ROBotic Open-architecture Technology for Cognition, Understanding and Behavior

Project no. 004370

RobotCub

Development of a cognitive humanoid cub

Instrument: Integrated Project
Thematic Priority: IST – Cognitive Systems

D 6.5 Studies on human-humanoid interaction kinesics

Due Date: **01/09/2008**
Submission date: **05/09/2008**

Start date of project: **01/09/2004** Duration: **60 months**

Organisation name of lead contractor for this deliverable: **University of Hertfordshire**

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Revision: **rev.no.**

Project co-funded by the European Commission within the Sixth Framework Programme (2002-2006)		
Dissemination Level		
PU	Public	**PU**
PP	Restricted to other programme participants (including the Commission Service)	
RE	Restricted to a group specified by the consortium (including the Commission Service)	
CO	Confidential, only for members of the consortium (including the Commission Service)	

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Executive Summary

WP6 continues to focus on interaction dynamics of social interaction during robot-human play and the prerequisites for gesture and non-verbal communication between robots and humans, as well as the realization of these capabilities in a robot. User studies are used to gain understanding of the kinesics and dynamics of social interaction during robot-human play and its development in ontogeny. At the same time, techniques for achieving these capabilities in an autonomous robot through grounded sensorimotor experience and interaction histories are investigated.

This deliverable brings together three areas of complementary research work relevant to gesture communication carried out by UNIHER:

1. **Timing and Non-verbal Cues in Interaction with a Humanoid Robot**.
2. **Ontogeny of Humanoid-Human Interaction Capability**.
3. **Robot-Mediated Play.**

Section 1 describes the *Drum-mate* work with the usage of gestures and turn-taking models in a call-and-response imitation based interaction game. Section 2 describes our work on Interaction Histories and the development of Peekaboo interaction games, and their implementation on humanoid robots. Finally section 3 describes research on Robot-Mediated Play.

1 Timing and Nonverbal Cues in Interactive Play with a Humanoid Robot

The first area of work applies *Drum-mate*, a human-humanoid drumming interaction game, designed to allow study of the kinesics and dynamics of interaction between a humanoid robot and human partners via a playful drumming experience. In this work, the aim is not to have the humanoid robot just replicate the human partner's drumming, but to autonomously engage with the human in a ‘social manner’. Specifically, we implemented a call-and-response turn-taking interaction inspired by games that children play. The game has several different versions where different issues in human-humanoid interaction kinesics are studied. In the first version, the turn-taking behaviour of the humanoid is deterministic. Presence vs. absence of head gestures of the robot accompanying its drumming were used to assess the impact of non-verbal gesturing on the interaction. The second experiment presents a novel computational framework that facilitates emergent turn-taking dynamics; here the aim is to have turn-taking and role switching which is not deterministic but is emerging from the social interaction between the human and the humanoid. Therefore the robot is not just ‘following’ and imitating the human, but could be the leader in the game and being imitated by the human. Results from the 48 human-robot interaction experiments belonging to both studies are presented and analysed qualitatively (in terms of participants' subjective experiences) and quantitatively (concerning the drumming performance of the human-robot pair). The first results from 24 participants have been presented in three conference papers; “Drum-mate: A Human-Humanoid Drumming Experience” (Kose-Bagci et al., *HUMANOIDS’07*, 2007) and “Emergent Turn-Taking Dynamics in Drumming Games with a Humanoid Robot” (Kose-Bagci et al., *IEEE RO-MAN’08*, 2008a), and “Drumming with a Humanoid Robot: Results from Human-Robot Interaction Studies" (Kose-Bagci et al., *LAB-RS08 –invited talk with published extended abstract*, 2008b). The results of the overall 48 participants are presented and discussed in a journal paper entitled as "Drum-mate: Interaction dynamics and gestures in human-humanoid drumming experiments" (Kose-Bagci et al., *submitted*). This article presents details of the implementation, including a simple but efficient novel method of detecting drumming beats, as well as experimental results. Results are consistent with the *temporal behaviour matching hypothesis* previously proposed in the literature which concerns the effect that participants adapt their own interaction dynamics to the robot's. This hypothesis was tested with KASPAR, a child-sized humanoid robot, and we are working on the implementation of these methods also on physical and simulated iCub. Another version of the drum-mate game was tested with 68 primary school students, where the importance of physical embodiment, together with its relation with the presence/absence of non-verbal gestures was studied recently. We are still working on the statistical analysis of the results.

1.1 Gestures in Human-Humanoid Drumming

This section summarizes results of a study focusing on interaction dynamics of social interaction during human-robot play. The study is an exploratory investigation of a drumming experience between KASPAR, a humanoid robot, and human partners. The social interaction was mediated through a drumming call-and-response game and was systematically modulated by non-verbal gestures and cues. The results were statistically analysed in terms of the game performance as well as the evaluation of the game by the participants.

The analysis of the first 12 participants (6 female, and 6 male) showed a clear effect due to the concomitant gestures during the interaction and also found significant results due to gender differences between the participants in terms of how they interacted with the robot under different gesture conditions (Kose-Bagci *et al*., 2007). Male participants tended to focus more on the accuracy of drumming rather than interaction as amount of gestures in the games increased since they are generally task-oriented. On the other hand, female participants tended to be more interaction-oriented, and enjoyed with the social interaction between robot and them, therefore preferred games with increasing amount of gesture. They also performed more drumming in these games, so gestures played a motivational role in the games. On the other hand it is observed that the subjective evaluation of the participants differed from their objective evaluation -- e.g. although the gesture+ condition had the highest error rate, it was mostly preferred by the participants. These results were confirmed when we repeated the experiments with 12 more participants.

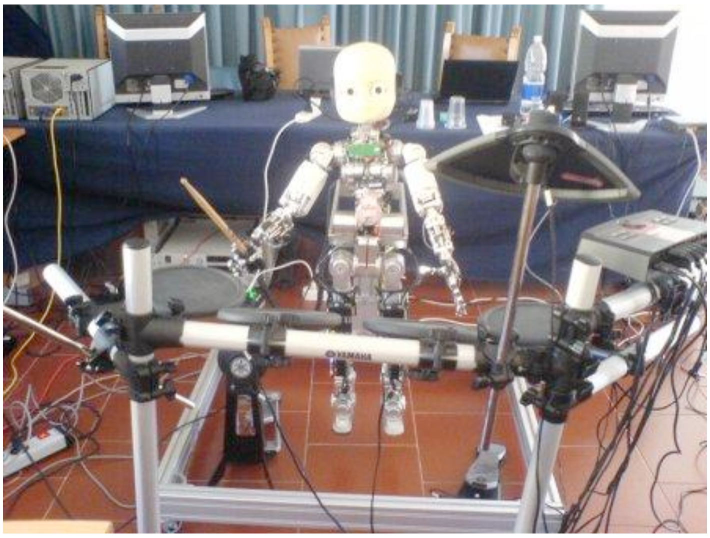

Fig 1. iCub playing with an electronic drum set

Implementations on the iCub. Three versions of the drum-mate game were tested on iCub during VVV'08 summer school in Sestri Levante, Italy in July, 2008. The first game was a limited version of the *drum-mate* game (without gestures) with deterministic turn-taking together with Audio Analyser module. The Audio Analyser module is the part of the game which analysis the drumming sound perceived by the robot and sending the pattern (number of drum bouts and durations between drum bouts) to an output port to be perceived by the drumming module. During the tests, iCub used an electronic drum set (Fig. 1), and a drum stick to hit the drum pads, which was grasped by its right hand (Fig. 2). The second version of the game in the repository involves several facial gestures. When the iCub hears a human participant's drumming and tries to play it in return, it also smiles. If the iCub cannot hear any human drumming when it is supposed to be the human's turn then the iCub only puts on a sad face and passes the turn to the human again. At the end of the game (currently it is time-limited, in this version the time limit is 2 minutes), the iCub holds up its left arm and waves its left hand several times to announce the end of the game (Fig. 3). There is also a third version working together with the drummingEPFL module (developed by EPFL-B), and using this module as the drummer part. The drummingEPFL module normally takes the input (number of drum bouts to be played and the frequency) from a file and its not interactive (not analysing the human's play and imitating it but play a fixed pattern). The Audio Analyser module sends the number of drum bouts and the frequency to this drumming module and together they produce an interactive application from this collaboration. In the other two versions we used our own drumming module, which can be found with the name drummerUH in the repository. Morever, we have also made available a standalone version of Audio Analyser module to be used as sound analysing module by other applications (e.g. different drumming programs) when needed. We also used the version of this module without the gestures together with the simulated iCub drummer implemented in the both WEBOTS simulator by EPFL, and the ODE simulator used in the summer school. We are still working on the improvement of the implementation of *drum-mate* game on the physical and simulated iCub.

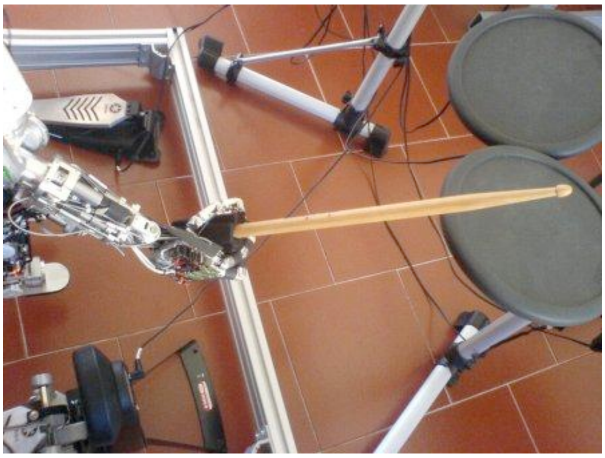

Fig. 2 iCub grasping the drumstick, and hitting the drum pads

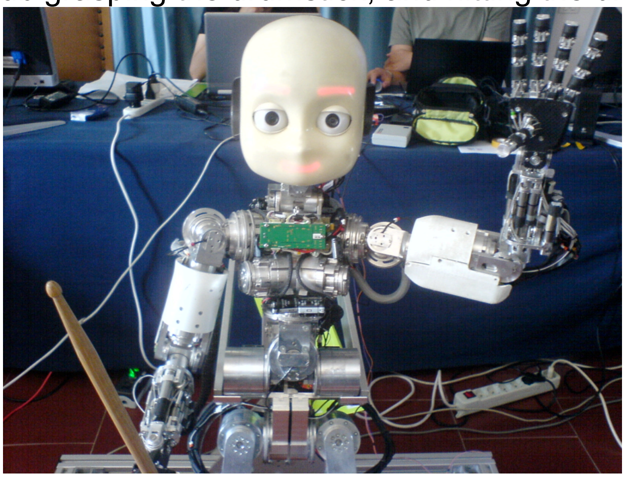

Fig. 3 iCub smiling and waving its left hand at the end of the game. It uses the left hand to hit the drum pads with the drum stick.

1.2 Kinesics of Interaction and Emergent Dynamics of Turn-Taking

In a further series of experiments, we studied emergent dynamics of turn-taking while regulating the manner in which the robot's actions were produced. It is observed from a vast exploration of the current research domain that timing plays a fundamental role in the regulation of human-human interaction. In the first study described above, some predefined fixed time duration heuristics were used for synchronization and turn-taking. KASPAR decided that the human participant finished his/her turn of play, and started playing if the human partner was silent for a few seconds. However, it was not always clear when the robot or human partner should initiate interaction in taking a turn. Parameters of turn-taking are not same for all participants, and can even change for a participant during different games, so the same fixed time durations may not suit to all participants, or during whole game of a participants. Therefore deterministic turn-taking had a negative impact on the synchronization and interaction of the participants.

In this second study, we instead used a probability-based algorithm to control timing and turn-taking. KASPAR used three different probabilistic computational models to decide when to start and stop its turn (KASPAR's and human participant's drumming). The parameters of these simple models (threshold, linear, hyperbolic) were based on the duration of the previous turn and on the number of beats played in the previous turn by the interaction partners. The temporal dynamics of turn-taking (in this case the number of beats and play times) were not deterministic but emerged from the interaction between the human and the humanoid.

Our research interests primarily focused on how different robot turn-taking strategies based on computational, probabilistic models impact the drumming performance of the human-robot pair, and the participants' subjective evaluation of the drumming experience. From the results of the first 12 participants, we observed in terms of subjective evaluation a significant difference between the first and third games in terms of order. Human participants got used to the game as they played more (Kose et al. 2008). In terms of observed behaviour, different models gave different amounts of playing time to KASPAR and the human participants, which affected participants' preferences and their performances during the games. Most of the participants did not prefer a linear model because it gave them the least playing time, whereby KASPAR ignored them and played on its own which influences social interaction negatively. Also KASPAR is not just imitating the human participant's drumming, but its drumming emerged from the probabilistic models and human participant's play dynamics, so can play different rhythms than human. Thus, some of the participants preferred to replicate KASPAR's drumming, and the "follower" and "leader" roles switched (unlike the first work (game with deterministic turn-taking), where KASPAR was always a "follower", and humans were always "leaders"). The tests were, later repeated by 12 more participants (Fig. 4) and the results of the first group were confirmed.
Analysis of the results showed an impact of the turn-taking model on the structure of the interaction in terms of duration and complexity of drumming by human participants as well as on their enjoyment of the interaction game; however, individual differences between participants played a strong role. Moreover participants' behaviour changed over the course of (order controlled) exposure to the models, indicating that they may have adapted their interaction to perceived capabilities of the robot.

Fig.4 Human participant playing *drum-mate* with humanoid KASPAR

Both of the versions of the *drum-mate* work showed that participants were not passive subjects in this game, but unconsciously adapted their own behaviour to the capabilities of the robot. The results of these works also suggest that deeper study of human-robot interaction kinesics and recipient design is warranted in the area of ontogenetic robotics where a robot develops by engaging in and sustaining social interaction with human partners.

Further descriptions of the experiments and results are to be found in Appendix A and (Kose-Bagci et al., 2007, 2008a, 2008b, 2008c submitted).

1.3 Physical Embodiment and Gestures

A version of the drum-mate game was tested with 68 primary school students, where the importance of physical embodiment, together with its relation with the presence/absence of non-verbal gestures was studied recently. Compared with the experiments with adults, simpler gestures were used, and the game duration was decreased to 2 minutes from 3 minutes. Deterministic turn-taking is used in the games, where half of the children played games with KASPAR making gestures during its drumming, and the other half of the children played games with KASPAR making no gestures, but just drumming. Also the time between turns was decreased to adapt the game better for children. At the time of submitting this deliverable we are still working on the statistical analysis of the results.

The human-robot interaction research described in section 1 will be further developed and completed in the final project year.

2 Ontogeny of Humanoid-Human Interaction Capability

The second area of work regards an architecture by which a robot can ontogenetically develop through social interaction and grounded sensorimotor experience. The early results were presented in a journal article (in *Adaptive Behavior* (Mirza et al., 2007)) detailing the architecture and experiments using the early interaction game, “peekaboo”, between a robot and human. The interaction history architecture was shown to be capable of supporting development of a turn-taking interaction in a robot which took appropriate actions or gestures based on its own grounded sensorimotor experience. Here we present the current state of research and implementation that brings together the interaction history architecture onto the humanoid KASPAR and onto the iCub to develop the capability to play the early social interaction game, “peekaboo”, acquired via appropriate interaction with a human social interaction partner.

Thus in the fourth project year work on interaction histories has continued in WP6. This research has been developed at UNIHER and resulted in a successfully defended PhD thesis (May 2008) by Dr. N. Assif Mirza, who then continued this work at IIT in the last quarter of the project year. Specifically, work has been continuing to move towards a demonstration of the Peekaboo developmental capability on the iCub platform while also preparing the Interaction History Architecture (IHA) for inclusion in the iCub released software code as part of the Cognitive Architecture.

Peekaboo on a humanoid was demonstrated using the KASPAR expressive-humanoid robot platform of UNIHER, and software delivered in D6.3 with results reported in D6.4 (April 2008). Appendix B (Mirza et al. *Artificial Life XI*, 2008) addresses the validation of the prospective ability of the IHA, while Appendix C (Mirza et al. 2008, submitted) briefly reports on the humanoid deployment of this architecture and peekaboo demonstration on the humanoid KASPAR platform); see deliverable D6.4 (note: Appendix C comprises a concise conference paper version of D6.4) and (N. A. Mirza, PhD thesis, 2008) for extensive details and more in-depth discussion and analysis of the peekaboo experiments with KASPAR). In the latter experiments, audio data was added to the sensory data available to the IHA and both audio and face-detection sensor data were used to provide a simple reward signal that peaked only when a face was seen along with a loud vocalization (peekaboo!). KASPAR was also able to provide feedback to the human interaction partner using facial expressions which directly reflected the level of reward it received. Results showed that KASPAR was able to deploy a series of actions in repeating sequence such that it was able to receive a high reward. The timing of the encouragement provided by the interaction partner was important in how the development proceeded, and delaying or preempting the encouragement would not result in the development of the capability to play peekaboo in the robot.

The entire Interaction History Architecture software tree has been re-engineered to bring it in line with the prevailing standards for iCub module development (see D6.3). The modules are listed in Table 1. Additionally run scripts were developed for the architecture.

TABLE 1: IHA Module List

Module Name	Type	Description
Debug	Library	Facilitates printing of debugging and log messages
Actions	Library	Reads and Interprets scripted actions and behaviours from sequence files
Action Selection	Module	Takes a Neighbourhood list as input and chooses an Experience and Action to execute
Experience Metric Space	Module	Takes sensor data as input and creates a history of experiences and places them in a metric space. Output is a Neighbourhood list.
ICub Control	Module	Control for ICub Robot
IHA Face Detect	Module	OpenCV facedetect
Motivation Dynamics	Module	Takes sound sensor data and face detector output and produces a reward value at every timestep
Sensor Motor Interface	Module	Collects all sensor information and outputs a consolidated Sensorimotor output
Sound	Module	Takes YARP streamed sound data as input and creates a single valued output for the sound sensor.
Sensor File Writer	Executable	Writes streamed sensor data to a file.
Sensor File Reader	Executable	Reads sensor data file and streams it to a YARP port.

The iCub control module has been tested on the existing iCub ODE simulator (iCub_YAIS). Testing on the new ODE simulator (iCub_SIM) and testing on the iCub hardware platform are under completion.

3 Robot-Mediated Play

This third area addresses robot mediated play in the context of autism. Here, we have both focused on (1) developing new approaches for designing the play sessions between a child with autism and an autonomous robot (Sony Aibo), (2) developing new computational methods to enable the robot to recognize and adapt online to the play styles of the children, and (3) testing the influence of an adaptive robot (vs. a reactive robot) on the child's play styles.

In (1), we have developed a new approach inspired by non-directive play therapy, where the experimenter takes part in the experiments. The child is the leader for the choice and the rhythm of play, but the experimenter can regulate the interaction under specific circumstances detailed in (François *et al.,* 2008a). The method has been tested through a long-term case study with 6 children. Results have been analysed along three dimensions, respectively Play, Reasoning and Affect and show that each child did progress in at least one of the three dimensions. Triadic play (child–robot--experimenter) was encouraged and children showed more and more initiative taking and proactive behaviours.

Research on (2) focused on computational methods that can enable a robot to adapt to different interaction styles. Here we developed a novel method for the recognition of tactile play styles, the Cascaded Information Bottleneck Method (François et al 2008b). We applied this method to the recognition of both the gentleness and the rhythm of the interaction. This method builds upon the Information Bottleneck Method, developed by Tishby and collaborators in (Tishby et al. 1999). It was tested both under laboratory conditions and in a real setting for robot –mediated play (i.e., a school with children with autism). Results showed a good capability of the method to make use of an existing temporal structure of the data, both for short term and long term scale events.

In work on (3), we have recently conducted a case study in the school with seven children with autism to compare the effect of a reactive robot versus an adaptive robot (using the Cascaded Information Bottleneck Algorithm in real-time). Results are currently being analysed.

Here we focus on *robot-mediated play for children with autism* and address three main directions:
(1) The design of new approaches for the play sessions – in other words: how are the play sessions best organized?; what precisely is the role of the experimenter in robot-mediated play?; what principles structure and regulate robot-mediated play sessions?
(2) The development of new computational methods to enable real-time recognition and adaptation of a robot to interaction styles.
(3) The investigation of the influence of the mode of an autonomous robot (reactive or adaptive) on the children's play styles through case studies.
The robot used in this study was the Sony Aibo robot which is safe to be used in this application. The work has been approved by the ethical committee of University of Hertfordshire.

3.1 A new approach for the play sessions inspired by non-directive play

We have developed a new approach inspired by non-directive play therapy, where the experimenter takes part in the experiments. The child is the leader for the choice and the rhythm of play, but the experimenter can regulate the interaction under specific conditions detailed in (François et al. 2008a). This approach is very much child-centred and encourages the children to progress differently, according to their specific needs, abilities and preferences. The progress of the children is analysed according to three dimensions: “Play”, “Reasoning” and “Affect”. “Play” is addressed through a play grid which classifies play situations in different levels, and enables to qualify the progress of the children qualitatively. The dimension “Reasoning” is analysed mainly according to the quadrology developed by Kahn et al. in (Kahn et al. 2003). The dimension of “Affect” is characterized by only obvious signs of like/dislike.
The method has been tested through a long-term case study with 6 children with autism. Results show that triadic play (child – robot - experimenter) was encouraged and children showed progressively more initiative-taking and proactive behaviours. Moreover, with respect to Play, children can be categorized into three groups. The first group is constituted by children mostly engaged in dyadic play with the robot. The second group is constituted by those initially playing solitarily and communicating mostly non-verbally but progressively experiencing more complex situations of verbal play and few pre-social or basic situations of play. The third group is constituted by the children who managed to play socially. Results shows that: a) children from the first group tended to progressively experience longer periods of uninterrupted play with the robot and started engaging in basic imitation during the last sessions; b) children from the third group and, at a more basic stage, those from the second group, tended to experience higher levels of play gradually over the sessions and constructed more and more reasoning related to the robot; they sometimes demonstrated specific reasoning on real life situations, too. Children from the second and third group tended to express verbally or physically some interest in the robot, including on occasions interest involving Affect.

3.2 A computational method for real-time recognition of Human-Robot Interaction Styles

The second part focused on computational methods that can enable a robot to adapt to different interaction styles. Here we developed a novel method for time series analysis, and more particularly, the recognition of tactile play styles, the Cascaded Information Bottleneck Method (François et al., 2008b). This method, which adopts an information theoretic approach, builds upon the Information Bottleneck Method, developed by Tishby and al. (1999). It relies on the principle that the relevant information can be progressively extracted from the time series with a cascade of successive bottlenecks, sharing the same cardinality of bottleneck states, but trained independently. This method is capable of extrapolating unseen cases - that is, time series which have not been used for the training- by an appropriate local extrapolation measure.
We applied this method to the recognition of both the *gentleness* and the *rhythm* in the kinesics of the interaction. It was tested offline both under laboratory conditions and in a real setting of robot-mediated play (i.e. in a school with children with autism). Results

showed a good capability of the method to make use of an existing temporal structure of the data, both for short term and mid-term time scale events (the percentage of mid term events correctly classified was 92% under laboratory conditions and 93% with data from child-robot interactions). The algorithm is capable of recognizing short term events very well with a very short delay (average of 0.17 seconds).
This methodology is entirely generic for applications with socially interactive robots (we only used the Aibo, but the approach is also applicable to other robots, including humanoids robots). Note, this method will be further developed and applied to humanoid robots as part of the final year of Robotcub and as part of the FP7 project RoboSkin that will probably start in 2009.

3.3 Influence of an adaptive robot (vs. a reactive robot) in children's play

We have recently conducted a case study in the school with seven children with autism to compare the effect of a reactive robot versus an adaptive robot (using a real-time algorithm). Here we want to see whether it is possible to guide the child towards more balanced levels of interactions by introducing a robot capable of reacting differently according to different tactile play styles. Again, here the robot used for the experiments is the Aibo robot, which reacts autonomously to tactile stimulations. The robot is on a "reactive mode" if it reacts in the same way whatever the intensity of the stimulation (i.e. whatever the stimulation is gentle or strong and whatever the rhythm of the interaction). In contrast, a robot is said to be in "adaptive mode" if it reacts differently according to the gentleness and the rhythm of the interaction, based on a reward for good frequency and a reward for gentle behaviours. Results of these experiments are currently being analysed.

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Appendices

A. Drumming with a Humanoid Robot: Results from Human-Robot Interaction Studies

B. Anticipating Future Experience using Grounded Sensorimotor Informational Relationships

C. Developing Action Capabilities in a Humanoid Robot using the Interaction History Architecture

D. A long-term study of children with autism playing with a robotic pet: Taking inspirations from non-directive play therapy to encourage children's proactivity and initiative-taking

E. Real Time Recognition of Human-Robot Interaction Styles with Cascaded Information Bottlenecks

Drumming with a Humanoid Robot: Results from Human-Robot Interaction Studies

Extended abstract

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Abstract

We summarise two human-robot interaction studies investigating a drumming experience with Kaspar, a humanoid child-sized robot, and human participants. Our aim[1] *is not to have Kaspar just replicate the human's drumming, but to engage in a 'social manner', i.e. in a call and response turn-taking interaction. The interactions are discussed in terms of imitation, turn-taking, and the effect of gender differences. This research is part of a project into developmental robotics with a particular emphasis of our work on gesture communication.*

1. Introduction

We present two exploratory studies investigating a drumming experience with Kaspar [1] and human participants. The primary goal of this work is to achieve *(non-verbal) gesture communication* between child-like humanoid robots and human beings, whereby drumming served as a test bed to study key aspects such as turn-taking and non-verbal gestures.

In the first presented study, turn-taking is deterministic and head gestures of the robot accompany its drumming to assess the impact of non-verbal gestures on the interaction [2]. The second study focuses on emergent turn-taking dynamics; here our aim is to have turn-taking and role switching which is not deterministic but emerging from the social interaction between the human and the humanoid [3]. Therefore the robot is not just 'following' and imitating the human, but can be the leader in the game and being imitated by the human. Details of the two studies summarized in this paper as well as related work can be found in [2,3].

[1] Acknowledgements: This work was conducted within the EU Integrated Project RobotCub ("Robotic Open-architecture Technology for Cognition, Understanding, and Behaviours"), funded by the EC through the E5 Unit (Cognition) of FP6-IST under Contract FP6-004370.

2. Using gestures as social cues

In this first study human participants played a rhythm which Kaspar tried to replicate, in a simple form of imitation (mirroring), by hitting the drum positioned in its lap. Then the human partner played again. This (deterministic) turn-taking continued for the fixed duration of the game. Kaspar did not imitate the strength of the beats but only the number of beats and duration between beats, due to its limited motor skills. Our primary focus was to study the possible impact that utilizing social gestures would have, not only on the game itself (in terms of performance), but also on the participant's subsequent subjective evaluation of the game.

We studied three conditions with increasing amounts of gesturing. In the first condition Kaspar did not use any gestures. Kaspar only imitated the drumming. This condition was called *no-gesture*. In the *gesture* game, simple head gestures and eye blinking were included in Kaspar's movements. Kaspar started drumming with one of the fixed gestures. If the human partners did not play their turn, then Kaspar as well did not do anything and the turn passed to the partner. In the *gesture+* condition, Kaspar simply repeated the sequence of gestures without playing even if the partners did not play their turn.

***Tests and results*:** The 3 conditions with all possible orders were tested with 12 adult participants (6 male and 6 female) who worked in computer science or similar disciplines at the University, and were overall not familiar with robots. .

According to the questionnaires, for the least preferred game type, there were significant differences due to gender ($\chi^2(1,11)=4.75, p= .03$). This difference manifests as males predominantly choosing the *gesture+* game type as their least preferred game type, while females predominantly chose the *no-gesture* game type as their least preferred game (Fig. 1).

According to the observed behaviours, although the error rate (describing how well Kaspar can replicate a human's drumming) in *gesture+* was less than in the *gesture* condition, male participants liked it the least overall. In contrast, although the error rate in *gesture+* was the highest, female participants liked it more than the *no-gesture* game which had the lowest error rate (Table 1).

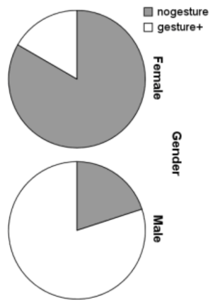

Fig. 1 A screen shot from the experiments (left) . Least preferred game type according to gender (right)

Table 1 Observed behaviour according to game type

Game type	Avg. error	
	Males	females
no-gesture	2.5 ± 2.7	2.7 ± 2.5
gesture	3.9 ± 3.6	3.1 ± 3.8
gesture+	3.0 ± 2.9	3.5 ± 3

While an exhaustive description of the qualitative analysis of the participants' responses is beyond the scope of this abstract, the above results are due to differences in task vs. interaction orientation between participants. Male participants tended to be more task oriented, while female participants tended to evaluate the interaction as a whole.

3. Emergent turn-taking dynamics

Timing plays a fundamental role in the regulation of human-human interaction. In the first study described above, some predefined fixed time duration heuristics were used for synchronization. Kaspar started playing if the human partner was silent for a few seconds. However, it was not always clear when the robot or human partner should initiate interaction in taking a turn. In this second study, we instead used a probability-based algorithm to control timing and turn-taking. The temporal dynamics of turn-taking thus emerged from the interaction between the human and the humanoid. Three simple models (threshold, linear, hyperbolic) were used to control the starting and stopping of the robot's drumming beats. This response was based on the duration of the previous turn and on the number of beats played in the previous turn by the interaction partners.

Our primary research interests were to study how different robot turn-taking strategies based on computational, probabilistic models impact the drumming performance of the human-robot pair, and the participants' subjective evaluation of the drumming experience. From the results of 12 participants, we observed in terms of subjective evaluation a significant difference between the first and third games in terms of order. Human participants got used to the game as they played more. In terms of observed behaviour, different models gave different amounts of playing time to Kaspar and the human participants, which affected participants' preferences. Most of the participants did not prefer a linear model because it gave them the least playing time, whereby Kaspar ignored them and played on its own which influences social interaction negatively. Some of the participants preferred to replicate Kaspar's drumming, and the "follower" and "leader" roles switched (unlike the first work (section 2), where Kaspar was always a "follower", and humans were always "leaders").

4. Conclusion

We presented the result of interaction games with 24 participants. Due to the small participant sample size the analysis is only descriptive.

In the first study Kaspar just repeated the beats produced by the human partner, and made simple fixed head gestures accompanying its drumming. The human partners' in return, perceived these simple behaviours as more complex and meaningful. Note, while Kaspar's drum playing did not change over time, and stayed the same in different games, the participants learned the limits of Kaspar and the rules of the game, and adapted themselves to the game better (future work will investigate this adaptation in more detail), so the success rate improved over time. It seems that participants were not passive subjects in this game, but unconsciously adapted their own behavior to the capabilities of the robot. In the second study involving emergent turn-taking dynamics, although we used very simple models, we were able to observe some very successful games in terms of coordinated turn-taking, and role switching emerging from social interaction between the human and the humanoid. These *gesture communication* studies can possibly be extended for use in the other robotic fields, e.g. entertainment, service robots, and educational/therapy robots.

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Anticipating Future Experience using Grounded Sensorimotor Informational Relationships

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Abstract

Operational definitions and applications of the sensorimotor *experience* of an artificial embodied organism are presented along with a mathematical metric for distance between experiences based on Shannon information. We describe a simple robotic experiment that illustrates how an artificial embodied agent can use its own history of experience combined with the experience metric to predict future experience. Present sensorimotor experience is used to find the most similar past experience using the geometry of its growing and changing experience metric space. This is then used to ground the ontogeny of autonomous prospective capability in interacting with the environment, e.g. to anticipate forthcoming changes in environment based on temporally extended past experiences.

Introduction

Increasingly, the importance of embodiment and situatedness within complex and rich environments are becoming recognized as a crucially important factors in engendering intelligence in an artifact (cf. for example Clancey (1997); Pfeifer and Bongard (2007), and the philosophical position regarding 'structural coupling' of Maturana and Varela (1987)). Living organisms in particular experience and re-experience particular recurring patterns of trajectories of interactions with the environment through their sensing and acting; and these habitual trajectories can form the basis of prospection, further development, and adaptation (Varela et al., 1991). [1]

Moreover, it is in how an artificial agent develops its capabilities over its life-time of interactions (*ontogeny*) that is important in building a *grounded* intelligence, able to adapt to unknown and changing environments (including long- and short-term variations in its embodiment and in its sensory or motor repertoire). Especially given the complexity of interactions in natural environments, and the richness of sensors available to modern robots, whose properties change over time in different environments or with changing embodiment, it is largely infeasible and impractical to attempt to foresee and model the situations a robot (or other artificial agent) may encounter and how to adapt to them in advance (e.g. Brooks (1999)). Instead, autonomous methods for bootstrapping development without prior knowledge of the structural coupling relationship based on enactive construction and development of intelligence behaviour warrant investigation, both from the perspectives of engineering applications as well as from the viewpoint of a generalized biology. Building on basic 'phylogenetic' capabilities, such an approach is hypothesized to allow for a basic of autonomous, enactive development in embodied models of developmental cognitive systems with expanded temporal horizon of their perception and action (Nehaniv et al. (2002),Vernon et al. (2007), Mirza et al. (2007)).

Our goal is to research methods that can be used by an artificial embodied agent to develop its capabilities through its ongoing interactions with its environment, while scaffolding its adaptation on the basis of previous experience and previously achieved adaptation. In earlier work we introduced formal mathematical metrics on sensorimotor experience and its geometry, as well as heir use as part of a developmental architecture for robots that bases future action on previous experience (Nehaniv, 2005; Mirza et al., 2005a, 2007). In this paper we present results from a robotic experiment that illustrates how a history of embodied experience, combined with a metric measure for comparing experiences, can be used to predict temporally extended future experience. This is an important result for our developmental architecture as it demonstrates the efficacy of the metric measure, and in turn its suitability for directing future action and behaviour based on the individual's past experience.

Other Related Work. Olsson et al. (2006) use information distance to develop basic sensorimotor maps in interaction with the environment, beginning from raw uninterpreted sensors. Independently of our work, Oates et al. (2000) have also described experiences as a time-series of multi-variate sensorimotor data (which is essentially identical to our operational definition of experience), but computing distance

[1]This work was conducted within the EU Integrated Project RobotCub ("Robotic Open-architecture Technology for Cognition, Understanding, and Behaviours"), funded by the EC through the E5 Unit (Cognition) of FP6-IST under Contract FP6-004370.

between time-series and clustering experiences to produce prototypes. Experiences are associated with the actions that initiated them, so robot can generalize about potential outcomes of its actions. Distances between experiences are calculated by using Dynamic Time Warping followed by measuring the area between the curves, and clusters formed by taking averages of time-warped experience curves. In contrast, our framework uses an information-theoretic metric on such experiences.

Kaplan and Hafner (2005) use information distances between sensors in an Aibo robot to compare simple behaviours of the robot. In that method, rather than reducing the dimension by summation within groups as we have done, they consider distances between different behaviours as distances between the full matrix of distances between all sensors. Long continuous examples of each behaviour (1000 timesteps) are used, and the whole sequence used rather than a moving window. The resulting distances between behaviours are shown as a projection onto a two-dimensional map, and they find that similar behaviours group together. This research supports the view that robot behaviour can be clustered using information relationships between sensor time-series. However, the incremental formulation of our approach allows us to propose a system that can be used for ontogeny, and the use of the experience metric allows for better comparison of past behaviour and experience.

Continuous Case-Based Reasoning (CCBR) (Ram and Santamaria, 1997) has many similarities to the approach described here. However, in our approach the information metric allows for a more robust comparison of sensorimotor details concentrating on the statistics of the particular time-series, and so better able to recognize regularities in time-series than a simple Euclidean metric. Also, the metric nature of the space is also able to recommend a number of increasingly distant matches (neighbours) and is able to weight their similarity along with a qualitative value from the environmental feedback to provide, potentially, more appropriate actions.

Sensorimotor Experience and Metric

A robot or other embodied agent's entire view of the world is experienced through its sensors, including those that measure internal factors such as temperature, actuator positions, and other more general internal variables. Any sensor can be modelled as a random variable $\mathcal{X}$ changing with time, taking values $X(t) \in \mathcal{A}_{\mathcal{X}} = \{x_1, \ldots, x_m\}$ from a probability distribution $\mathcal{P}_{\mathcal{X}}$. Time is taken to be discrete (i.e. t will denote a natural number). A robot's experience, then, can be considered as the stream of all readings $(X^1(t), \ldots, X^n(t))$ from all these variables $\mathcal{X}^i$ over a given time period (i.e. $t \in [t', t'+h]$ for some *temporal horizon* $h > 0$). This is a purely operational sensorimotor view of experience and, by itself, says nothing about the quality or meaning of that experience.

Formally, an agent's *experience* from time t over a temporal horizon h can be defined as

$$E(t,h) = (\mathcal{X}^1_{t,h}, \ldots, \mathcal{X}^N_{t,h}) \tag{1}$$

where $\mathcal{X}^1_{t,h}, \ldots, \mathcal{X}^N_{t,h}$ is the set of random variables available to the agent constructed or estimated according to time-series of sensorimotor readings from N sensorimotor variables $(X^1, \ldots, X^N)$ ending at time t with a horizon h timesteps (from time $t-(h-1)$ to t).

Experience Metric

Given a definition of Sensorimotor Experience and the information metric, a formal measure of distance between experiences can be defined. This is useful as it allows a direct, scaled comparison between different sets of sensorimotor readings of a robot or agent. A metric for comparison of sensorimotor experiences is important as it is then possible to talk of proximity and distance between different experiences in a quantitative and geometrically meaningful way.

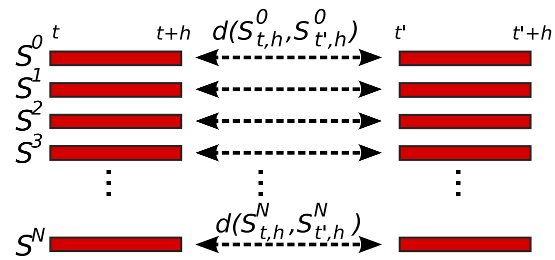

Figure 1: *Experience Metric.* A visual illustration of the experience metric. Each experience is shown as a collection of sensor readings of length h starting at time t and t'. The information distance between each respective sensor over time is summed to give the Experience Metric.

We define the *Experience Metric*, a metric on experiences of temporal horizon h, as

$$D(E, E') = \sum_{k=1}^{N} d(\mathcal{X}^k_{t,h}, \mathcal{X}^k_{t',h}) \tag{2}$$

where $E = E(t,h)$ and $E' = E(t',h)$ are experiences of an agent at time t and t' over horizon h, and d is the Crutchfield-Rényi information metric (Crutchfield, 1990), or more simply, the *information distance* between jointly distributed random variables. That is, $d(\mathcal{X},\mathcal{Y}) = H(\mathcal{X},\mathcal{Y}) - I(\mathcal{X},\mathcal{Y})$, where H denotes entropy and I denotes mutual information (see (Cover and Thomas, 1991) for an introduction to these concepts of information theory)[2]. D is measured in *bits*; see also Figure 1. That D is a metric follows from the fact that the metric axioms (equivalence, symmetry, and the triangle

[2] $d(\mathcal{X},\mathcal{Y}) = 2H(\mathcal{X},\mathcal{Y}) - H(\mathcal{X}) - H(\mathcal{Y})$ and is estimated directly from the frequency distributions of binned sensor values.

inequality) hold for each of the components in the summation, since d is a metric (Nehaniv, 2005). For a visual proof that d (and hence D) is a metric, see (Nehaniv et al., 2007).

Earlier Experiments

In Mirza et al. (2005b) we describe an experiment showing ball-path prediction using the experience distance measure. In that experiment an Aibo robot (see Figure 2 and below) remained stationary while a ball was moved in view of its head mounted camera. The predicted ball path was plotted in real-time overlaid on the images from the camera. This experiment illustrated that sensor experience can be used to match experience successfully. This experiment builds on that result, but uses the full embodied experience to match previous experience. The camera images do not, by themselves, give information about the position of the ball so self-experience is important.

Experiment

Interactive Path Prediction

A simple robotic experiment was devised that would illustrate how an artificial embodied agent can use its own history of experience combined with the experience metric described above to predict future experience. The robot follows the motion of a ball moved in front of it by using a simple reactive behaviour to adjust its head motors to attempt to centre the ball in its field of vision. The robot continually builds a metric space of experiences from its ongoing sensorimotor experience, including its own proprioceptive sense of movement arising through interaction with the environment. A closest historical experience, in terms of experience distance, to the current one is then found. Experiences temporally following the historically closest experience then provide a model for anticipation of future experience. How good this model is depends on both the predictability and consistency of the environmental interaction as well as how "good" the historical matching is. Thus, the analysis of the experiment focuses on measuring how well matched the historical experience is to the current one. Note that predicting the trajectory of the tracked object corresponds to prospection regarding part of a future temporally extended interval of sensorimotor experience.

It is important to note that, the robot is not matching current ball position with previous ball position, rather all sensory and motor variables are used as information sources to detect similarity between experiences.

Implementation and Experimental Setup

The robot used was a Sony Aibo ERS-7. The control and sensory collection software was implemented in Java with URBI (Baillie, 2005) providing the robot control layer and ball detection. Sensor readings are sent over wireless to a personal computer approximately every 80-120ms. Reception of each frame of data defines a *timestep*. Video images were received from the robot head camera approximately every 400ms, however visual sensors were computed at the rate of the sensor data using the most recent image from the camera. Experiences were formed from data streams from 33 internal sensors (including proprioceptive motor positions and infrared distance measurements, and 9 sensors formed from average pixel values in a 3×3 grid over the image.

Figure 2: *Sony Aibo ERS-7, and Pink Ball*

The robot was stationary in a "sitting" position, with the head pointed forward (Figure 2). A pink ball was moved in the air in view of the robot's head camera at a distance of approximately 30cm. No particular effort was made to "sanitize" the environment to aid ball-detection against the background. Thus, it is likely that other items in the environment provided potentially useful information about any interaction. The robot executes a continuous reactive behaviour to follow the motion of a ball with its head. The algorithm is simple, making appropriate incremental adjustments to the neck, headTilt and headPan motors, such that the position of the ball is brought closer to the centre.

The metric space creation and prediction was implemented in Java and ran on-line in real-time. The horizon length of the experiences was $h = 20$ timesteps or approximately 1700ms. The data was quantized into $Q = 10$ bins in the probability distribution estimation algorithm.

The ball was moved such that the time for the ball to describe a circle (or to move horizontally or vertically for a complete cycle) was 6-7 seconds. Thus the horizon length was shorter than, but of the same order of magnitude as, a single cycle of the repeated behaviour and the experiences would comprise approximately a half of a cycle.

The full interaction sequence lasted 965 timesteps (~ 84 seconds) constituting 945 experiences of horizon length $h = 20$. The movements of the ball consisted of a number of horizontal and vertical movements, and a number of clockwise circles; see Table 1.

Visualizing Ball Path: A projection of the current ball position relative to the robot is plotted in two dimensions by estimating the direction in which the head is pointed from

Table 1: Path Prediction Experiment - Sequences of Movements (TS denotes time step number)

Start TS	End TS	Movement Type	Iterations
91	185	Horizontal, Left to Right	2 full
201	272	Vertical movements, Top to Bottom	2 full
283	361	Horizontal, Right to Left	1 full
376	453	Vertical, Top to Bottom	2 full
463	534	Horizontal, Right to Left	1 full
548	593	Vertical, Top to Bottom	1 full
607	852	Circular, Clockwise	4 full
866	929	Vertical, Bottom to Top	2 full

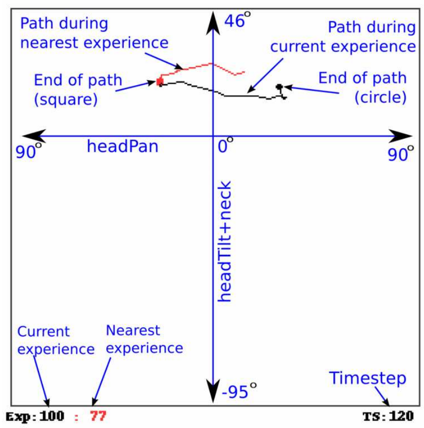

Figure 3: *Ball Path Traces.* The diagram shows the parts of the ball path diagrams used to visually analyse the traces of the ball in a neck-centred coordinate system derived from motor positions. See Figures 6 and 7.

the positions of three motors contributing to head motion. The coordinates for the ball position in the plot are given by:

$$(x, y) = (W \times headPan, H \times (headTilt + neck)/2)$$

where W and H are the image width and height, and $headPan, headTilt$ and $neck$ are the motor values at any instant normalized into the range $(0, 1)$. See the explanatory diagram of Figure 3. Note that the plots are created for analysis of the experiments, and this abstraction of the sensoriomotor flow is *not* available to the robot. Instead it allows us as external observers to gain insight into what the robot 'expects' will happen in an interval of the near future based on its own previous experiences, and how accurate these expectations are (again to an external observer).

Error Measurements: Two different measurements of path error were used. The first measured the sum of the Euclidean distance between each corresponding point of the paths. The second calculated a vector direction for each path and returned the angular difference in radians between the vectors as the error.

Table 2: Improvement of Experience Matching Over Time

Type	Iteration	Number $< \pi/4$	Total Number	Percentage $< \pi/4$
HORIZ	1	0	41	0.0%
HORIZ	2	27	73	37.0%
HORIZ	3	25	75	33.3%
HORIZ	4	27	72	37.5%
VERT	1	0	34	0.0%
VERT	2	8	51	15.7%
VERT	3	15	30	50.0%
VERT	4	42	61	68.9%
VERT	5	32	52	61.5%
VERT	6	27	49	55.1%
CIRCLE	1	9	65	13.8%
CIRCLE	2	13	54	24.1%
CIRCLE	3	27	66	40.9%
CIRCLE	4	31	63	49.2%

Results and Analysis

Figures 4 and 5 show, using different methods of error estimation, the error between the current path and the path corresponding to the nearest previous experience in terms of information distance. Figures 6 and 7 show traces of the paths from experiences in regions where horizontal and vertical movements were taking place. As can be seen from the traces, which are selected from regular intervals, it is often the case that the paths are similar and so the experiences are well matched. However, the objective measure of error indicates that the actual path is not exactly the same. This is to be expected as there do not exist any *precisely* identical experiences in a real situation.

The opposite direction path (but of the same type) is regularly matched. As the sensors are not biased left or right, and the experience distance measure is the sum of information distances between variables, then a symmetric error such as this is likely. Indeed, such experiences are *informationally* very close to their 'opposites'. Out-of-phase periodic variables can have a small or zero[3] information distance.

In terms of angle, the error is less than $\pi/4$ (*i.e.* closer to parallel than orthogonal) 55.13% of the time and is greater

[3]Variables that have a zero information distance are *recoding equivalent* and are not necessarily identical (see Crutchfield, 1990).

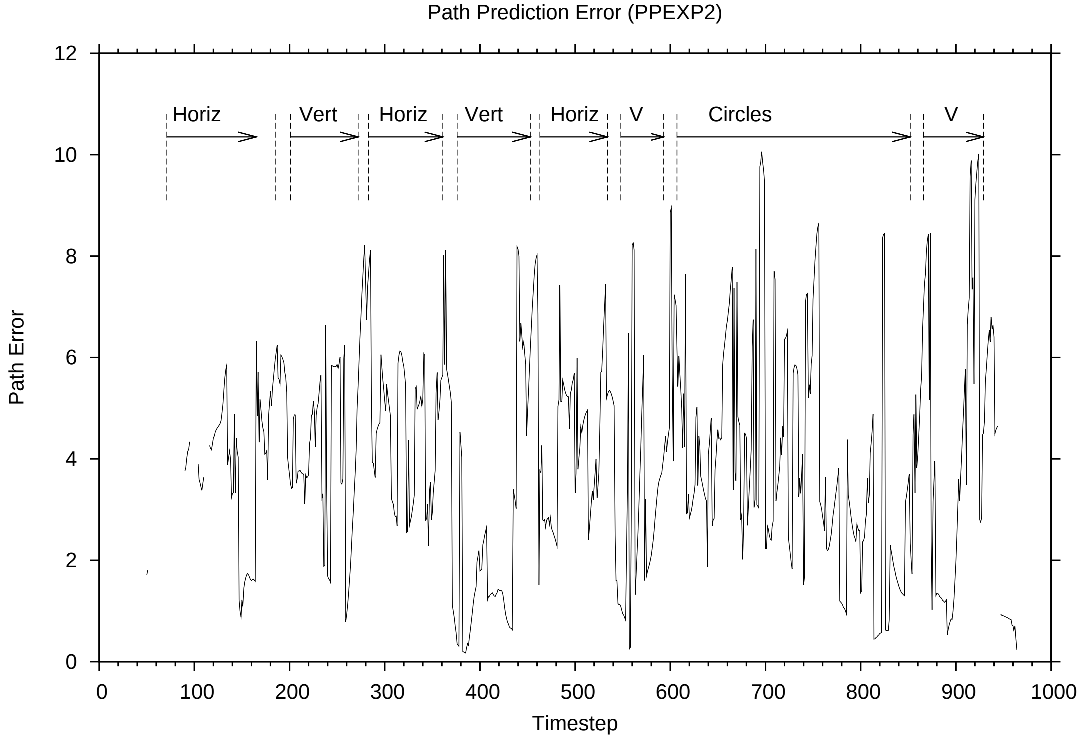

Figure 4: Euclidean distance (error) between the paths of the ball during the current and nearest previous experience. The error is often exaggerated as experiences of paths of the same type but opposite direction are often matched. The top part of the graph shows the behaviour (See Table 1). The *Path Error* (pixels) in this case is the sum of the Euclidean distance between corresponding points. Temporal horizon $h = 20$, number of bins $Q = 5$.

than $3\pi/2$ (*i.e.* closer to opposite than orthogonal) 29.21% of the time. This indicates that the path and therefore the experience is generally well matched, however due to the nature of the measure, experiences from the opposite phase in a cycle are often selected. This error is compensated for in Figure 5 by reflection about $\pi/2$. It is interesting to note the opposite phase corresponds to time-reversed motion, and that the present metric relies on probability distributions constructed from sensorimotor flow and that these distributions do not encode the directionality of time.

Examining the progression of the error over time in these data, one would expect to see an improvement as the same kinds of behavioural interaction are re-experienced. How the matching of experiences improves over time is examined, referring to Table 2 and Figure 5. During the horizontal motions after one full cycle, 37% of experiences can be matched to similar ones in the history. Vertical motions show that the success rate peaks at 68.9% with the 4th presentation. The success rate drops slightly thereafter as there are more experiences to select from. The Circle movements also show marked improvement as experience grows. The initial 13.8% success rate of the very first circular motion reflects the fact that parts of the circular motion are being matched with previous horizontal and vertical experiences, with some limited success, even before any such motions had been observed.

Conclusions

The work describing the construction and use of information metrics for the comparison of robot behaviour demonstrates achievement of a degree of temporally extended prospection by an embodied agent, based on its raw sensorimotor experience. The experience metric was first described in (Mirza et al., 2005a) and with mathematical proofs of the mathematical metric properties along with some alternative metrics on experience in (Nehaniv, 2005). As mentioned, an operational formulation of experience (but not of the metric) was previously described in (Oates et al., 2000). A non-metric measure of distance between experiences was described there that used the area between time-warped experience curves. The fact that independent research groups both developed essentially the same notion operationalizing an agent-centred definition of experience suggests that this definition is a natural one.

Experiments were described that use fairly large numbers of robotic sensors to describe robotic experience such that a simple sort of prediction can be achieved by the matching of present experience with experiences in the history and

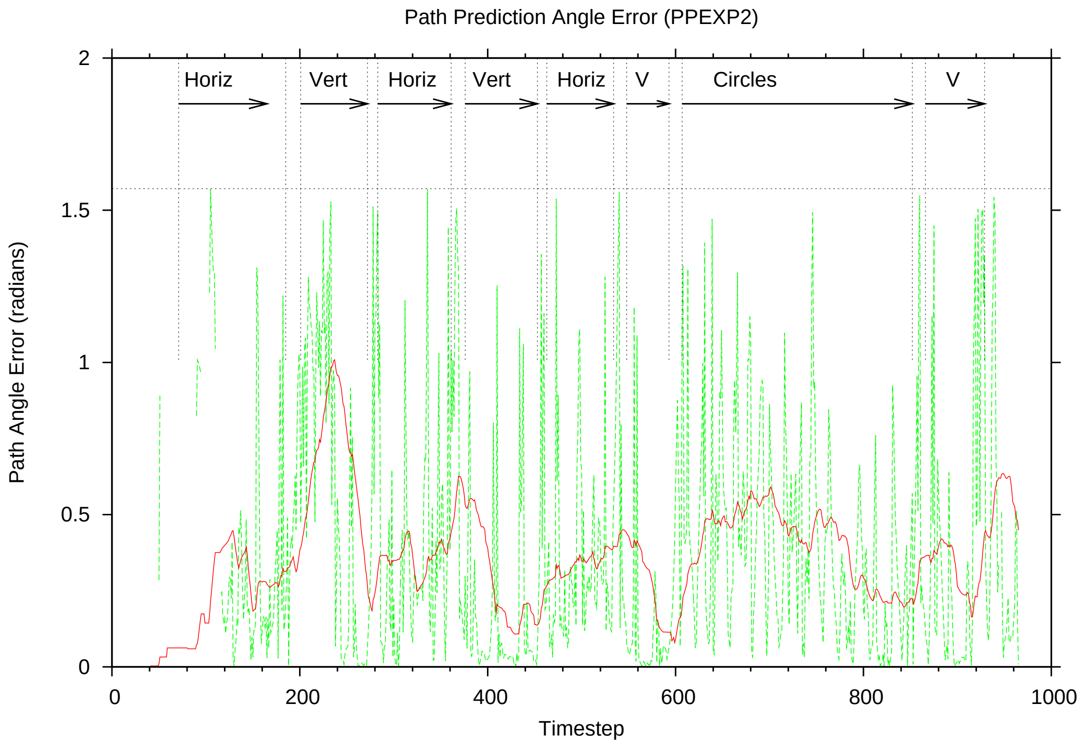

Figure 5: Angle error and the average angle error (over the last 40 timesteps) between the paths of the ball during the current and nearest previous experience. The graph shows the error reducing, on average, *within* a given behaviour sequence. The top part of the graph shows the behaviour (See Table 1). The *angle error* is the difference in radians between the vector direction of each path. For errors$>\pi/2$, $\pi - error$ is shown (reflection about $\pi/2$). Temporal horizon $h = 20$, number of bins $Q = 5$.

extrapolating forward from the matched past experience. It was found that *proximity in terms of experience metric corresponds well with an external observer's notion of similarity of experience.* Future research may consider using the anticipated experience for active perception and in human-robot interaction.

The sensorimotor variables were treated by the autonomous robot in an uninterpreted "agnostic" manner, that is, no sensor is regarded as being different from any another or special in any way, in terms of finding close experiences. This performance was achieved despite many of the sensors not providing any seemingly useful information about the current experience. Proprioceptive motor experience was important in this experiment in determining the experience and matching it to the appropriate past experience.

The capability of the experience metric to find suitable matching experiences was found to increase as more examples of a particular type of behaviour were presented. This appears to level-off, and potentially become worse as more examples are presented. However, the experiments described had too short a run time for a definitive conclusion to be drawn on the latter observation. Another important aspect of the experience metric is that it appears to confuse a behaviour with its 'opposite' (phase-shifted or time-reversed counterparts), as these are informationally nearly identical. This can be seen clearly in both the simple and interactive ball-path prediction experiments as opposite direction of path.

Needless to say, the ontogeny of prospective ability of children and other mammals is an extended process lasting years and we cannot yet hope to mirror its complexity and success in artificial systems, although the work presented here suggests that we have made a small start in this direction.

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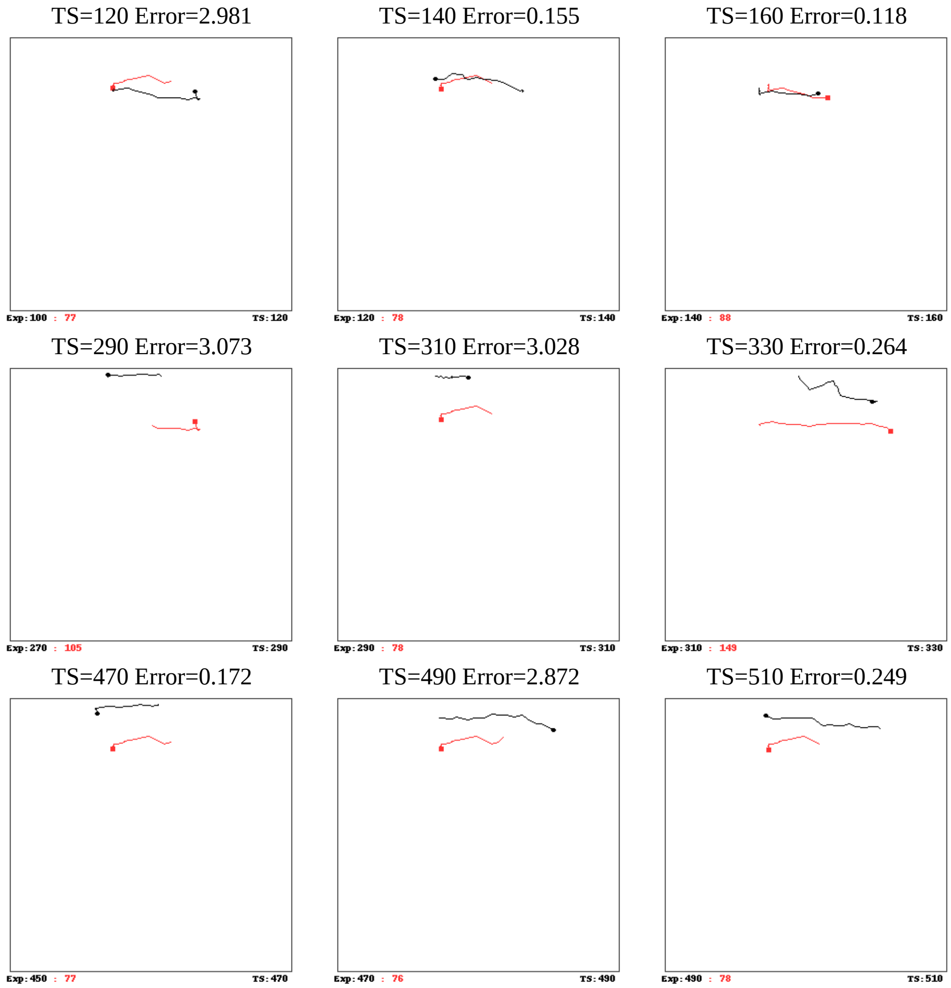

Figure 6: *Head Movement Traces and Matched Historical Traces for Prediction.* Images are from evenly spaced timesteps from three separate *horizontal* movement regions starting at timestep TS=120, 290 and 470. Each diagram shows the path of the ball, as determined by robot head movements, for both the current experience at that timestep (dark line) and for the matched (nearest previous) experience (red/grey line). Path direction indicated by circle/square at the end of the path. (See Figure 3). The angle error between the path directions is used to analyse how well the path and thus experience are matched. Temporal horizon $h = 20$, number of bins $Q = 5$.

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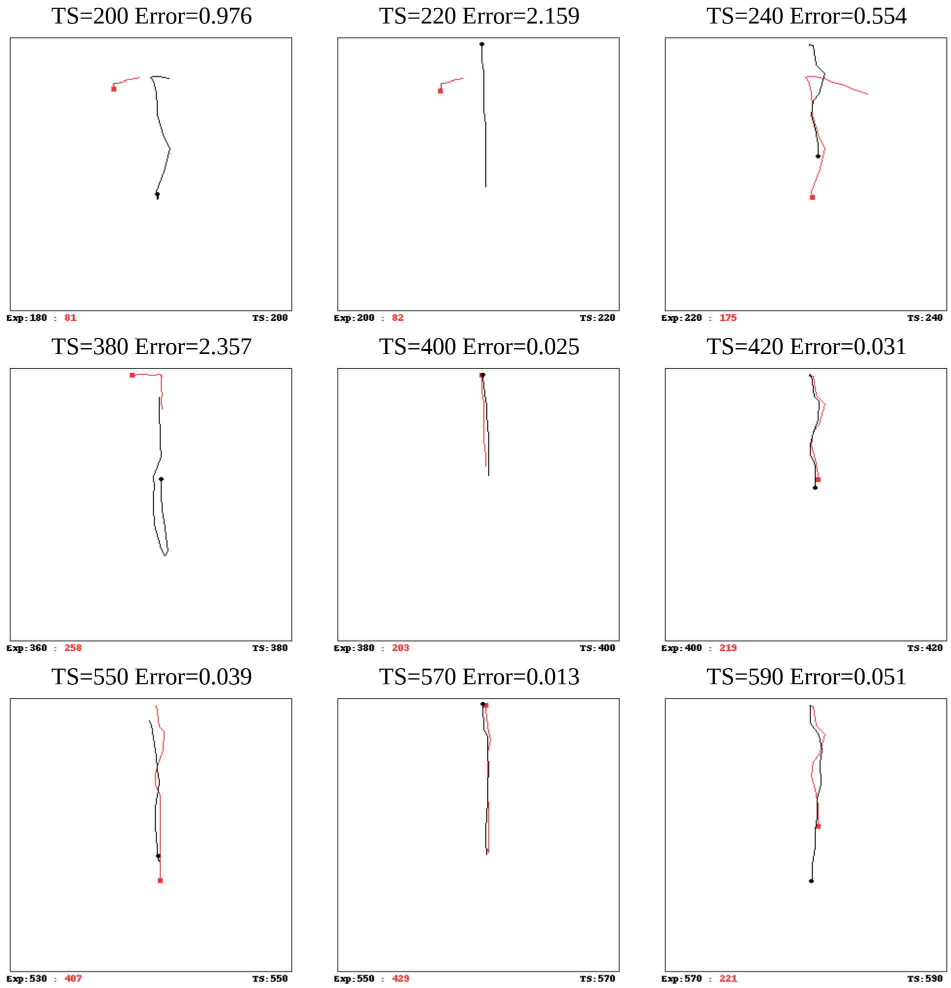

Figure 7: *Head Movement Traces and Matched Historical Traces for Prediction.* Images are from evenly spaced timesteps from three separate *vertical* movement regions starting at timestep TS=200, 380 and 550. Each diagram shows the path of the ball, as determined by robot head movements, for both the current experience at that timestep (dark line) and for the matched (nearest previous) experience (grey line). Path direction indicated by circle/square at the end of the path. (See Figure3). The angle error between the path directions is used to analyse how well the path and thus experience are matched. Temporal horizon $h = 20$, number of bins $Q = 5$.

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Developing Action Capabilities in a Humanoid Robot using the Interaction History Architecture

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***Abstract*— We present experimental results for the humanoid robot Kaspar2 engaging in a simple "peekaboo" interaction game with a human partner. The robot develops the capability to engage in the game by using its history of interactions coupled with audio and visual feedback from the interaction partner to continually generate increasingly appropriate behaviour. The robot also uses facial expressions to feedback its level of reward to the partner. The results support the hypothesis that reinforcement of time-extended experiences through interaction allows a robot to act appropriately in an interaction.**

I. Introduction

This paper reports the results of an experiment showing a humanoid robot (Kaspar2 - Fig 1) using its history of interaction to acquire the ability to engage in the early interaction game "peekaboo" with a human interaction partner. The robot is a simple upper-body humanoid that can display a range of facial and bodily expressions. The peekaboo engagement is developed by the robot using the Interaction History Architecture, a developmental control architecture based on the grounded history of sensorimotor interactions.

In earlier experiments (see [1]), this architecture was shown to be capable of supporting development of a turn-taking interaction in a non-humanoid robot which took appropriate sequences of actions or gestures based on its own grounded sensorimotor experience. This new experiment uses interaction history-based control architecture, relying on temporally extended grounded sensorimotor experiences, deployed on an expressive an expressive humanoid for the first time. The humanoid embodiment enhances the richness of the possible interaction for instance by adding the ability to feedback reward through facial gestures. An audio modality is also added to the visual and other sensorimotor data, and is employed in perception of reward along with face recognition. Furthermore, for the first time in a robotic platform, we show how continual modification of the space of experiences through merging and forgetting builds a more adaptive and focused interaction history.

A. Interaction Histories

We define an interaction history for an embodied agent as *the temporally extended, dynamically constructed, individual sensorimotor history of an agent situated and acting in its environment, including the social environment, that shapes current and future action* [1]. The history is grounded in the sensorimotor coupling of the agent with its environment and therefore the development of the action capabilities of an agent based on such a history are also grounded and meaningful from the agent's perspective.

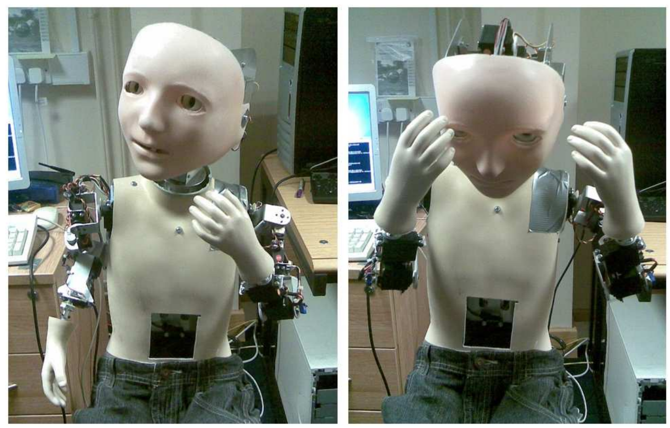

Fig. 1. The Kaspar2 robot (University of Hertfordshire) has two 5 DoF arms, a 3 DoF neck, two coupled 2 DoF eyes containing colour cameras and a flexible face actuated by two further motors at the mouth.

This aligns with the "embodied cognition" hypothesis, that "*cognition is a highly embodied or situated activity and suggests that thinking beings ought therefore be considered first and foremost as acting beings.*" [2]. Lakoff & Johnsson [3] also argue that all cognition, including representations and memory of categories, eventually grounds out in embodiment and Glenberg [4] also argues that the purpose of perception and memory for the natural environment is to guide action, and that even abstract concepts can be interpreted in terms of physical actions and properties. In general we can say that memory *manifests* itself as embodied action of some kind. That is, it is in actions resulting from recall that one witnesses memory and that recall itself is dependent on embodiment.

Autonomous embodied artificial agents that make use of interaction histories in guiding their actions can be thought of as extending their temporal horizon beyond that of a simple *reactive agent* and become *post-reactive* systems when acting with respect to a broad temporal horizon by making use of temporally extended episodes in interaction dynamics [5].

We hypothesize that a dynamically constructed history that is used to generate and select actions in an embodied agent can also serve as the basis for *ontogenetic development* of the agent. Self-organization (merging and deletion of) experiences in the history can provide abstraction as well as anticipation [6]. Development in this case can be seen as *the increasing richness of the connections of experience with action*, mediated by suitable mechanisms. Such a history can facilitate incremental development at the borders of experience (*cf.* Vygotsky's "zone of proximal development" [7])

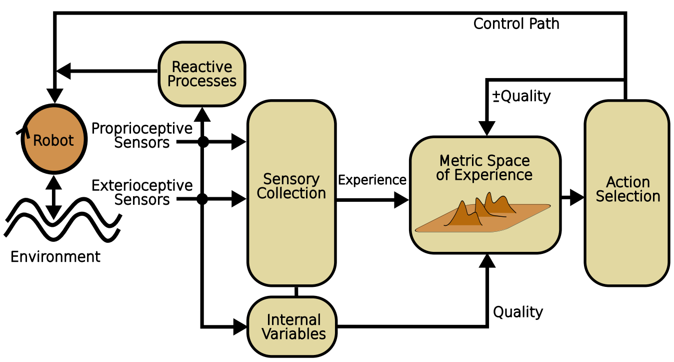

Fig. 2. Schematic of the Interaction History Architecture

II. Interaction History Architecture

The Interaction History Architecture is shown schematically in Figure I-A. The approach is as follows:

1) to continually gather sensorimotor data and find "suitable" episodes of sensorimotor experience in the history *near* (in terms of the experience metric) to the current episode;
2) depending on the course of subsequent experience, to choose from among actions that were executed when these episodes were previously encountered;
3) where no suitable experiences are found, to choose random actions.

There are two key aspects of this architecture. The first is the *metric space of experience* whereby new experiences appear as points in a growing and changing high-dimensional metric space. The metric space is enhanced with *quality* information, potentially received from the environment, from internal drives or from other sources such as affective state. Each experience is also associated with actions executed during the experience. The second is the *action selection* system. This "closes the perception-action loop" and also closes an internal loop feeding back and modifying the experience space. The quality associated with each experience combined with proximity in the metric space is used to select experiences from the history and select actions associated with those experiences.

A. Interaction History Space

Briefly[1], the *Interaction History Space* consists of:

Sensorimotor Experiences: Time-series of sensor readings from all available sensors of a robot, from time t to another time $t+h$ where h is the *horizon length* of the experience.

The Experience Metric: A metric measure of distance between sensorimotor experiences. Based on an information-throetic measure of distance between sensor time-series viewed as values of random variables. (Crutchfield-Rényi Information Metric [8]).

Next Action information: The next action executed after an experience is associated with that experience.

Quality information: A value representing environmental reward received after the experience (for a particular time span).

Thus the metric space of experience in the Interaction History Architecture, the *interaction history space*, can be described by the tuple $(\boldsymbol{\epsilon}, \boldsymbol{D}, \boldsymbol{q}, \boldsymbol{a})$, where $\boldsymbol{\epsilon}$ is a collection of quantized "experiences", $\boldsymbol{D}$ is the a matrix of distances between elements of $\boldsymbol{\epsilon}$, $\boldsymbol{q}$ is a vector of quality values and $\boldsymbol{a}$ a vector of actions.

The metric space is constructed continuously as the robot experiences its environment. A new experience is created every *Granularity* G timesteps, and consists of Horizon h timesteps counting back from the current timestep. Where $h > G$ the experiences will overlap. Each sensor reading is quantized into Q evenly-sized bins. Each new quantized experience is compared to other experiences in order to determine its neighbours. This process, if all experiences are compared, results in a distance matrix between experiences which defines the structure of the metric space as it is experienced by an individual robot.

B. Action Selection

A simple mechanism is adopted for action selection whereby the robot can execute one of a number of "atomic" actions (or no action) at any timestep. The actual action selected will either be a random selection of one of the atomic actions, or will be an action that was previously executed *after* an experience in the history. Both "quality" and proximity to the current episode in the space affect the chance of an historical experience (and therefore action) being selected.

This process ensures the robot may still choose a random action as this may potentially help to discover new, more salient experiences This has the advantage of emulating body-babbling, i.e. apparently random body movements that have the (hypothesized) purpose of learning the capabilities of the body in an environment [9]. Early in development, there are fewer, more widely spread experiences in the space, so random actions would be chosen more often. Later in development, it is more likely that an the action selected will come from past experience.

[1]For further details see [1].

An advantage of this approach is that behaviour can be bootstrapped from early random activity, and later behaviour built on previous experience.

1) Roulette-Wheel Action Selection: An experience is selected from K *candidate experiences* near to the current experience $E_{current}$. The chance of random action selection is also represented in that list. The probabilities are calculated using a "gravitational model" where each experience is represented as a point mass a particular distance from $E_{current}$. The probability of selecting an experience E_i from $E_1, \ldots, E_K$ is:

$$p_i = \frac{m_i q_i}{D(E_{current}, E_i)^2} \tag{1}$$

where q_i is the *quality value* of E_i, m_i is the mass (*i.e.* how many experiences have been merged into this experience) and $D(E_{current}, E_i)$ is the experience distance[2].

The chance of random is added to the list as:

$$p_0 = \frac{\sum_{i=1}^{K} p_i}{(r_{max}/\tau)^2} \tag{2}$$

where r_{max} is the radius of the ball that includes the ranked experiences and τ is a *temperature* factor, that controls the chance of random action selection.

Then the weighting on the "roulette wheel" is given by:

$$w_i = \frac{p_i}{\sum_{i=0}^{K} p_i} \tag{3}$$

C. Update of Environmental Reward

The quality value q has bearing on the selection of the experience, and in turn on the action-selection process. The quality value is intended to reflect how useful the experience is in terms of positive or negative environmental feedback, and is derived directly from the internal reward function or an external reward measured by the robot's sensors.

In the simplest case, the immediate (instantaneous) reward received from the environment is associated with the current experience. An alternative scheme is for the quality associated with an experience to be dependent not only on the current reward, but also on the future reward. In the present implementation the *future reward* for an experience $E_{t,h}$ for some given horizon h_{future} is the maximum reward over the next h_{future} following the experience.

D. Merging and Deletion of Experiences in the Interaction History Space

It is necessary to employ strategies such as *merging* and *forgetting* if storage and computation requirements are to be controlled. However, employing such a strategy also provides a powerful mechanism for continually changing and adapting the experience space and is therefore of fundamental importance.

The merging strategy is to merge any two experiences closer than a threshold T_{merge}. T_{merge} was fixed for the most part, however alternative strategies were trialled during development of the algorithm, including adapting the threshold such that the maximum number of experiences in the space remained constant.

The meta-information associated with experiences that are merged are also assimilated. Actions from both merged experiences are accumulated, resulting in an action probability distribution; the quality values are averaged; and, a weight value, indicating the number of experiences that have been merged together, is set to the sum of the weights of the merged experiences.

Experiences may also be deleted, that is, forgotten. There are a number of different strategies to decide which experiences should be forgotten, and the one used here is to forget those experiences which have lower quality values and thus will have little or no impact on future action selection. Specifically, experiences older than h_{future} with a quality less than or equal to T_{purge} will be deleted.

[2]The "Experience Metric" -see [10].

III. Development using Interaction Histories Through Playful Interaction

We describe an experiment that illustrates how a robot can develop action capabilities based on its history of interaction with the environment through the use of the architecture presented. The scenario is a simple communicative interaction game, "peekaboo", that uses simple non-verbal gestures. The peekaboo game as a research tool is discussed, followed by a description of an experiment using an upper-body humanoid robot that uses its interaction history to develop the capability to engage in a peekaboo interaction with a human partner.

A. Peekaboo as a Research Tool

The development of gestural communicative interaction skills is grounded in the early interaction games that infants play. In the study of the ontogeny of social interaction, gestural communication and turn-taking in artificial agents, it is instructive to look at the kinds of interactions that children are capable of in early development and how they learn to interact appropriately with adults and other children. A well known interaction game is "peekaboo" where classically, the caregiver having established mutual engagement through eye-contact, hides their face momentarily. On revealing their face again the care-giver cries "peek-a-boo!', "peep-bo!", or something similar. This usually results in pleasure for the infant which, in early development, may be a result of the relief in the return of something considered lost (*i.e.* the emotionally satisfying mutual contact), but later in development also may be a result of the meeting of an expectation (*i.e.* the contact returning as expected along with the pleasurable and familiar sound), and the recognition of the pleasurable game ensuing [11].

Bruner and Sherwood [12] studied peekaboo from the viewpoint of play and learning of the rules and structures of games. They also recognize that the game relies on (and is often contingent with) developing a mastery of object permanence as well as being able to predict the future location of the reappearing face.

In relation to the development of social cognition in infants, "peekaboo" and other social interaction games, that are characterized by a building and then releasing of tension in cyclic phases, are important as they are considered to contribute developmentally to infant understanding and practise of social interaction. Peekaboo provides the caregiver with the scaffolding upon which infants can co-regulate their emotional expressions with others, build social expectations and establish primary intersubjectivity [13].

B. Peekaboo with the Humanoid Robot Kaspar2

We describe an experiment that demonstrates how a robot can use its history of interactions with a human partner to engage in the peekaboo game. The implementation audio used both as an extra sensory modality as well as an additional environmental reward feedback for the peekaboo game that results directly from the human-robot interaction.

1) Method: The robot and human partner[3] were positioned facing each other at a distance of a few feet, with their eye-level at approximately the same height. The robot control software was started with the interaction history containing no previous experiences. Interaction then commenced with the robot executing various actions and the human offering vocal encouragement when it was thought appropriate. The interaction then continued for approximately two to three minutes.

Three different conditions were tried. Firstly, any hiding action was encouraged with a call of "peekaboo" when the robot revealed its face again. The second condition encouraged an alternative actionand the final condition was to offer no vocal encouragement at all during the interaction.

The experimental hypothesis was that encouraging the hiding action would result in a higher rate of peekaboo sequences than would be expected from random action selection. Furthermore, this should also be the case when other actions are encouraged instead. Finally, this hypothesis was also tested by the no-encouragement condition with the expectation that no action would be selected in preference to any other.

2) Interaction History Architecture Components and Settings: **Metric Space of Experiences:** The sensor rate during these experiments resulted in an average timestep length of approximately 300*ms*. Experiences were created every $G = 2$ timesteps - permitting real-time creation of the metric space, quantizing the sensor data into $Q = 5$ bins. The horizon h for experiences was either 16 or 20 depending on the run. Quality was assigned to experiences as the maximum environmental reward received in the subsequent $h_{future} = 32$ or $h_{future} = 40$ timesteps (again, depending on the run). These values were chosen as reasonable values, the horizon approximately matching the duration of a single behavioural sequence.

The thresholds for merging and deletion were set at $T_{merge} = 0.6bits$ and $T_{purge} = 0.9bits$ respectively. With these values, a combination of the merging and forgetting processes resulted in a manageable sized metric space for real-time operation.

Action Selection: The closest $K = 4$ neighbours of the current experience within a radius of $r_{max} = 2.0$*bits* of $E_{current}$ were considered in the action-selection process.

3) Motivational Dynamics: In this experiment, motivation feedback (reward) is provided through two mechanisms: observation of a face, and audio feedback.

Face: Human-like faces were detected in the robot's camera image[4] and this provided direct positive reward R_f, constrained to be in the range $[0, 1]$. Habituation causes this reward to drop-off over time.

Sound: Sound was captured from a microphone, and used both as an additional sensory signal as well as providing further environmental reward. The sum of the amplitudes of the sound signal samples over the period of a timestep, ε_{sound}, provides a new sensory input to the robot and is normalized to the range [0,1].

Resulting Reward Signal: The final reward signal R generated by the robot in response to it's environmental interaction is a combination of the sound and face reward signals. $R = \max(1, \alpha(R_f + R_s))$ where α, in the range [0,1] attenuates the reward signal and is set at 0.75 for this experiment meaning that neither reward signal on its own can result in a maximum R, but requires support from the other reward signal.

4) Experimental Materials and Methods: **Robot:** The robot used was the upper-body humanoid Kaspar2 robot created at the University of Hertfordshire, see Figure 1. The robot has 17 individually controlled DC servo motors: three in the neck controlling head orientation, two controlling the coupled eyes, two controlling the mouth for facial expression, and five controlling each arm. The interaction history architecture and control software was written in C++ as multiple interacting modules, with the communication layer and abstraction of hardware control provided by the YARP framework [15].

Actions:

A total of 17 actions were available to the robot, and these can be considered in 3 groups: movement actions, facial expressions and resetting actions. These are listed in Table I. The types of action that the robot can execute at any time depends on which action was last executed. This is so that the robot does not attempt to execute actions that could possibly damage it. The configuration therefore defines the set of next actions possible after any given action and the action selection process is responsible for ensuring that these conditions are met.

5) Defining a Peekaboo Sequence: A "peekaboo" sequence is defined to be a sequence of actions beginning with the robot hiding its face (action 6 - HID), followed by any number of "no-action" actions (action 7 - NA) and ending with the robot back in the resting position (action 0 - Rst). Furthermore, for the purposes of evaluating the results of this experiment the actions should be selected from previous experience rather than executed randomly.

[3]Note that for all these experiments the lead author took the role of the human partner and so was fully aware of the capabilities of the robot and of the software.

[4]Using the OpenCV library implementation [14] of Viola-Jones HAAR cascades.

TABLE I

KASPAR2 PEEKABOO: ACTIONS

Group	Number	Action	Description
Movement Actions	3	HL	Head Left
	4	HR	Head Right
	6	HID	Hide Head with Hands
	8	RAU	Right Arm Up
	9	LAU	Left Arm Up
	12	RAW	Wave Right Arm
	13	LAW	Wave Left Arm
	14	TR	"Think" Right - raise right arm to chin and look right
	15	TL	"Think" Left - raise left arm to chin
Facial Expressions	1	Smi	Smile
	2	Neu	Neutral
	16	Frn	Frown
Resetting Actions	0	Rst	All motors to resting position
	7	NA	No Action
	5	HF	Head to forward position
	10	RAD	Right Arm Down
	11	LAD	Left Arm Down

To measure the relative amounts of peekaboo in any given period of behaviour, $p_{sel}(A^{HID})$, the percentage of times the hiding action was *selected* as compared to other "movement" actions, was used as a measure and is calculated as follows. Given N possible actions $\{A^1, A^2, \ldots A^N\}$ and a period of behaviour consisting of K actions executed (selected or random), action A^n will be executed $F(A^n) = F_{rand}(A^n) + F_{sel}(A^n)$ times, where F_{rand} indicates the frequency of random executions and F_{sel} the frequency of the action being deliberately selected. Then the percentage of times the Hiding action A^{HID} was selected is given by $P_{sel}(A^{HID}) = 100F_{sel}(A^{HID})/K$ Note that for the purpose of evaluating "peekaboo", only actions in the "movement actions" group were considered (see Table I).

6) Success Criteria: To consider a run successful the encouraged behaviour should be executed repeatedly for some extended period of the run. Remembering that the system starts by executing random actions and building-up experience before potentially using its history to execute the appropriate action repeatedly, then we might reasonably consider the run to be successful if the behaviour made up at least a third to half of overall behaviours executed. Furthermore, a full peekaboo cycle would be comprised of more than one (usually 2 or 3) selected actions that together make up the selected behaviour. So from an action perspective if the encouraged action was selected more than around $10 - 15\%$ of the time, then the run could be considered successful. However, the percentage of selection alone was not the sole criteria for judging success. Instead, each trace was examined to see when, if, and how often repeated behaviour was executed. Ultimately however, some runs were still considered borderline - that is they may have failed to satisfy some aspect of the criteria. The comments in Table II offer explanations for the decisions in these and other cases.

C. Results

TABLE II

IHA ON KASPARII: EXPERIMENTAL RUNS SUMMARY

Run	Type	h	Comment	HID Chosen	Result
d0032	Pkb	16	HID executed early and repeated	55.17%	Success
d0033	Pkb	16	HID executed early and repeated	41.18%	Success
d0034	None	16	HID only twice randomly	0.00%	Success
d0035	Alt HL	16	HL action chosen often. HID also chosen. HL=36.59%	14.63%	Success
d0036	Pkb	16	HID chosen often.	42.11%	Success
d0037	Pkb	16	3 HID actions selected, but RAW selected more often	13.64%	Fail
d0038	Pkb	16	No random HID to encourage.	0.0%	Fail
d0039	Pkb	16	Run too short	12.50%	?
d0041	Pkb	16	Mixed actions - some HID	5.49%	Fail
d0042	Pkb	16	Mixed actions	9.68%	Fail
d0043	Pkb	16	HID only twice	1.09%	Fail
d0044	Pkb	16	HID throughout	18.87%	Success
d0045	None	16	Few random HID actions	0.00%	Success
d0046	Alt HL	16	HL chosen many times HL=11.84%	2.63%	Success
d0049	Pkb	20	Few HID actions	3.26%	Fail
d0050	Pkb	20	HID chosen often	26.32%	Success
d0051	Pkb	20	HID chosen often	19.32%	Success
d0052	Pkb	20	HID not chosen enough for success over run. However, regular peekaboo was begining to occur at the end.	4.96%	?
d0053	Pkb	20	HID chosen often	17.46%	Success
d0054	Pkb	20	HID chosen often	61.76%	Success
d0055	Alt TR	20	TR (Think-Right) encouraged. TR=26.00%	0.00%	Success
d0056	None	20	Some HID chosen	2.53%	Success

A total of 22 runs were completed. 16 of these for the first condition (encouraging the Hiding action), 3 for the second condition and 3 for the no-encouragement condition. The results are summarized in Table II.In most of the experimental runs it was fairly straightforward to estimate whether the experiment successfully supported, or clearly failed, the hypothesis that the interaction history would result in increases in frequency of the encouraged action. However, in 2 of the runs, this was not possible ("?" in Table II). In run d0039, the hiding action was the only one to be selected (rather than chosen randomly) however the run was too short for successful evaluation. In run d0052, the figures for the whole run do not indicate success, however, the results are borderline as the peekaboo behaviour was clearly beginning to occur towards the end of the run.

Where a result could be determined, 14 out of 20 runs (70%) were successful. In the following sections representative results from each condition are discussed.

1) Peekaboo Encouragement Condition: Figure 3 shows for the first run (d0032), how the motivational variables (face, sound and resultant reward) vary with time, along with the actions being executed . The interaction partner encourages the first "peekaboo" sequence ("hide-face" on the diagram). Note that a "peekaboo" action is actually a combination of the action to hide the face (action 6), any number of "no-action" actions (action 7) and an action to return to the forward resting position (action 0) (for clarity only the primary action is shown on the trace). This results in a maximal reward shortly after the hide-face action, and as the interaction partner continues to reinforce the peekaboo behaviour with vocal reward, this pattern can be seen repeated throughout the trace.

As the chance of choosing a random action rather than selecting one using the history gradually declines the early part of the run will be more exploratory (have more randomly selected actions) whereas towards the end of the run, actions will be more likely to be deliberately selected using past experience. It can be seen that during the first half of the run various different actions are tried, but during the second half of the run, the "hide-face" action is chosen regularly.

The timing of the motivational feedback given by the interaction partner to the robot is important in determining what actions are executed. In Figure 4 from run d0050, the encouragement for the hiding action (and subsequent actions to return the robot to the resting position) is only received *after* the robot additionally turns its head to the side. The result is that when the robot decides to repeat the hiding action, it generates experiences which are likely to generate the actions that were executed following the original hiding action, *i.e.* the robot hides its face, returns to face the front and immediately turns its head to the side.

This behaviour (of the architecture) is an important part of how not just single actions are repeated, but instead how sequences of actions and robot behaviour are replayed, and it is this that encourages a fuller development of capabilities of the robot. It is important to note also that a specific sequence of actions are not learnt, instead it is the continuing generation of experience through the structural coupling of the embodied agent and its environment that drives this observed repeated behaviour. This can be clearly seen from Figure 4 in that the timing of the subsequent head-turn following a hiding action is not always the same, and indeed does not always occur.

2) Alternative Action Encouragement Condition: To illustrate that the operation of the interaction history is not limited to the peekaboo behaviour, the interaction partner also encouraged certain alternative actions rather than hiding. In two cases the "head left" (HL) action was encouraged (once also with a different call of "hello!" instead of "peekaboo!") and in one case the "think right" (TR) action was encouraged instead. In each of these cases the predominant action after some time was the encouraged one.

3) No Encouragement Condition: The final condition where the interaction partner offered no or very little encouragement resulted in various kinds of behaviour, none of which reinforced any particular action over any other, other than "doing nothing".

Run d0045 was completed without an interaction partner present and so offered no reward feedback at all. The result showed some random actions being chosen at first but as time goes on, "movement actions" are not chosen and the robot executed actions that keep it stationary.

In the other cases where no encouragement was offered (runs d0034 and d0056) the robot did receive some reward albeit not a maximum reward. In these cases the robot did have actions from recent behaviour to choose from, however, the behaviour did not become repeated over the long term as continual merging and purging of experiences that do not result in near maximal reward resulted in only transitory behaviour. Thus the modification of the space through merging and deletion plays an important role.

D. Emergent Classes of Experience

Analysis of the results shows that there was an extensive reduction in the number of experiences in the metric space through forgetting and merging, usually reducing the number of experiences by between 40% and 90%. Between 5 and 20% of experiences were merged, the others were deleted ("forgotten").

Examining a typical example; run d0033, a successful peekaboo run, merged 15 experiences out of a total of 181 experiences and deleted 63. One experience that was merged with many later ones was experience number 1 (the second experience). That experience was merged with 8 other experiences and was associated with action 6 (HID - the "hiding" action). Often when the HID action was chosen, it was experience number 1 which was found to be similar to the current experience. Thus it is possible to say that a class of experiences was emerging during this run that "represented" to the robot that it should next execute the peekaboo "hiding" action.

IV. Related Work

The concept of an agent learning from its past experience is one also used by the Case-Based Reasoning (CBR) approach [16]. Extension to the continuous domain [17] and combination with a Reinforcement Learning approach, however, brings the approach much closer to our IHA. However, in our approach, the use of an information theoretic metric measure to compare past experience with present experience can potentially uncover different and more interesting relationships in the history of experience as well as offering an ordered list of near experiences to choose from. Furthermore, the application to the social domain is unique and challenging.

Our approach is also related to reinforcement learning [18], particularly those examples that use intrinsic motivation

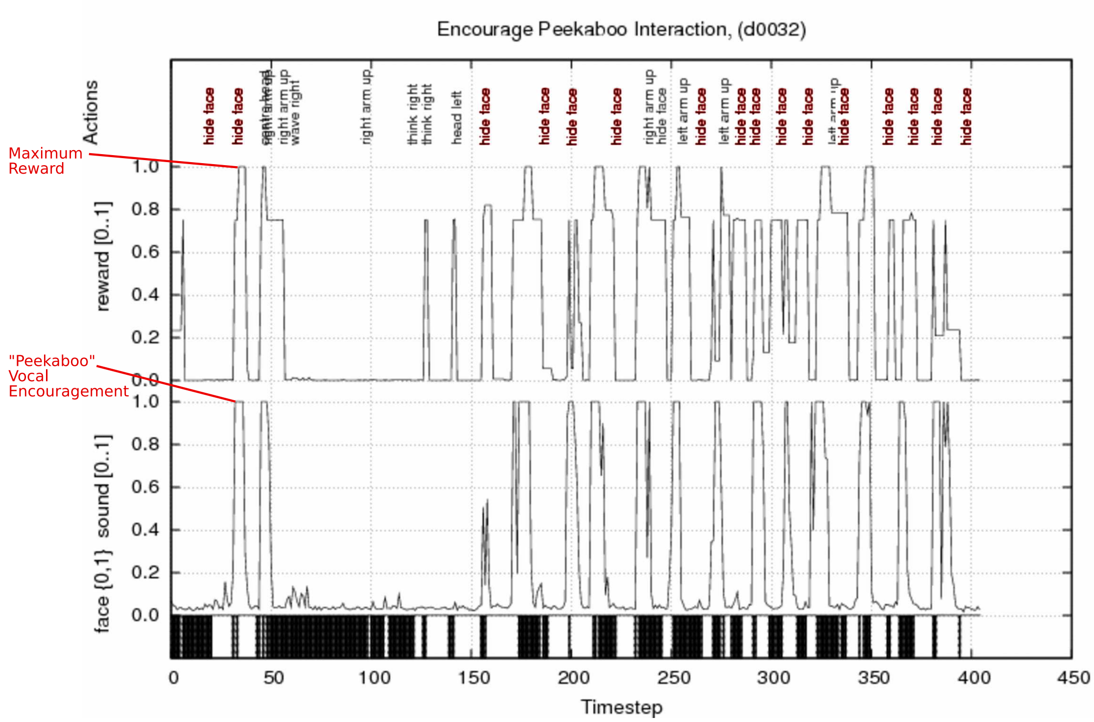

Fig. 3. *Kaspar2 Results d0032. Example of Peekaboo Encouragement Condition.* The trace shows, against time, the detection of the face and audio encouragement as well as the resulting reward. Along the top are shown the actions executed.

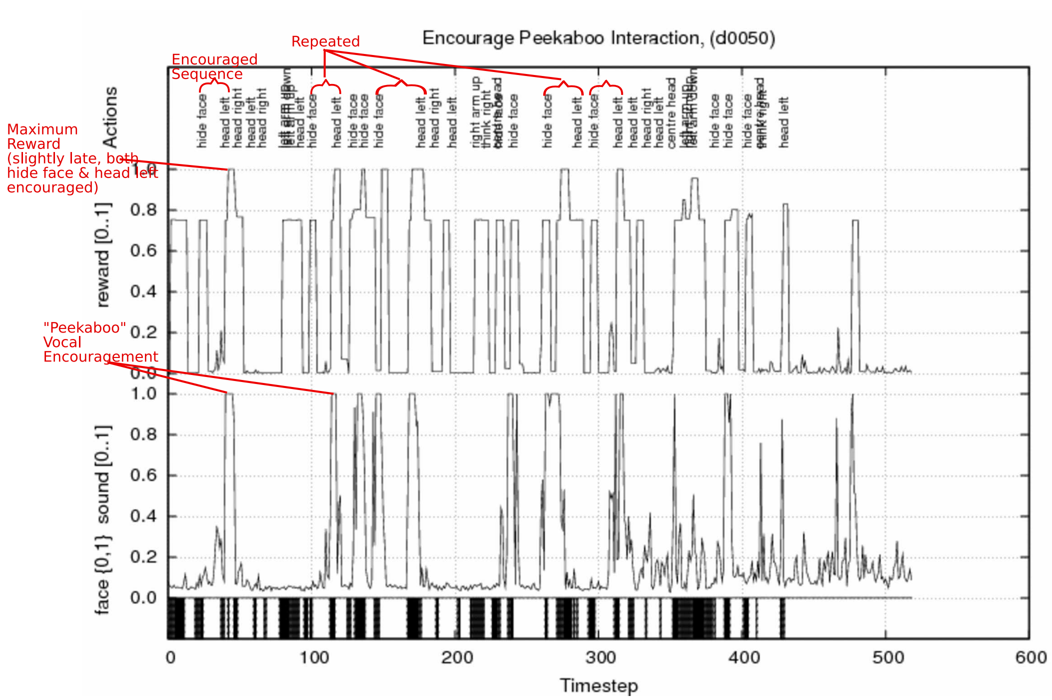

Fig. 4. *Kaspar2 Results d0050. Showing a repeated action sequence.* A multiple action sequence is encouraged and repeated here.

e.g. [19] [20] and memory-based approaches *e.g.* [21] [22] [23]. In contrast to traditional reinforcement learning, the Interaction History Architecture approach uses temporally extended experience rather than the instantaneous values of the sensorimotor and internal variables (*state*). This distinction is important as, particularly where there is an interaction partner or other agents, the environment cannot be modelled as a simple Markov Decision Process.

[24] also studies the acquisition of a peekaboo-style communicative ability although in a virtual agent. The human

caregiver hides the face instead of the robot while also saying "peek-a-boo" as reassurance and surprise. The model matches simplified state (internal emotion state, face sensor and reward) to predict when to expect a reward. Our work thus differs from this in many important ways, the most significant being the generality of our approach, using complex sensor stream and episodes of experience, and the potential to develop and adapt action capabilities over ontogeny.

V. Future Work

While short term behaviour acquisition is illustrated here, future research work should look at how behaviour can be altered over the long term in response to changing encouragement and reward by the interaction partner. Furthermore, showing how different behavioural responses can be developed for different experiences would be important next step.

Further experiments should also utilize interaction partners that do not have prior knowledge regarding the operation of the robot and software.

VI. Conclusion

The Interaction History Architecture was implemented for the upper-body humanoid robot Kaspar2. The peekaboo interaction game was used to evaluate the architecture in terms of how the robot could use its own personal interaction history to develop the capability to engage in the game. Results show that giving appropriate encouragement to the robot as it executes certain series and groups of behaviours can result in those behaviours being selected in preference to others in equivalent conditions. This result supports the hypothesis that encouraging the hiding action would result in a higher rate of peekaboo sequences than would be expected from random selection. Furthermore, encouraging alternative action sequences resulted in those actions being repeated, inviting the conclusion that this behaviour of the architecture is general and not limited to the peekaboo game. Additional support for the hypothesis was found in the conditions that offered no encouragement. In these cases no single action or sequence was selected in preference to any other, emphasizing the importance of the interaction of the environment with the robot in producing a history of interaction that can be used to develop action capabilities.

It was found that classes of experiences emerged through the process of merging of experiences as the interaction progressed. These classes of experience and their associated next-action can be said to be emergent, grounded "representations" that have "meaning" from the robot's own perspective in the actions they generate.

Acknowledgment

This work was conducted within the EU Integrated Project RobotCub ("Robotic Open-architecture Technology for Cognition, Understanding, and Behaviours"), funded by the EC through the E5 Unit (Cognition) of FP6-IST under Contract FP6-004370.

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A long-term study of children with autism playing with a robotic pet: Taking inspirations from non-directive play therapy to encourage children's proactivity and initiative-taking

27 May 2008

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Technical Report 477

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May 2008

A long-term study of children with autism playing with a robotic pet: Taking inspirations from non-directive play therapy to encourage children's proactivity and initiative-taking

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Abstract

This paper analyses a long-term study with 6 children with autism over 10 sessions in the context of play with a robotic pet. The study draws inspiration from non-directive play therapy. The sessions relied on free-play with a mobile autonomous robotic pet and the trials involved one child at a time. Besides, the experimenter took part in the experiments and strongly encouraged the child's proactivity and initiative-taking with respect to the choice of play, the rhythm of play and verbal communication. Beyond inspiration from non-directive play therapy, a regulation process was introduced: the experimenter could occasionally regulate the current situation of play or non-play in order to a) confer an appropriate pace to the game if the child was "standing still", b) guide the child towards other play styles under appropriate circumstances. The profile of each child was analysed according to three dimensions: Play, Reasoning and Affect. Results suggest a spectrum of profiles according to these three (intertwined) dimensions. Moreover, with respect to play and more specifically solitary vs. social play, children can be categorized into three groups. The first group is constituted by children not playing or mostly engaged in dyadic play with the robot. The second group is constituted by those initially playing solitarily and communicating mostly non-verbally but progressively experiencing more complex situations of verbal play as well as few pre-social or basic social situations of play. The third group is constituted by the children who managed to play socially (i.e. play in a triad including both the robot and the experimenter). Results show: a) children from the first group tended to progressively experience longer periods of uninterrupted play with the robot and started engaging in basic imitation during the last sessions; b) children from the third group and, at a more basic stage, those from the second group, tended to experience higher levels of play gradually over the sessions and constructed more and more reasoning related to the robot; they sometimes demonstrated specific reasoning on real life situations as well. Last but not least, children from the second and third group tended to express verbally or physically some interest in the robot, including on occasion interest involving affect.

Key words: Human-Robot Interaction, Robot-Mediated Therapy, Non-Directive Play Therapy, Autistic Spectrum Disorders.

1 Introduction

This study is part of the Aurora Project [1] , an ongoing long-term project which investigates the potential use of robots to help children with autism overcome some of their impairments in social interactions (Dautenhahn and Werry, 2004, 2000).

Children with autism have impairments in communication, social and imagination skills. Autism is a spectrum disorder and children with autism have very different abilities and skills. From the perspective of this study, any robotic-mediated therapy needs to be able to adapt to each child with respect to his/her specific needs and abilities. The advantage of enabling the child to interact with a robotic platform is to reduce the complexity of the interaction and to create a relatively predictable environment for play to begin with, so that it can be easier for the child with autism to feel at ease. It also aims at enabling the child to understand better the interaction taking place.

The Aurora Project is constituted of two main streams of research. One stream focuses on the robot as an autonomous toy and notably addresses the question of on-line recognition and adaptation to human-robot interaction styles (François et al., 2007) . The second one focuses on the potential role of the robot as a mediator (Davis et al., 2005; Robins et al., 2005), i.e. as a salient object that helps children interact with other children or adults. This second stream has largely explored the use of imitation in child-robot interaction (Robins et al., 2005b, 2004) . The study presented in this paper shows a different perspective on robot-mediated therapy, which is not "task-oriented" but rather draws inspiration from non-directive play therapy (Axline, 1946, 1947; Ryan, 1999; Josefi and Ryan, 2004). In this study, the experimenter takes part in the experiments and strongly encourages the child's proactivity and initiative-taking with respect to the choice of play, the rhythm of play and

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[1] http://www.aurora-project.com/

verbal communication. While a task-oriented approach might expect the child to complete a specific task, such as for instance performing imitation, our approach, here, inspired by non-directive play, enables the child to proactively experience various situations of play, from simple exploration of the robot's features and capabilities to more complex situations of play, possibly involving an understanding of the notion of causality as well as an ability to actually play symbolically, or take on a specific role in play. Furthermore, at any moment, the child can appeal to the experimenter's participation in play, thus enabling the child to experience triadic play. Though, as will be explained in Section 3, beyond inspiration from non-directive play therapy, the approach presented in this paper introduces a regulation process. This process notably enables the experimenter to regulate the interaction proactively in order to guide the child towards other play styles when needed or modify slightly the rhythm of play if she feels the child is "standing still". The study presented in this paper explores the potential of this pioneering approach with respect to robot-mediated therapy through a long-term study with 6 children with autism. This study should be regarded as a preliminary exploration of the feasibility of such a technique in the context of robot-mediated therapy for children with autism. Several research questions are addressed:
a) Does such an approach of robot-mediated therapy, inspired by non-directive play therapy, help the child experience higher levels of play and enable him/her to develop new play skills?
b) Does this approach encourage the child to play socially?
c) Might this approach be appropriate for children who play solitarily and speak mostly by onomatopoeia[2]? Might it help him/her experience social play? If not, what might be the additional requirements necessary for such experience?

The remainder of this paper is structured as follows. The rest of Section 1 details both the motivation of this research and the core ideas of non-directive play therapy. Related work is presented in Section 2. Section 3 explains the method in terms of procedures and measures. Further to this, results are provided in Section 4 and discussed in Section 5. Implications for future work are detailed in Section 6. The Conclusion (Section 7), closes the paper.

1.1 Motivation

Autism. Autistic spectrum disorders can appear in various degrees and refer to different skills and abilities (Powell, 2000). Detailed diagnostic criteria for autistic spectrum disorders are provided in the Diagnostic and Statistical

[2] Onomatopoeia is a word that imitates the sound(s) associated with objects or actions it refers to, e.g. 'buzz'

Manual of Mental Disorders (DSM-IV, 1994) [3] . In brief, the main impairments highlighted by the National Autistic Society [4] are:
a) *Impaired social interaction*: difficulties to make sense of a relationship with others, difficulties to guess or even understand what the other's intentions, feelings and mental states are;
b) *Impaired social communication*: difficulties with verbal and non-verbal communication (e.g. facial gesture);
c) *Impaired imagination* notably resulting in difficulties to experience imaginative play.
As a consequence of the above impairments, children often seem to operate in a world of repetitive patterns and some of them tend to restrict play to solitary play.

Play. Play involves many aspects of human development. This is reflected by the coexistence of various definitions and multiple classifications of play. Boucher (Boucher, 1999; Boucher and Wolfberg, 2003) suggests a particularly relevant classification for this study which merges the notion of exploration with the one of social interaction.

Play is a vehicle for learning (Chaillé and Silvern, 1996). Various types of play enable children to construct some understanding, in the sense of active construction of meaning. Play can thus develop skills in many fields such as a) logical memory and abstract thought; b) communication skills and c) social skills. Moreover, play is a medium for self expression (Boucher, 1999).

Children with autism and Play. It is arguable that children with autism have a relative potential for play but often encounter obstacles, the causes of which are still not clear. These impairments -among them, impairments in socio-emotional inter-subjectivity, joint attention and theory of mind (Baron-Cohen, 1997)- impair interactions in general and, more specifically, imply a lack of spontaneous and social reciprocity during play. These three impairments, in addition to the potential deficits in higher order representation, may explain the difficulties encountered in symbolic and pretend play (Chaillé and Silvern, 1996). It should perhaps be further noted that children with autism often tend to perceive objects in their parts and not as a whole, which is part of the weak central coherence theory (Fritz, 1989). This frequent inability may also partly influence the way the child plays.

[3] DSM-IV (Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition) was published in 1994 and is the last major revision of the DSM
[4] NAS: http://www.nas.org.uk/

1.2 Non-directive Play Therapy

This section summarizes the core ideas of non-directive play therapy as mainly developed in (Axline, 1947) and explained and illustrated by case studies in (Ryan and Wilson, 1996).

Non-directive play therapy has its roots in Rogerian client-centred therapy with adults (Rogers, 1976), adapted to child therapy with a focus on play as the principal medium of communication (in contrast to verbal exchange). Rogerian theory relies on the idea that all human beings have a drive for self-realisation; it means that any human being tends to develop towards maturity, independance and self-direction. The individual needs to completely accept himself/herself as well as be accepted by others.

In non-directive play therapy, the child, rather than the therapist, chooses the type of play and the activity in general in the playroom. This contrasts with other play interventions. Let us cite Axline who primarily developed the method of non-directive play therapy (Axline, 1947): "Non-directive play therapy is not meant to be a means of substituting one type of behaviour, that is considered more desirable by adult standards, for another 'less desirable'. It is not an attempt to impose upon the child the voice of authority that says 'You have a problem. I want you to correct it'." Few limitations in the behaviour of the child are set, though, which refers to safety and security reasons.

A relationship is progressively built up between the child and the therapist. This relationship enables the child to share his/her inner world with the therapist and, "by sharing, (the child) extends the horizons of both their world" (Axline, 1947). Ryan et al. state that this relationship, with the help of the therapist, progressively facilitates the child to choose freely the feelings he/she wishes to focus on as well as the way how he/she wants to explore them (Ryan and Wilson, 1996). Three mediums may be used for communicating these feelings: action, language and play.

The therapist participates in the therapy. He/she observes, listens and answers to the child. The therapist is reflecting the child's feelings or emotionalized behaviours in order to help him/her build a better understanding of himself/herself. The therapist's role has been characterized by eight basic principles set out by Axline (Axline, 1947), see Fig. 1.

It should be noted that in the study presented in this paper, the experimenter was not trying to engage in therapy; the study only drew inspiration from non-directive play therapy, thus the context may be a therapeutic one, but the experimenter, a human-robot interaction researcher, was not behaving exactly

1. ``The therapist must develop a warm, friendly relationship with the child, in which good rapport is established as soon as possible."
2. ``The therapist accepts the child exactly as he is."
3. ``The therapist establishes a feeling of permissiveness in the relationship so that the child feels free to express his feelings completely."
4. ``The therapist is alert to recognize the *feelings* the child is expressing and reflects those feelings back to him in such a manner that he gains insight into his behavior."
5. ``The therapist maintains a deep respect for the child's ability to solve his own problems if given an opportunity to do so. The responsibility to make choices and to institute change is the child's."
6. ``The therapist does not attempt to direct the child's actions or conversation in any manner. The child leads the way; the therapist follows."
7. ``The therapist does not attempt to hurry the therapy along. It is a gradual process and is recognized as such by the therapist."
8. ``The therapist establishes only those limitations that are necessary to anchor the therapy to the world of reality and to make the child aware of his responsibility in the relationship."

Fig. 1. Eight basic principles set out by Axline for practice of non-directive play therapy: quotations from (Axline, 1947).

like a therapist. The experimenter was not applying strictly the eight principles set out by Axline (Axline, 1947), see Fig. 1. She very much drew inpiration from principles 1, 2, 3, 5 and 8, but she was not dealing with the fourth one; and, concerning principles 6 and 7, she was considering these principles with more flexibility. It is worthy of note here that this study is a first step towards a proof-of-concept and required robotics expertise; in future, play therapists may use this approach.

2 Related Work

2.1 Non-directive play therapy for children with autism.

Non-directive play therapy has been largely used for children and adolescents with a wide variety of emotional and behavioural problems (Ryan, 1999, 2004; Ryan and Needham, 2001). Only recently have researchers started to investigate the feasibility of such techniques with children with autism. A pioneering case study is presented in 2004 in (Josefi and Ryan, 2004). In that paper, Josefi et al. present a long-term study with a 6-year-old-boy with severe autism by using the non-directive play therapy technique. Before starting the experiments, the boy was mostly communicating non-verbally, and hardly controlled his sudden excess of energy. He was described as never playing with his brother and sisters and whenever he played, he only engaged in playing mechanically with toys. The child attended 16 non-directive play therapy sessions of an hour over a 5-month period in the child's special school. The room was empty except from specific materials selected for their "expressive, imaginative, relaxing and interactive properties". Results were analysed both qualitatively and quantitatively. The findings showed an increase in the child's autonomy and initiative-taking. Besides, the child developed attachment to the therapist. According to Josefi et al. it was shown that non-directive play therapy itself may provide children with autism with: "(i) emotional security and relaxation, (ii) an enhanced and attentive adult environment in which playing together is emphasized, and (iii) the acceptance by therapists of children's ability to instigate therapeutic change for themselves under favourable conditions". These conditions constitute the basis for therapeutic progress as written in play literature (Axline, 1947). Besides, the child's repertoire of play appeared to expand and the child managed to concentrate progressively longer during the sessions. During the last sessions the child proactively engaged in play requiring more joint attention and direct social interactions with the therapist. He started to become more and more interested in toys that have symbolic characteristics. He also communicated more and more verbally with the therapist. It is perhaps worthy of note here that the symbolizing capacities have similarities with, and may overlap capacities, to learn language during normal development; in return, it is very likely that learning a language requires some symbolizing capacities and processes. Though, repetitive and obsessive behaviours were not considerably reduced. As a conclusion, Josefi et al. stated that non-directive play therapy with children with autism may be complementary to behaviour therapy, non-directive play therapy likely to be more efficient in the child's gaining autonomy, taking initiative, joining attention and developing social and symbolic play, while behaviour therapy would be more efficient in reducing ritualistic and obsessive behaviours.

2.2 Robot-mediated therapy

Within the Aurora Project, Robins et al. carried out long-term studies analyzing on the one hand the role of the robot as a mediator (Robins et al., 2005) and on the other hand the role of the experimenter (Robins and Dautenhahn, 2006) which, by being part of the trials, can notably enable and facilitate triadic interaction. In Robins et al.'s experiments, children interacted with the small humanoid robot, Robota, which was either simulating a dance or being controlled remotely by the experimenter. Thus, there was no autonomous reaction from the robot to the child's interactions in their study. Moreover, child-robot interaction situations taking place during these trials were mainly concerned with encouraging imitation of gestures (position or movement of arms and legs).
In a diffferent study, Werry et al. encouraged free-play with a mobile autonomous robotic platform, Labo-1 (Werry et al., 2001). Its shape is rectangular (30cm wide by 40cm long) and it weights 6.5kg. The range of behaviours of Labo-1 focused on mobility of the robot in addition to a rudimentary speech

synthesiser unit; a typical behaviour of that robot was following the child around the room or play approach and avoidance games whereby turn-taking emerged from the interactions of the children with the mobile robot (Dautenhahn, 2007). The Labo-1 robot did not have any pure tactile sensors, but infrared and heat sensors. In Werry et al.'s experiments, none of the experimenters participated in the experiments; they only responded to the child when the child initiated communication or interaction with them (Dautenhahn and Werry, 2002). The child played therefore in a relatively unconstrained environment on his/her own with the robot (Werry and Dautenhahn, 1999), or two children interacted at the same time with the robot (Werry et al., 2001).

Outside the Aurora Project, Kozima et al. used a small dancing creature-like robot, Keepon, in a long-term study with children with autism, most of the time in partly unconstrained conditions (Kozima et al., 2005). During these experiments, the small creature-like robot was manually controlled by the experimenter who was not part of the trials. Rather, carers were part of the trials with the child. The experiments highlight the role of Keepon as a pivot in triadic interaction by notably studying the emergence of joint attention. This result reinforces the idea that child-robot interaction may be valuable for children with autism with respect to being a medium towards possible social interactions.

Long-term studies with the seal robot Paro have shown that specific everyday life situations exist in which human-robot interaction can have a positive effect on well being of human beings; they may even be a significant factor of performance in therapy. A first study conducted by Shibata et al. focused on elderly people (Shibata et al., 2005): Paro was introduced on a daily basis into the everyday life of some elderly people in two different institutions, in one of them for a daily duration of 20 minutes over 6 weeks and in the second one for 1 hour over more than a year. Elderly people were free to interact with the robot. Results showed that on average interacting with Paro improved the mood state of the participants and made them more active and more communicative with each other as well as with the caregivers. A second long-term study with Paro designed engaging rehabilitation activities that would combine physical and cognitive rehabilitation (Marti et al., 2005). The participant, a child with severe cognitive and physical delays, interacted with Paro on a weekly basis over three months as follows: Paro was introduced in the Bobath protocol [5]. Results showed that the introduction of Paro in the Bobath protocol may have strenghtened its efficacity with respect to this specific child.

[5] The Boobath protocol (http://www.bobath.org.uk/) is a method used for the rehabilitation of physical functional skills (Knox and Evans, 2002).

2.3 Long-term child-robot interaction studies outside the therapeutic context

In the broader field of child-robot interaction, Tanaka et al. lead a long-term study on human-robot interaction with a focus on the context of dancing (Tanaka et al., 2006, 2005). The main purpose of this ongoing study, named "Ruby Project", is to find principles for realizing long-term interaction between a human and a robot. In the first year of the project, typically developing children, from age 18 to 24 months, encountered the Sony humanoid robot QRIO at school, in a context of dancing. Off-line analysis of the interactions between the children and QRIO showed that the children tended to progressively adapt their behaviour to the robot's characteristics. Besides, a further analysis on 45 successive sequences of interaction of those children with QRIO spanning 5 months (Tanaka et al., 2007) showed those children tended to progressively consider QRIO as their peer rather than as a toy: The way they touched the robot was reorganised so that, in the end, the distribution of their touch towards the robot was converging to the one observed when they were touching their peers. Note, this study relied mostly on design by immersion, which means here that scientists, engineers and robots are present in the everyday life environment of those children while shaping both hardware and software and addressing scientific questions early in the development process (Movellan et al., 2007). For instance, this design by immersion enabled Tanaka et al. highlighting some basic necessary units for long-term human-robot interaction, respectively "sympathy" between the human and the robot and "variation" within the interaction styles (Tanaka et al., 2006).

3 Method

3.1 Participants

All the children taking part in the experiments have a diagnosis of autism and are from the same school based in Hertfordshire, UK. This school is dedicated to children between 4 and 11 years old with moderate learning difficulties. Within the school an Autism Base exists which provides extra care and a specific education program for children with autism to start with in the school. When the child gets older or when he/she has made sufficient progress (especially if he/she improved social skills) then the child can be integrated in a more general class within the school, which gathers children with specific needs and abilities but not only children with autism.

Two boys from the Autism Base, Child D (7 years old) and Child J (8 years old) were invited to take part in the experiments. Both of them find it hard to express themselves verbally and their behaviour often includes repetitive gestures or onomatopeia. While Child D is generally afraid of dogs and not at ease with doors, Child J is described by the teachers and carers as 'single-minded' thus he is very likely to have obsessions and repetitive behaviours. He has a fascination for computers. Child E took part in the experiments too. She is a 7 years old girl. During the experiments, she was part of the Autism Base but in the process of being integrated to another class with children with moderate learning difficulties but not only children with autism. She therefore started to follow part-time the education program of this class and the rest of the time stayed in the Autism Base. She masters verbal communication pretty well and teachers describe her behaviour as proactively social, as far as play at playtime is concerned. Therefore teachers suggested that she may currently act as a catalyst for the other children from the Autism Base. Besides they agreed she may rapidly need to be fully integrated in the new class so that she can evolve in a different context which would play the role of a catalyst in social skills with respect to her this time: this context would enable her to activate more intensively social skills she recently developed in contact with the children of the new class.

Three older children also took part in the experiments. All of them are integrated in classes for general moderate learning difficulties. Child C, 10 years old, is described by his teacher as a solitary child. In the class he even has his own space, bigger than the one of other children (more than twice as big), and his desk is on the extreme left-hand corner of the classroom in order to make the distance between him and the other children sufficiently large. Child C understands pretty well when one addresses him verbally but mostly speaks by onomatopeia. At school, he often uses the computer to do exercises, especially exercises on words and writing. Two other children, Child H, 10 years old and Child N, 9 years old, both from the same class, also took part in the study. They communicate verbally and are not described as solitary children. Child N is originally from Canada and therefore masters few basic french vocabulary which is a relevant point since the experimenter is originally from France.

Note, other details, such as mental age of the children, was not available.

The study was carried out with approval of the University of Hertfordshire Ethics Committee. The parents of all the children who took part in the study gave written consent, including permission to videotape the children and utilize photos in publications.

Fig. 2. Aibo ERS-7.

3.2 Artifact

The main artifact used in this study is a white robotic mobile autonomous dog, the Sony Aibo ERS-7 (Fig. 2). Aibo ERS-7 weights approximately 1.65kg and measures approximately 180(w) x 278(h) x 319(d) mm. It is equipped with a great variety of external sensors (e.g. infrared sensors, stereo microphones, tactile sensors). In our study, tactile sensors play a major role, notably, the head sensor, the chin sensor and the three back sensors. Aibo's control programming is achieved using URBI (Universal Real-Time Behaviour Interface (Baillie, 2005)).

3.3 Procedures and Measures

3.3.1 Procedures

Experimental Setup. The experiments took place once a week, on Wednesday mornings, in the school for children with autism. Each child took part in a maximum of ten sessions. Not everybody could take part in 10 sessions because some of them may have been away for a day or on a trip with their class. Note, an exception was made for one child who showed some apprehension towards the robot: for this specific child, experiments were stopped after 5 sessions and only restarted on the last day of the experiments when he proactively came to the trial.

The rooms used for the experiments changed several times due to circumstances at the school. In each case, the child may encounter possible distractive objects, like toys or mirrors. Thus these experiments took place in a context of possible distraction. The different rooms used for these experiments are described in Fig. 3 and a list of the rooms used for each session is provided in Fig. 4.

Room	Description	Dimensions	Furniture in the room	Objects in the room
R 1	Small room	Approx. 10feet * 8feet	-small longitudinal window on the very top (children can't see through it), -cupboard, -low rectangular table, -2 children's chairs, -decoration on the wall (a clown's head drawn on a paper board).	Regular objects: - game with individual letters to form words, reflective blue metallic support, - coloured cubes (25mm*25mm) - rectangular paperboard 3D decoration, 1m*30cm*20cm , vertically in a corner. On occasion: man's like face drawn on a paperboard that children could hold in front of their face.
R 2	Small room in the Autism Base	Approx. 10feet * 12feet	-big window on a wall, -second internal window (semi-transparent, semi-reflective) with view on another classroom; -vertical mirror, children can see their whole body by reflection -shelves on the very top, children can't access -table & small chairs (session8 only)	- games in open boxes on the shelves (e.g. a doll); children can see them but can't access them.
R 3	Large meeting Room: library, kitchen and living room corners. Experiments took place in the living room corner.	-room: Approx. 35feet * 40feet; -living room corner, approx. 10feet * 12feet	-Large windows on two walls -2 sofas made of joint comfortable chairs -4 comfortable additional chairs -rectangular dinner table, 6 chairs -2 low coffee tables -shelves (at the entrance) -kitchen corner	-magazines on the coffee table -on the shelves, objects such as cloth samples in open boxes -small calculator -small alarm clock
R 4	Classroom; experiments took place in the library corner	-room: Approx. 30feet * 30feet; -library corner: approx. 10feet * 7feet	Library corner: -2 shelves separating the library corner from the rest of the classroom -small children's bench	Library corner: -books

Fig. 3. Desccription of the school's rooms used for the experiments.

Session	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Room	R1	R1	R1	R1	R1	R3	- Child C : R3 - Other children : R4	- Child C: R3 - Other Children: R2	R2	R2

Fig. 4. List of the school's room(s) used for each session.

Each trial involved one child with autism, the experimenter [6] and possibly another researcher from the Aurora Project. The latter often helped the experimenter film the trials and occasionally took part in a verbal communication process by answering a child's question directly addressed to her. Note that the children were quite familiar with her since she was at the same time doing a different long-term study with them that involved the use of interactive software (Davis et al., 2007).

The duration of the sessions was variable. The child was free to play as long as he/she wanted with the following restrictions:
Restriction 1: the upper limit of time is 40 minutes (so that the child does not miss too much of his/her courses at school); Restriction 2: if the child has an obligation due to his/her planning, the session will be shortened.

[6] in this study, the experimenter was the first author of the paper

The Aibo robot was programmed in order to show simple behaviours, tailored progressively by immersion according to each child's needs and abilities. Note that "tailored by immersion" means here that the repertoire of appropriate robot's behaviours with respect to each child specific needs, abilities, dislikes and preferences was progressively refined as the experiments progressed. The mapping between the sensors and the reactions of the robot (also called behaviour-mode) could therefore vary from one session to the other and also during a session in order to meet as close as possible the needs, abilities and demands of the child at a given moment. The robot reacted autonomously to the activation of its sensors, with respect to the specific behaviour-mode it had been endowed with. The switch between various behaviour-modes was done manually by the experimenter through a wireless connection with a laptop. The laptop was located in the same room as the children, and thus constituted an additional source of distraction for the children.

Methodology of the approach. During the session, the child was invited to play with the Sony robotic pet Aibo. The experimenter took part in the experiment but the child was the major leader for play: the child was free to choose the game to focus on, the pace of playing and he/she could engage in free-play (unconstrained play) with the robot and/or the experimenter; he/she was also free to engage in communication with the experimenter whenever he/she wanted. If the child appealed to the experimenter's participation, then the experimenter did take part in the game. If the child initiated verbal or non-verbal (e.g. smile, eye gazing) communication with the experimenter then the experimenter answered appropriately. With respect to verbal communication, the experimenter tried to answer every question of the child and rewarded him/her verbally whenever appropriate. Note that this approach is mainly child-centred, relies strongly on the child capabilities of designing his/her own trajectory of progression and on total respect and consideration towards the child from the experimenter. In this sense, this approach draws inspiration from non-directive play therapy.

Beyond inspiration from non-directive play therapy, this approach adds a regulation process under specific circumstances which are detailed below:
a) *to prevent from or get rid of a repetitive behaviour*: If the child was starting or about to start a repetitive behaviour, the experimenter intervened and tried to help the child play a different game;
b) *to help the child engage in play*: if the child did not engage in interaction with the robot, then the experimenter encouraged him playing with the robot, verbally and/or non-verbally (e.g. by stroking the robot and encouraging verbally imitation);
c) *to give a better pace to the game if already experienced by the child*:
If the game was "standing still" but the child already experienced this game and had shown he/she was capable to play this specific game, then the exper-

imenter could intervene punctually to confer a better pace to the game.
d) *to bootstrap an upper level of play*: if the child was about to reach an upper level of play but still needed some bootstrapping (some light guidance), the experimenter could provide it
e) *to proactively ask questions related to affect or reasoning*: the experimenter could proactively ask the child simple questions related to affect or reasoning such as: "Do you think Aibo is happy today? or "Do you like playing with Aibo?".
Note that e) enables: i) to test the ability of the child to answer and/or ii) to show the child a specific point for reasoning. Let us take several examples within various levels of reasoning:
1) technical issue: show the child how to change the battery of the robot so that he/she can do it next time in a context of cooperative task;
2) ask the child if he/she thinks Aibo is happy;
3) help the child reason on causal effect: stimulation of a sensor implies a specific reaction of the robotic dog;
4) show the child that a reaction can be interpreted: e.g. if I press this specific button, then Aibo wags his tail; and wagging the tail can mean that Aibo is happy; thus if you press this button, you can show that Aibo is happy.

3.3.2 Measures

Each session was filmed unless the child explicitly asked for not being filmed which rarely happened. First, the experimenter viewed the video recordings and wrote down notes on the events constituting each session. These notes described the events in detail and contained as few interpretation as possible. As a second step, the experimenter analysed the data in terms of more abstract criteria that would enable her to identify, for each child, both the profile according to the three dimensions (Play, Reasoning and Affect) and the progresses made over the 10 sessions. This methodology allows to first gather as much information as possible before deciding on the specific criteria; it has the advantage of not restricting the analysis to predefined criteria which might reveal a posteriori not being the optimal ones to base the analysis upon. This is especially relevant in the case of an exploratory study. Note, this procedure follows the procedure described by Schatzman and Strauss, stating that: "the researcher requires recording tactics that will provide him with an ongoing developmental dialogue." (Schatzman and Strauss, 1973). Schatzman and Strauss underline the importance of recording observations from the very beginning of research. They also suggest taking notes separately, categorizing notes into three different packages: a)"observational notes" based on events, without interpretation; b) "theoretical notes" representing an attempt to confer or denote the meaning from an observational note; c) "methodological notes" dedicated to methodological comments.

Results of the experiments were analyzed according to three (intertwined) dimensions, respectively Play, Reasoning and Affect.

Play. This study aims at testing the feasibility of this approach to encourage the child to learn new play skills and enable him/her to experience more and more complex play situations with respect to the following main criteria:
a) social aspect of play,
b) proportion of symbolic and/or pretend play,
c) understanding/use of causality,
d) ability to handle the pace of a specific play and possibly the chronology or the transitions between two logical segments of play.
That is why, concerning the dimension of Play, what particularly matters is a) to extract information qualitatively about play situations that the child has experienced in each session, and b) see if the child really experienced a large repertoire of play and more complex levels of play gradually over the sessions.

For this purpose, a Play Grid was built based on the children's plays objectively observed during the experiments. This grid is exhaustive with respect to the variety of play situations which took place at least once during the experiments for at least one of the children. Besides, the different play situations were classified into 6 sets, each set denoting a specific level of complexity of play (Level 1 being the lowest and then gradually incrementing the level of complexity until Level 6). The level of complexity is defined according to four criteria:
a) social play,
b) proportion of pretend and/or symbolic play
c) exploration of the use of causality/reaction,
d) chronology and/or number of different phases in the play, i.e. a simple reaction to a sensor is constituted of two phases while a search and rescue game involves many phases to handle chronologically: i) initial situation, ii) search phase, iii) rescue phase, iv) final situation.
The level of complexity is then deduced from an average evaluation over the four components which explains that the same level may contain play with a predominant component of "d)" and other with a predominant component of "b)". Consequently, within a same level of complexity, the different play situations are not ordered since they may be very different in nature. Ideally, the child would experience higher levels of play over the time and, within a same level of complexity, different play situations in nature.

The systematic analysis with the grid for each child and each session shows the trajectory of each child (i.e. the profile of the child). Any cell in the grid is filled in if and only if it corresponds to a play situation experienced by the child at least once during that specific session; and the content depends on the play situation being acted proactively or reactively (i.e. the child was slightly guided towards this play situation by the experimenter).

Though, this grid is much enlightening for children who manage to play socially and manage to diversify their play. For those who do not play much with the robot, and when playing, engage only in exploration and mostly solitary exploration, a more adapted tool to evaluate their progresses was used. That evaluation was quantitative and relied on measuring for the whole duration of each session:
a) the total time spent in interaction with the robot,
b) the duration for each single uninterrupted phase (period) of pure interaction (note that the total duration is the sum of the duration of each single uninterrupted phase of play),
c) the amount of gestures imitated by the child and the number of gestures explicitly asked by the experimenter to be imitated.

Reasoning. Through play, children can notably construct some understanding of social situations and gain experience of some situations they encountered while playing. If a child can reason on abstract concepts, infer mental states and make a sense of social rapports, it will be easier for him/her to play symbolically. Reciprocally, while the child experiences symbolic play, he/she manipulates abstract concepts such as inferring an emotion or handling social rapports. Both play styles and reasoning are therefore intertwined and both views should therefore be used to analyse the results of the experiments carried out for this study. Note that with respect to "Reasoning", what is particularly relevant are both questions and answers emerging from play situations. The context of play enables the use of imagination, whereby Aibo may be assigned a specific role by the child, and it allows the child to attribute specific capacities to the robot such has having mental states (e.g. it enables to imagine that Aibo is taking on a specific role and make further assumptions on his mental state or his social status). Consequently the context of play enables the robotic pet to be attributed with mental states as well as a social role, and possibly moral standing. In this way, it is possible to explore quite largely the quadrology about the robot as presented by Kahn et al. (Kahn et al., 2003).

This quadrology is part of the components of the reasoning coding system developed by Kahn et al. (Kahn et al., 2003). It consists of the following four entities:
a) "Essence":
Does the child consider Aibo as an artefact or a biological entity?
b) "Mental states":
Does the child attribute mental states to Aibo? Does the child consider that the robot develops in terms of age for instance? Does the child consider Aibo has a personality? Does he consider Aibo could live autonomously?

c) "Social rapport":
How does the child position Aibo relatively to himself/herself;
d) "Moral standing":
Can Aibo be physically or morally hurt? Can he be held responsible for something? Can Aibo be punished when necessary? could Aibo be praised?

Note that Kahn et al.'s coding manual has been developed in a different context than the one of this study: they targetted typically developing preschool children who only encountered Aibo once and, after few minutes of play with the robot, immediately answered specific questions about "reasoning" (Kahn et al., 2003, 2005) — while answering questions, children could however carry on interacting with the robot. Here, the context used in our study is really different since the succession of sessions enabled the child to progressively build some reasoning and understanding, along with the progressive building of a shared space of expressions and routine activities between the child and the experimenter. Therefore, the reasoning was enriched. Besides, "reasoning" here is part of play in itself. In the study presented here, the context of play is actually used to enable the child to explore issues such as mental states or social rapports, and the robot in itself is a support for embodying such issues through the imaginary context that comes with play. Moreover, since the experimenter took part in the experiments, not only social rapport between the child and the robot should be considered, but also the child's view on the notion of social rapport between the robot and the experimenter and between himself/herself and the experimenter. Consequently, here, the dimension of "Reasoning" is analysed as follows:
a) the main features of the quadrology are extracted from Kahn et al.'s coding manual (Kahn et al., 2003)
b) the issue of whether and how the child addresses those features is investigated for each child, in a perspective of questioning through play rather than giving firm answers.
Note, that since the experimenter is not a therapist, and since the behaviour of children with autism might sometimes be interpreted differently from typically developing children, in the analysis we only consider events which are objectively and reliably identifiable. Verbal events are particularly reliable events; they can be statements or questions arising from the child (major events) or answer to the experimenter's question (minor events). Below are some examples: a) Essence: "He's a robot, he is a robot dog", "He has short teeth, he doesn't bite. Robot dogs don't bite, do some do?"; b) Mental states: "Aibo is happy", "How old is Aibo", "Aibo, answer me, do you like toys?" ; c) Social Rapport: "It is your robot" d) Moral standing: the child accidently kicks the robot and apologized verbally to the robot directly. Besides, in many cases, as already explained, reasoning and play are intertwined; for instance, when the child and the robot's relative social position in an enacted situation of pretend play is well-defined by the child (e.g. a competition, with two participants, the

1) Proactive (major) event related to affect:

i) Child's statement or question referring directly to himself/herself liking the robot or the robot liking him/her. No hug or kiss from the child to the robot.
Examples: ``I like Aibo", ``Aibo likes me".

ii) Child's verbal compliment to/concerning the robot. No hug or kiss from the child to the robot.
Examples: ``good doggy", ``nice dog", "he is a nice dog".

iii) Child's hug to the robot, clearly identifiable, accompanied by a kind word from the child to/concerning the robot or verbal statement qualifying the hug.
Example: the child hugs the dog and asks the experimenter to hug the dog: ``Put your hands and hug, hug, hug!"

iv) Child's kiss to the robot, clearly identifiable, accompanied by a kind word from the child to/concerning the robot.
Example: the child gives a kiss to Aibo after saying ``Goodbye Aibo, have a good sleep"

2) Reactive (minor) event related to affect:

i) Child's answer to a question about himself/herself liking the robot or the robot liking the child.
Example: the experimenter asks the child: ``Is it a nice robot?" and the child answers ``Yes".

ii) Child's answer to a question about himself/herself being happy to play with the robot.
Example: the experimenter asks the child: ``You are happy playing with the robot?" and the child answers ``Yes".

Note, reactive events related to affect are considered very cautiously in this study; they are not considered as sufficient to make firm deductions about the child addressing the notion of ``Affect".

Fig. 5. Criteria for coding events related to Affect. An event is related to 'Affect' if it corresponds to one of the items provided in the table; in some of the following figures, events related to affect are qualified by a corresponding code: the code of an event related to affect is given by its corresponding item's index, e.g. 'I like Aibo' is [1i].

child and Aibo), the notion of social rapports is certainly addressed. Another example is a play situation of asking the robot about its mental states and answering with the activation of a sensor.

As a further step in reasoning, the child may tackle a more general issue related to his/her mental states for instance, or to social rapport, concerning himself/herself or even the experimenter. This is a relevant point for this study: it would show the potential reuse in another context of skills the child may develop or practise through reasoning about the robot during play.

Affect. The "affect" dimension represents any expression indicating whether the child likes the robot or not, or if the child makes an assumption on the robot liking him/her. Here, only obvious signs of like/dislike are considered. It means that the range of possible events considered as related to affect in this study is very limited (see Fig. 5 which provides the table of criteria for the coding of events related to affect). This is made in order to ensure events considered as related to affect are clearly identifiable. For instance, a gentle stroke is not classified as an event related to affect in this study, neither a gesture such as a kiss or a hug, which would not be accompanied by an appropriate child's statement.

3.4 Coding and Reliability

Inter-rater reliability testing was carried out for each of the three dimensions, respectively, play, reasoning and affect. A second coder who was not familiar with the aims of the study re-coded part of the data. Good reliability was shown: a) On play, 80.7% agreement (13min50s of videos coded divided among two children, Child H and Child E); b) On reasoning, 80.3% agreement (18min24s of videos coded divided among two children, Child H and Child N); c) On affect, 93.3% agreement (22min of Child E's videos coded).

4 Results

Child D Child D showed some apprehension towards the robot and did not interact at all during the five first sessions. The experimenter therefore decided not to require the child to come for the following sessions and let the child proactively decide whether he wanted to take part in the further trials or not. In the last session (Session 10), Child D proactively came for the trial. In that session he engaged in an interaction with the robot with the help of the experimenter: one interaction event happened between the child and the robot, during which the experimenter showed the child how to stroke the robot and the child imitated. Afterwards, the child both showed signs of light apprehension (he moved his body slightly backwards) and enjoyment (he smiled).

Child J Child J took part in 9 sessions. Child J naturally showed attempts to play with the laptop rather than the robot. It was a big challenge to get the child away from the laptop and get his attention focused on something else. The experimenter used a simple trick by hiding the laptop with a cloth. But for practicality reasons (e.g. to connect or reconnect Aibo during the session), the cloth had to be removed from times to times during the session thus introducing an important source of distraction for Child J. Progressively though, the child seemed to understand that he was allowed to punctually have a look at the laptop (as part of his well-being) but that he should mostly engage in interactions with the robot. The table provided in Fig. 6 shows the average amount of time Child J spent engaging in play with the robot during each session. The tendency is clearly that the child played longer with the robot in the two last sessions than in the previous ones and almost doubled his play time between the 9th and 10th session. If we consider in detail the duration of single phases of play, i.e. uninterrupted periods of time when the child continuously plays with the robot, then, again, this table shows that the child experienced longer non interrupted periods of play with the robot during the last sessions.

Typically, two uninterrupted periods of play are often separated by an attempt of the child to play with the laptop. This shows that the child progressively learnt to focus more and more on the robot and on engaging in playing with the robot. Nevertheless, the experimenter also often intervened to help the child carry on playing and keep focusing his total attention to the robot; this intervention usually happened in two ways: a) encouraging and rewarding the child verbally, or b) showing an example, e.g. stroking the robot and asking for the child to do the same. In this context, b) is very relevant indeed since the child does not speak verbally and encouraging imitation is favourable for both relaunching the child's engagement in play and bootstrapping social play. It should be noted that in that specific context, imitation is very rudimentary: the experimenter either touches a specific sensor or gently strokes the robot (e.g. on the head) and explicitly asks the child to do the same. The child is considered to imitate the experimenter's gesture if he initiates within 10 seconds the same nature of gesture, i.e. either a touch of a sensor or a stroke, and if the gesture is applied on the same part of the robot's body; for instance, i) the experimenter touches the head sensor and, within 10 seconds, the child presses the same sensor (with or without activation depending on the child's precision of touch) ; or ii) the experimenter gives a gentle stroke on the back of the robot and, within ten seconds, the child gives a stroke on the back of the robot. Results show that Child J progressively experienced more situations of imitation. Besides, they also reveal that during the last session he imitated some gestures proactively, i.e. without being explicitly asked by the experimenter to imitate.

Concerning the "Reasoning" dimension, Child J did not address the issue verbally. Thus, no firm conclusions should be drawn. However, the detailed study of the child's gestures shows that the exploration of the child became progressively richer and richer over the sessions. The child varied his position relative to the robot, from sitting to kneeing and lying, and thus looked at the robot from various viewpoints. Moreover, he progressively varied his way of touching the robot: during the first sessions, he progressively abandoned random-like touch to develop more targeted touch. Note that targeted touch can be, for instance, trying to touch a single sensor precisely or stroke the robot gently and then activate many sensors. Besides, during the last session, the child experienced proactively a combination of two previous sensor activations: first, he imitated the experimenter and stroke the back of the robot; second, he imitated the experimenter again and touched the head; third, his next behaviour was the simultaneous activation of back sensors and the head sensor.

Concerning the third dimension, "Affect", no event that was related to affect (with respect to Fig. 5) was recorded.

	Total duration of play (min:sec)	Repartition of the play time in single phases of play (min:sec and + between 2 single phases)	Aspects of imitation: In each single phase of play, numbers of gestures: Imitated by the child	Explicitely asked by the experimenter to be imitated	Verbal expression involving either the word 'dog' or 'robot'
Session1	0:06	0:06	0	0	
Session2	1:30	1:00 + 0:30 (mostly looking attentively at Aibo)	0	0	
Session3	0:40	0:40	0	0	
Session4	Almost null	Almost null	0	0	'The little dog was easy'
Session5	0:15	0:15 the experimenter helps by holding the child's hand to show him	0	0	
Session6	0:00	0:00	0	0	
Session7	away				
Session8	1:05	1:05	1	2	
Session9	2:21	0:40 +1:16 +0:16	0 +1 +0	0 +2 +0	
Session10	5:24	0:20 +1:47 +0:18 +2:46	0 +3 +0 +3	0 +3 +0 +1	

Fig. 6. Child J. Dimension of play: quantitative results: For each session, the following indicators are reported: a) total duration of play; b) duration for each specific single session of play ; c) aspects of imitation with respect to i) the occurrence of gestures (touch or stroke of the robot) that the child imitated and ii) the occurrence of gestures that the experimenter explicitly asked the child to imitate); d) verbal expressions including the word "dog" or "robot".

Child C Child C was away for Session 3 and Session 6 and therefore took part in 8 sessions in total. The analysis of the Play Grid in Fig. 7 shows that Child C played mostly solitarily. He engaged largely in exploratory play which became progressively more and more enriched. Two main aspects objectively illustrates the phenomenon a) a progressive change of position (from sitting orthogonal to the robot and not facing the experimenter to facing the robot and the experimenter) and b) a more diversified way of touching the sensors. Moreover, the child practised "solitary mirror play" frequently. It consists of looking at one's image in the robot's reflecting face. Child C experienced situations of looking at his image with other reflecting surfaces too, such as a window, partially reflecting, or a mirror, perfectly reflecting (room R2 contained a mirror). All of these play situations, consisting of looking at one's image, were often fascinating for Child C, and sometimes prevented him from engaging in other kinds of play situations. Besides, Child C did not experience plays involving explicitly causal reactions, such as showing a specific reaction of the robot through the sensors' activation.

Though, progressively, Child C experienced situations with some components of social play. From a cooperative point of view, the child did take part, both reactively and proactively in cooperative technical tasks such as turning on the robot. Furthermore, Child C, who mostly speaks by onomatopeia did develop

		1	2	3	4	5	6	7	8	9	10
L1	*Solitary* Exploration	P	P		P			P	P	P	P
	"Imitation" of robot's bark										
	Solitary mirror play – look at oneself in the robot's reflecting face	P			P	P		P	P	P	P
L2	*"Pre-social" or basic-social* exploration – stroke Aibo immediately after the experimenter (possibly basic imitation of the gesture)				P	P		P	B		
L3	*Social* exploration (social play)										
	Simple Bite/Save or Give/Food - no use of the sensors										
	Position or locomotion game – with verbal qualification of the game										
	Cooperative technical task: change the battery, or turn on/off Aibo				P	P		B	P	P	B
	Verbal order towards Aibo: e.g. "sit", "walk", "wake up"										
	Basic pretend & social play – imitate Aibo's snoring & verbal comment										
	Basic play on affective gestures – give/receive a kiss and/or a lip to/from Aibo										
	Repeat after me - ask the experimenter to repeat verbal expressions										
	Look at Aibo through the camera (Possibly stroke Aibo & look at its reaction through the camera)										
	Speak French with Aibo - e.g. "Hello" or "Bye-Bye" in French										
	Show Aibo to other children (social play) Express verbally the willing/intention to show Aibo to the other children										
	Simple play with accessory (symbolic play)										
	Social Mirror play (social play) - look at oneself (and possibly at the experimenter) in the robot's reflecting face & express verbal comments, e.g. "Look at my arm!"										
	Social Hug – hug Aibo & ask the experimenter or the second researcher to hug Aibo										
L4	*Complex* Give Food/Drink (cause-reaction play & symbolic play & social play) - use of sensors										
	Complex Bite/Save (cause-reaction play & pretend play & cooperative play) - use of sensors										
	Complex turn off Aibo to sleep (symbolic play)										
	Speak directly to Aibo about Aibo's feeling (symbolic play)										
	Cause-reaction play & mental states: Ask a question to Aibo (e.g. identity, feeling), answer with a sensor										
	Cause-reaction play, Aim at a physical reaction of the robot, show it with a sensor										
	Cause-reaction play & basic pretend play, "caught on the act"										
	Telling a story									P	P
L5	Cause-reaction play and explicit Social rapport: Ask a question to Aibo, answer with a sensor (e.g. press the sensor which opens the mouth), translate verbally the answer for the experimenter										
	Symbolic & pretend play Complex play with an accessory										
	Symbolic & pretend play Complex nap with Aibo										
	Symbolic & extrapolation play : "RobotCat" - Speak about the idea of a robotic cat (possibly imagine how one would play with it)										
	Causal composition of plays: Bite/Save & Give Food/Drink										
	Causal composition of plays: Kiss & Bite/Save										
	Pretend play & causal reaction & social rapports: Ask verbally Aibo to act a situation, use of sensors										
L6	Pretend play & focus on Aibo's mental states: Mimic Aibo's cry, and explain Aibo is never crying but pretending to cry										
	Pretend play & social rapports: Look after Aibo and set up rules										
	Pretend & symbolic & chronological play & social rapports: Search and rescue										
	Pretend & symbolic play & social rapport & cause-reaction play & chronological play: competition (drink fast) between the child or the experimenter and Aibo ; the non-competitor activates Aibo's sensor										

Fig. 7. Child C. Play Grid. The first column describes the corresponding level of play, the second column details the various play situations for each level that the child experienced at least once; the following columns refer to the sessions, ordered chronologically. The table is then completed according to the following rules: a) if the child did not experience the play situation during the specific session, leave the corresponding cell blank; b) if the child experienced the specific play situation at least once during the session, then write "P" (if the child experienced it proactively only — i.e. it was his/her own initiative). Write "r" if the child never experienced it proactively (only reactively: the experimenter guided the child towards the play situation). Write "B" if the child experienced this play situation many times , sometimes proactively and sometimes reactively. Note, Child C was away for Session 3 and Session 6.

some ways of expressing himself, by dancing in front of the mirror and/or the robot and even probably telling a story by using not proper words but onomatopeia. The situation described below, that Child C experienced, may actually be interpreted, with caution though, as a storytelling situation: Child C chronologically a) pressed the button to "wake up" Aibo (i.e. turn Aibo on), then b) stood in front of the wall mirror in the room, still watching Aibo "waking up"; c) once Aibo's woken up, the child started dancing and saying onomatopeia in front of the mirror. At some point, the robot disconnected. During the whole process the experimenter told Child C many times that she thought he was telling a story and asked him if she was right. She got no answer. When the robot disconnected the child stopped dancing and the experimenter reiterated her question: "Was it a story that you were telling me? Yes or no?" and the child answered "Yes". Then she asked: "Can you tell me another story, yes or no?" and the child answered "yes". Then the child repeated the same succession of behaviours a), b) and c) and she asked: "Is it about a boy the story?" And he answered "Yes". It is worthy of note here that the child might have simply repeated the word 'yes' after each question without giving a 'real' answer to the questions. Nonetheless, that example shows how the child may have progressively opened up to more communication with his surrounding social environment for play (notably the experimenter).

This storytelling situation took place in the last sessions while the child was starting to answer some questions about reasoning as well as using proactively verbal expressions to express intention. An in depth study of the verbal answers the child formulated shows that over the first sessions, the child almost only answered "yes" or "no", whenever he answered. Then, progressively, the child answered some questions by repeating words from the question: e.g. in Session 4 the experimenter asked "Do you want to play with the robot or go back to the classroom?". The child answered: "play with the robot". And in the last two sessions, the child did use expressions to express his own intentions; for instance, the expression "sitting down" means that he wants to remain sitting down on the ground to carry on playing with the robot. In Session 9, the experimenter actually asked the child: "Do you want to go back to the classroom or play with him (the robot)?" and the child answered "play with him". Then later in the session, the experimenter asked the question "Shall we go back to the classroom now?". And the child answered: "Sitting down". During the last session, the child reused exactly the same expression ("sitting down") to answer the experimenter's question: "Would you like to go back to the classroom soon?".

Regarding the analysis of the reasoning dimension, the child answered reactively very basic questions about Aibo's mental states, such as "Do you think Aibo is happy today?" or about his own mental state: "Do you like playing with the robot?" but there was no proactivity from the child with respect to mental states.

Session	**Events objectively related to Affect** (ordered chronologically with respects to first appearance, event only mentioned once per session)
S1	
S2	• **[2i] "Do you like it?"** (Experimenter); **"Yes"** (Child C)
S3	
S4	• **[2i] "Is it a nice robot?** (Experimenter); **"Yes"** (Child C); • **[2ii] "You are happy playing with the robot?** (Experimenter); **"Yes"** (Child C)
S5	
S6	
S7	
S8	
S9	• **[2i] "Do you think Aibo likes you?"** (Experimenter); **"Yes"** (Child C)
S10	• **[2i] "You like the robot?"** (Experimenter); **"Yes"** (Child C)

Fig. 8. Child C. Events related to Affect. Events are separated by bullet points, and provided with their context (normal font) in the table. Events written in bold are coded according to Fig. 5 (the code is provided in brackets in front of the event); please note, that when the child answers a question, the event in itself is the child's answer, but, in this table, in order to make it clear to the reader, the question that the answers refers to is also written in bold.

Concerning "Social rapport", the child progressively grasped the fact that Aibo belonged to the experimenter. In the first sessions, the experimenter had to explain many times to the child that he could not take the robot with him back to the classroom. In contrast, at the end of the last session, the child hesitated a short time and gave the robot back to the experimenter proactively. Apart from that, the child did not explicitly show any reasoning on "Social rapports". Neither did he on Aibo's "Moral standing".

The dimension of Affect has been mostly addressed indirectly (Fig. 8), through simple questions from the experimenter: in Session 4, the child answered affirmatively to the following questions: a) "Is it a nice robot?" and b) "You are happy playing with the robot?". Later, in session 9, the child answered affirmatively to the question "Do you think Aibo likes you?" And in Session 10, the child answered affirmatively to the question "You like the robot?". Note that since these inputs did not emerge proactively we should be careful with too much interpretation. Though, it should be underlined that most of the time the child said he preferred playing with the robot rather than going back to the classroom, which shows the child was having fun playing with the robot. It is perhaps worthy of note here that the experimenter is aware that the child may just have given a stereotypical answer. For instance, the experimenter did not ask the question: "Does the robot hate you?", which the child might have said "yes" to as well.

Child E Child E was away for Session 7 and thus took part in 9 sessions in total (among them Session 6 where she had a very limited time of play, approximately 10 minutes, because of a class trip). The Play Grid in Fig. 9 shows that Child E experienced more and more complex levels of play during

		1	2	3	4	5	6	7	8	9	10
L 1	*Solitary* Exploration										
	"Imitation" of robot's bark				P	P			P		
	Solitary mirror play – look at oneself in the robot's reflecting face										
L 2	*"Pre-social" or basic-social* exploration – stroke Aibo immediately after the experimenter (possibly basic imitation of the gesture)										
L 3	*Social* exploration (social play)	P	P	P	P	P	P		P	P	P
	Simple Bite/Save or Give/Food - no use of the sensors						r				P
	Position or locomotion game – with verbal qualification of the game	P				P	P		P		
	Cooperative technical task: change the battery, or turn on/off Aibo		P	P	P		r		r	P	
	Verbal order towards Aibo: e.g. "sit", "walk", "wake up"		P	P	P				P	P	P
	Basic pretend & social play – imitate Aibo's snoring & verbal comment		P								
	Basic play on affective gestures – give/receive a kiss and/or a lip to/from Aibo			P	P	P	P				
	Repeat after me - ask the experimenter to repeat verbal expressions										P
	Look at Aibo through the camera (Possibly stroke Aibo & look at its reaction through the camera)				P						
	Speak French with Aibo - e.g. "Hello" or "Bye-Bye" in French										
	Show Aibo to other children (social play) Express verbally the willing/intention to show Aibo to the other children										
	Simple play with accessory (symbolic play)										
	Social Mirror play (social play) - look at oneself (and possibly at the experimenter) in the robot's reflecting face & express verbal comments, e.g. "Look at my arm!"										
	Social Hug – hug Aibo & ask the experimenter or the second researcher to hug Aibo			P							
L 4	*Complex* Give Food/Drink (cause-reaction play & symbolic play & social play) - use of sensors								B	B	P
	Complex Bite/Save (cause-reaction play & pretend play & cooperative play) - use of sensors										
	Complex turn off Aibo to sleep (symbolic play)										
	Speak directly to Aibo about Aibo's feeling (symbolic play)										
	Cause-reaction play & mental states: Ask a question to Aibo (e.g. identity, feeling), answer with a sensor						P				
	Cause-reaction play, Aim at a physical reaction of the robot, show it with a sensor						r		P		r
	Cause-reaction play & basic pretend play, "caught on the act"										
	Telling a story				P		P		P	P	
L 5	Cause-reaction play and explicit Social rapport: Ask a question to Aibo, answer with a sensor (e.g. press the sensor which opens the mouth), translate verbally the answer for the experimenter										
	Symbolic & pretend play Complex play with an accessory										
	Symbolic & pretend play Complex nap with Aibo										
	Symbolic & extrapolation play : "RobotCat" - Speak about the idea of a robotic cat (possibly imagine how one would play with it)										
	Causal composition of plays: Bite/Save & Give Food/Drink										
	Causal composition of plays: Kiss & Bite/Save										
	Pretend play & causal reaction & social rapports: Ask verbally Aibo to act a situation, use of sensors										
L 6	Pretend play & focus on Aibo's mental states: Mimic Aibo's cry, and explain Aibo is never crying but pretending to cry										
	Pretend play & social rapports: Look after Aibo and set up rules										P
	Pretend & symbolic & chronological play & social rapports: Search and rescue										P
	Pretend & symbolic play & social rapport & cause-reaction play & chronological play: competition (drink fast) between the child or the experimenter and Aibo ; the non-competitor activates Aibo's sensor										

Fig. 9. Child E. Play Grid. See Fig. 7 for a detailed caption. Note, Child E was away for Session 7.

the sessions (see Fig. 10). She experienced in play situations involving the activation of a specific sensor to generate a precise reaction only a bit. She rather proactively experienced firstly play situations where "affect" is largely addressed (e.g. "Social Hug"). Secondly, she developed play situations where the robot embodied a character in a story she was telling. Finally, in a third and last phase, she initiated play situations where she was able to tackle issues on social rapports or mental states (Session 10: "look after Aibo and set up rules" and "search and rescue" play situations).

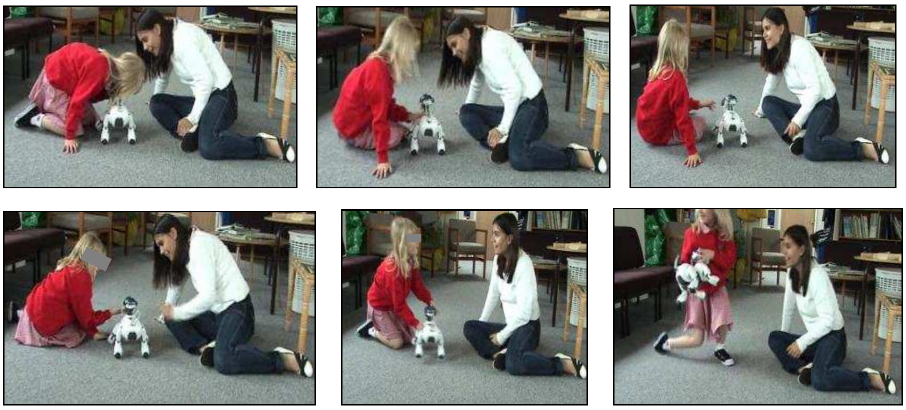

Fig. 10. Child E involed in social play with the experimenter. 2 sequences are displayed, one on each line. Each sequence is orgnised chronologically from left to right; on the first line, picture on the right and on the second line, picture in the middle, Child E is making eye contact with the experimenter.

The "looking after Aibo" game dealt with deciding that she and the experimenter would take care of Aibo, and Child E proactively suggested that, as a consequence, she and the experimenter would have to define rules the robot would have to respect; and she enumerated the rules (among them, a detailed list of what the robot is not allowed to eat, and the statement: "dogs must go outside and must walk", followed by "I need to make him walk"). This game also gave rise to proactive inferences of state, the child even saying: "Look! He is smiling!" in the proper context. The social status that she took of taking care of Aibo led her to show the experimenter how to do specific things such as to make Aibo go forward: "You see, you must do like this, see".

Furthermore, this game was followed by a "search and rescue game" which was extremely rich in many ways:
a) the child led the rhythm, the pace, and the four steps of the play situation (chronologically): step1) initial situation where Aibo is lost, the goal of finding Aibo is stated, step2) the experimenter and the child are looking for the dog, step3) final situation: the experimenter and the child find the dog.
b) the child slightly dilated step2 over time so that she could deal with emotional states, particularly sadness: "You think we've lost him for ever" said Child E; "Oh, that's sad" said the experimenter; and the child replied: "I think we're sad actually" thus conferring a socio-dramatic dimension to the current play situation.
c) during step3, when the robot was found, the child introduced some reasoning about categories: she introduced the notion that it might be another robot than Aibo that she and the experimenter had found; she introduced this reasoning step by step and she might not have been really at ease with these concepts, but the point is that she practised them through experiencing them: Child E's reasoning started with "Oh no, there are two Aibos here" and, after several steps in the reasoning, she drew the following conclusion: "No there are two dogs, only one Aibo. The clever one!" and she threw up her hands

Fig. 11. Child E's social hug to the robot. photos ordered chronologically from left to right. The child brings the robot to a second researcher (who helped out during this trial) while saying "Put your hands and hug, hug, hug" and both of them hug the dog. On the third picture from the left, Child E makes eye contact with the researcher.

accompanied by a big smile. Again, here is illustrated that both "reasoning" and "play" dimensions are highly intertwined.

Concerning the notion of "Essence" for the Reasoning dimension, Child E mixed the use of artefacts and biological statements such as saying within the same session: "He's a robot, he's a robot dog" and "Nice dog", "He is a nice dog", "I love dogs", "A boy or a girl?" (Session 10).

Except in the last session, the notion of "Mental states", was addressed mostly reactively: the child answered to questions asked by the experimenter such as "Do you think Aibo is hungry" (which usually initiates the game "Give food/drink"). There were two exceptions: a) the child proactively said that the robot liked her, and b) the child may refer to mental states when telling stories she adapted from well-known children's books. During the last session, the child proactively referred to mental states of the robot as mentioned above in both "look after" and "search and rescue" play situations. During the "look after" play situation, she said: "We play, want to make the dog happy, make the dog feel pretty".

Moreover, as already mentioned above too, she experienced "Social rapports" a lot e.g. either simply by saying (in Session 9) "Look at Aibo, Aibo is your dog" or in taking on specific social roles in more elaborated play situations (e.g. in Session 10, during "look after" and "search and rescue" games).

Concerning "Moral standing", no objective event related to it happened.

The dimension of affect played an important role for the child (Fig. 12). In Session 1 already, she started saying "good doggy" with respect to the robot. Then, in Session 3 she introduced the notion of social hug (see Fig. 11), which consisted of asking the experimenter (or the second researcher present) to help her hug the dog: "Put your hands and hug, hug, hug" Child E asked. Later in the same session, as well as in session 4, the child said, "The dog really likes me". Note that end of session 3 is the first time she answered to

Session	**Events objectively related to Affect** (ordered chronologically with respect to first appearance, event only mentioned once per session)
S1	• **[1ii] "Good doggy"** (Child E) while stroking the robot and looking at me (eye contact)
S2	
S3	• **[1iii] "Help me hug the dog: put your hands and hug, hug, hug"** (Child E) while bringing the robot near the assistant and showing how to hug • **[1ii] "Good doggy"** (Child E) • **[1i] "The dog really likes me"** (Child E). The experimenter answer "yes" • **[2i] "Do you like it?** (Experimenter). **"Yes"** (Child E)
S4	• **[1ii] "Good doggy"** (Child E), while stroking the robot • **[1i] "The dog really likes me"** (Child E) and she starts mimicking the noise that would do the dog by lapping her.
S5	• **[1ii] "Good doggy"** (Child E) and she looks at the experimenter; "yes very good doggy" (Experimenter).
S6	
S7	
S8	• **[1ii] "Good doggy"** (Child E) after the robot has "woken up" (i.e. is connected)
S9	• **[2i] Are you happy to see Aibo?** (Experimenter); **"Yes"** (Child E)
S10	• **[1ii] "Nice dog"** (Child E) • **[1i] "I love Aibo. I love Aibo"** (Child E) and she strokes the robot • **[1ii] "Good boy, good boy"** (Child E) and she strokes the robot • **[1i]** "Do you like the walk E, please tell me? (Experimenter); **"Yes, this is all about dogs like me"** (Child E) • **[2i] You like Aibo, right?** (Experimenter); **"Yes"** (Child E)

Fig. 12. Child E. Events related to Affect. See caption of Fig. 8 for details.

the question "Do you like it(Aibo)?" (she answered affirmatively). From that session onwards, the child confirmed several times the fact that Aibo liked her (e.g. session 4 "The dog really likes me") and that she liked Aibo (e.g. in session 10: "I love Aibo" and "Nice dog").

Child H. Child H took part in the 10 sessions of experiments. The Play Grid in Fig. 13 shows that Child H progressively experienced more and more complex levels of play over the sessions. During the first sessions, he explored very attentively the reactions of the robot and in the following sessions, he experienced more and more simple causal reactions through the following games: a) "ask about a feeling, answer with a sensor", e.g. in Session 10 the child asked: "are you happy?" and pressed the head button which made the robot wave the mouth as to say "yes". b) "aim at a physical reaction, show it with sensors": e.g. the experimenter asked "Do you think Tornado (the name the child gave to the robot) can wag the tail today?" and Child H activated the right sensor at the first attempt and commented: "That's the tail one". Child H also proactively played the game of giving food or drink to the robot as well as a cooperative play situation of Bite/Save (see Fig. 14). Bite/Save play situation consisted of two chronologically steps: i) the robot bite the finger of either the child or the experimenter (through the use of the sensors) and ii) the person remaining (child or experimenter) saved the latter by freeing her/his finger: the freeing was done either by activating the sensor ("Complex Bite/Save") or by directly taking the finger out of the mouth of the robot

		1	2	3	4	5	6	7	8	9	10
L 1	*Solitary* Exploration										
	"Imitation" of robot's bark										
	Solitary mirror play – look at oneself in the robot's reflecting face			P							
L 2	*"Pre-social" or basic-social* exploration – stroke Aibo immediately after the experimenter (possibly basic imitation of the gesture)										
L 3	*Social* exploration (social play)	P	P	P	P	P	P	P	P	P	P
	Simple Bite/Save or Give/Food - no use of the sensors						r	r			
	Position or locomotion game – with verbal qualification of the game	P		P					P		P
	Cooperative technical task: change the battery, or turn on/off Aibo	P	P	P	P	B	P	P	P	P	P
	Verbal order towards Aibo: e.g. "sit", "walk", "wake up"		P			P					
	Basic pretend & social play – imitate Aibo's snoring & verbal comment										
	Basic play on affective gestures – give/receive a kiss and/or a lip to/from Aibo										
	Repeat after me - ask the experimenter to repeat verbal expressions										
	Look at Aibo through the camera (Possibly stroke Aibo & look at its reaction through the camera)										
	Speak French with Aibo - e.g. "Hello" or "Bye-Bye" in French										
	Show Aibo to other children (social play) Express verbally the willing/intention to show Aibo to the other children										
	Simple play with accessory (symbolic play)							P			
	Social Mirror play (social play) - look at oneself (and possibly at the experimenter) in the robot's reflecting face & express verbal comments, e.g. "Look at my arm!"		P	P		P	P	P	P		
	Social Hug – hug Aibo & ask the experimenter or the second researcher to hug Aibo										
L 4	*Complex* Give Food/Drink (cause-reaction play & symbolic play & social play) - use of sensors						B	B	B	B	B
	Complex Bite/Save (cause-reaction play & pretend play & cooperative play) - use of sensors			P		B	r	P	P	P	P
	Complex turn off Aibo to sleep (symbolic play)							P			
	Speak directly to Aibo about Aibo's feeling (symbolic play)						P	P		P	P
	Cause-reaction play & mental states: Ask a question to Aibo (e.g. identity, feeling), answer with a sensor					r		r		P	P
	Cause-reaction play, Aim at a physical reaction of the robot, show it with a sensor			r		B			r		r
	Cause-reaction play & basic pretend play, "caught on the act"										P
	Telling a story										
L 5	Cause-reaction play and explicit Social rapport: Ask a question to Aibo, answer with a sensor (e.g. press the sensor which opens the mouth), translate verbally the answer for the experimenter						P		P	P	
	Symbolic & pretend play Complex play with an accessory										
	Symbolic & pretend play Complex nap with Aibo										
	Symbolic & extrapolation play : "RobotCat" - Speak about the idea of a robotic cat (possibly imagine how one would play with it)										
	Causal composition of plays: Bite/Save & Give Food/Drink							P			r
	Causal composition of plays: Kiss & Bite/Save										
	Pretend play & causal reaction & social rapports: Ask verbally Aibo to act a situation, use of sensors									P	
L 6	Pretend play & focus on Aibo's mental states: Mimic Aibo's cry, and explain Aibo is never crying but pretending to cry										
	Pretend play & social rapports: Look after Aibo and set up rules										
	Pretend & symbolic & chronological play & social rapports: Search and rescue										
	Pretend & symbolic play & social rapport & cause-reaction play & chronological play: competition (drink fast) between the child or the experimenter and Aibo ; the non-competitor activates Aibo's sensor							P			

Fig. 13. Child H. Play Grid. See Fig. 7 for a detailed caption.

("Simple Bite/Save").

Furthermore, in Session 7, the child proactively combined 2 games, "Give food/drink" and "Bite/save" and said: "He (the robot) is saying: give me a drink or I bite your fingers".

Another interesting play situation the child proactively experienced in Session 7 consisted of a competition between the robot and himself: both of them had to drink as fast as possible their invisible drink; the robot could only drink

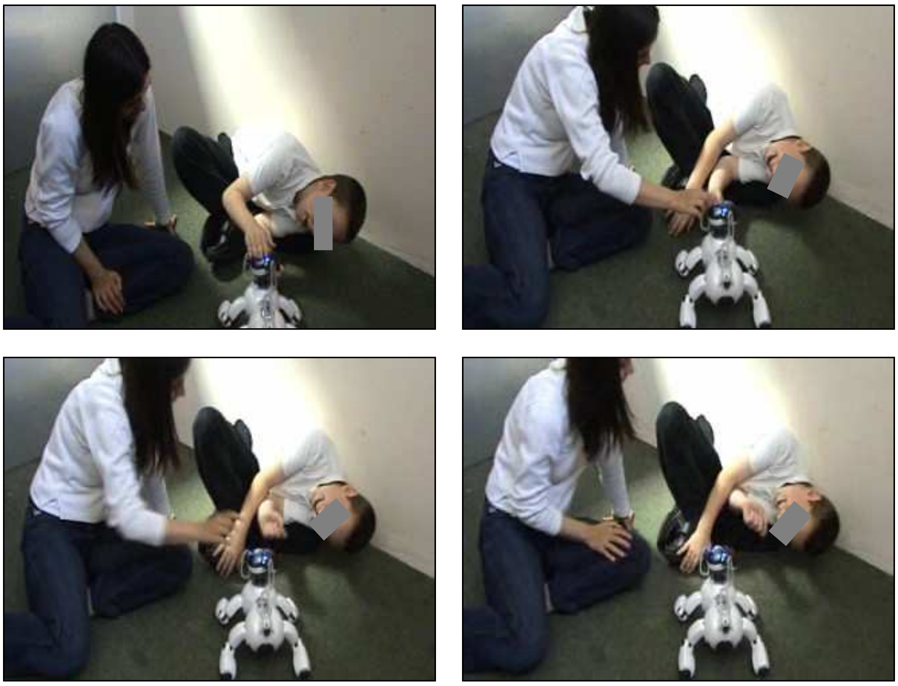

Fig. 14. Child H. playing the game ‘Bite/Save’ with the experimenter. Chronological order of the photos: from left to right and top to down. First photo: the child activates the head sensor of the robot which make the robot open the mouth and enable the robot to ‘bite’ his finger. Second photo: the experimenter brings her hand close to the head of the robot in order to activate the head sensor. Third photo: the experimenter activates the robot’s head sensor to make Aibo open the mouth in order to ‘save’ the child’s finger; when the mouth opens, the child pull of his finger (third and fourth photos).

with the help of the experimenter (the experimenter was asked to activate the sensor linked to the opening of the mouth as fast as possible). At the end of the competition, Child H decided that the robot had won. This play situation presupposes the child to be able to:
a) deal with rules of competition,
b) handle the temporal aspects of the game and the various chronological phases,
c) take on the role of the participant (as a competitor) and the one of the organizer who announces the winner,
d) play with abstract entities (invisible drink),
e) play socially.

Concerning the reasoning dimension, it should be first noted that the child decided to rename the robot after the first session and call him “Tornado”. Moreover, in the first sessions, most of his questions addressed the issue of the robot’s technical capabilities and how to control the robot. In Session 2, for instance, the child said: “How is he doing that?” and “What’s being on the head to make him walk” (because when he touched the head (and activated the head sensor), the robot walked). And later in the same session, while looking at the laptop he said “this must be the controller”. Furthermore, in Session 3, the child said: “I found how he might open his mouth”; the experimenter asked “is he moving the mouth?” and the child answered: “yes, when I stroke on the head, you see”. This example illustrates that the child actively developed technical and causal reasoning about behaviours and capabilities of the robot. This questioning can be related to the “Essence” part of the quadrology, and shows, that the child considered primarily Aibo (Tornado) as a proper robot. It should be noted here that the child invented the concept of “invisible drink” as well as the way of calling it (very logically): “invisible robot drink”. This illustrates the ability of the child to make links with real dog’s life while adapting it correctly to the characteristics of robots.

The “Mental state” part of the quadrology was addressed during later sessions (from session 5 onwards). In session 5 the child actually said “he is wagging the tail”; the experimenter answered: “yes, that shows he is happy”; and the child replied “He likes me” and he stroked the robot. The experimenter reinforced the positive feeling: “yes, he likes you”. That first step was expanded into the game “speak directly to Aibo about Aibo’s feeling”. In session 6 and onwards, the child addressed proactively the question of emotions but he tended to deal with a restricted repertoire of emotions only, such as “ being scared” or “being terrified”(e.g. session 7 the child said: “You’re scared Tornado, in fact you’re terrified”).

Child H dealt with “Moral standing” in session 5 when he accidentally kicked the robot and, in return, apologized to him directly (“Sorry Tornado”) and comforted him by stroking him.

Finally, Child H addressed indirectly the question of “Social rapports” through play. For instance, in session 10, he conferred a specific role to the robot for the competition; the robot thus became his adversary, but on a very kind level, since the child decided at the end of the game that the robot had won the competition. Another example took place in Session 8 where the child asked directly questions to the robot (e.g. “Do you want to drink something Tornado?”). Then, he made the robot bark as an answer and the child “translated” the answer verbally for the experimenter: “He said yes”. In this case, the child proactively played the social role of an intermediary position (like an interface) between the experimenter and the robot.

The dimension of affect (Fig. 15) appeared from Session 5 and onwards where the child proactively said “he (the robot) likes me”. And the experimenter replied “Yes he likes you. You like him?” The child then answered “Yes”. Then later, in Session 8, the child said “he (the robot) is very happy”. The

Session	**Events objectively related to Affect** (ordered chronologically with respects to first appearance, event only mentioned once per session)
S1	
S2	
S3	
S4	
S5	• **[1i]** "Yes that shows he (the robot) is happy" (Experimenter); **"He likes me"** (Child H); "Yes he likes you" (Experimenter); • **[2i]** **"You like him** (the robot)**?"** (Experimenter); **"Yes"** (Child H)
S6	
S7	
S8	• **[1i]** "He (the robot) is very happy" (Child H) while making the robot bark; "Yes he is" (Experimenter)**,"Tornado likes me"** (Child H); "Yes he likes you" (Experimenter)
S9	• **[1ii] "Tornado is very friendly, isn't it?"**(Child H); "yes, he is"(Experimenter)
S10	

Fig. 15. Child H. Events related to Affect. See caption of Fig. 8 for details.

experimenter agreed with him and then Child H added "Tornado likes me" and the experimenter reinforced the positive feeling: "Yes he likes you". In Session 9, Child H commented on the robot, qualifying him as 'friendly': "Tornado is very friendly, isn't it?" and the experimenter agreed verbally.

Child N. Child N was away for session 5. Thus he took part in 9 sessions. Note that on his explicit demand, session 7 and session 8 were not recorded (the experimenter had permission from the parents to videotape the child but she decided to value the child's request); thus information from sessions 7 and 8 is missing in the corresponding columns in the Play Grid. The Play Grid Fig. 16 shows that Child N engaged in social play almost all the time. He used verbal language a lot and progressively experienced some more complex levels of play notably pretend play with respect to "play with accessory". The first situations of "play with accessory" happened in Session 3. In this session, the child borrowed the mouse of the laptop and put it on the ground in front of Aibo at approximately 30 cm distance and asked the robot to touch the mouse with the paw. Then he activated the right sensor to make Aibo walk forward and approach the mouse. The child carried the robot for the 5 remaining centimetres separating the robot's paw from the mouse and finally the robot touched the mouse with his paw. Later, in session 4, the child experienced further situations of "play with accessory" in two successive steps. As a first step, he proactively played very simply with an accessory. For instance, Child N used the face of a character drawn on a piece of cardboard that he held in front of his face and told Aibo: "Stay here Aivo, I got something to show you". Note that the child slightly changed the pronunciation of the name of the robot and referred to Aibo as 'Aivo'. As a second step, later in the same session, the child proactively played a more complex accessory game with the robot, the "ghost dog". That play situation consisted of putting a cloth on top of Aibo and pretending Aibo was a ghost dog (Child N told Aibo: "You can be a ghost dog Aivo"); vocally, the child used classical onomatopeia mimicking ghost's "voice and presence". Moreover, in Session 6, the child decided

Level	Play	1	2	3	4	5	6	7	8	9	10
L 1	*Solitary* Exploration										
	"Imitation" of robot's bark	P	P	P			P			P	
	Solitary mirror play – look at oneself in the robot's reflecting face										
L 2	*"Pre-social" or basic-social* exploration – stroke Aibo immediately after the experimenter (possibly basic imitation of the gesture)										
L 3	*Social* exploration (social play)	P	P	P	P		P			P	P
	Simple Bite/Save or Give/Food - no use of the sensors									P	P
	Position or locomotion game – with verbal qualification of the game	P			P		B			B	P
	Cooperative technical task: change the battery, or turn on/off Aibo	r		P	B		r			P	B
	Verbal order towards Aibo: e.g. "sit", "walk", "wake up"	P	P	P	P					B	P
	Basic pretend & social play – imitate Aibo's snoring & verbal comment										
	Basic play on affective gestures – give/receive a kiss and/or a lip to/from Aibo									P	P
	Repeat after me - ask the experimenter to repeat verbal expressions										P
	Look at Aibo through the camera (Possibly stroke Aibo & look at its reaction through the camera)			P	P		P			P	P
	Speak French with Aibo - e.g. "Hello" or "Bye-Bye" in French				r		B				r
	Show Aibo to other children (social play) Express verbally the willing/intention to show Aibo to the other children	P	P								
	Simple play with accessory (symbolic play)			P	P						
	Social Mirror play (social play) - look at oneself (and possibly at the experimenter) in the robot's reflecting face & express verbal comments, e.g. "Look at my arm!"										
	Social Hug – hug Aibo & ask the experimenter or the second researcher to hug Aibo										
L 4	*Complex* Give Food/Drink (cause-reaction play & symbolic play & social play) - use of sensors										
	Complex Bite/Save (cause-reaction play & pretend play & cooperative play) - use of sensors										
	Complex turn off Aibo to sleep (symbolic play)						P				P
	Speak directly to Aibo about Aibo's feeling (symbolic play)		P								
	Cause-reaction play & mental states: Ask a question to Aibo (e.g. identity, feeling), answer with a sensor		B	P	r		B				
	Cause-reaction play, Aim at a physical reaction of the robot, show it with a sensor		P	B	B		r			P	P
	Cause-reaction play & basic pretend play, "caught on the act"										
	Telling a story										
L 5	Cause-reaction play and explicit Social rapport: Ask a question to Aibo, answer with a sensor (e.g. press the sensor which opens the mouth), translate verbally the answer for the experimenter										
	Symbolic & pretend play Complex play with an accessory			P	P		P				
	Symbolic & pretend play Complex nap with Aibo				P						
	Symbolic & extrapolation play : "RobotCat" - Speak about the idea of a robotic cat (possibly imagine how one would play with it)									P	P
	Causal composition of plays: Bite/Save & Give Food/Drink										
	Causal composition of plays: Kiss & Bite/Save										P
	Pretend play & causal reaction & social rapports: Ask verbally Aibo to act a situation, use of sensors										
L 6	Pretend play & focus on Aibo's mental states: Mimic Aibo's cry, and explain Aibo is never crying but pretending to cry										P
	Pretend play & social rapports: Look after Aibo and set up rules										
	Pretend & symbolic & chronological play & social rapports: Search and rescue										
	Pretend & symbolic play & social rapport & cause-reaction play & chronological play: competition (drink fast) between the child or the experimenter and Aibo ; the non-competitor activates Aibo's sensor										

Fig. 16. Child N. Play Grid. See Fig. 7 for a detailed caption. Note, Child N was away for Session 5 and, on his request, was not filmed during Sessions 7 and 8.

to make the robot wear clothes and this game was expanded by:
a) a series of questions on inferring states of the robot with respect to like/dislike,
b) a direct communication with the robot to explain him what he was wearing (Child N told Aibo: "Look at you Aivo! You've got some paper on in to be black");
c) a version of the game "aim at a physical reaction of the robot, show it with a sensor" (the experimenter asked "How do you make him walk with all these clothes?", the child replied "Walk?", and the child made the robot walk).

In addition to the accessory games, the child appeared to experiment with pretend play with the robot in a social context, e.g. pretending having a nap with the robot (in session 4) in a detailed (and complex) way resulting of:
a) using a cloth as a blanket to cover both of them,
b) deciding on the duration of sleep and asking for watching the clock to respect the time predefined for the nap,
c) pretending to snore,
d) both of them waking up again.
Besides, another way of tackling pretend play as well as robot's mental states happened in session 10 when the child imitated Aibo's crying, and then argued that Aibo was not crying but pretending to cry. And this notion of pretending to cry for the robot was reused many times during the last session (e.g. Child N said: "No, he's not crying, he is only pretending to cry").

The reasoning dimension is really an important component of the profile of Child N. Child N principally addressed three of the four components, respectively, "Essence", "Mental States" and "Social Rapport", and, in minor importance, the issue of "Moral statement".
Concerning "Essence", the child really tackled the question of artefact or biological features, processes and categories. Categorywise, he often questioned about robot dogs boundaries, e.g. in Session 2: "Have you seen dogs that are not robot dogs, yes or no?" he asked to the experimenter, and later in the same session: "He has short teeth, he doesn't bite. Robot dogs don't bite, do some do?"

The part on "mental states" is very rich since the child addressed all the aspects defined in the coding manual of Kahn et al. in (Kahn et al., 2003) except probably the "autonomy" one. Actually, he attributed "intentions" to the robot in Sessions 1 and 2. He explicitly considered robot's "emotional states" in sessions 2, 4, 6 and 10. He also both tackled "emotional states" of the robot and his "personality" when he asked him questions about his likes/dislikes (e.g. Session 4: "Do you like toys Aivo, yes or no?"). Furthermore he pretended the robot had some "cognitive abilities" and developed play upon it: in Session 4, for instance, he disguised himself with an accessory in order to "show" Aibo and thus presupposed, for the game, that Aibo could see. Later, in Session 6, again, the child presupposed for the game that the robot could see and told him: "Look at you Aivo. You've got some paper on to be black". The last aspect of "mental states" is the notion of "development" of the robot. Child N really questioned about it, from the very beginning of the sessions onwards. More than the notion of development, the child seems to have been willing to build a biography for the robot (i.e. the past of the robot) and therefore asked questions to the experimenter such as: a) in Session 1: "Where was this robot dog from?"; b) in Session 2: "Where was he born?"

and “Has he travelled in a car?”; c) in Session 3: “Where did you get him from?”, “Where does he live?”, “How old is he?”, etc.

Concerning the part on “Social rapports”, the child really investigated the social links between the robot and the experimenter, who was considered by the child as being the “mum” of the robot (Child N told the experimenter “it’s your dog son”, meaning that Aibo is the experimenter’s dog, and that the experimenter, in a way, is considered as being Aibo’s ‘mum’). Besides, he investigated the social links between the robot and himself, through situations of pretend play but also verbally. In Session 2 for instance, the child presupposed that there was a social rapport between the robot and himself since he told the robot: “When it is lunch time Aivo I got to go. And don’t cry Aivo”. Later, in Session 6, the child stated that the robot was his cousin: “Aivo is my cousin”. And when the experimenter asked: “Aivo, do you like playing with N? Can you tell me? Can you ask for his answer N?[7]” then the child told Aibo: “Aivo do you like me? You’re my cousin. I’m your cousin Aivo”. Besides, the child investigated beyond social rapports involving Aibo and questioned the experimenter about her family and explained about his family and himself. Let’s write a few examples below: a) in Session 4, the child asked about the experimenter’s French accent: “What accent do you speak”, which was further investigated in Session 6: “Why do you speak French?” and “Why were you born in France?”; b) in Session 6, he asked her about her family: “What are your parents’ names?”; he investigated more broadly questions on the experimenter’s family in session 10.

On the affect level (Fig. 17), the child expressed himself a lot, both by gestures (e.g. giving a kiss to Aibo after saying “Goodbye Aivo, have a good sleep” in Session 6) and verbal expressions (e.g. in Session 4 when he dresses up Aibo: “Put this on, Aivo, my dog, my friend, Aivo”). It is perhaps worthy of note here that it might be the case that some gestures related to Affect from a non-autistic perception (e.g. giving a kiss), don’t have the same interpretation for a child with autism: for a child with autism, giving a kiss might, for instance, just be an imitated response. Concerning Child N, it might be the case that the child reproduced the gesture “giving a kiss” from a situation he had encountered or witnessed before; though it should be further mentioned that his gesture was made proactively, with no previous reference from the experimenter to such a gesture.

[7] Child N is designed by N in the dialogue, in order to protect his anonymity.

Session	**Events objectively related to Affect** (ordered chronologically with respects to first appearance, event only mentioned once per session)
S1	• **[1ii] "Ooh he is a nice dog"** (Child N) and he strokes the robot
S2	
S3	
S4	• **[1ii]** Child N brings a towel to put on the robot : **"Put this on Aivo, my dog, my friend, Aivo"** (child N)
S5	
S6	• **[1i] "Aibo, do you like me?** You're my cousin. I'm your cousin Aivo**"** (Child N) • **[1iv]** Child N gives a **kiss** to the robot on the muzzle after saying **"OK, Goodbye Aivo, have a good sleep"**
S7	
S8	
S9	
S10	• **[1iv]** Child N has covered Aibo with a coat; he gives the robot **a kiss** on the forehead and says **"Goodnight Aivo"**

Fig. 17. Child N. Events related to Affect. See caption of Fig. 8 for details.

5 Discussion

Results from these experiments show that the children progressed differently, and their profiles according to the three (intertwined) dimensions "Play - Affect - Reasoning" are unique. This highlights how the experimental approach presented in this study allows many trajectories for progressing and more specifically how it can adapt to the child's specific needs and abilities.
Furthermore, concerning the dimension of play, and, more precisely, concerning the children's progression with respect to solitary vs. social play, three groups can be highlighted. The first group, group 1, is constituted by children who mostly played solitarily and possibly encountered rudimentary situations of imitation, but no further components of social play. This group would include both Child D who encountered imitation in session 10 and Child J. Note, both of them find it very hard to communicate verbally. The second group, group 2, would be constituted by Child C who mostly communicates non-verbally but progressively experienced more complex situations of verbal communication and showed pre-social or basic social play during the last sessions. The third group, group 3, is constituted by Child E, H and N. Those children proactively played socially (i.e. in a triad including both the robot and the experimenter). Results show that a) Child J experienced progressively longer uninterrupted periods of play and engaged in basic imitation during the last sessions; b) children from group 3 tended to experience higher levels of play gradually over the sessions and constructed more and more reasoning about the robot (and sometimes experienced specific reasoning about real life situations as well). Child C seems to have started experiencing some reasoning as well, especially technical reasoning about the robot such as "turning on" and "turning off" the robot as well as changing the battery. In the last sessions different elements suggested that he may also have experienced some reasoning about social rapport.

Besides, the children's proactivity was encouraged, thus also facilitating taking initative and expressing intentions (cf. the proportion of proactive activities vs. reactive activities in the Play Grids).

These results are in agreement with Josefi et al.'s findings when they conducted their pioneering long-term therapeutic study with a child with autism, applying the non-directive play therapy technique (Josefi and Ryan, 2004). Their experiments and results have been detailed in Section 2.1 of this paper. In a comparable way to Josefi et al.'s study, our approach has shown that the children's proactivity and initiative-taking was encouraged. Further to this, Josefi et al.'s study has shown that non-directive play therapy may encourage symbolic play, which is an important finding of our approach, too: In our study, children from group 3 progressively experienced situations of symbolic or pretend play. It is probably worthy of note here that, as already explained in Section 1.2, the study presented in this paper took place in a therapeutic context but the experimenter was not behaving exactly like a therapist.
A further conclusion of Josefi et al.'s study was that non-directive play therapy with children with autism may be complementary to behaviour therapy, non-directive play therapy likely to be more efficient in the child's gaining autonomy, taking initiative, joining attention and developing social and symbolic play, while behaviour therapy would be more efficient in reducing ritualistic and obsessive behaviours (Josefi and Ryan, 2004).
Note, it is very difficult to evaluate quantitatively and very objectively the results of non-directive play therapy. This may be a reason why many researchers seems to stick to behavioural therapy only. In robot-mediated therapy, it may be the same reason why experiments mostly remain task-oriented.

Davis et al. compared different robotic or computer platforms used in the Aurora Project and compared their specific focus in (Davis et al., 2005). It shows that mobile autonomous robots are adequate to unconstrained play situations, while the use of the humanoid robot Robota focuses mostly on imitation of movements and gestures. Though, limited attention has been accorded so far to proper unconstrained play situations with an autonomous mobile robot and most experiments have been carried out using Robota and focussing on imitation. In Robins et al. long-term studies with the non-mobile doll-like robot Robota (see Section 2.2), situations of child-robot interactions which actually happened were mostly restricted to situations of imitation of a gesture or a movement (Robins et al., 2004). Thus, even if the experiments were not qualified as such, they were in fact much more task-oriented, at least with respect to the dyadic child-robot interaction. Nadel et al. showed that imitation skills have a significant impact on the acquisition of social skills for children with autism (Nadel et al., 1999). Though, focusing on imitation tasks only may not be sufficient when the child reaches some higher levels of play (cf. children from group 3 in the experiments presented in this study); Howlin and Rutter underlined the necessity of incorporating developmental aspects in pure be-

haviour principles (Howlin and Rutter, 1987).
Werry et al.'s trials (presented in Section 2.2) tended to encourage relatively unconstrained situations of play by using a mobile autonomous robotic platform (Werry et al., 2001; Werry and Dautenhahn, 1999). Shape, weight, sensors and the range of possible behaviours of the robot used (Labo-1, see more details in Section 2.2 of this paper) are in contrast with Aibo's properties: Labo-1 is heavier, not pet-like, and has only few sensors. The Werry et al. study only used very few simple behaviours, compared to Aibo's rich behaviour repertoire used in this study. Thus, interactions enabled by the robotic platform Labo-1 were very different in nature than the ones enabled by the use of Aibo robot, and less varied in ways the robot could react to the child's 'stimulations'. It should be noted moreover that in the present study, Child H most of the time asked for Aibo not to walk: the use of Aibo in trials enabled the child to play with Aibo either in a mobile or non-mobile mode (robot walking or non-walking mode), whatever choice the child prefers. Even when not walking, Aibo can still react in various ways (e.g. turning head, wagging the tail, barking etc.). The second main point is that in Werry et al.'s experiments, none of the experimenters participated in the experiments. The child played on his/her own with the robot (Werry and Dautenhahn, 1999), or two children interacted at the same time with the robot (Werry et al., 2001), but none of the experimenters did take part in the trials —they only responded to the child when the child initiated communication or interaction with them- (Dautenhahn and Werry, 2002). The approach inspired by non-directive play therapy presented in this study is therefore very different from Werry et al.'s work.

The study presented in this paper goes beyond these previous experiments, since it provides the child with a relatively highly unconstrained environment of play: due to the mobile autonomous robotic pet, the child can engage in a larger repertoire of play situations (note that Robota is fixed in place) and notably experience causal reaction play and symbolic play. Imitation is used as a bootstrap to initiate more complex situations of interaction or to help the child reengage in the interaction. The experimenter is part of the trial and her role is both to answer child's solicitations and to reward the child. Furthermore, the latter is empowered under specific circumstances:
a) if the child is about to enter a repetitive behaviour, then the experimenter can proactively intervene to try to prevent the child from entering that repetitive behaviour or stop it; note that "a)" aims at counterbalancing the fact that repetitive behaviours may not be considerably reduced by pure non-directive play therapy as stated in Josefi et al.'s study (Josefi and Ryan, 2004).
b) if the child does not engage in the interaction, then the experimenter may encourage him/her engage in playing with the robot,
c) if the game is "standing still" but the child has already experienced this play and has shown he/she is capable to play this specific game, then the experimenter can intervene at certain moments to give a better pace to the

game;
d) if the child is about to reach an upper level of play but still needs some bootstrapping (or some guidance), then the experimenter may provide it,
e) the experimenter may proactively ask the child simple questions related to reasoning or affect such as: “do you think Aibo is happy today?” or “do you like playing with Aibo?”.
The promising results from the experiments conducted in this study reinforce the idea that this approach may be a vehicle for the child to develop a broad range of play skills as well as communication and social skills.

Besides, there are many advantages of introducing a robotic pet in the experimental setup:
a) the use of a robot allows to simplify the interaction and to create a more predictable environment for play to begin with, thus facilitating the child’s understanding of the interaction (e.g. by giving the robot a simple predictive behaviour to start with)
b) children tend to express interest in the robot, and occasionnally affect towards Aibo, as our findings show;
c) here, one of the findings is that, in these experiments, with this new approach, through play with the robotic pet, children tend to develop reasoning, and make comparisons to real dogs’ lives.
Thus, the robotic pet can be considered as a good medium for developing reasoning on mental states and social rapports upon, and for learning about basic causal reactions too.

This study is explorative in nature, and more research needs be done to investigate more systematically the contribution of such an approach in the specific field of robot-mediated therapy.

6 Future Work

Looking back at the results, specifically considering group 1, group 2 and group 3, the existence of group 1 shows that some children did remain playing dyadically with the robot most of the time, and did not manage to experience aspects of social play, except maybe, occasionally, some rudimentary imitation gestures. For those children, it is particularly crucial to develop basic play skills through this dyadic interaction first, in order to help them reach higher levels of play and ideally, experience later triadic situations of play with the experimenter and the robot.

As part of future work, the question should therefore be investigated as to how to further facilitate children's play with the robot, for the children who remain at the level of solitary play; In this case, the robot should be able to appropriately adapt to the child's needs and abilities and encourage the child to progress towards more complex play styles autonomously. This issue has been first addressed in some previous work (François et al., 2007) where the robot adapts its behaviour on-line and autonomously to specific play styles of the child in order to guide him/her towards more balanced interaction styles.

Furthermore, it would be very interesting to investigate how to tailor the behaviours of the robot in order to guide the child towards more and more complex levels of play, drawing inspiration from Child C's profile, who started with solitary play and progressively developed basic aspects of social play. This study, preliminary in nature, indirectly explored various types of play the children did proactively experience with the robotic pet (cf. Play Grids). It may be feasible to enable the robot to guide the child towards some of these play situations, very basic ones, such as simple cause-reaction play situations. Ideally, at some point, the child would naturally move towards group 2 and be able to engage in simple situations of social play (with both the experimenter and the robot).

This study is preliminary in nature and more experiments would be required to investigate further the potential of the approach. Moreover, classical quantitative microscopic indicators to analyse the videos, such as the number of gestures imitated or the number of events related to joint attention are insufficient to extract all the relevant information and meaning about the child's specific profile according to the three dimensions Play - Reasoning - Affect. It might be appropriate for children from group 1 but for those from group 2 and *a fortiori* group 3, a mesoscopic approach involving a qualitative analysis is required. Note that, "mesoscopic" is an intermediary scale between "microscopic" and "macroscopic". It is indeed necessary to look at the events constituting an uninterrupted play as connected events, and as a whole. Note, two similar play situations might actually happen to be different in the way the child experiences them, such as for example, the fluency, the rhythm, the coherence etc. This current paper has mostly focused on a mesoscopic qualitative analysis for children from group 2 and group 3 because the authors were interested in the emergence of specific play styles, questions or statements related to reasoning and events that could be objectively related to affect, and not about the occurrences or the duration of each of them. A further step would be to further develop and formalize the methodology for analysing the results in order to facilitate its systematic use for further studies following this experimental approach.

7 Conclusion

This paper highlighted a new approach in the context of robot-mediated therapy with children with autism. This approach draws its inspiration from non-directive play therapy, notably encouraging the child's proactivity and initiative-taking. Beyond inspiration from non-directive play therapy, the approach introduces a regulation process. The experimenter, who takes part in the experiment, can indeed regulate the interaction under specific conditions detailed in Section 3; in brief:
a) to discourage repetitive behaviour,
b) to help the child engage in play,
c) to give a better pace to the game if it has already been experienced by the child,
d) to bootstrap a higher level of play,
e) to ask questions related to reasoning or affect.

A long-term study was carried out with six children which highlights:
a) the capability of the method to adapt to the child's specific needs and abilities through a unique trajectory of progression with respect to the three dimensions, Play - Reasoning - Affect;
b) each child made progress with respect to at least one of the three dimensions progressively over the sessions;
c) with respect to the dimension of play and more precisely to the criteria of solitary vs. social play, children can be categorized into three groups. Besides, the children who managed to play socially experienced progressively higher levels of play and constructed progressively more reasoning related to the robot; they also tended to express some interest towards the robot, including on occasions interest involving positive affect.

Nevertheless, for the children remaining playing solitarily, it may be necessary to enable the robot to adapt more accurately to the child's specific needs and abilities, also being able to autonomously adapt on-line its own behaviour to the child's specific play style. Tailoring the behaviours of the robot consistently and efficiently with respect to each child's needs and abilities is a big challenge. Ideally, the dyadic interaction with the robot should lead to a triadic interaction with both the robot and the experimenter, when the child has made sufficient progress. As a first step towards this goal, the robot should autonomously help and guide the child experience various play situations, both in levels and in nature. Projecting some features of basic triadic play, such as cause-reaction play into a dyadic situation of play could be a first step in that direction.

Finally, this paper presents a preliminary study towards a broader investigation of this pioneering approach and further experiments will be carried out to confirm the promising results of this first long-term study. The first author of the paper is currently carrying on experiments in the same school with different children. Future work should also focus on formalizing more systematically, for this specific approach, appropriate techniques to analyze the videos, including a mesoscopic qualitative analysis of the situations of play.

It is hoped that this study represents a step forward in the investigation of robot-mediated therapy through play for children with autism.

8 Acknowledgments

The first author is supported by a research scholarship of the University of Hertfordshire. The work described in this paper was partially conducted within the EU Integrated Project RobotCub (Robotic Open-architecture Technology for Cognition, Understanding and Behaviours) and was partially funded by the European Commission through the E5 Unit (Cognition) of FP6-IST under contract FP6-004370.

The authors would like to thank Colnbrook School: the teachers, the children who took part in the experiments, and their parents. The authors would like to thank Megan Davis for assisting in some of the experiments.

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Faculty of Engineering & Information Sciences

Real Time Recognition of Human-Robot Interaction Styles with Cascaded Information Bottlenecks

27 May 2008

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Technical Report 478

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May 2008

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***Abstract*—We present a novel algorithm for pattern recognition, the Cascaded Information Bottleneck method. We apply it to real time autonomous recognition of human-robot interaction styles. This method uses an information theoretic approach and enables the progressive extraction of relevant information from times series. It relies on a cascade of bottlenecks, the bottlenecks being trained independently, one after the other, according to the existing Agglomerative Information Bottleneck algorithm. We show that a structure for the bottleneck states along the cascade emerges, which enables to extrapolate unseen data. This algorithm is tested in the context of human-robot interaction and, particularly, play between children with autism and an autonomous robot. We demonstrate that it can classify interaction styles in real time, with a good accuracy and a very acceptable delay.**

***Index Terms*—human-robot interaction, pattern recognition, information theory, autism.**

I. Introduction

This study is part of the Aurora project [1], an ongoing long-term project investigating the potential use of robots as a therapeutic toy for children with autism. One main stream of this project focuses on developing methods enabling the robot to analyze in real time the interaction styles and adapt its own behaviour appropriately with respect to a child's specific needs and abilities[1]. As a first step towards this goal, the robot should be able to recognise in real time the gentleness of the interaction and the rhythm of play. This paper presents a novel recognition algorithm, the cascaded information bottleneck method, which enables to recognise in real time the interaction styles. The method uses an information theoretic approach and takes inspiration from the "Information Bottleneck Method" developed by Tishby et al. in [13]. It may be used for various applications of time series analysis for pattern recognition and, more precisely, in our context, for the recognition of various interaction styles. Importantly, this work goes beyond prior work that either classified and characterized interactions off-line, i.e. after the interactions had taken place, or relied on explicit criteria tuned by hand (vs. automated training phase of the recognition algorithm). It also goes beyond previous work of the authors which enabled real time recognition of interaction styles with respect to one criterion, the gentleness, using a different method, based on self-organizing maps.

The remainder of the paper is structured as follows. Section 2 details the motivation of this research. Section 3 summarizes related work. Section 4 presents the Cascaded Information Bottleneck Method. The implementation is detailed in Section 5 and experiments are described in Section 6. Section 7 analyses the results which are discussed in Section 8. Conclusion and Future work close the paper (Section 9).

II. Motivation

Children with autism have specific needs and abilities and autism should be considered as a spectrum disorder[2] whose main impairments highlighted by the National Autistic Society[3] are: impaired social interaction, impaired social communication and impaired imagination.

Through play, children can engage in diverse situations and experiment in various domains, such as abstract, imaginative, communication and social skills. It is hoped that, through play, children with autism may experience and develop some basic social and communicative skills. Children with autism often encounter obstacles to express their play potential and play should be facilitated to help them reach progressively higher levels of interaction. In child-robot interaction, a first step towards this goal is to enable the robot to recognize the specific child's interaction style in real time, so that it can adapt its own behaviour appropriately and eventually influence positively the child's behaviour. Here, we consider two criteria for qualifying the interaction styles, namely the gentleness and the rhythm of the interaction. An interaction is classified as 'gentle' (resp. 'strong') if the participant strokes the robot gently, without signs of force (resp. with signs of force). The rhythm of interaction is categorised into four classes $Si\ i = 0...3$, defined by their typical periodicity of interaction T (in seconds): i) S0: 'very low' ($T > 15$ seconds), ii) S1: 'middle inferior' ($5 < T \leq 15$), iii) S2: 'middle superior' ($1 < T \leq 5$), and iv) S3: 'very high' ($T \leq 1$ second).

III. Related Work

The role of tactile human-robot interaction in educational and therapeutic applications has been well highlighted by long-term studies with the seal robot Paro which have proven that specific everyday life situations exists in which human-robot

[1]We consider the child's abilities as they are expressed through interaction with the robot, resulting in different play styles.

[2]Diagnostic and Statistical Manual of Mental Disorders, $4th$ Ed., 1994

[3]NAS: http://www.nas.org.uk

interaction can have a positive effect on well-being of human beings [10] and even play a role in a therapeutic context of cognitive and physical rehabilitation [6]. The Huggable robot, a teddy-bear like robot, equipped notably with a full body sense of touch, has proven to be a promising support to investigate the quantitative characterisation of social affective content of touch [12]. Offline characterisation of interaction styles in general, moreover, has been investigated recently with diverse approaches. In [9], Scassellati focused on providing quantitative and objective measurements to assist in the diagnosis of autism. Measurements refers to the position in the room, vocal prosody and gaze pattern – whose characterisation relies on linear discriminant analysis. Kanda et al. conducted a study [4] that highlighted the feasibility to link quantitative robot and human's data characterizing body movements with a subjective evaluation made by the participant. Later, in [7] Salter et al. showed the possibility, in the context of child-robot interaction, to reflect some traits of personality of the children with an offline clustering technique based on the empirical probability distribution of the activation of the sensors.

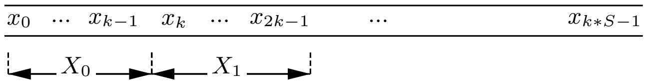
Concerning real time classification of interaction styles, in [8], Salter et al. have presented a real time simple recognition algorithm for four interaction styles ('alone', 'interacting', 'carrying' and 'spinning') using the robotic platform Roball. The algorithm is based on a decision tree whose conditions are set up manually, by visual inspection of sensor data. In [2], Derakhshan et al. present an interesting real time classification algorithm of interaction styles for children playing on an adaptive playground that is made of tiles equipped with sensors. The algorithm relies on a multi-agent system approach of BDI (Belief—Desire—Intention) in combination with neural networks using supervised learning. It shall be further noted that in the slightly different context of gesture recognition, Hidden Markov Models have been largely used for real time recognition [5].

IV. The cascaded Information Bottleneck Method

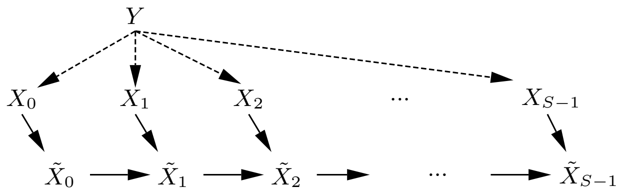
Background: The Information Bottleneck Method [13] is a clustering method based on an information theoretic approach which purpose is to extract the relevant information[4] in a signal $x \in \mathcal{X}$ that is, extract features of a random variable (r.v.) X that are relevant to the prediction of Y. This problem is modeled by the following Bayesian network with Markov condition: $\tilde{X} \longleftarrow X \longleftarrow Y$ where $\tilde{X}$ is the variable that extracts information about Y through X. The rationale is that the best trade-off between the compression of the signal and the preservation of the relevant information is the one that keeps a fixed amount of relevant information about the relevant signal Y while minimizing the number of bits from the original signal, i.e. maximizing the compression. The Agglomerative Information Bottleneck algorithm [11] maximizes the mutual information between $\tilde{X}$ and Y and induces a hard partition of the data.

[4]The relevant information being defined in this context as the information that the signal $x \in \mathcal{X}$ provides about another signal $y \in \mathcal{Y}$.

The principle: Based on the Information Bottleneck Method, we have developed a novel recognition algorithm particularly adapted for time series analysis. Let x $\in X$ be the time series input signal of length l, $x = [x_0, ..., x_{l-1}]$. It is possible to find k and $S \in \mathbb{N}$, with $l = k * S$, such as x can be divided into S disjoined parts of cardinality k, X_s, $s = 0, ..., (S-1)$ in the following way :



The Cascaded Information Bottleneck method relies on the principle that the relevant information can be progressively extracted from the time series with a cascade of successive bottlenecks sharing the same cardinality of bottleneck states but trained independently. The agglomerative bottleneck algorithm is applied for each bottleneck successively, the first one being trained in the standard way while the next ones depend on the previous bottleneck states, as the following graph shows:



Extrapolation: The Cascaded Information Bottleneck method progressively extracts the relevant information from an input sample $X = [X_0, ..., X_{s-1}]$ by a recall on the successive components (X_0 for the first step of the cascade $(\tilde{X}_{s-1}, X_s)$ for the other steps s). In the case of an unseen pair $(\tilde{x}_{s-1}, X_s)$ at step s, the cascade can a priori make no inference on $\tilde{X}_s$ because there is no preexisting default continuation of the cascade due to the fact that the bottlenecks have been trained independently. For such cases, it is necessary to introduce a 'default' way leading from $\tilde{X}_{s-1}$ to $\tilde{X}_s$ and, for this purpose, we apply a 'natural' reorganisation of the bottleneck states at each possible step s (i.e. a one to one mapping of the bottleneck states at step $s-1$ and the ones at step s, that we call a permutation). For this purpose, we introduce the following measure $d_{(s-1,s)}$ allowing to directly compare the reorganised bottleneck states from step s with those from step $s-1$. Let $\tilde{\mathcal{X}}_{s-1}$ (resp.$\tilde{\mathcal{X}}_s$) be the set of bottleneck states $\tilde{x}_{s-1}$ (resp. $\tilde{x}_s$) and $p(\tilde{x}_{s-1})$ (resp. $p(\tilde{x}_s)$) the empirical probability; for each permutation r of the bottleneck states $\tilde{X}_s$:

$$d_{(s-1,s)}(r) = \sum_{\tilde{x}_{s-1} \in \tilde{\mathcal{X}}_{s-1}} p(\tilde{x}_{s-1}) \log \tilde{p}(\tilde{X}_s = r(\tilde{x}_{s-1}) | \tilde{X}_{s-1} = \tilde{x}_{s-1}) \quad (1)$$

Note that if $\tilde{p}(\tilde{X}_s = r(\tilde{x}_{s-1}) | \tilde{X}_{s-1} = \tilde{x}_{s-1}) = 0$ then, by convention, $d_{(s-1,s)}(r)$ is ∞. The permutation of the bottleneck states that extracts the most similarity between bottleneck states at step $s-1$ and those at step s is given by:

$$R(s-1, s) = \arg\min{}_r d_{(s-1,s)}(r) \quad (2)$$

R(s-1, s) is the 'default' path between $\tilde{X}_{s-1}$ and $\tilde{X}_s$, i.e. the criteria for extrapolating an unseen event at step s.

V. IMPLEMENTATION

A. Implementation

Preprocessing: In our work, we are studying interactions of children with an Aibo robot (Sony). In this context, five of the robot's external tactile sensors play a major role, namely the head sensor, the three back sensors and the chin sensor. The criteria that we consider (gentleness and the rhythm of the interaction) do not necessitate to treat the sensors separately (i.e. we can remove the spatial information on the identity of the sensor activated). The input data is therefore a time series of a global parameter g which represents the overall activity on the external sensors, respectively the five ones for the rhythm of the interaction and the four continuous ones for criteria gentle/strong. The variable g is build by normalizing the sensor data, summing and binning them quantitatively (i.e. according to their values) into five bins.

Extra-conditions for the training: The constraints are the following: a) for gentle/strong, the algorithm does not learn null samples (i.e. samples made of null events only) , b) for the rhythm of interaction, we constrain the system to deal only with samples whose first component is not null . In both cases, a sliding window proceeds on the sensor data time series and a first selection is made before the sample can enter the cascade with respect to the condition explained above.

Parameters for the cascade: There are four main parameters: l (length of the input vector), k (length of the individual subsequences), S (length of the cascade), m (number of bottleneck states). For the rhythm of interaction, $l = 472$ (equivalent to 15.1 seconds), $k = 2$, $S = 236$, and $m = 6$. For the criterion gentle/strong, the corresponding parameters are: $l = 50$ (1.6 seconds), $k = 2$, $S = 25$ and $m = 4$.

Postprocessing: The postprocessing is straightforward and relies on a 'winner takes all' principle: the last bottleneck state of the cascade $\tilde{x}_{S-1}$ equivalent to the input signal has conditional probabilities on the output state Y, $p(y|\tilde{x}_{S-1})$. The selected (winner state) is defined by $\arg\max_{y \in Y} p(y|\tilde{x}_{S-1})$.

B. Features of the trained cascade

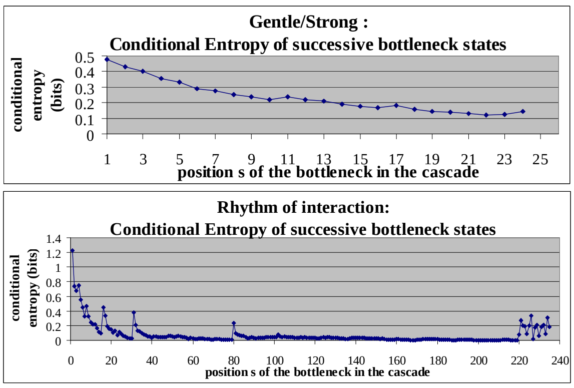


Fig. 1. Conditional entropy $H(\tilde{X}_{s+1}|\tilde{X}_s)$

The mutual information is 0.8 bit for the criteria gentle/strong and 1.9 bits for the rhythm of the interaction. The conditional entropy Fig. 1 $H(\tilde{X}_{s+1}|\tilde{X}_s)$ is globally decreasing over the cascade, pretty quickly, which suggests that a structure is progressively and rapidly emerging over the cascade. For the rhythm of interaction, $H(\tilde{X}_{s+1}|\tilde{X}_s)$ has some small local peaks though, both at the very beginning of the cascade and at the very end[5], which suggest that at these steps s, the input data X_s may influence a bit more in the choice of next equivalent state $\tilde{X}_{s+1}$. This measure is pretty directly linked to the reorganisation measure for extrapolating $d_{s-1,s}(R(s-1, s))$ (equation (1) and (2)) which presents, respectively to each criterion of interaction, similar shapes (with mean, resp. 0.037 bits for Gentle/Strong and 0.129 bits for the rhythm of interaction). In the rest of the paper, the algorithm will extrapolate between step 5 and 24 (resp. 5 and 216) of the cascade for the gentleness (resp. rythm of interaction).

VI. EXPERIMENTS

The experiments aim at assessing statistically: a) the soundness of the recognition of interaction styles by our algorithm, i.e., i) for the criterion 'gentleness', whether a behaviour that has been classified as gentle (resp. strong) by a human is indeed going to be classified as gentle (resp. strong) by our algorithm, or ii) for the rhythm of interaction, whether a frequency of interaction that has been tagged by a human is indeed going to be recognised as such by the algorithm. b) the delay for the recognition of local events. Importantly, the criterion 'gentle/strong' characterizes local events, and the algorithm should be able to recognise each specific event 'gentle' or 'strong' within a short delay. In contrast, the criterion 'rhythm of the interaction' requires the algorithm to classify mid-term time scale events. This study deliberately focuses on such different criteria in order to show the flexibility of the algorithm. The algorithm has been tested with data generated in two different contexts, firstly under laboratory conditions and secondly during real interaction between children with autism and an autonomous robot.

A. The artifact

The artifact, the ERS-7 Aibo (Sony), reacts autonomously to the participant's tactile stimulations on any of the five external sensors detailed in Section 5 with simple behaviours programmed in URBI. Sensor data are sent to a laptop through a wireless connection every 32ms.

B. Experimental setup under 'laboratory conditions'

1) Participants: Two adults took part in the trials in order to also assess the robustness of the method.

2) Procedures: The experiments in the laboratory are used as a first step in the statistical assessment of the soundness of the recognition of the interaction styles. These trials involve one participant at a time. The participant is asked to interact with the robot for a few minutes in a predefined way constraining either the gentleness or the rhythm of the interaction.

[5]Note that the small local peaks at the end of the cascade may reflect the importance of the last steps for distinguishing the classes S0 and S1.

Rhythm of the interaction: The *p*redefined ways contain only ‘pure styles of interaction’, i.e one class[6] exclusively.

Gentle/strong: The *p*redefined ways are of two types. In a first step, it is pure styles exclusively[7]. In a second step, the participant is asked to alternate gentle and strong behaviour and, just before generating the first event of the new class, he/she must name the style (i.e. “gentle” or “strong”). All the sessions are video recorded and this tagging enables to determine very precisely the transitions for a further measure of the delay of the recognition process.

C. Experimental setup in a school

A further step in the validation of the algorithm is the testing with data obtained under natural situations, that is, in our context of study, involving interactions between children with autism and a robot in an environment that the children are familiar with, i.e. their school.

1) Participants: The experiments took place in Colnbrook School, Hertfordshire, UK, a school dedicated to children with moderate learning disabilities. Five children with a diagnosis of autism took part in the experiments.

2) Procedures: These experiments took place in a small classroom dedicated to the study, one child at a time being present in the room. Each child was invited to play freely for several minutes with the robot (the duration of play depended on the child’s needs and abilities) in an unconstrained environment. The experimenter was present in the room and answered the child’s questions. The experimenter also, on occasion, rewarded the child verbally.

D. Measures

The experiments were all videorecorded and sensor data were stored. Note, the validation of the algorithm must be assessed offline but the recognition algorithm is designed to operate in real time.

1) Samples excluding transitions from one class to another: These samples are useful for testing the ability of the algorithm to recognise the actual interaction style. Sensor data are preprocessed according to the procedure detailed in section 5 and the profile of the classification by the algorithm can be analysed with a confusion matrix. This matrix displays the probability distribution that events from class Si are recognised by the algorithm as events of class $S'i$ ($i = 0$ or 1 for gentle/strong, $i = 0...3$ for the rhythm of interaction).

2) Samples with transitions for the criterion gentle/strong: These samples enable us to test the ability of the algorithm to recognise a transition and reach, after a short transition phase, a new equilibrium phase. One can model this process by a temporal curve that would indicate the state of the system for a transition happening at time t_0. Three typical domains can be identified: for $t < t_0$ the curve is constant, indicating a stable state; from $t = t_0$, the curve’s value alternates to indicate an hesitation between the two possible states (thus identifying a change in the behaviour observed); from $t = t_0 + \tau$ the curve would keep the same value (the new state). Ideally, the second phase should be very short (i.e. τ is very small). We will study three typical measures here: a) the number of transitions recognised by the algorithm; b) the time elapsed to reach the new equilibrium state, c) the ratio of errors made within this new equilibrium state. Note, a transition will be considered broadly as either a transition from a gentle (resp. strong) behaviour to a strong (resp. gentle) one, or from a state where no classification occurred (i.e. no interaction occurred during the past 1.6 seconds) to gentle or strong.

3) Samples with hybrid behaviours for the rhythm of interaction: For this criterion, some samples generated in school can be hybrid, the hybridity originating from i) a local tendency different from the global one, or ii) the coexistence of features from two neighbouring styles. In order to encapsulate hybrid behaviours, the human classifies the behaviours on a ‘two choices’ basis, i.e. he/she selects either the two styles characterising the hybridity or one single style when the behaviour is not hybrid. In the context of hybridity, we consider the algorithm’s classification is successful if it agrees with one of the two choices made by visual inspection.

Practically, for ‘2’) and ‘3’) the video and graphs of the temporal global variable are first manually tagged. In a second step, the classifications Si resulting from the manual tagging are compared with the classifications $S'i$ made by the algorithm.

VII. Results

A. Criterion: Gentle/Strong

1) Training set of data: The $20,018$ samples used for the training were classified by the algorithm with an overall success of 97.82% and, respectively, for gentle and strong, 96.83% and 98.81%.

2) Samples excluding transitions: They constitute 1 hour 2 minutes 49 seconds of interaction. $100,111$ samples have been classified with a ratio of success for correct classification of 0.948. 97.7% of samples were classified without extrapolation with 95.22% of success while the samples classified with extrapolation (3.3%) were well classified in 75.54% of cases which, considering that it results from an extrapolation, is quite a good result. Note that the parameters of the cascaded bottleneck method were chosen in such a way to have a good balance between the extrapolation and the precision, which is reflected here in the low percentage of cases extrapolated.

3) Samples with transitions under laboratory conditions: The four runs constitute 19 minutes and 40 seconds of interaction to analyse. They contain $53,192$ samples to classify and 0.01% of the samples were not classified because they could not be extrapolated by the algorithm[8]. 212 transitions were to be recognised, 99.1% of which were indeed well classified by the algorithm[9] with an average delay of 0.17

[6] very low, middle inferior, middle superior, or very high.

[7] gentle or strong only.

[8] these samples had to be extrapolated outside the range of steps considered for the extrapolation.

[9] A transition is considered as wrong classified if the transition phase is very long compared to the new equilibrium phase.

seconds. The probability distribution of the delay is displayed in Fig. 2. The curve grows very rapidly, thus showing that most of the delays are very small. Transitions recognised without any delay occur particularly in the case of a transition from no event to classify to any event to classify. The longest delay is 2.05 seconds, which we consider very acceptable for human-robot interaction kinesics. The average error ratio in the equilibrium phase is 0.02 and the probability distribution is displayed in Fig. 3. Here again, the curve grows rapidly and shows that the probability of the highest error ratios is very low which remain acceptable for real human-robot interaction.

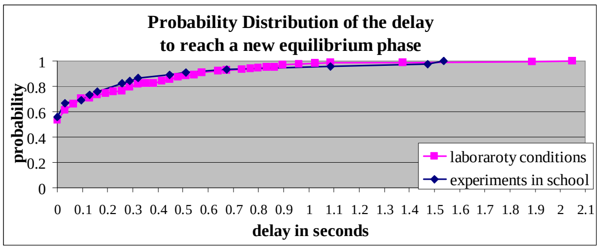


Fig. 2. Probability Distribution of the delay for recognising the transition. We display the probability that an event is recognised within (less or equal) n seconds for a given n. The delay corresponds to the length of the transition phase when a transition occurs.

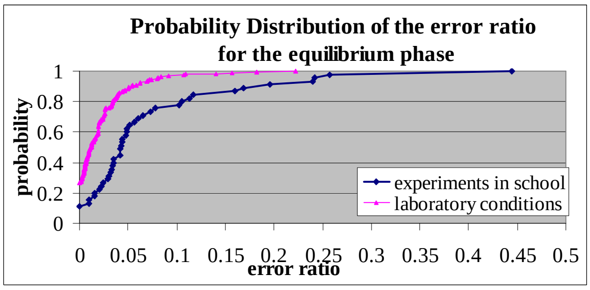


Fig. 3. Probability Distribution of the error ratio for the equilibrium phase. The ratio measures the number of errors of classification made during a phase of equilibrium divided by the number of samples to classify during this phase. The figures displayed give, for a given r, the probability that the error ratio is inferior or equal to r.

4) Samples generated by the children in the school: Videos from five different children were analysed, which constitute 12 minutes and 52 seconds of interaction. These runs contain $6,660$ samples to classify: 97.49% of these samples have been classified by the algorithm. These samples contain 45 transitions. 91.1% of these transitions were indeed well classified by the algorithm within an average delay of 0.17 seconds. The probability distribution of the delay is represented in Fig. 2. The curve grows very rapidly, thus showing that most of the delays are very low. Transitions recognised without any delay occurs, and, at the far end, the highest delay is 1.54 seconds, which is very acceptable for human-robot interaction kinesics. The mean error ratio in the equilibrium phase is 0.1 and the probability distribution of this ratio is displayed in Fig. 3. Here again, the curve grows rapidly. It is worthy of note that the highest value obtained is 0.44 and the second one is much lower (0.26) which indicates that the first highest value can be seen as an extraordinary case. Looking at the sequential classification of the results, it appears that this highest error ratio was obtained while a child interacted in a very instable way that is, within 1.76 seconds three successive transitions were observed that are 1) no event to gentle (gentle phase lasted 1.37 seconds), 2) gentle to strong (the phase with strong style lasted only 0.26 seconds), 3) strong to gentle. It is the strong phase, after the transition from gentle to strong behaviour that was recognised with the highest error ratio (0.44), but it lasted for such a short time that it is not really a concern here (0.26 seconds is very low compared to the typical time for human-robot interaction which usually lasts a few seconds). Therefore, we can consider to omit this highest value in the probability distribution and looking at the resulting values, the results are good and comparable to the results obtained in the laboratory.

B. Criterion: Rhythm of the interaction

1) Training set of data: It constitutes 36 minutes 34 seconds of interaction and contains $4,865$ samples to classify (resp., 450 for S0, $1,208$ for S1, $1,484$ for S2 and $1,723$ for S3). 99.98% of these samples are well classified; the ratio of success specific to each class is displayed in Fig. 4.

	S'0	S'1	S'2	S'3
S0	1	0	0	0
S1	0.0008	0.9992	0	0
S2	0	0	1	0
S3	0	0	0	1

Fig. 4. Confusion Matrix for the training set. The ratio is the one among events from type Si. Si represents the real class and $S'i$ the recognised class, $0 \leq i < 4$.

2) Samples generated under laboratory conditions: They constitute 51 minutes 44 seconds of interaction and contain $5,395$ samples to classify (resp. $1,017$ for S0, 855 for S1, $1,933$ for S2 and $1,590$ for S3) 91.16% of which were classified with an overall ratio of success of 0.922. 99.4% of the samples not extrapolated were well classified, and 76.41% of samples classified through extrapolation were well classified. Fig. 5 displays the confusion matrices.

No Extrapolation	S'0	S'1	S'2	S'3
S0	**1**	0	0	0
S1	0	**0.972**	0.028	0
S2	0	0	**0.999**	0.001
S3	0	0	0.006	**0.994**

Extrapolation	S'0	S'1	S'2	S'3
S0	**1**	0	0	0
S1	0.115	**0.864**	0.022	0
S2	0.083	0.146	**0.768**	0.003
S3	0	0	0.368	**0.632**

Fig. 5. Confusion Matrices for pure sets of data for, respectively, non extrapolated and extrapolated data. see Fig. 4 for more details.

3) Samples generated by the children in the school: Three runs of interaction were used for the validation of the rhythm of interaction in a real situation, from three different children. They constitute 14 minutes 41 seconds of interaction and contain $5,288$ samples to classify. 91% were classified (including 26.81% that had to be extrapolated) and 93% were classified correctly. Among samples classified with no extrapolation, the ratio of success for a sound classification was 0.96. while for samples classified with extrapolation, it was 0.84.

VIII. Discussion

The algorithm has proven sound for the recognition of the two criteria of interaction. Concerning the criterion gentle/strong, results show that the two classes are well recognised and the delays very acceptable for human-robot interaction. The extrapolation works well, which shows the capability of the system to make a sound decision in case of unseen events. These results can be compared with a previous study of ours where we used Self-Organising Maps to classify this criterion of interaction [3], whereby the average delay to recognize transitions was much higher and the postprocessing a bit heavier to handle with. Importantly, one might wish to define the styles slightly differently to the definition given here, such as, for instance, focusing on more details (in order to describe substyles for instance). This can be easily done by adjusting relevant parameters, mainly the number of bottleneck states, the binning and the training sets which condition the learning.

Concerning the rhythm of interaction, the algorithm has proved very capable of classifying pure samples of data, and has shown the ability to adapt to the real context of often hybrid behaviours. Furthermore, in slight contrast with Hidden Markov Models which are typically used to identify short-term events, this algorithm has proven, for the rhythm of interaction, capable to classify mid-term time scale events.

This method is designed for real time use during natural human-robot interaction and little research has been done so far on real time recognition of tactile interaction styles. Salter et al.'s adaptation algorithm [8] was a first important step towards real adaptation. Yet, the system did not learn its own categorisation, which was completely described by a hand-tuned decision tree. In the present study, the recognition and the decision are made algorithmically, after a real learning phase and a capacity to extrapolate unseen events, with very small delays. Furthermore, the method is very easy of use and can be tuned easily to adapt to other criteria of interaction. In a broader application, it may be powerful for the analysis of time series from other human-robot interaction or other contexts.

IX. Future work and Conclusion

In this paper, we have developed a novel method for time series analysis in the context of human-robot interaction. This method, namely the Cascaded Information Bottleneck method, has its roots in the Information Bottleneck method developed by Tishby et al. [13] and uses the agglomerative bottleneck algorithm [11] to build individual bottlenecks linked successively within a cascade. This cascade has the property of extracting progressively the information of the time series and an adequate measure for extrapolating unseen cases has been highlighted. We have shown the soundness of the method through extensive experiments, using successively samples of data generated in laboratory conditions and samples from natural situations of child-robot interaction in a school for children with autism. Results have shown the ability of the algorithm to classify accurately short-term time scale events within a short delay as well as mid-term time scale events. This ability to classify in real time the interaction styles is a first step towards the challenging goal of enabling an autonomous robot to influence positively children's interaction styles to guide them progressively towards higher levels of interaction.

Acknowledgments

Dorothée François is supported by a research scholarship of the University of Hertfordshire. The work described in this paper was partially conducted within the EU Integrated Project RobotCub (Robotic Open-architecture Technology for Cognition, Understanding and Behaviours) and was partially funded by the European Commission through the E5 Unit (Cognition) of FP6-IST under Contract FP6-004370. The authors thanks at Colnbrook school the children, their parents and the teachers.

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