to expectations of the human, but can also

be described as an interaction that results in a satisfying experience for the human requiring a low cognitive load. It also means that the person does not have to learn a specific interaction protocol for the human-robot interaction, but that the robot adapts to the type of interaction initiated by the person. Intuitive interaction is still possible in case the human has no strong expectations on the robot, its capabilities, and reactions, but enters the interaction scenario with his or her expectations about interactions with other people, animals or even non-intentional agents or objects.

We have identified three different kinds of prerequisites for intuitive interaction:

a) *Physical prerequisites for intuitive interaction.* These are properties of the morphology, sensors types, and appearance of the robot. End-effectors with a large number of degrees of freedom, and a variety of sensors, ideally similar to those of a human, would facilitate the interaction and increase the interaction experience for the user. The properties of the environment or of the user interfaces also seem to be of importance when used as tools for interacting with robots (see for example [6]).

b) *Representation of self and other.* In [7], the authors claim that perspective taking and Theory of Mind skills are crucial for engaging in sensible short time interaction. For implementing such abilities, the robot must be aware of its own body and abilities. A prerequisite for HRI is, thus, the ability to build a body map, which can be done through body babbling, through interaction with the world or through interaction with others. Meltzoff et al. demonstrated in [2] that body babbling provides experience mapping movements to the resulting body configurations. Hafner et al., in [8], argued that self-other distinction is crucial for the development of sophisticated forms of social interaction and proposed a unified representation of a body schema in order to solve the body correspondence problem. Self-other representation is also necessary for simulating the action of the interacting partner through perspective taking.

c) *Social skills and expectations.* When interacting, the robot and the human constitute a dynamic system [9]. Each agent might be able to predict and react to the actions and intentions of the other, often without any verbal communication. Developmental research supports the idea that actions are learnt incrementally and one of the most powerful social skill to do that is imitation. A robot might be able to learn by imitation and to generalize the learned behaviours in different environments and situations. Adapting to physical and social circumstances is a fundamental prerequisite for HRI. Without any doubt, moreover, a robot able to express emotions enhances naturalness of human-robot interaction [10].

We chose to investigate one of those prerequisites of intuitive interaction - representation of self and others - through body babbling.

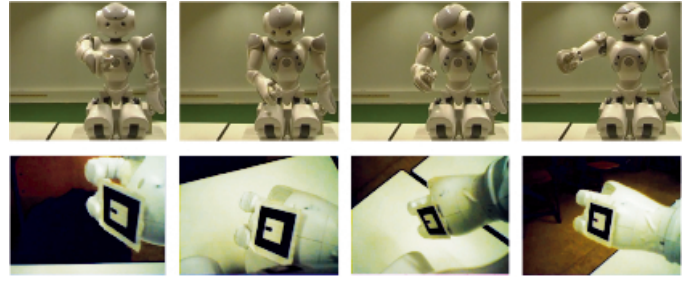


Fig. 1. A typical babbling sequence using the Nao platform. In the lower part are the corresponding frames grabbed by the onboard camera (note that the camera is placed below the fake eyes of the Nao).

III. MOTOR BABBLING IN A HUMANOID ROBOT

We implemented learning through self-exploration on a humanoid platform¹ whose dimensions resemble those of a child, actually simulating the real visual input perceived by a young human subject (see Figure 1).

During the learning process, the robot performs random arm movements and tries to estimate the position of its end-effector (the hand, where a marker is placed on), analysing the frames grabbed from its head camera. We implemented an attentive system composed by two modules: marker detection² and motion detection. When a marker is detected, the head of the robot is rotated in order to focus on it, and the current configuration of the joint angles of the arm and of the neck are stored and coupled with the estimated 3D position of the marker (representing the hand). Due to the limited opening angle of the camera and the robot's short arms (like a child), for most of the time the robot has to rotate its head searching for the marker. The motion detection module is used in order to find the moving arm. Frame by frame, when the head is not moving, the optical flow between the current frame and the previous one is computed. The magnitude of the optical flow is fed into the CAMShift algorithm to find the centroid of the fastest moving area of the video to look at. Figure 2 shows the scheme of the learning algorithm.

IV. RANDOM MOVEMENT STRATEGIES

The results we present here refer to three different types of movement strategies for motor babbling: Purely Random (PR), Random Walk (RW) and Inertial Random Walk (IRW).

The babbling is performed on 4-DoF of the Nao arm: two each for shoulder and elbow. In PR, random values are sampled from a uniform distribution over the range of each joint of the arm; in RW, random steps (increase/hold/decrease the joint by *angle-step*) are sampled from a uniform distribution; IRW is a kind of smooth random walk algorithm which simulates the inertia that a moving mass has when it changes the direction of the motion. Instant by instant, a random step is sampled from a uniform distribution, as in RW, and a small amount of

¹Nao robot from Aldebaran. We adopted the NAO-TH framework (<http://www.naoeamhumboldt.de>)

²We use the ARToolkit for detecting markers (<http://www.hitl.washington.edu/artoolkit>).

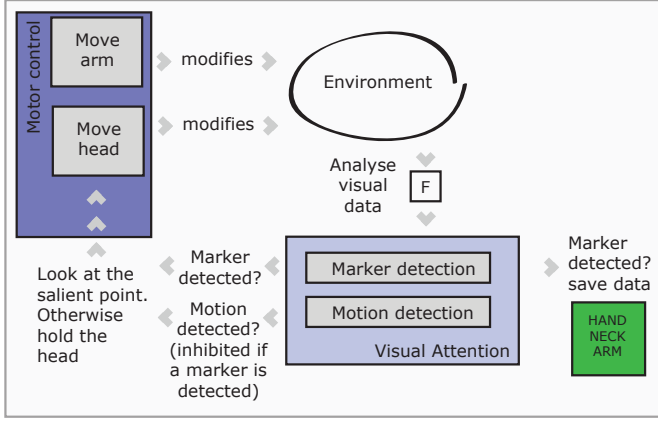


Fig. 2. Learning Algorithm. The marker detection module inhibits the motion detection module, giving a higher saliency to the hand of the robot.

the previous step is added to the current one, simulating the fact that the change of direction is not immediate, as the mass tends to follow the past movement by inertia.

V. MOTOR BABBLING RESULTS

We simulated each strategy for 8 minutes. Figure 3 shows typical trajectories of the arm joints and of the neck joints for each type of babbling. PR generates sparse random commands in the action space; even if it can be thought as a good strategy able to explore uniformly the action space, the long jumps in the arm joints configuration very often increase the probability to lose the sight of the hand. This results in a very time consuming strategy with a low marker detection rate. Table I shows some results for each strategy. Low detecting rates depend on a high probability that movements go outside the field of view of the camera, and on the time needed to find again the arm by moving the head.

Even if IRW is the strategy that better resembles human motion, up to now RW seems to be the best strategy in terms of learning speed. IRW seems to perform worse than RW due to its tendency to follow the motion inertia towards areas wherein the hand is partially occluded by the shoulder of the robot. The last row of Table I represents, for each strategy, the maximum jump in degrees that a random movement can perform³.

We also measured the sum of all the distances (in degrees) covered by each joint for each strategy during a certain amount of time, and compared these values between the three strategies. We used this measurement as an estimate of energy consumption. In simulation, IRW seems to be the cheapest strategy. Consider, for a moment, that the arm is moving toward a given direction. If a new control command is generated toward the opposite direction of the current motion, the simulated inertial strategy will not change instantaneously the direction. Instead, it would lower the speed, first, and then change direction. Going directly on the other direction (as

³The ranges are (in degrees): ShoulderPitch, from -120 to 120; ShoulderRoll, from -95 to 0; ElbowRoll from 0 to 90; ElbowYaw from -120 to 120. In RW and IRW, only a maximum step of 10 degrees is allowed for each joint.

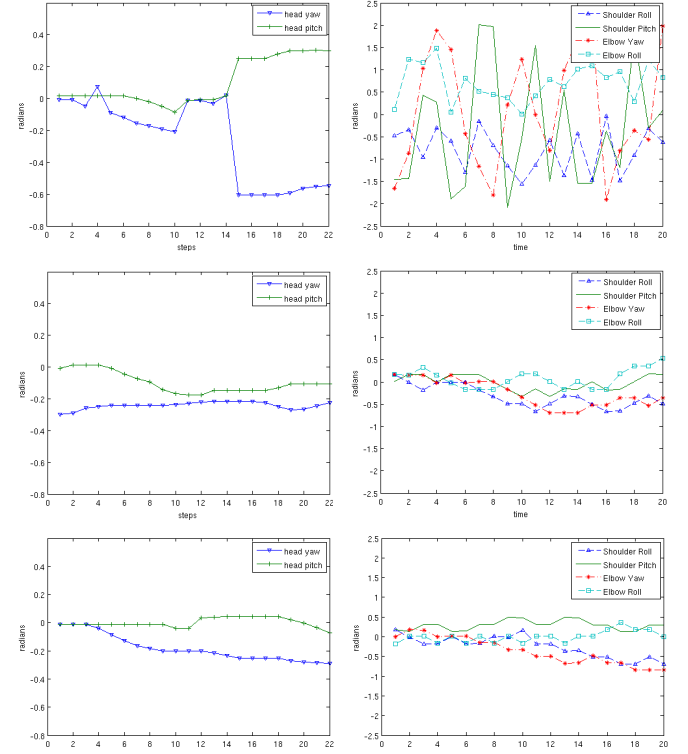


Fig. 3. In the left column of the figure, typical values of the joints angles of the neck for each strategy (PR, RW, IRW) are shown. The right column shows the values of the joint angles of the arm.

RW might do), would consume more energy. Due to its fast changes of direction and movements, PR seems to be the worst strategy, again.

The sum of the distances is an estimate of energy consumption but, on the other hand, will give us the same amount of energy spent for a continues movement from 0 to 40 and a movement going from 0 to 20 and then back to 0, for instance. For that reason, we also measured the electric current applied to each servo and compared the averages of the total current applied to all the motor between the three strategies.

We also considered the two servos of the neck (which move accordingly to the attention system), measuring again the distance (in degrees) covered by all the joints, (inclusive the neck ones) for both energy measurements.

All the results confirm that PR is the worst babbling strategy in learning a mapping between the joints configuration of the neck and that of the arm, because of the low marker detection rate and of the high energy dissipation.

Analysing qualitatively the expectation of a human observer on the sensorimotor coordination skills of the robot, it can be noted that PR has also a significantly low rating. The robot is most of the time babbling and searching for the marker, due to the often long jump between an arm movement and the next one. RW and IRW have a higher rating.

TABLE I
DETECTION RATES FOR THE DIFFERENT STRATEGIES

	PR	RW	IRW
Detections per sec.	1.04	4.63	2.63
Max jump in deg.	665	40	40

TABLE II
ENERGY CONSUMPTION ANALYSIS

		PR	RW	IRW
Simulation	Distance Covered			
	PR	1.000	0.696	0.616
	RW	1.436	1.000	0.885
	IRW	1.622	1.130	1.000
Real Robot	Electric Current			
	PR	1.000	0.752	0.766
	RW	1.330	1.000	1.018
	IRW	1.306	0.982	1.000

VI. LEARNING BODY MAPS THROUGH BODY BABBLING

Learning the mapping between the proprioceptive sensory data and the visual acquired information does not consist only in collecting the data through body babbling. The knowledge base represented by the set of stored vectors $[markerPosition; neckConfiguration; armConfiguration]$ can be used for inferring data given some evidences. For example, given a point in the hand's action space, a learned body map can be used to predict the neck's and arm's configurations which let the visually detected marker (representing the hand) be as close as possible to the desired point.

In this work, a mapping between the proprioceptive data, represented by the 6D vector $[neckConfiguration; armConfiguration]^4$, and the external data, represented by the (x, y) image coordinates of the marker placed on the hand of the robot, has been used to perform a simpler forward prediction: given a configuration of the neck and arm joints, infers where the position of the hand will be (here: the coordinates of the marker, if detected, in the image).

Given a query (neck and arm joints), we used a k -Nearest Neighbours algorithm to find the k closest vectors in the knowledge base (using the OpenCV's FLANN library). For each vector, the elements related to the marker position are extracted. The prediction of the outcome is computed as the mean of these values. A control command is then applied to each joint both of the neck and of the arm, as the mean of the relative elements of the k vectors. This algorithm has been adapted from [11], [12]. For each prediction, the error is measured as the distance between the predicted point in the image and the detected (if any) marker position resulting from the applied control command.

Preliminary results on the prediction performance have been collected from babbling samples using the RW and IRW

random movement strategies. A knowledge base has been created from a session of RW babbling, resulting in 662 samples. Test data were extracted from the babbling with a probability of 0.05 from the knowledge base (resulting in 27 samples). Given a frame of 320×240 pixels, the average distance between the centre of the detected marker and the predicted position of the marker has been measured as 15.29 pixels, using $k = 5$ in the k -NN algorithm.

Contrary to our expectations, RW results in better predictions of the position of the hand than IRW. This might be due to the joint space covered being smaller for IRW.

A learned body map using IRW babbling has also been tested. With 548 samples in the knowledge base and $k = 5$, 25 testing predictions (extracted as before from the collected set) gave an average error of 21.74 pixels.

It has to be mentioned, that during motor babbling the robot attempts to follow the hand with its gaze, trying to maintain the marker close to the centre of the image. This means that the knowledge base is dense around the centre of the image (approximatively an ellipse whose axes are $2/3$ of the image's width and height) and sparse at the edges of the image, resulting in better predictions when the arm and neck query configuration is close to those stored configurations resulting in a marker position near the centre of the image. This leads to a more exact prediction when the marker is in the center of the visual field.

VII. FUTURE WORK ON BODY BABBLING

In this work, we analysed three random movement strategies in self-exploration for a humanoid robot. However, further interesting strategies could be introduced.

Infants, for the essence of play, engage in particular activities for their own sake. This suggests the existence of a kind of intrinsic motivation system [11] which provides internal rewards during these play experiences. In [13], the authors show a curiosity-driven robot which explores its environment in search of new things to learn: the robot gets bored with situations that are already familiar, and also avoids situations which are too difficult.

However, establishing which is the best random movement strategy is not the only aim of our work.

Imitation of hand trajectories of a skilled agent could be done through a mapping of the proprioceptive and external data. Behaviours, or motion trajectories, could be modelled by mapping regions of the action space with the states of a discrete probabilistic model [14], [15].

Learning performance could be improved using a head equipped with a pan-tilt camera mechanism to reproduce both neck movements and saccades. These learned skills are the prerequisites for imitation learning in human-robot interaction.

Moreover, the simple adopted attentive system is the precursor for a more complex system able to detect faces and eye-gaze directions. Studies on the development of cognitive functions in infants (i.e., Baron-Cohen [16]) identify this set of skills as necessary for the acquisition of complex social behaviour, like joint attention. These abilities are fundamental

⁴2 DoF for the neck and 4 DoF for the arm.

in the simulation theory of mind reading and compose part of the so called Theory of Mind, that is that set of skills necessary for understanding behaviours and intentions of others. A very interesting robotic example is the system developed by Scassellati [17] in an embodied theory of mind architecture for a humanoid robot.

VIII. DISCUSSION

We showed and analysed three different random movement strategies for generating control commands for the arm of a humanoid robot and we showed how sensorimotor coordination can be performed using a simple attentive mechanism which drives the robot's head movements to focus its gaze towards the moving hand. We used a simple technique for learning the mapping between different sensory modalities and we equipped the robot with predicting abilities of sensory consequences (the position of a marker placed on the hand of the robot) from control commands applied to its neck and its arm.

Possessing a body map allows the robot to become aware of itself. Self-awareness is a prerequisite for a robot interacting in an intuitive way with a person. We discussed how body maps are important for a robot for having an intuitive human-robot interaction and we demonstrated how body maps can be learnt through body babbling. A robot behaving as self-aware can increase the success in fulfilling the expectations of the interacting partner.

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Exposure to Cinematic Depictions of Robots and Attitudes Towards Them

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ABSTRACT

We present an exploratory study that surveys 287 people from a wide range of ages and cultural backgrounds on both their attitudes towards robots and which of 12 fictional films portraying robots they have seen. Our preliminary findings suggest a relationship between overall movie watching and NARS scores (more robot movies seen correlates with more positive attitudes towards robots), and between certain positive portrayals of robots and NARS scores (*Bicentennial Man*, *Moon*, and *Wall-E* contribute to more positive attitudes).

Categories and Subject Descriptors

K.4.2 [Computer and Society]: Social Issues; I.2.9 [Artificial Intelligence]: Robotics

General Terms

Experimentation

Keywords

robots, human-robot interaction, film, culture

1. INTRODUCTION

Whenever a person encounters a robot for the first time they bring with them a plethora of prior beliefs, attitudes, and expectations. These ideas can come from many places, including cultural beliefs [8, 13], user expectations [14], robot role assumptions [12], and so on. However, perhaps the most oft mentioned “robot topic” we the authors hear about, both in experimental and lay settings, is film. We are asked if we’ve seen *The Terminator*. We are asked if we’ve seen *I, Robot*. Occasionally we are asked if we have seen the latest (real) robots from ATR, CMU, or MIT, but most typically we are asked about fictional robots depicted in film.

It is not surprising that most people’s attitudes about robots come from popular media; in 2009, only 5.6 million domestic service robots and 3.1 million entertainment



Figure 1: A few of the people at the London Secret Cinema exhibition interacting with our face-mimicking robot. *Photo credit: Guerilla Science.*

and leisure robots were purchased globally [4]. These figures indicate that a relatively low percentage of the global population has daily contact with a personal robot. Moreover, the types of personal robots purchased were largely vacuum-cleaning robots, lawn-mowing robots, robotic toys and hobby systems - none of which resemble the advanced, futuristic humanoid robots often portrayed in popular culture.

Thus, it is highly likely that people’s attitudes toward robots are largely shaped by popular culture and media such as films, newspapers and television. Indeed, Ray et al. [7] report that while only half of their participants stated that they had had some previous contact with robots in reality, more than two-thirds had seen robots on TV and 65% had seen robots in movies.

In this work, we wanted to explore how these cinematic portrayals of robots relate to people’s attitudes towards them. Breazeal [3], MacDorman et al. [5], and Bartneck et al. [2] all touch upon the role of cinema in shaping our views towards robots; here we sought to delve a bit deeper.

We present an exploratory study that surveys 287 people from a wide range of ages and cultural backgrounds on their attitudes towards robots (via the NARS measure [6]) and which of 12 films portraying robots (half positive/half negative) they have seen. Our preliminary findings suggest an overall relationship between movie watching and NARS scores (more robot movies seen correlates with more posi-

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tive attitudes towards robots), and between certain positive portrayals of robots and NARS scores (viewing *Bicentennial Man*, *Moon*, or *Wall-E* contributes to more positive attitudes).

2. METHODOLOGY

We conducted two within-subjects studies. The first was conducted in person at the London Secret Cinema during a week in June 2010, and the second was conducted online via Survey Monkey during the months of November and December 2010.

2.1 Measures

We prepared two self-report measures for this study. The first was the Negative Attitudes Toward Robots Scale (NARS) [6]. This is a summed measure that assesses negative attitudes toward robots via a 5-point attitudinal scale. The measure contains three sub-scales: “negative attitudes toward emotions in interaction with robots,” “negative attitudes toward the social influence of robots,” and “negative attitudes toward situations of interaction with robots.” [10]. We used the abbreviated, 11-item version of NARS introduced by Syrdal et al. [11] due to its high validity in predominantly English-speaking/Western populations.

Our second measure was a list of twelve films, and participants indicated which they had seen. Each film on the list involved robots as main characters and the release dates of the films spanned across several decades. Half of the films portrayed their robot protagonists generally in a positive way (*Bicentennial Man*, *Moon*, *Short Circuit*, *Star Wars*, and *Wall-E*) and the other half generally in a negative one (*Artificial Intelligence*, *I, Robot*, *Metropolis*, *Surrogates*, *Terminator*, and *2001: A Space Odyssey*). Further details about each of the films can be found in Fig. 4.

2.2 Data Collection

In June of last year, the first author was invited to bring her real-time mimicking robot [9] to be part of a science exhibition at a London “Secret Cinema” event. (See Fig. 2). Attendees purchase tickets in advance to an unknown film, and are told to dress up in unusual styles of clothing and bring various props (e.g., sunglasses and umbrellas). Also, before the film is screened they explore a large warehouse filled with artists, musicians, and actors, all interacting with sets and scenes from the film.

June’s Secret Cinema film was *Bladerunner*, and the author brought her robot and joined other scientists (zoologists and perceptual scientists) to be part of a “stealthy science” exhibition embedded within a room in the warehouse. Our robot was installed for a week at the warehouse, and attendees were opportunistically asked to complete our survey before entering the room with the robot.

Following the initial data we received from the film exhibition, we wanted to expand our sample of respondents, and therefore also conducted a study on Survey Monkey.

2.3 Participants

In the first study, participants were recruited by an experimenter by word of mouth, asking them if they would be willing to answer a few questions. In the second study, participants were recruited via a University electronic bulletin board, Gumtree, Facebook, and word of mouth. Neither set of participants were compensated, though for the online

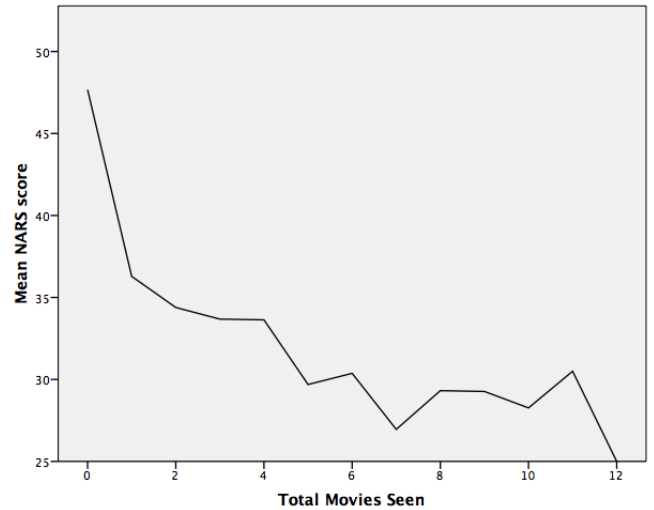


Figure 2: Overall, the more robot films one saw, positive or negative, the more positive their attitudes toward robots.

study participants could enter a raffle for a \$20 gift certificate to Amazon.com.

287 people participated in our two studies, 132 in the in-person study and 155 in the online study. In terms of reported nationality, the largest group was British (39%) followed by American (24%), and the rest came from all over the world, including Bulgaria, China, Brazil, Taiwan, Turkey, Israel, Latvia, Korea, Romania, and many others. Nearly all respondents considered themselves fluent in English (97%). 114 participants were male and 173 female, and their ages ranged from 19-73 (s.d. = 7.65).

3. RESULTS

3.1 Overall movie watching

We first looked to see if overall movie watching was associated with lower NARS scores, and used Pearson’s correlation to compare these normally distributed variables. We found a significant relationship - more movies seen is associated with lower NARS scores (thus, more positive attitudes toward robots), $r = -.281$, $p < .001$.

3.2 How particular films affect NARS scores

To determine how individual films related to negative robot attitudes, we ran a univariate factorial ANOVA with our 12 films as fixed factors, and NARS score as our dependent variable. Because these films only had two levels, watched or didn’t watch, we did not run any planned contrasts or post hoc tests. (Thus, this was effectively a regression).

Three movies that portray robots in a positive light had a significant main effect on NARS Score; seeing them led to lower score (i.e., more positive attitudes). These films include: *Bicentennial Man*, $F(1, 274) = 4.97$, $p < .05$, $r = .13$, *Moon*, $F(1, 274) = 4.19$, $p < .05$, $r = .12$, and *Wall-E*, $F(1, 274) = 3.87$, $p = .05$, $r = .12$. All reported tests are Bonferroni corrected.

No other films, with positive or negative robot portrayal, had a significant impact on NARS score.

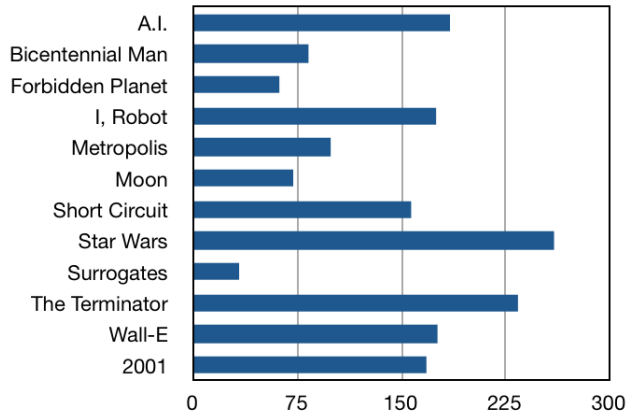


Figure 3: Frequency of films seen across all participants.

4. DISCUSSION

We presented an exploratory study with 287 participants that examined how seeing particular films might influence attitudes toward robots. Our findings suggest that seeing more films portraying robots (whether positive or negative) is negatively correlated with NARS scores. Thus, seeing more of these films tends to be associated with more positive attitudes towards robots. We also found significant relationships between three films in particular that are significantly inversely proportional to NARS scores: *Bicentennial Man*, *Moon*, and *Wall-E*, though with small effect sizes.

In this work we did not control for how recently someone saw a particular film, how many times they saw it, if they watched it in its entirety, and so on. Also, it is likely that people who enjoy watching science fiction films are more able to envision a future with robots among us, due to being interested in technology in the first place.

Despite these limitations, we believe these results are of interest, in that they offer some support for Allport's Contact Theory - the more exposure people have to "out-group" members (i.e., robots), the more positive their attitudes toward them [1]. It also lends support to Bartneck et al. [2] who found that previous exposure to robots has a positive effect on a person's attitude toward robots. This suggests further work is warranted in exploring how exposure to fictional robots may influence interaction.

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Title	Year	Plot Description	Role of Robots
2001: A Space Odyssey	1968	When the computer running the spaceship malfunctions, the two astronauts onboard become its targets as it tries to cover its mistake.	The spaceship's computer tries to kill its passengers.
AI: Artificial Intelligence	2001	A grieving couple adopt and then subsequently abandon a sentient robot boy that has been programmed to love its "mother" unconditionally.	Generally robots are depicted in a dystopian way.
Bicentennial Man	1999	A family buys a domestic android butler who slowly learns how to feel emotions and think creative thoughts.	The robot becomes even more human-like with the help of a scientist. The viewer is made to empathize with the robot protagonist.
Forbidden Planet	1956	When his spaceship disappears on an exploratory mission, a philologist is the only survivor and creates his own Eden-like world that is protected by his robot.	Robby the robot is the unwaveringly obedient protector of the philologist.
I, Robot	2004	A robot-hating homicide detective investigates a case where the prime suspect of the murder is a robot.	Robots perform menial tasks and are programmed to be unable to harm humans, yet they are often feared and hated by humans.
Metropolis	1927	A city where a large population of working class people support the luxurious lives of the city's elite is thrown into chaos when the master of the city replaces an influential working class leader with a duplicate robot to incite the workers to violence.	The evil robot twin of the working class leader is indistinguishable from the real leader and is used to deceive the workers.
Moon	2008	A human is alone on a lunar station, and his only companion is GERTY, a robot.	GERTY is programmed to look out for the human's well-being, and generally serves as a companion to the human.
Short Circuit	1986	A robot escapes from an military experimental firm and finds safety with a human who teaches the robot about pop culture.	Advanced mechanical-looking robots built as soldiers are able to update their own electronics to experience "emotions".
Star Wars	1977	A farm boy sets out on a quest to rescue a princess from the ruling Empire and Darth Vader.	While the film has some "evil robots", in general R2D2 and C3PO are beloved robot protagonists in the film.
Surrogates	2009	Humans wire themselves up and live, work and play through android robotic surrogates.	Ultimately robots surrogates are viewed unfavorably, and portrayed in a very dystopian way.
The Terminator	1984	Humans are under the rule of machines. One human and one machine are sent back in time with opposite goals: the human must save a woman from assassination and the machine must ensure that she is killed.	Robots are destructive machines bent on ruling over humans and will kill anyone that gets in their way.
Wall-E	2008	When humans have disappeared from the Earth, one robot remains to clean up the mess - and falls in love with a new generation robot in the process.	Robots are depicted as overwhelmingly friendly and helpful to humans.

Figure 4: A list of the films used in the study. Six films portrayed their robot protagonists generally in a positive way (*Bicentennial Man*, *Moon*, *Short Circuit*, *Star Wars*, and *Wall-E*); and six generally in a negative way (*Artificial Intelligence*, *I, Robot*, *Metropolis*, *Surrogates*, *Terminator*, and *2001: A Space Odyssey*).

How does Difference between Users' Expectations and Perceptions about a Robotic Agent (Adaptation Gap) Affect Their Behaviors?

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ABSTRACT

We describe how the notion of “adaptation gap” can be used to describe the differences between the functions of a robotic agent that the users are expecting from it before starting their interactions and the functions they perceive after their interactions in this paper. We investigated the effect of this adaptation gap on the users’ behaviors toward a robotic agent. The results show that the positive or negative signs of this adaptation gap significantly affect the users’ behaviors towards the agents.

Categories and Subject Descriptors

H5.2 User Interfaces: Evaluation/methodology; J.4 Social and behavioral sciences: Psychology.

General Terms

Experimentation, Human Factors.

Keywords

Adaptation gap, users’ expectations and perceptions, users’ behaviors toward agents.

1. INTRODUCTION

Various interactive agents such as robotic agents [1] and embedded conversational agents (ECA) [2,3] have been developed to assist us with our daily tasks. In particular, researchers in the human-computer interaction and human-robot interaction communities are working hard to create such interactive agents. In these fields, the issue “how the users’ mental models of an agent formed before the interactions affect their interaction with it” is keenly focused on. Since users supposedly base their mental models about an agent on its appearance, its behaviors, and their preferences for the agent, the

users’ mental model significantly affects their interaction [4]. For example, when a user encounters a dog-like robot, s/he expects a dog-like behavior from it, and s/he naturally speaks to it using commands and other utterances intended for a real dog, such as “sit,” “lie down,” and “fetch.” However, s/he does not act this way toward a cat-like robot.

Several studies have focused on the effects of the users’ mental models about an agent on their interactions. Matsumoto et al. [5] proposed a “Minimal Design Policy” for designing interactive agents and concluded that the agent’s appearance should be minimized in its use of anthropomorphic features so that the users do not overestimate or underestimate the agents’ competences. In fact, they applied this minimal design policy to developing Muu, their interactive robot [6] and Talking Eye, a life-like agent [7]. Kiesler [8] argued that the design of an agent should include a process that anticipates a user’s mental model about the agent on the basis of the theory of common ground [9]; that is, individuals engaged in conversation must share knowledge (so-called, common ground) in order to be understood and have a meaningful conversation. In particular, she stated that the agents should be designed in such a way that a user could easily estimate her/his common ground (shared knowledge) with them. We believe that this design approach would be quite effective for users, especially at the beginning of an interaction, because it may determine whether or not the user would actually start interaction with a given agent.

2. ADAPTATION GAP BETWEEN A HUMAN AND AN AGENT

However, approaches like Matsumoto et al.’s [5] or Kiesler’s [8] have a serious problem when the agent expresses behaviors that completely deviate from the users’ mental model. Imagine that a user meets a human-like robot that looks very much like a real human being. This user would intuitively form a mental model of the robot, expecting fluent human-like speech, dialogue, and dexterous limb motions. However, if this particular robot could only express machine-like speech and halting limb motions that completely deviate from her/his mental model, s/he would be immediately disappointed with this robot because of its unexpected behaviors. The user would then stop interacting with it. To solve this problem, we need to carefully design the users’ expectations and perceptions of the agents during their

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interactions, because such expectations and perceptions would assist users in determining whether this agent is worth interacting with or not.

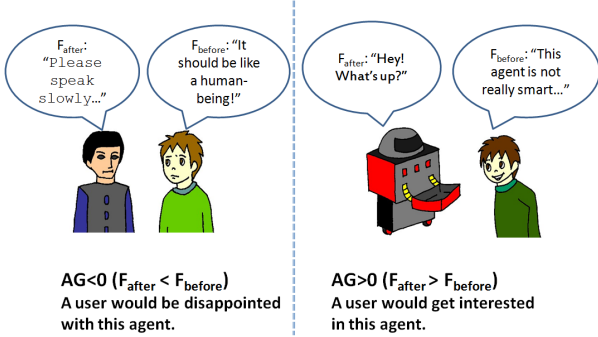


Figure 1. Intuitive Concept of Adaptation Gap

In this study, we focus on the difference between the users' expectations regarding the function of the agent and the users' actual perceived function, which is one of the factors that affects the users' impressions. We called this difference the *adaptation gap* (AG). In particular, AG can be defined as $AG = F_{after} - F_{before}$. Here, F_{after} is the function that a user actually perceives of the agent, and F_{before} is the users' expected function of the agent. We assume that this AG would have the following three properties [10,11].

- $AG < 0$ ($F_{after} < F_{before}$): When the users' expected function exceeds their perceived function, there is a negative adaptation gap. In this case, most people would be disappointed by the agent, would not believe the robot's outputs, and stop interacting with it.
- $AG > 0$ ($F_{after} > F_{before}$): When the users' perceived function exceeds their expected function, there is a positive adaptation gap. In this case, most people would not be disappointed by the agent, would believe the robot's outputs, and continue interacting with it.
- $AG = 0$ ($F_{after} = F_{before}$): When the perceived function equals the expected function, there is no adaptation gap. In this case, the agent would be regarded as just an instrument for users.

For example, when F_{before} is larger than F_{after} (say, when a user meets the human-like robot on the left in Figure 1), AG would have a negative value ($AG < 0$), and the user would most likely be disappointed. However, when F_{after} is larger than F_{before} (say, when a user meets the machine-like robot on the right in Figure 1), AG would have a positive value ($AG > 0$), and the user would be interested in interacting with this agent.

In particular, we assume that the sign of AG value strongly affects the user's behaviors toward the agents. Therefore, we investigated the relationship between the signs of AG and the user's actual behavior toward the agents, e.g., whether the users accept the agents' suggestions or not, in this study. Therefore, the independent variable in this study is the sign of AG while the dependent variable is the users' behaviors. We assumed that this investigation would lead to verification of the above three properties concerning AG . Namely, if the users' behaviors are

significantly influenced by AG ($=F_{after} - F_{before}$), we can conclude that the properties of AG are verified.

3. EXPERIMENT

3.1 Overview

We conducted an experiment to investigate how the positive or negative signs of AG affected the users' behaviors towards an agent. This experiment consisted of two phases. The first phase was to measure the sign of the AG as an independent variable (exploration phase), while the second phase was to measure the users' behaviors as a dependent variable (exploitation phase).

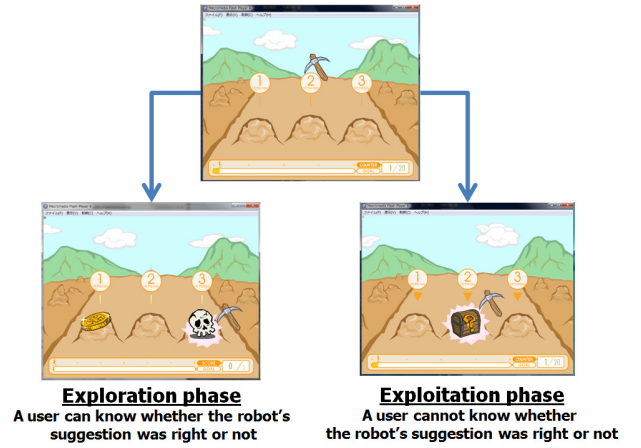


Figure 2. Treasure Hunting Video Game

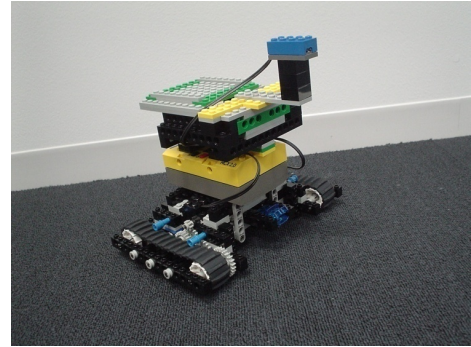


Figure 3. MindStroms Robotic Agent

We chose a "treasure hunting" video game (Figure 2) as the experimental environment for observing the interaction between a user and an agent in both phases. In this game, a character on a computer monitor operated by a user walks on a straight road, with three tiny hills appearing along the way. A gold coin is inside one of the three hills, while the other two hills have nothing. In the exploration phase, the game ends after the character meets 40 sets of hills and the approximate duration of the game is about 3 minutes, while in the exploitation phase, the game ends after 20 sets of hills. The goal of this game is to get as many gold coins as possible. A robotic agent (MS; MindStroms, LEGO Corporation, Figure 3), which was placed next to the user, told the participant where it expected the coin would be each time. MS told the user

the expected position by beeping the number, e.g., one beep meant the first hill, two beeps meant the second hill (middle), and three beeps meant the third hill. The participant could freely accept or reject the agents' suggestions. The participants were allowed to know whether the robot's suggestion was right or not in each trial in the exploration phase, while they were not allowed to know whether the given suggestion was right or not in the exploitation phase (actually, the selected hill just showed a question mark and a closed treasure box, see Figure 2). Note that this experimental setting was introduced because we needed the participant to estimate the robotic agent's function and the sign of AG was determined only in an exploration phase, not in an exploitation phase.

The participants were informed that 1 point was equivalent to 10 Japanese yen (about 10 US cents) and that, after the experiment, they could purchase some stationery (e.g., file holders or USB flash memories) of equivalent value with their points. The position of the coin in the three hills was randomly assigned.

3.2 Participants

Thirty Japanese university students (22 men and 8 women; 19 - 25 years old) participated. These participants were randomly divided into the following two groups in terms of their expectations of the robot's ability before the experiment.

- Lower Expectation Group (15 participants): Before the exploration phase, an experimenter gave the following instructions to these participants, "The rate at which this robot succeeded in detecting the position of a coin was 10%." Therefore, their expectations (F_{before}) were forced set at 10%.
- Higher Expectation Group (15 participants): Before the exploration phase, the experimenter gave these instructions to them, "The rate at which this robot succeeded in detecting the position of a coin was 90%." Therefore, their expectations (F_{before}) were forced set at 90%.

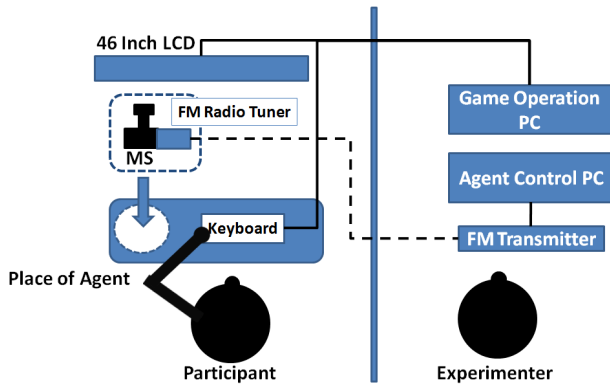


Figure 4. Experimental Setting.

We conducted a manipulation check in both groups just before the experiment to ask them, "What rate will this robot succeed in detecting the position of a coin?" However, no participants were eliminated because no one answered the totally deviated rates (e.g., "100%" in Lower Expectation Group). Actually, the rate at which the robotic agent succeeded in detecting the position of the

coin in the exploration phase was set at 33%. This 33% should have become F_{after} for all the participants in both groups, so the values (and sign) of AG would be automatically determined; that is, the ideal values of AG in the Lower Expectation Group should be around +23 (i.e., $F_{after} - F_{before} = 33\% - 10\%$), and the ideal AG in the Higher Expectation Group should be around -67 ($F_{after} - F_{before} = 33\% - 90\%$).

The speech sounds of the robotic agent were remotely operated by an experimenter in the next room performing in the Wizard of Oz (WOZ) manner via an FM transmitter and radio tuner loaded on the MS. The treasure hunting video game was projected on a 46-inch LCD screen in front of the participants (Figure 4). The order of the beeping sounds from the robotic agent was counterbalanced across the participants.

3.3 Analysis

We investigated the effect of the signs of AG on the users' behaviors towards the robotic agents. Therefore, the independent variable was the sign of AG and the dependent variable was the participants' behaviors. The sign of AG would be automatically determined in the exploration phase; that is, the participants in the Lower Expectation Group would show the positive sign of AG while the ones in the Higher Expectation Group gave the negative sign of AG. Also, in order to acquire the users' behaviors as dependent variables, we then calculated the acceptance rate, indicating how many of the agent's suggestions the participants accepted in the exploitation phase; because the 20 sets of hills appear in the exploitation phase, the maximum acceptance rate was 20.

The purpose of this experiment was to compare the participants' acceptance rates among the two experimental groups. If we could observe the phenomenon in which the participants in the Lower Expectation Group showed higher acceptance rates than the ones in the Higher Expectation Group, we would have concluded that the signs of AG significantly affected the users' behaviors towards the agents in the way we expected. Moreover, we could argue that the properties of AG were verified.

3.4 Results

At first we checked whether the acquired independent variables (e.g., signs of AG) were appropriately set in the exploration phase; specifically, whether the participants in the Lower Expectation Group showed the positive signs of AG and also the ones in the Higher Expectation Group gave the negative sign of AG. For the 15 participants in the Lower Expectation Group, the average value of AG was +6.0 (SD=8.79), and for the 15 participants in the Higher Expectation Group, the average values of AG was -43.9 (SD=25.2). Although these values were not really similar to our ideal AG values (i.e., +23 in Lower Expectation Group and -67 in Higher Expectation Group), there was a significant difference between the two values ($F(1,28)=49.12, p<.01 (**)$). Therefore, we confirmed that the independent variables were appropriately set.

We then calculated the acceptance rate as a dependent variable. For the 15 participants in the Lower Expectation Group, the average acceptance rate of the robot's 20 suggestions was 9.40 (SD=4.33), and for the 15 participants in the Higher Expectation Group, the average rate was 5.13 (SD=4.47, see Figure 5). The acceptance rates for both experimental groups were then analyzed

using a one-way analysis of variance (ANOVA) (between-subject design; independent variables: signs of AG, positive or negative, dependent variable: acceptance rates). The result of the ANOVA showed a significant difference between the two experimental groups ($F(1,28)=6.58, p<.05 (*)$); that is, the participants in the Lower Expectation Group showed a significantly higher acceptance rate compared to the ones in the Higher Expectation Group. Therefore, we could conclude that the signs of AG significantly affected the participants' behaviors towards the agent, and moreover, we also confirmed that the properties of AG was clearly verified; *when the users' expected the function to exceed their perceived function, most of the people would be disappointed with the agent and would stop interacting with it, while when the users' perceived function exceeded their expected function, most people would not be disappointed with the agent and would continue interacting with it.*

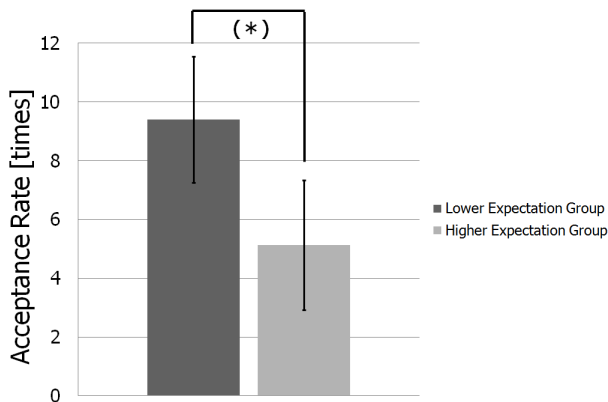


Figure 5. Acceptance Rate in Two Groups.

4. DISCUSSION AND CONCLUSIONS

From the results of our experiment, we observed that the participants with a positive sign of AG showed a higher acceptance rate compared to the ones who showed a negative sign of AG. Therefore, we confirmed that the signs of AG significantly affected the users' behaviors towards the robotic agents. These results clearly supported the properties of AG mentioned in the Section 2, so they will contribute in proposing a novel interaction design strategy, e.g., "the agents that evoke higher expectations compared to the actual functions should not be used for the interaction task with users."

At a glance, these results seem to recommend that a specific design strategy like " F_{before} should be set as low as possible to make the signs of AG positive." However, such a lower F_{before} would have some possibilities to make users deeply disappointed with the agent before the interaction, and eventually they would not start the interaction. Therefore, clarifying the appropriate range of F_{before} would be a significant issue for utilizing this AG for actual interaction design strategy.

In this study, we did not focus the values of AG, but on the signs of AG, since it was quite difficult to precisely comprehend or measure the users' digitized, expected, and perceived functions of the agents. Moreover, it is assumed that such digitized values for the agents' functions would be affected by various aspects, e.g., gender, educational level, religious belief, or preferences. We are

now planning to tackle the issue of "how to handle the values of AG" in collaboration with product designers and social psychologists. We believe such collaborations would control the values of AG in a more elegant manner and would lead to contributing to a much more sophisticated concept of AG.

5. ACKNOWLEDGMENT

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What Users Expect of a Proactive Navigation Robot

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ABSTRACT

This paper presents two user studies conducted in the framework of the FP7 EU Project IURO, Interactive Urban Robot. Within these user studies we wanted to explore which expectations users could have towards the robot during itinerary requests in terms of (1) appearance and (2) communication style respectively. The results of these two studies indicate that people expect the robot to look anthropomorphic, but not completely humanoid and to communicate in accordance to social norms, with a special focus on turn taking and feedback provision.

Categories and Subject Descriptors

H.5.2 [Information Interface and Presentation]: User Interfaces—*Evaluation/methodology*; I.2.9 [Artificial Intelligence]: Robotics—*miscellaneous*

General Terms

Theory, Verification

Keywords

Navigation Robot, User Expectations, Appearance, Communication Style

1. INTRODUCTION

In general, interactive service robots provide people with information they need or want to have, like mobile museum guides. People address the robot and know what to obtain from it. However, what would happen if the perspective is inverted and the robot arbitrarily addresses passers-by in public (urban) areas in order to obtain 'vital' information from them: In which direction is square X? Where can I find shop Y? What would pedestrians expect from a robot behaving like this? That is one of our main research interests in the IURO project - Interactive Urban Robot. In the first year of this three-year project we wanted to analyze the interaction context public space and the user requirements for the IURO robot.

In this position paper, we are going to present and discuss two user studies, conducted within this project. Both studies were based on a scenario, in which the IURO robot is sent to a pharmacy to buy medicine and deliver it to a patient. It is assumed that the IURO robot was instructed to buy the medicine at the "Alte Hofapotheke" which is located at "Alter Markt No. 6", in the old town of Salzburg, Austria. Figure 5 shows a similar interaction scenario with the ACE robot (Autonomous City Explorer) which was the national pilot project for the international IURO project [1].

The main idea was to challenge the pre-assumption that an anthropomorphic design and a human-oriented communication style are suited best for the IURO robot. Thus, we wanted to explore the expectations of inexperienced users towards an autonomous navigation robot to incorporate them into the overall system design.



Figure 1: ACE Robot Asking for the Way in the City Center of Munich

The goal of these studies was to identify expectations towards the (1) appearance and (2) the communication style of the IURO robot. The first study was a focus group in which we wanted to explore if people actually expect IURO to have a humanoid shape. In the second study, we wanted to find out how people imagine an itinerary request dialogue, in order to achieve a successful route description, by means of a Wizard-of-Oz experiment. The paper closes with a discussion about the meaning of the expectations of inexperienced users towards the IURO robot. Moreover, we discuss general implications for future work in the research field of expectations in HRI, which are in our opinion relevant to explore.

2. MOTIVATION AND RELATED WORK

Several studies in the research fields of Human-Computer Interaction (HCI) and Human-Robot Interaction (HRI) indicate that people tend to respond differently towards autonomous interactive systems than they do towards “normal computing systems” [2]. The Media Equation Theory in the 1990ies already revealed that people treat media and computing systems in a more social manner, like real people and places [14]. However, not only the responses differ, the expectations also vary and tend into a more social direction, the more anthropomorphized the system design is [10].

As previous studies could show, inexperienced users tend to set up a mental model about the robot’s tasks and functionalities even before the actual interaction starts [13, 5, 10, 9]. For instance, when an inexperienced user has to interact with a robot for the first time, the first impression of the robot is paramount to successfully initiate and maintain the interaction. Thus, it is important that the robot’s appearance matches with its task to increase its believability. Exploratory studies in the research field of HRI indicate that people have very clear assumptions that anthropomorphic robots should be able to perform social tasks and follow social norms and conventions.

It is assumed that a humanoid form will ease the interaction with sociable robots, because the rules for human social interaction will be invoked and thus a humanoid robot will provide a more intuitive interface [19]. In 1970 Masahiro Mori, proposed the well known hypothetical graph of the uncanny valley, which predicted that the more human a robot looks, the more familiar it is, until a point is reached at which subtle imperfections make the robot seem eerie [20].

However, anthropomorphic design carries a lot of baggage with it, in terms of specific expectations, such as intelligence, adaptation towards user behavior, and following social norms and human-oriented perception cues [3]. Thus, we are interested in exploring the necessity of anthropomorphic design and natural language for successful navigation of the IURO robot.

Regarding the investigation of design spaces, focus groups are considered to be a good tool to explore and collect participants’ ideas, perceptions, attitudes and expectations. Similarly, the method has been applied in the research field of HRI to generate data on user experience and design issues, for instance in the design process of a growing robot [6]. The focus group performed by Green et al. [17] was used to inform the design and functionality for an assistive robot. Weiss et al. [18] used a focus group to investigate differences in perception of an autonomous and a tele-operated robot, putting special emphasis on user experience and social acceptance.

Regarding the the investigation of the communication style we assumed in a pre-study of human dialogues for direction retrievals [11] that the factor “politeness” would have a major influence on the successfulness of the dialog, as politeness is also mentioned as important influence factor in several human-computer communication studies [14]. However, the pre-study did not support this assumption, but resulted in the factor “feedback” being the most powerful influ-

encing factor regarding the successfulness in human-human dialogues. Moreover, feedback is known to be an important factor in usability engineering [12], in human-robot communication [7], and in natural language [15, 16].

3. THE USER STUDIES

In the phase of requirement analysis for the IURO robot, we conducted two user studies to identify the expectations towards the robot in terms of (1) appearance and (2) communication style respectively.

3.1 User Study on Appearance

The first study was a focus group, in which we discussed how the robot should look like [4] with our participants. At the beginning of the focus group, the participants were introduced to the interaction scenario of the IURO robot, each participant had to describe and/or draw his/her imaginations and present it to the others. Subsequently, the group was asked to create a common design solution. Therefore, we provided them our so-called “robot-building-set” [18] containing the most important parts of a robot (feet, arms, head, torso) in three different variations (functional, human-like and animal-like, see figure 2) to investigate the preferred robotic embodiment. All parts were presented to the participants completely mixed with the request to create their notion of an interactive urban robot.

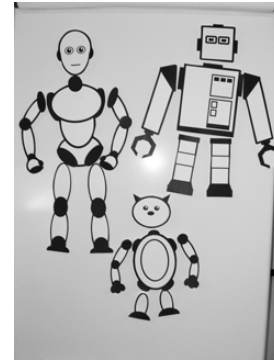


Figure 2: The Robot Building Set

In a next step, the participants were shown 18 pictures of existing robots, categorized in accordance to [8] into anthropomorphic, zoomorphic and functional design, randomly put together figure 3 shows some examples of these categorized robots. The aim of these primes was to ground their design solution on state of the art in robotic design and thus minimize the ideas based on robots displayed in science fiction. Subsequently, the participants were asked to re-discuss their solution. In a last step, the participants discussed potential interaction modalities.

3.2 User Study on Communication

The second study was a laboratory-based, controlled experiment with a NAO robot, in which we investigated the influence of the factor feedback on the participants’ perception of the communication. The study was set up as between subjects design with a total of 40 participants. Condition 1 = “feedback”, Condition 2 = “no feedback”. The robot was wizarded in a way that made the participants thought that the robot is acting autonomously.



Figure 3: Robot Primes

The robot acted according to the findings of previous studies on natural language interaction in four steps: introduction, giving/receiving directions, confirmation, and conclusion [1], whereby the step “confirmation” differed between the conditions “feedback” and “no feedback”. In accordance to our findings from the pre-analysis of the human-human dialogues on itinerary requests we decided to include four types of feedback:

1. affirmative verbal feedback: the robot says “Ok”
2. verbal fact feedback: the robot repeats direction information
3. affirmative non verbal feedback: the robot nods its head after it processed an information
4. non verbal fact feedback: the robot points into the direction

To test if the existence of feedback improves the successfulness and/or the efficiency of short term interaction in the context of asking for directions, the robot interacted as follows (20 times with a male voice, 20 times with a female voice):

1. The robot approached the participant, greeted him/her and asked for the way to the “Alte Hofapotheke”. [Robot: “Excuse me, could you please tell me how to get to the Alte Hofapotheke?”]
2. The participants were then advised to explain the directions as naturally as possible to the robot (free choice of words).

3. The wizard thanked the participant, if he understood the route description, otherwise he asked for an alternative.

- Condition 1: During the explanations of the participant, the robot uttered an affirmative ok and nodded its head to indicate that it is receiving and processing the information. After the participant provided the information, the robot repeated the most important facts verbally (e.g. “Ok, first I go straight, then right, and then there it is”) and by pointing towards the indicated direction, and then it waited for the participant to confirm. After the confirmation the robot thanked the participant for the help and moved towards the “Alte Hofapotheke”. [Robot: “Thank you for your help. Good bye!”]
- Condition 2: During the explanations of the participant, the robot stood completely still and uttered not a single sound. After approximately three seconds the robot thanked the participant for the help and moved towards the “Alte Hofapotheke”. [Robot: “Thank you for your help. Good bye!”]

The scenery for the itinerary request was rebuilt as a model town (a reconstruction of the real scenario of the preceding study) in order to achieve comparable results to the human dialogue study. By means of projecting photographs of the real location on the wall of the laboratory and playing city sounds in the background, an additional city atmosphere was created. Successfulness was defined as the fact, if a participant was able to explain the destination to the robot without help from the researcher and without walking around the model town.

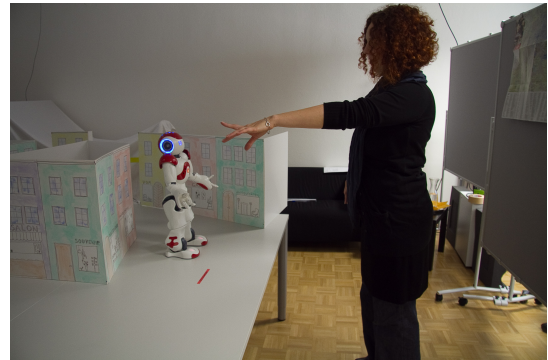


Figure 4: Study Setting of the Second User Study

3.3 Expectations in Terms of Appearance

Most of the participants associated the terms of accuracy and rationality with robots, for two persons robots are further associated with perfection. The design issues brought up within the workshop could be divided into functional (weather-proof, robust, stable) and non-functional requirements (height, cute, non-threatening, friendly appearance, cordial materials) and general ideas. Most surprising was that in the first discussions only one participant imagined a IURO robot of a humanoid shape. His design idea was

strongly inspired by humanoid robots known from the movies. Two participants stressed that it is most important for the robot to have a friendly appearance, neither being a machine nor human-like, and one participant asked for a “human within the machine”: human-like components to be added to the robot as a machine. When consolidating their ideas into one common design, the participants’ solution was a robot that was neither anthropomorphic nor merely functional (see figure 5).

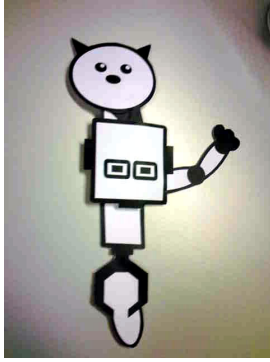


Figure 5: The participants’ design of an interactive urban robot

3.4 Expectations in Terms of Communication

By means of a requirements study on human-human communication during itinerary requests, the most important influencing factor liable for the success or failure of a dialogue regarding direction-retrieval in public space could be detected: “Adequately timed feedback” [11]. Adequately timed feedback ensures that the conversation runs smoothly and the interaction partners are able to track if the communication partner can follow the conversation and the provided directions. It is important that the feedback is given in time, as too late or missing feedback causes confusion.

The second study with the NAO robot approved this assumption. Our main assumption of feedback being a crucial influencing factor for the successfulness of information retrieval in the context of asking for directions in public space could be proved on both, an objective (1) and a subjective level (2):

1. A highly significant difference could be made out between the two feedback conditions regarding the fact if the participants said “You are welcome” to the robot after it had thanked them for providing the desired information. Participants in the condition “feedback” more actively engaged in the interaction and were more likely to see the robot as an equal interaction partner in applying human interaction patterns (a polite phrase like “you are welcome”) to this human-robot interaction scenario. A trend could be shown for the questions if the participants had to concentrate to interact with the NAO robot and if it is on the whole easy to interact with the NAO robot. For both questions those participants in the feedback condition gave a better rating (“I have to concentrate less” and “The interaction with NAO is on the whole easier.”).

2. Participants with condition “feedback” mentioned more positive and less negative aspects after the interaction with NAO as participants in the condition “no feedback”. Repeating the retrieved information at the end of the conversation and inquiring in case the robot does not understand the directions, was considered the most important actively perceived feedback modalities. Almost all participants thought that the provision/withholding of feedback influences the course of an interaction. Participants in the condition “feedback” were influenced positively, participants in the condition “no feedback” said that they missed to receive feedback from their robotic interaction partner. In total 13 participants in the condition “no feedback” stated that they would want to receive feedback from the robot. Five participants in the condition “feedback” wanted the robot to display facial expression and 4 participants from both conditions wanted to improve the robot’s reaction time. Finally, nine participants of both conditions mentioned that the robot was in their opinion very polite, which is again a form of feedback.

4. DISCUSSION

Overall, our two user studies haven shown how deeply the expectations of inexperienced users towards robotic systems are embedded and entangled within our social world and that the development of technologies cannot be analyzed separated from society. Even though research can never be free of methodological biases, an obvious weakness of our studies are the pre-assumptions about anthropomorphic shape and natural dialogue, which we however tried to challenge.

Regarding interpersonal communication, it seems that the IURO robot is first of all expected to conform to social norms. However, we have to keep in mind the potential bias in the results do to the Wizard-of-Oz set-up: did we measure the user’s perception of the robot or of the human wizard, who stands behind the scenes? In this context it is relevant to mention that our wizard was sitting in a different room in a different part of the building and that in the debriefing of the experiment all our participants mentioned that they did not expect that the robot was remote controlled.

To avoid wrong expectations which may occur due to the limited conversational skills of the IURO robot, it is as well important that the robot’s utterances and actions are coherent. Regarding input, the robot must be able to process the following information that is possibly provided by the pedestrians: verbal directions potentially completed with gestures, reference points (e.g. sights, restaurants, etc.), context information (e.g. color of a building, old or new building, etc.), and explicit (100 meters) as well as implicit distances (for a short way).

In the IURO project a statistical semantic interpretation model is currently developed by the project partners. This model will include methods for fusing speech input with gesture input, as well as assigning confidence scores to semantic interpretations. Additionally a dialogue manager will be developed which decides the system’s actions, whether it should try to elicit more information, switch to more direct questions or end the dialogue and ask another human.

Regarding appearance it seems that the IURO robot should be a combination of human-oriented perception cues with an anthropomorphic, but not 100% humanoid appearance. Therefore we aim in the project to combine a zoomorphic robot head [21] with a functional designed body. As the robot will not be able to grasp anything, we decided to use a pointer, mounted on the head of the robot, for showing directions, instead of an arm, to avoid wrong expectations.

But, what about the temporal aspect of expectations? Expectations change, as they change with the degree of establishment of a technology. Regarding expectations towards robotic systems, we assume a complex interrelationship between the materiality (e.g. the embodiment of robots and mass media), the degree of involvement in the development process, and previous interaction experiences with the robot. Thus, longitudinal analysis in the field of HRI will be relevant in future, to observe how expectations change. Furthermore, in future, expectations will play a major role in the establishment process of robots. Thus, we have to be aware that our research also fosters the creation of certain expectations in order to achieve successful interaction scenarios and in order to reinforce technologies in our society.

5. ACKNOWLEDGMENTS

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Expectations regarding the interaction with a learning robotic system

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ABSTRACT

Providing robotic systems with the ability to learn from past interactions with the user generates a host of new challenges for the design of the human-robot interaction. One of the major issues that need to be considered is user expectations regarding such a learning, adaptive robotic system. This paper briefly outlines several aspects of user expectations regarding robotic systems with learning capabilities which impact the interaction with the system and interface design.

1. INTRODUCTION

Today's robots perform relatively poorly in unknown, unpredictable, and dynamic situations [4], so humans are usually needed to control the robot [2; 7]. One of the major challenges in current robot research is to give the robots the ability to adjust to a changing environment and to become increasingly autonomous.

To allow these dynamic changes, robots should have some adaptive or online learning capabilities. Much research deals with learning mechanisms for robots [3]. However, in addition to the technical and computational challenges of implementing learning capabilities, these new abilities also change the users' interaction with the system. A learning robotic system becomes less predictable, and the interface and the controls will need to be adjusted to these new properties of the system.

One issue that will strongly affect the acceptance of robotic systems and the efficiency of the use of such systems is their correspondence with user expectations. Expectations are beliefs about the most likely course of events. As such, they are a critical factor for control. Users will try to perform actions according to their expectations about the system capabilities, they will make control actions they expect to lead to desired results, and they will evaluate system behavior, relative to their expectations. Consequently, systems that behave according to user expectations will probably be more efficiently used, system control will be easier to learn and less error prone, and users will evaluate the systems more positively. Thus one should strive to develop a robot system that corresponds closely to the users' expectations.

2. FACTORS INFLUENCING USER EXPECTATIONS ABOUT A ROBOTIC SYSTEM

User expectations regarding a robotic system result from a number of factors. These include prior knowledge and beliefs regarding the human-robot system before the beginning of the interaction, experience gained by the user while using the system and information provided by the user interface during the use of the system.

2.1 Initial user expectations of the human-robot system

Before beginning to interact with the robotic system, the user already has some expectations about the system. These expectations derive from a number of factors:

1. *Previous user experience with a similar system.* If the user has already interacted with a similar system, he or she is likely to expect the new system to react similarly. This can pose a problem, if the behavior of the new system differs from the one the user previously encountered. For instance, users will be more likely to crash a mobile robot if they have previously used a similar mobile robot with automatic obstacle avoidance. Hence one should ensure that users are aware of the capabilities of the system before they start using it. However, explaining all functions of a robotic system in detail can be fastidious and against the goal of intuitiveness. Thus the interaction should avoid violating common heuristics or habits if this is possible. This recommendation is similar to the informal "principle of least astonishment" [1] in human-computer interaction.
2. *Prior user beliefs about robotics.* The beliefs people have about robotics influence their expectations about robotic systems. For users who are not familiar with robots, these beliefs come mostly from their cultural background and hence from the image of the robots in the media, on TV, in books or in movies. Thus users may have high expectations about the degree of interactivity and the intelligence of a robotic system, especially if they are told that the system has learning capabilities. Furthermore, as these beliefs are linked to

culture, they can differ greatly between users and especially between users from different countries [6].

3. *Interface appearance.* The appearance of the interface will influence the initial user expectations [5]. Interfaces can show visual cues and explicitly depict the predicted result of an action. For instance, in the case of the control of a mobile robot, a button displaying a graphical representation of the action it is linked to, like a curved arrow for rotating, should give an idea of its purpose and of the expected result if this button is pressed.
4. *Prior instructions.* The instructions and information given to the users will influence their expectations. For instance, if users are told that a robot implements voice recognition, they will expect the robot to understand verbal commands.

It has to be noted that the parameters *Previous user experience with a similar system* and *Prior user belief about robotics* cannot be controlled by the system designer and depend on the background of each user. Thus they can cause important variability one has to cope with. In contrast, the parameters *Interface appearance* and *Prior instructions* can be controlled by the system designer who can try to generate appropriate expectations regarding the system.

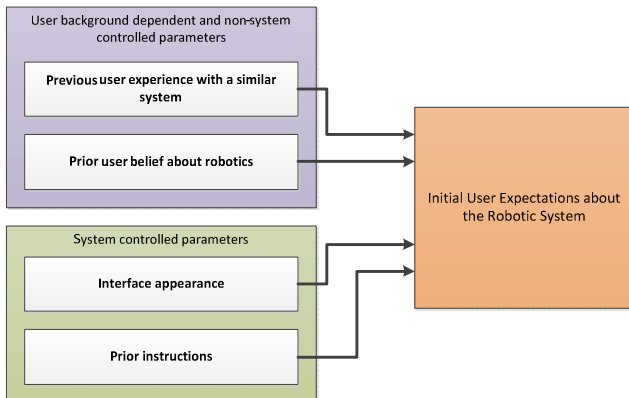


Figure 1: Parameters influencing the initial user expectations about the robotic system

2.2 Experience gained by the user while using the system

While using the system, users can compare their expectation with the results of actions. When the results differ from expectations, they can correct their expectation for the next time they will have to perform the same action. This process has been described by Roesse and Sherman [8] as the regulatory feedback loop. With sufficient experience with a robotic system users should be able to predict the results of their actions and match their expectations with the robot behavior. In other words, user expectations evolve with the user learning of the system. However, this process of updating the expectation by comparing them to events is limited in complex robotic systems where users do not receive direct feedback about the results of their inputs.

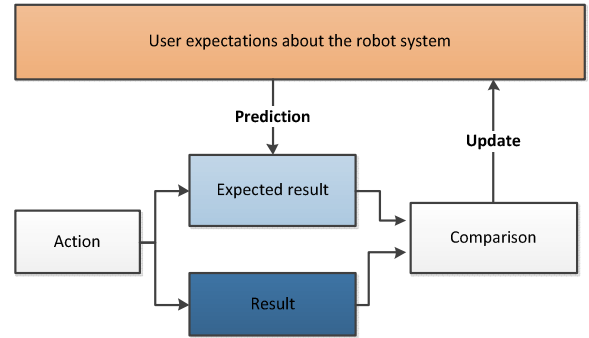


Figure 2: Update of user expectations by comparing the result and the predicted result of an action

2.3 Information from the interface

The user interface can convert the raw data about the states of the robot and its relation with its environment into relevant information. Hence users can monitor the robot state and actions through the interface and constantly update their expectation from the information given by the robot. For instance, an interface explicitly displaying the heading of a differential-drive mobile robot will help the user correctly predict in which direction the robot will advance if it moves forward.

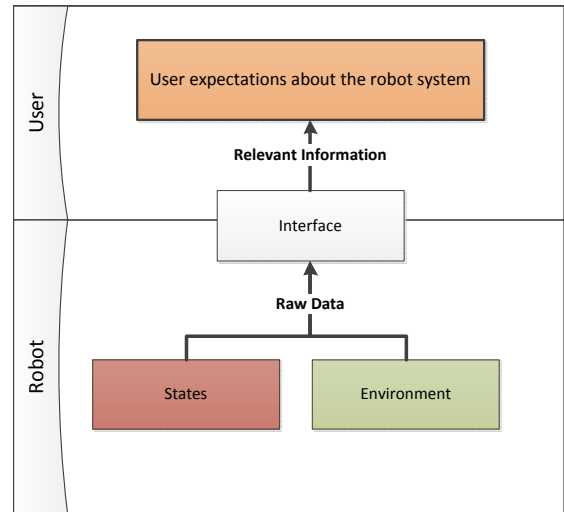


Figure 3: Continuous update of user expectations from the presentation of relevant information about the robot states and environment

3. EXPECTATIONS IN THE CASE OF A LEARNING ROBOTIC SYSTEM

On a classic robotic system, the user has to understand the direct relation between the inputs and the robot actions to form correct expectations. However, in a robotic system with learning capabilities the user has to understand much more complex relations between actions and consequences, and hence it is more difficult to form correct expectations. The user has to understand the relation between the timing of the inputs, the robot behavior over time, the constraints of the environment, the overall performance of the system, the level of autonomy of the robot, etc., depending on the parameters used and controlled by the learning algorithms. Consider the example of a mobile robot

which, while driven to a destination by the user, learns to repeat the path autonomously by recording the relative position of landmarks to the path. To be able to predict if the robot will actually reach the target destination on its own and at which accuracy, the user will have to understand that the robot needs specific landmarks for its navigation. If so, the user will correctly expect the robot to fail navigating autonomously to a destination if no landmarks are located near the destination; or the user can predict correctly that moving landmarks will disrupt the robot's navigation. Similarly, the user will expect the robot to successfully and accurately reach its target if many landmarks are available.

The expectations the users need to form in order to understand the links between inputs and actions can be classified in three categories according to their complexity. From lower to higher complexity: expectations regarding the low level control of the robot, expectations regarding the learning process and expectations regarding the execution of the learned situations.

3.1 Expectations regarding the direct control of the robot

Without any robot learning, users' expectations regarding the low level direct control of the robot generally converge rapidly with the actions performed by the robot. The user receives immediate feedback on the results of command inputs and can compare the results to expectations. After a few trials the user may be able to map the robot actions to the inputs. The number of trials needed for the user expectations to match the robot behavior depends on the quality of the interface and the situational awareness that it is able to provide. For instance, in the case of a mobile robot controlled by a limited voice interface, it may take more than one trial for the user to understand how to pronounce the words to command the robot.

If the system implements learning, the consistency of the control interaction can be broken. An action that led to a specific result in the past does not necessarily do so anymore after learning occurred. In this case, if the learning mechanism is not transparent to the user, he or she may be unable to predict the results of an action after a change in the interaction. The user expectations and the robot behavior will differ until the user understands what has been modified by the learning process. For instance, if a mobile robot learns to avoid obstacle, the user will be surprised when the robot stops executing the learned process for the first time because the user may not expect such an action from the system. To keep user expectations consistent with the robot behavior, the user should be notified by the interface about the changes generated by the learning. Hence the expectation problem in the case of a learning robot is linked to the design of the interface.

3.2 Expectations regarding the learning process

Enabling the user to predict what the robot can learn and how to teach it is more complex than matching user expectations and robot behavior for simple, control oriented tasks. When users interact with the robot, they usually do not receive immediate feedback on what the robot is learning. Rather, the learning process needs to be completed and a situation needs to arise in which the learning can be applied before users can compare their expectations with what the robot actually learned. As a result, the convergence of expectations and robot behavior will be longer than for simple tasks. Therefore the initial user expectations are

particularly important, and they should ideally match the actual system properties as closely as possible. Hence the following questions related to the parameters influencing the initial user expectation are relevant here:

1. What are the users' previous experiences with a learning system? What are the adaptive technological systems that users may have encountered before? Is there any existing similar system, and if so, are there any generally accepted design guidelines?
2. What are the users' beliefs about learning processes in robotic systems? Most users know very little about robot learning, and the most common physical learning entity the users are basing their beliefs on are humans.
3. How should the interface design indicate that learning is implemented on the system? Should it be explicitly specified on the interface even before the system starts to learn?
4. What information or instructions should be communicated to the users before they start using the robotic system? Providing critical information about the use of the learning system may help users form correct expectations about the capabilities of the system. For instance, informing the users that the system implements a learning process can save them the time needed to discover this fact by themselves (and wondering about the apparent inconsistencies in the system).

As pointed out above, the interface also influences the formation of user expectations. In contrast to the other relevant factors, the interface is created by the system designer, so it can be built to support appropriate expectations. It can be used to provide information to make the learning system transparent to the user. The interface should assist the learning process and shape user expectations, guiding users during all steps of the learning and explicitly showing them what the system has learned. It could also offer editing options to modify or cancel what has been learned to create a system that more closely matches user expectations. Thus in this case the expectation problem is also linked to the design of the interface.

3.3 Expectations regarding the execution of the learned situations

User expectations regarding the execution of the learned actions are very difficult to control because of the learning itself. If the learning is defined as a continuous process which constantly alters the robot's behavior, the users' predictions, built on the comparison of previous expectations and robot behavior, are never valid, as long as the learning process continues. To be able to form correct expectations about the execution of the learning actions by comparison, at least the following conditions have to be fulfilled:

- The learning process has ended and the user is aware of this fact.
- The user already encountered the same situation and no learning has occurred since.

- The user remembers how the robot behaved the last time the same situation was encountered.

Those conditions are too restrictive for dynamic and changing environments. In these environments the goal of learning is not to simply repeat a previously learned sequence of actions but to be able to react autonomously to a new situation, based on previous similar experiences. Hence the users' expectations should be built by other means than simple comparison with the robot behavior. Ideally, users should correctly understand the capabilities of the robot. For instance they should be able to understand what degree of similarity the robot is capable of dealing with to perform actions autonomously. Therefore the robot should constantly communicate information to the users for them to understand the robot. It is not required, and it won't be possible, for the user to know all states and variables of the robot, but the user should at least be aware of the robot's "intention" to be able to form accurate expectations.

Hence here, the role of the interface is even more critical than in the previous parts. It should be able to communicate the robot's intention to the users. How the interface will achieve this goal is a complex research question. It could use visual cues, for instance marking an object (such as an obstacle) on a map to indicate that the object has been taken into account. Alternatively, the system can use graphical previews, like displaying the path a mobile robot is planned to follow.

Again, the role of the interface is critical in this part for shaping proper user expectations about the behavior of the robotic system.

4. SUMMARY

This paper started a reflection about user expectations regarding robotic systems with learning capabilities. First, we discuss factors influencing user expectations with robotic systems in general. We point to initial expectations of the user about the system, the experience the user gains using the system and the way the interface presents information about the robot to the user. We then discussed these factors in the case of a robot with learning capabilities, arguing that the robots ability to learn greatly increases the complexity of the influence of these factors on user expectations. Here users need to adjust their expectations to the changes in the system, adjusting them dynamically with the adaptations that occur in the system. We point to three categories of expectations specific to learning systems: expectations regarding the direct control of the robot, expectations regarding the learning process and expectations regarding the execution of the learned situations. The main conclusion that can be drawn is that when learning is implemented in a robotic system, the influence of interface design on user expectations becomes critical. The interface must reflect the changes in robot functionality that occur with learning, avoiding situations in which the user is not aware of the learning that has occurred and will be surprised by its consequences. However, such an adjustment will necessarily introduce inconsistencies in the interface, which may make it less easily comprehensible for users. Hence the interface should be designed in order to dynamically shape user expectations according to the system changing behavior and capabilities due to learning, while maintaining maximal consistency in the basic interaction principles by which the user controls the robot.

More empirical studies are needed on the different factors that affect user expectations. Also, more research is needed on the

effects expectations have on the interaction with robotic systems and on the user satisfaction with the system. Eventually these studies should allow us to define guidelines for interface design and user training that will create expectations for interacting efficiently with robotic systems, and in particular robotic systems that can adjust their behavior to the individual user and to the changing environment.

We are aiming to contribute in the future to the empirical studies about the effects of expectation on human-robot interaction. In this perspective, an experiment focused on the study of the interface design for robot with learning capabilities is currently in development.

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