Robots That Can Play with Children: What Makes a Robot Be a Friend

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Abstract. In this paper, a playmate robot system, which can play with a child, is proposed. Unlike many therapeutic service robots, our proposed system is implemented as a functionality of the domestic service robot with a high degree of freedom. This implies that the robot can use its body and toys for playing high-level games with children, i.e., beyond therapeutic play, using its physical features. The proposed system currently consists of ten play modules, including a chatbot, card playing, and drawing. To sustain the player's interest in the system, we also propose an action-selection strategy based on a transition model of the child's mental state. The robot can estimate the child's state and select an appropriate action in the course of play. A portion of the proposed algorithms was implemented on a real robot platform, and experiments were carried out to design and evaluate the proposed system.

Keywords: Playmate robots, child's mental modeling, and Markov decision process.

1 Introduction

Several problems, such as, child neglect by caregiver and deterioration in the quality of play for a child, exist in the circumstances surrounding children. We believe that "robotic playmates" would greatly help to solve these problems. In this study, we propose a playmate system for humanoid robot that can play with a child using its body and toys. The robot is designed to have ten play modules covering important play areas for development, and can play with a child by switching among these modules.

Playmates are required to play with children for as long as possible. To ensure that their play with a child lasts for a long duration, human playmates observe a child well. For sustaining a child's interest, the playmate estimates the child's mental state to select appropriate actions from a finite set of actions in a timely fashion. Therefore, playmates should sustain a child's interest in play and forge a

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good relationship with the child. We think that two factors, which we call "degree of interest" (DOI) and "degree of familiarity" (DOF), are very important and are improved by selecting actions according to the child's estimated mental state.

We propose an action-selection strategy based on a transition model of the child's mental state, which enable the robot to sustain a child's interest and forge good relationship with the child. The regularity of the gaze, smile intensities, and the motion are measured for this estimation, and the play modules are switched with the strategy of sustaining the child's interest in the play. Moreover, the robot selects appropriate actions according to the child's estimated mental state, which is based on the Markov decision process (MDP).

Several robotic playmates have been proposed [1]–[4]. Works in [1] and [3], were aimed at achieving robots that could engage in therapeutic play with autistic children. Attempts to extract play primitives have also been made [2] and [4]. In contrast to these works, our contributions are (1) the implementation of actual play modules, (2) the development of the action selection model based on the child's estimated inner state, (3) integration of the play modules with the action selection model, and (4) evaluation of the proposed playmate robot.

2 Overview of the Proposed Playmate Robot

The playmate system is implemented as a functionality of a domestic service robot. The robot is designed to play with a child using the implemented play modules, which cover several types of play to promote child development. The robot plays interactively with the child, switching play modules according to the child's mental state. Moreover, the most important purpose of the proposed system is to ensure its ability to play with a child for as long as possible. To this end, the system switches among play modules and selects strategies such as praise and competition according to the player's mental state. The player's mental state (e.g., bored) is estimated from the player's gaze, smile, and motion.

2.1 Robot Platform

In this work, the robot platform "DiGORO" was used. This robot has two arms with six degrees of freedom (DOF) each, a two-DOF neck, and a one-DOF waist. Thus, the robot can play with toys and its body. The underbody is based on omnidirectional wheels and has the capability to move around in an indoor environment using laser-based online simultaneous localization and mapping (SLAM). A real-time 3D sensor, which consists of calibrated CCD and time-of-flight (TOF) cameras [5], is mounted on its head. This sensor enables the robot to record the appearance of persons and objects online and recognize them with high accuracy [6]. Five onboard PCs work in parallel by coordination through TCP/IP connections. All computations are carried out inside the robot, and hence, it works properly even when no wireless network is available.

2.2 Modules of Play

The robot is designed to play using the implemented ten play modules, which cover all types of play to promote child development. The ten play modules that we are currently working on are (a) chatbot, (b) card playing, (c) drawing, (d) rock–paper–scissors, (e) picture-book reading, (f) hide and seek, (g) rhythmic movement, (h) blocks, (i) make-believe play, and (j) learning of novel play.

3 Action Selection and Mental State Estimation

To ensure continuous play with a child for a long duration, the robot predicts the mental state of the child and selects its next action accordingly. It is natural for us to select an action based on the observed child's behavior, and when the child gets bored with the current play, we usually engage the child in another play. Obviously, if the robot continues the same play in such a situation, the play will soon end. To this end, we first conducted an observation to analyze the play between a kindergarten teacher and a child. The results were used for designing the interaction between the robot and a child based on MDP. Next, experiments on the play between the robot and a child were conducted to test the mental state estimation method and to estimate the parameters for the model of action selection.

3.1 Observation of Play

We videotaped the play between a professional kindergarten teacher and a child. Two children (one boy and one girl) participated in this experiment. The children individually played with the teacher for thirty minutes each. The teacher selected which games to play. After each play period, we interviewed the teacher while watching the recorded video. The purpose of this interview was to discover the behavioral strategy of the teacher for engaging the child in play.

3.2 Modeling a Child's Play

We generated a child's play model including the child's mental state transition and the kindergarten teacher's action strategy from the observation (Fig. 1 (a)). It is a state transition model of the children's mental states, the action strategy of the teacher, and the process of becoming bored, which is a full complex model. "Nervous," "Familiar," "Enjoying," "Bored," and "Change of interest" represent the child's mental state transitions. The output from the child's mental state is the child's behavior, and the input is the kindergarten teacher's action strategy which is taken according to child's DOI in the play.

The model in Fig. 1 (a) is simplified to make it implementable on the robot, and we generated an action selection model. The child's mental state transition model, which corresponds to the action selection model for the robot, is illustrated in Fig. 1 (b). The playmate robot uses this model to select an action for sustaining the child's interest in the current play. It can predict the next state of the child by taking a specific action using the mental state transition model. Therefore, it is possible for the system to select an action that can keep the child engaged in play, i.e., by trying to confine the child's state to S_1 or S_2.

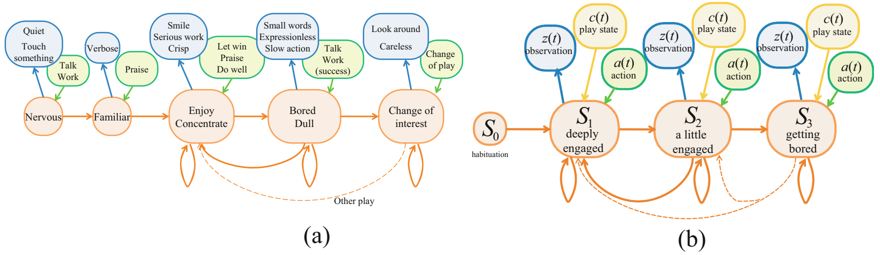

Fig. 1. Child's mental modeling: (a) Model of child's play including the child's mental state transition and the kindergarten teacher's action strategy and (b) Child's mental state transition model in play

Child's Inner State. In the figure, S_0, S_1, S_2, and S_3 represent the child's inner states of "habituation," "deeply engaged," "a little engaged," and "getting bored," respectively. The "habituation" state occurs once when the child first meets the robot. Therefore, during the play between the robot and the child, the states shift among S_1, S_2, and S_3.

Observation. $z(t)$ in Fig. 1 represents observable features for estimating the child's mental state. The output probability of $z(t)$ prescribes the child's current mental state. Details pertaining to the state estimation are described later.

Play State. In the model, $c(t)$ represents the state of play, such as types of play, a turn, and success or failure of the action. The play state is important since the available actions depend on the current state. Therefore, $c(t)$ is always referred to by the robot to select its action. The total number of play states is $(kind) \times (turn = 3) \times (success = 3)$. $kind$ represents types of play, which include a card game, rock–paper–scissors game, and so on. $turn$ has three values: child's turn, robot's turn, and the other turn. $success$ takes the values success, failure, or nothing.

Actions. The variable $a(t)$ indicates a set of robot actions, which is designed with reference to the strategy of the kindergarden teacher. There are eight actions in total at the abstract level: (1) make a willful mistake, (2) react to the child's action, (3) react to its own action, (4) tantalize, (5) change the tempo of the play, (6) do nothing special (simply continue to play), (7) recommend changing to a different type of play, and (8) recommend continuing the same type of play.

The possible actions of the robot are constrained by the play state $c(t)$; e.g., the robot cannot flip over the card when it is the child's turn. Thus, each play state has a set of available actions $a\{c(t)\}$. The robot selects an action from the current list of available actions accordingly. The child's mental state transition model in Fig. 1 (b) has transition probability $p(S_k|S_n, a_n, c)$ as a parameter. The number of values this parameter can take is 8 $(number\ of\ state\ transitions) \times (number\ of\ play\ states) \times 8\ (number\ of\ actions)$. This parameter is calculated based on the experiment of observing the play between two children and a kindergarten teacher.

Action Selection of the Robot. The robot acts based on the strategy of the kindergarten teacher. One important strategy is selecting an action according to the child's mental state. The process of the robot performing an action selection entails the following: (1) observing the child, (2) estimating the child's current mental state, (3) deciding the play state and set of actions available, and (4) selection of the action. The robot first estimates the child's mental state S_n from the observation $z(t)$. The set of available actions is automatically determined from the current play state $c(t)$. The robot then selects an action that has a high probability of transition to S_1 or S_2:

$$a(t) = \underset{a}{\operatorname{argmax}}\, p(S_n(t+1)|S_n(t), a\{c(t)\}). \tag{1}$$

The robot performs this action selection with each change in the play state.

3.3 Mental State Estimation

In the proposed system, the regularity of the gaze, smile intensities, and the motion are used for estimating the child's mental state. These three features appeared to be useful in our foregoing observational analysis. In [7], the authors found that similar cues are valid for detecting child engagement with a robot.

The regularity of the gaze $d(t)$ is defined as the frequency of the player's gaze on the robot or the area related to the play. Let $h(t) \in \{0, 1\}$ represent a state of the face direction at time t. $h(t)$ takes the value one when the player's face is in the direction of the play-related region and takes zero otherwise. Then, $d(t)$ can be calculated as $d(t) = \sum_{k=t}^{t+\ell-1} h(k)/\ell$, where ℓ denotes the length of a frame. The direction of the child's gaze is estimated via head tracking based on the 3D head-pose estimation [8]. The method in [9] is used for estimating smile intensities $s(t)$. $s(t)$ is averaged over a frame, and it ranges from 0 to 1. The motion cue is also useful since the motion of children becomes large as they lose interest. The motion $m(t)$ is measured by the distance between the current and previous positions of the face. $m(t)$ is normalized by the distance between the eyes to eliminate individual variation. $m(t)$ is also averaged over a frame, and it takes a value between 0 to 1. The length of a frame is chosen to be 5 s.

The output probability $p(z(t)|S_n)$ of each feature $z(t) = d(t), s(t), m(t)$ at the state S_n is modeled by a normal distribution using the foregoing experimental data. The likelihood $L_n(t)$ of the state S_n when the observation $z(t) = d(t), s(t), m(t)$ was observed is

$$L_n(t) = p(d(t)|S_n) \times p(s(t)|S_n) \times p(m(t)|S_n). \tag{2}$$

The state that has the highest likelihood is determined as the estimated mental state,

$$S_n(t) = \underset{S_n}{\operatorname{argmax}}\, L_n(t). \tag{3}$$

(a) (b)

Fig. 2. (a) Scenes of the experiment: the playmate robot, top view of the experiment, and children playing with the robot, are respectively depicted from left to right. (b) Action selection model based solely on play states.

4 Experiments

4.1 Experimental Setup

The model discussed in the previous section was implemented on DiGORO. To compare with our proposed method, we defined the state model (Fig. 2 (b)). In the state model, the robot selects an action randomly from the available actions at the play state $c(t)$. This means that the robot selects an action depending only on the current play state, and it does not care about the child's mental state.

We conducted a verification experiment using the robot in the decorated room as shown in Fig. 2 (a). Six children (three boys and three girls, with an average age of 5.5 years) participated in this experiment. Each participant was asked to sit in front of the robot and play card playing (concentration) and the game of rock–paper–scissors with it. This was because these two kinds of play work stably and are suited to the experiment from a safety viewpoint. The experiment started with five minutes of icebreaking conversation soon after the child entered the room. Then, the child played with the robot for about thirty minutes before leaving the room.

4.2 Estimation of the Child's Mental State

The child's mental states were estimated by using images from a camera that was set in front of the robot at 5-s intervals during the experiment. The proposed model used this estimated result for selecting the robot's next action. To compare with the teacher's evaluation, which will be explained later, 2 is assigned to S_1, 1 is assigned to S_2, and 0 is assigned to S_3. We call this the estimated degree of interest (DOI).

4.3 Evaluation and Questionnaires

We requested three professional kindergarten teachers to annotate each child's mental state in the range from 0 to 4, which we call annotated DOI, at 5-s intervals, by watching a video capturing the frontal view of the child. The average of the three teacher's ratings was used as the baseline. All the teachers were also asked to complete a questionnaire about the target child, which consisted of 13 items (that are listed below) concerning robots and the experiment, and 10 items about the personality of the child.

Table 1. Correlation coefficient between estimated DOI and annotated DOI

Child's ID	C1	C2	C3	C4	C5	C6
Correlation coefficient	0.22	0.21	0.12	0.01	0.52	0.53
Minimum value of ref.	0.59	0.91	2.00	2.00	1.41	0.67

Q1: Is the child interested in generic robots? (no / yes)
Q2: Does the child like generic robots? (yes / no)
Q3: Through this experiment, did the child get more interested in generic robots? (lost / developed interest)
Q4: Through this experiment, did the child come to like generic robots? (come to dislike / like)
Q5: Does the child like the robot used in this experiment? (no / yes)
Q6: How does the child find the robot used in this experiment? (scary / friendly)
Q7: How does the child feel about the robot used in this experiment? (uncool / cool)
Q8: How does the child feel about the size of the robot used in this experiment? (small / large)
Q9: How does the child feel about this experiment? (boring / enjoyable)
Q10: Was the child in a good mood before playing with the robot? (in a bad / good mood)
Q11: Did the child get into a good mood after playing with the robot? (get in a bad / good mood)
Q12: Does the child want to play with the robot again? (no / yes)
Q13: Does the child think of the robot as a human? (as a machine /as a human)

4.4 Results

Four children (two with the proposed model and two with the state model) out of the six played with the robot until the prescribed end of the experiment period. Because the remaining two children (one with the proposed model and one with the state model) refused to continue the play, the experiment was aborted after about fifteen minutes. One of these two children was scared of the robot and the height of the seat. These things were directly responsible for the child's refusal to continue the play. The other child tested the robot to see if she could trust it. She frequently took actions irrelevant to the play, such as shaking the table and showing an injury to the robot, among other actions. Since the robot could not respond to these actions, the play between the child and the robot was disrupted.

4.5 State Estimation

We smoothed estimated DOI values for 5 points and calculated the correlation coefficient between smoothed estimated DOI and each child's annotated DOI values. Table 1 shows the correlation coefficients. The estimated DOI is positively correlated with the annotated DOI in all six children($p < 0.05$, two-sided, sign test). This result is acceptable from the viewpoint of action selection using the model.

For the case where the minimum value of the annotated DOI is larger than 2, the correlation coefficients are low. This implies that the estimation accuracy of the state "the child is interested in the play" is not high. To discover the cause of this bad performance, we examined the data, finding that S_1 and S_2 share similar feature vectors in this experimental setting. This means that discriminating S_1 from S_2 by the feature vector used in this experiment is difficult. However, both S_1 and S_2 can be said to be the interested states of children, and actions

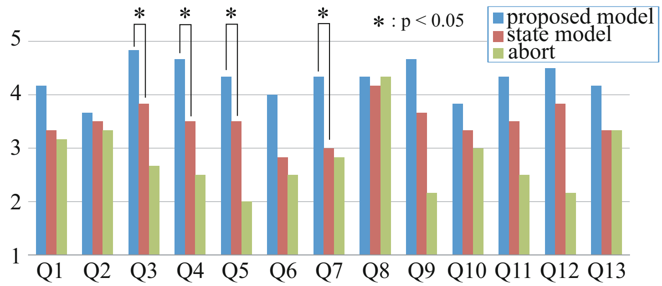

Fig. 3. Average scores for each questionnaire. See the text for details on Q1–Q13.

selected in both states are behaviors that encourage the children in the states of engagement. Therefore, the inability of the system to discriminate between S_1 and S_2 can be disregarded. Estimating S_3, the state in which the child gets bored, is more important during the play.

We thus measured the accuracy of estimating the child's state with two levels, i.e., $S_1 + S_2 = S_1^{'}$ and S_3. In this case, the recognition accuracy increased from $\sim$40% to $\sim$70%.

4.6 Comparison between Proposed Model and State Model

The subjects can be divided into three groups. The first group consists of subjects playing with the robot that selects its action using the proposed model (model group). The second group contains subjects playing with the robot that selects its actions using the state model (state group). The last group consists of subjects who aborted the play in the experiment (abort group). Figure 3 shows the average questionnaire scores for each group. The responses to Q3, Q4, Q5, and Q7 exhibit significant differences between the model and state group according to a t-test ($p < 0.05$). Q3 to Q5 are questions pertaining to whether the experiment affects the result, such as "Does the child like the robot used in this experiment?" In contrast, responses to other questions that pertain to the robot in general, such as Q2 "Does the child like generic robots?," show no significant differences. This implies that the proposed model leads to a better impression of the robot and the experiment than the state model. Given that the average scores of Q9 "How does the child feel about this experiment? (boring / enjoyable)" and Q12 "Does the child want to play with the robot again?" for the model group are higher than those for the state group, the selecting actions by the proposed model may affect the relationship between the robot and the child, and the relationship influences whether the robot can play with the child over a long duration.

To validate this questionnaire's result, we try to evaluate a relationship between the robot and the child in quantitative form. Figures 4(a) and (b) show the DOIs (annotated) of two participants, one from the model group (Fig. 4(a)) and one from the state group (Fig. 4 (b)). Figures 4(c) and (d) illustrate the frequency of gazing at the robot and the table by the children. This plot is the 5-minute

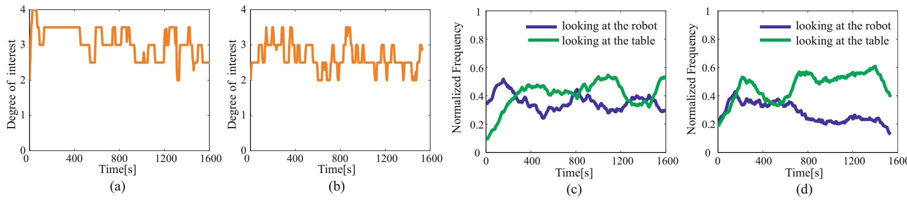

Fig. 4. The results of two participants: (a) plot of the baseline DOI for the model group, (b) plot of the baseline DOI for the state group, (c) plot of the normalized frequency of gazing at the robot and the table for the model group, and (d) plot of the normalized frequency of gazing at the robot and the table for the state group‘.

moving average. The figures indicate that both DOIs have no tendency of causing children to get bored. This suggests that every child enjoyed playing. However, the frequency of the child gazing at the robot and the table greatly differed between the two groups. Both groups often gazed at the robot at first, and the model group gazed at the robot and the table at about the same rate over time (average: table 54%, robot 46%). In the state group, the frequency of gazing at the table gradually reduced (average: table 62%, robot 38%). A particularly noteworthy point is that at the end of a card game, which is at about 700 to 1300 s in Fig. 4(c) and 500 to 1050 s in Fig. 4(d), the frequency of gazing at the robot increases and exceeds the frequency of looking at the table at 700 and 1300 s in Fig. 4(c) and at 500 s in Fig. 4(d). This implies that the child gazed at the robot to observe the robot's reaction at the end of the card game. This is similar to the situation in which the child looks at the kindergarten teacher after finishing something because the child wants to observe the teacher's reaction. In contrast, despite the card game also ending at 1050 s in Fig. 4(d), the frequency of gazing at the robot did not increase. In the state model, the child provides less attention to the robot during the play. The same thing can be said for the remaining two children who played until the prescribed end of the experiment period.

This result shows that selecting actions by using the mental state transition model for the play between the child and the robot is as effective as indicated by the questionnaire's result. Appropriate behavior of the robot based on the model helps to maintain a good relationship with the child.

The DOIs exhibit no difference between the model and state groups; however, the frequencies of the child's gaze differ. These results indicate that there are two important factors involved for the robot to be able to play with the child for as long as possible. One is the engagement in play, represented by the DOI. The other factor is the relationship between the robot and the child, represented by the regularity of the gaze. The relationship affects the child's urge to play with the robot again, which is indicated, for example, by the response to Q9 "How does the child feel about this experiment? (boring / enjoyable)" and Q12 "Does the child want to play with the robot again?" Therefore, this factor is certainly important to sustain play for a long duration. In addition, these results indicate that the relationship can be measured directly from the regularity of the gaze.

5 Conclusion and Future Work

To continuously play with a child for a long duration, a robot has to sustain the child's interest and forge a good relationship with it. This study proposes a playmate robot system consisting of multiple, switchable play modules that help to sustain a player's interest for as long as possible. We also propose a model of the inner state of the player, which is used by the robot for action selection. We implemented basic functions of the play modules in our service robot and verified that they work reasonably well through experiments involving child–robot interactive play. The result shows that the robot's action selection using the proposed model created a good relationship between the robot and the child. However, many challenges remain to be addressed in a future work, for example, the implementation of the modules and, in particular, the testing of the playmate robot with a larger number of children.

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