On-line Behaviour Classification and Adaptation to Human-Robot Interaction Styles

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ABSTRACT

This paper presents a proof-of-concept of a robot that is adapting its behaviour on-line, during interactions with a human according to detected play styles. The study is part of the AuRoRa project which investigates how robots may be used to help children with autism to overcome some of their impairments in social interactions. The paper motivates why adaptation is a very desirable feature of autonomous robots in human-robot interaction scenarios in general, and in autism therapy in particular. Two different play styles namely 'strong' and 'gentle' are investigated experimentally. The model relies on Self-Organizing Maps and on Fast Fourier Transform to preprocess the sensor data. First experiments were carried out which discuss the performance of the model. Related work on adaptation in socially assistive and therapeutic work are surveyed. In future work, with typically developing and autistic children, the concrete choice of the robot's behaviours will be tailored towards the childrens interests and abilities.

Keywords

Interaction styles, adaptation in interaction, behaviour classification

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 to overcome some of their impairments in social interactions [7].

Children with autism have impairments in communication, social and imagination skills. Autism is a spectrum disorder and children have very different abilities and skills. In our perspective, any robotic mediated therapy therefore needs to consider the individual nature of child-robot interactions. One constraint is to make sure that the interaction between children and the robot will be 'playful' for the children (we need to consider here the notion of playfulness as it applies in autism, cf. section 2.2 below). The advantage of making the child interact with a robotic platform is to reduce the complexity of the interaction and creating a predictable environment for play to begin with, so that it can be easier for the child to feel at ease during the interaction in order to experience and understand better the interactions taking place. The premise of our work is that, progressively, the complexity of the environment can be increased if the child is making sufficient progress.

One stream of research in the Aurora project is focusing on the potential role of the robot as a mediator, i.e. as a salient object that helps children to interact with other children or adults [14, 15, 16] . In the other stream of research we focus on the robot as an autonomous toy. Here, a main objective in our research is for the robot to be able to recognize on-line the type of interaction induced by the child so that the robot can adapt to the interaction in order to behave more appropriately to the child's specific abilities and needs. At first step towards this goal, the robot should be able to maintain 'appropriate' (i.e. intermediate, balanced) levels of interaction, e.g. not too strong and not too weak. Note, we consider the child's abilities as they are expressed through interaction with the robot, resulting in different play styles. The child's therapeutic needs in this context are not addressed directly, but only indirectly by encouraging therapeutically relevant interactive behaviour involving touch [7]. The present paper presents a proof-of-concept of a robot that is adapting its behaviour on-line during interactions with the children according to detected play styles. Specifically, we show an Aibo robot that can classify specific child-robot interactions on-line, using self-organizing maps. We demonstrate how the robot can adapt its behaviour on-line to the child (i.e. to the interaction). Importantly, this work goes beyond preliminary work that classified and characterized interactions off-line, i.e. after the interactions had taken place [17, 18, 19] .

The remainder of the paper is structured as follows. Section 2 explains more precisely the motivation of this research. Section 3 characterizes the classification process. The implementation of the algorithm is described in section 4. Section 5 describes preliminary trials. Related work is discussed in more detail in section 6. Conclusions and future work close the paper.

2. MOTIVATION

2.1 Autism

Autism refers to autistic spectrum disorders which can appear at many different degrees and refer to different skills and abilities. The main impairments highlighted by the National Autistic Society are:

Impaired social interaction: Difficulties to make a sense of a relationship with others, difficulties to guess or even understand what the other's intentions, feelings and mental states are.

Impaired social communication: Difficulties with verbal and non-verbal communication (for example, difficulties to understand facial gestures).

Impaired imagination: Difficulties to have imaginative play, for example.

As a consequence of the above impairments, children often choose a world of repetitive patterns (e.g. they often play in a repetitive way).

2.2 Play

There is no precise definition about play, mostly because many fields are involved. This multidisciplinarity also results in the coexistence of various classifications of play. Among them, a classification given by Boucher [4, 5] is particularly relevant for our study in the sense that it merges the notion of exploration with the idea of social interaction.

Play is a vehicle for learning [6]. Through certain kinds of play, children can construct some understanding, in the sense of active construction of meaning. Play can thus develop skills in many fields: logical memory and abstract thought, communication skills and social skills. Moreover, it is a medium for self expression.

Children with autism have a relative potential for play but they often encounter obstacles, the causes of which are still not clear. These impairments (among them, impairments in socio emotional inter-subjectivity, in joint attention and in Theory of Mind) 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 pretend play. The disability in perceiving the coherence of categories and concepts can also be a reason why autistic children perceive objects in their parts and not as the whole which is part of a weak central coherence theory.

As a result, to facilitate autistic children's play with a robot, it is necessary to focus on the interaction, because interaction is decisive in the process of learning through play. If the robot is able to identify on-line the way a child interacts with the robot, then it can adapt to it more accurately. The adaptation should lead to a level of interaction encouraging the child to continue playing, and it should lead to robot's behaviours that are more appropriate to the current child's needs. For example, the robot should be able to detect forceful interaction and regulate the interaction so that the child is still engaged in the interaction but without signs of force. From this point of view, the process of adaptation would become bidirectional: firstly the robot adapts to the child and secondly, the robot may influence the child's behaviour in return.

3. CLASSIFICATION OF INTERACTION

People are used to describing an interaction verbally, by observing and listening to what constitutes the interaction. In a natural context we evaluate interaction subjectively, which means we usually don't use any objective measure to decide if e.g. an interaction is gentle or strong, repetitive or non repetitive etc. Instead, we use our own human senses and we may use as well our previous experience from similar interactions to classify and evaluate any interaction we are involved in. The challenge in this study is to classify the interaction objectively (i.e. automatically) from the robot's point of view. The interface between the child and the robot (Aibo robot) are the different sensors of the robot. This implies that we can use these quantitative measurements to evaluate, analyze and classify any interaction. Our initial idea was to run some experiments by playing with an Aibo robot according to a predefined interaction type, thus collecting all the sensor data necessary for the later analysis in order to see if and how it could be possible to match subjective human description of interaction with quantitative data. To simplify the problem, we decided to classify the interaction into two classes only: Gentle and Strong. An interaction is classified as 'gentle' if the participant is touching the robot gently, without signs of force. Note, this may also include an interaction with a child not or almost not touching the robot. On the contrary, if the participant touches the robot with signs of force, then the interaction is classified as 'strong'.

For such a classification, what is important is how a participant touches the Aibo and not which part of the robot the participant is touching. Consequently, the sensors which will contribute to the input data for the classification will be regarded as one global variable. This is possible by normalizing the input data values (repartitions into 10 bins) and computing the sum of these normalized data.

Moreover, in this first approach we wanted the classification process to be as independent from the robot's behaviour as possible. That is why we only focussed on sensors which are (almost) not influenced by the Aibo's motion and sounds it emits but are at the same time determined by an interaction with a child. Therefore, we considered as input sensors for the analysis only sensors corresponding to the touch of the head (1 sensor), the touch of the chin (1 sensor) and the touch of the back (3 sensors).

3.1 Analysis of temporal data

We conducted some preliminary experiments to get sensor data to analyze during the explorative phase of the study. The experimental setup was a participant interacting with an Aibo for around five minutes, who was asked to play during the whole session in the same way (either gently or strongly). In total, we did 6 runs, 3 with 'gentle interaction' and 3 with 'strong interaction'. The experiment involved two different adult participants, one person did one run with 'gentle' interaction and one with 'strong' interaction and the other participant did the other 4 runs. The idea of having two different participants was initially to decrease the risk of having a classification depending on the person interacting with the robot, however, one of the participants ended up doing most of the experiments. Note, this particular experiment is preliminary in nature, future work will involve a larger number of participants and experimental runs.

We analyzed the changes over time of the sum of the five external sensor data distributed into bins. Differences appeared clearly: when graphically displayed, temporal data from 'Gentle interaction' trials were made of many 'blobs' (see Fig. 1), while temporal data from 'Strong interaction' trials were mainly made of 'peaks' (see Fig. 2). Only one run with strong interaction was showing more confusing results but it was also because the participant was not interacting purely strongly during this run. We therefore excluded the results of this run for the further analysis. Given the visually different patterns, methods for automatic classification were investigated.

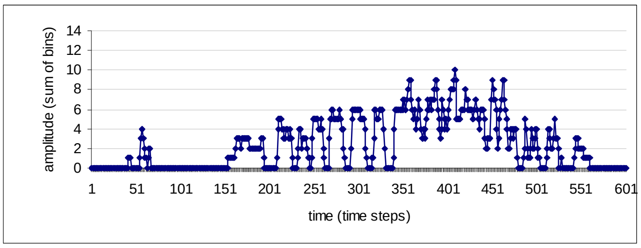

Figure 1: Gentle interaction: typical 'blobs' in temporal data.

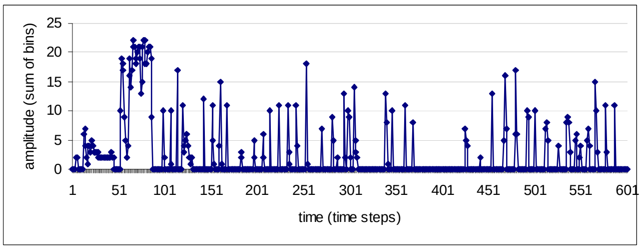

Figure 2: Strong interaction: typical 'peaks' in temporal data

3.2 Fast Fourier Transform

Since the temporal data from 'Gentle interaction' trials were made of a lot of blobs, while temporal data from 'Strong interaction' trials were mainly made of peaks it became interesting to focus on the frequency spectrum which would exhibit clear differences: for gentle interaction, there would be higher magnitudes for lower frequency and it would be the contrary for strong interaction. Moreover we wanted the method to be able to not distinguish similar patterns exhibited at different time steps: the method should be shift invariant.

Both these reasons made us select the Fourier Transform as a further step in our analysis [9]. Fourier transform is an invertible function which has, among other properties, the property of being shift invariant, and which decomposes a function into a continuous spectrum of its frequency components. Several variants coexists; among them the Fourier Transform for discrete signals and the Fast Fourier Transform which is also for discrete signals but has a complexity of $O(n \cdot \ln n)$ instead of $O(n^2)$ for the discrete Fourier Transform.

3.3 Self-Organizing Map

In a next step of the study, we wanted to automate the classification of the interaction properly, so that differences observed by eye on the magnitude of the FFT could be reflected in the quantitative analysis. Since we had no a priori information on the topology of the data, we decided to use a method which only requires poor or no a priori knowledge of the present problem and also allowed the model to learn from the data and generalize. Therefore we decided to use Artificial Neural Networks and more specifically the Self Organizing Map (SOM) which provides a topology preserving mapping from high dimensional space to map units.

SOM relies on unsupervised, competitive learning. A specific weight, from the same dimension as the input data, is attached to each neuron (node) of the network. Each node is connected to the adjacent ones according to a neighborhood rule which influences the topology of the map. The SOM is made of two phases: the training phase during which weights of the nodes are updated and the mapping phase, during which the classification or categorization of data can be made [12].

Training phase. First of all the network is initialized (either by random initialization, by initial samples, or through linear initialization). This process defines initial weight vectors, one for each node of the network. Then, input data are presented one by one to the network (random selection). For each input data, the distance is measured according to a predefined metric between the input vector and each node of the network. The node minimizing the distance is called the Best Matching Unit (BMU). Afterwards, the weights are updated according to the following equation [3] :

$w'_j = w_j + \epsilon(t) \cdot h_{rs} \cdot (v - w_j)$ $j = 1, ..., \|K\|$ where

- w_j is the weight for the node j
- w'_j is the updated weight for the node j
- $\|K\|$ is the size of neighbourhood $K(w_i(v))$ for the winner node $w_{i(v)}$.
- $h_{rs} = \exp(\frac{-d(r, w_{i(v)})^2)}{\sigma(t)^2})$ $\forall r \in K(w_{i(v)})$
- ϵ and σ are monotonic decreasing functions of time.

By simplifying, we can say that time being static, the closer a node is from the BMU, the more it will learn; and globally, the network will learn less and less when time is growing. The presentation of the entire set of input data constitutes what we call an 'epoch'. A training phase can result from the succession of many epochs.

Mapping phase. Once the network has been trained, it can be used for classifying (categorizing) data from the same space as the input data used for the training phase. A data from the latter space will be presented to the nodes successively. The node activated is the node corresponding to the BMU with regards to the same metric as used for the training phase.

3.4 Whole process of classification

The whole process of classification of interaction styles can be synthesized as follows: globally, temporal sensor data will be preprocessed to be used in the process of classification. The preprocessing results in a computation of the magnitude of the FFT algorithm which itself uses preprocessing of temporal data to consider the input sensors data as a whole global variable (see Fig. 3). The training phase of the SOM is made off-line (see Fig. 4) while the mapping phase and its coresponding preprocessing are made on-line (see Fig. 5).

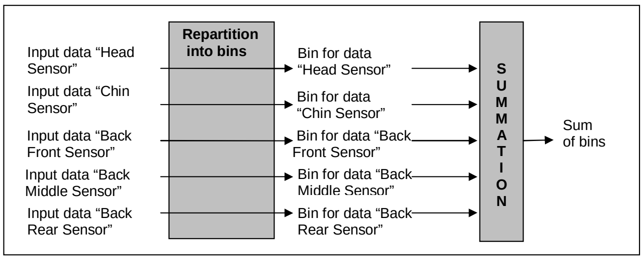

Figure 3: Data Preprocessing for FFT

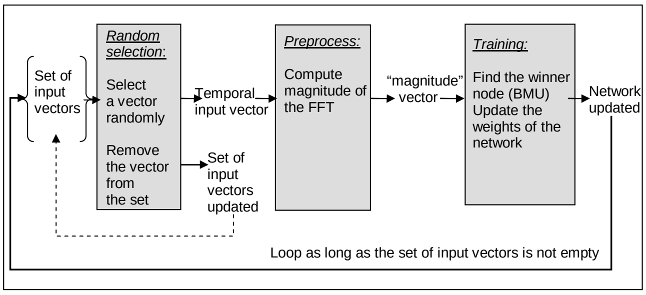

Figure 4: One Epoch of training

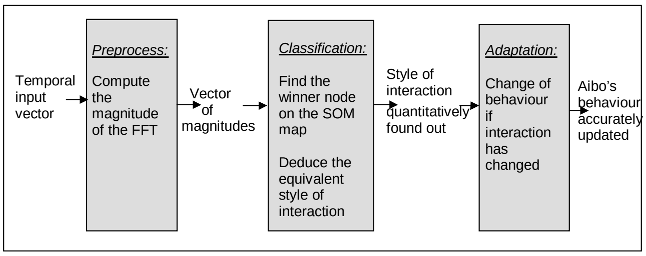

Figure 5: Unit process of classification and adaptation to the interaction style

4. IMPLEMENTATION

4.1 Communication process

The robot used in this study is the Sony Aibo ERS-7. Its control programming is achieved using URBI (Universal Real-Time Behaviour Interface) [2]. Sensor/motor data are transmitted through a wireless LAN to a laptop. The Aibo sends current states of its sensors every 32ms. The laptop analyzes periodically the sensor data, classifying on-line the interaction correspondingly and sending the information back to the Aibo which then changes its behaviour accordingly. The process of classification of the interaction is written in Java.

4.2 Parameters for the process of classification and adaptation

We needed vectors of sufficient dimension to get a good result for the SOM. Experimentally, we got good results by using an input vector of dimension 512 (it had to be a power of 2 due to the FFT algorithm we were using). Input vectors for the SOM were therefore of dimension 512 and each component of the vector was respectively the magnitude of the component of the vector resulting from the FFT. The network had a rectangular topology and was made of 10*10 nodes. We used random initialization and 5 epochs for the training which was made off-line.

However, once the training phase had been finished, all the behaviour classification was made on-line, the FFT algorithm being computed on-line as well as the activation of nodes for the SOM. But since this process was time consuming, and since the magnitude of the Fourier transform did not change significantly over a few time steps, we decided to set a frequency which would be more suitable. Experimentally it was found that updating the magnitude on the FFT once in 120 updates of the sensor data was efficient. After every update of the interaction state through the classification, the Aibo got informed of the result in order to adapt its own behaviour on-line. Note, future work will consider to run the classification on-board the robot. For monitoring and practicality purposes the use of the laptop seemed appropriate.

5. VALIDATION OF THE MODEL

5.1 Validation of the topology of the SOM map

We did two different trainings, each of them with a random intialization. We then characterized the nodes of each of the network according to the following rules: a node activated only by data from Gentle interaction is called 'gentle node'; a node activated only by data from Strong interaction is called 'strong node'; a node activated by both data is called 'hybrid node'; a node never activated is called a 'null node'.

We analyzed the topological repartition of gentle nodes on the one hand and of strong nodes on the other hand, and looked at the ratio of hybrid nodes and the ratio of null nodes. For having a performant and coherent classification of the interaction, a necessary condition is that the SOM map clearly distinguishes topologically two regions, one corresponding to the 'gentle' nodes and the second regrouping the 'strong' nodes. Moreover, the proportion of hybrid and null nodes should be very low compared to the proportion of gentle and strong nodes so that there are not two many cases in which the Aibo will not be able to 'decide' between strong and gentle interaction. Besides, hybrid nodes should be mostly on the border or next to the border between gentle and strong regions (by opposition to any of the inner part of the regions): this would correspond to a smooth transition between the two regions.

The SOM maps give both good results (see Fig. 6 which provides a graph of the first map). For each of them, the number of hybrid nodes is respectively 9 and 7 out of 100, while the number of null nodes is respectively 1 and 0. For the first map, all the hybrid nodes are on the border. For the second map, 3 hybrid nodes are not directly on the border but 2 of them are first neighbours of border nodes and the third on is second neighbour. This corresponds to a smoother transition between the two regions.

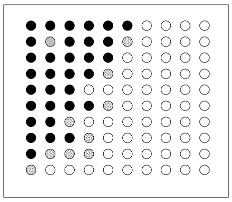

Figure 6: Map of a SOM. **legend : white for 'gentle' node, black for 'strong' node, stripes for 'hybrid' node, blobs for 'null' node**

5.2 Validation of the on-line classification and the on-line adaptation of the robot

The model is accurate if it satisfies the following constraints:

- A gentle interaction does not activate a strong node but activates one of the three other kinds of nodes; a strong interaction does not activate a gentle node but activates one of the three other kinds of nodes.
- The classification can be made on-line.
- The Aibo detects a change of the class of interaction and classifies the new interaction accurately (with an eventual short delay).
- The Aibo can adapt its behaviour on-line with respect to the kind of interaction recognized.

To test these different constraints we did various experiments with a human playing with the Aibo robot. The set of Aibo's possible behaviors remained the same in all the experiments: it was standing and waiting for at least one of its five external sensors to be activated. Whenever one of the latter sensors was activated, it started a) wagging the tail if it had detected a gentle interaction, or b) barked if it had detected a strong interaction. The rationale behind this choice was as follows: as described above, in child-robot play we want the robot to be able to maintain an intermediate level of interaction, not too strong, not too gentle. In this work, barking was used as a representative behaviour that might induce a human to 'back off', thus calming the interaction. Wagging the tail was used as an indicator to encourage interaction. Note, in future work with typically developing and autistic children the concrete choice of these behaviours will be tailored towards the children's interests and abilities.

If the Aibo had detected a middle interaction (corresponding to an activation of either null or hybrid node on the SOM map), its current reaction to tactile stimuli remained the same. Its initial state corresponded to a gentle interaction.

We ensured that the succession of interaction levels detected by the robot and the corresponding node activated on the SOM map were stored in a file. According to the experiment, the participant had to play either gently or strongly, or alternating gentle and strong interactions. The participant had to maintain the same level of interaction until the Aibo had classified and adapted to this level.

Each time the participant changed her way of interacting with the robot, the time at which it happened was stored as well as the time at which the Aibo adapted its behavior accordingly.

Note, future work will cope with more frequent changes in play style, since child users will not be instructed how to play.

Experiment 1.
In this experiment, we wanted to ensure the Aibo was able to recognize each type of interaction and keep recognizing it for the whole duration of the interaction.

This experiment consisted of two runs of three minutes each. The participant interacted with the Aibo on a gentle level of interaction only during the first run and on a strong level of interaction only during the second run. For each run, 42 updates of the classification of the interaction happened with no errors in the classification. Actually, during the 'gentle' interaction, 39 times the winner node of the SOM was a 'gentle' one, 3 times it was a 'hybrid or null' one and it was never a 'strong' one. In the same way, during 'strong' interaction, 41 times the winner node of the SOM was a 'strong' one, once it was a 'hybrid or null' one and it was never a 'gentle' one.

Experiment 2.
In this experiment, we tested the capacity of the Aibo to adapt its behaviour in a changing interaction. The participant was asked to interact gently and strongly with no constraints on the changes of the interaction styles. The only constraint was to touch quite regularly the five tactile sensors. The purpose of the experiment was to test the Aibo's capability of adaptation over time involving all five tactile sensors. We did one run that lasted around eight minutes. The Aibo adapted correctly to the interaction (see Fig. 7) but with a certain delay (which was comprised between 10s and 19s). Fig. 7 compares the Aibo's behaviour transitions (as a consequence of adaptation) to the changes in the participant's behaviour scored subjectively.

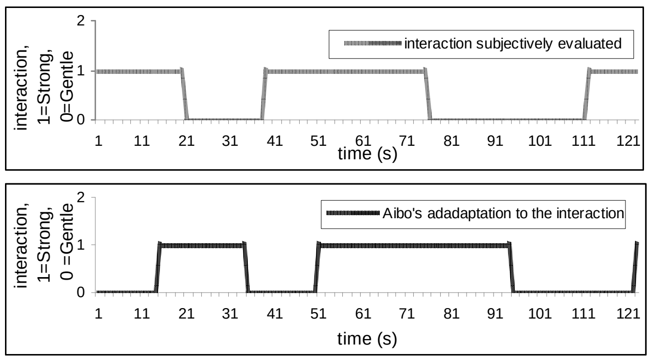

Figure 7: Example of the dynamics of the robot's adaptation to the interaction: **The first graph represents the subjective interaction level over time; the second graph shows the robot's accurate adaptation with a delay. On the y-axis, 1 stands for 'Strong' and 0 for 'Gentle'**

Experiment 3.
Since autistic children sometimes play in a repetitive way, it is very likely that some of them will continue touching the same sensor. We therefore needed to test our model in this special case and also especially because the Aibo's sensors involved in the interaction were different in nature: while the sensor on top of the head and the three sensors on the back returned values that could all vary continuously from a minimum value to a maximum value (analogical sensors), the chin sensor value could be either zero or one (numeric or boolean sensor) which means that its equivalent after repartition into bins is either 0 or bin 9.

We conducted five trials. For each of them the participant had to touch only one sensor, respectively the chin sensor, the head sensor, the back sensor on the front, the back sensor in the middle and the back sensor on the back. For each trial, the participant could change the level of interaction (from gentle to strong, from strong to gentle) whenever she wanted. Results showed that the Aibo adapted correctly to the interaction for trials focussing on the head and the three back sensors while there were some surprising results for the trial focusing on the chin sensor. We observed two kinds of possible errors in the adaptation: a) The Aibo was not able to detect a gentle interaction within 1 minute (1 minute is a long time compared to the average time of adaptation to a new interaction level), or b) The Aibo had detected a gentle interaction for a very short time (around 4 seconds), the participant was keeping interacting subjectively gently but the Aibo started barking, which means it appeared to her the interaction had become strong. This situation happened when the subjective gentle interaction was done in a way that the chin sensor was still activated (the Aibo wagged its tail). As explained above, the chin sensor can take only two values which are 0 or 1, which means, after repartition into bins, that value 1 (activation of the chin sensor) will correspond to a very high value (bin 9), even if the activation is done quite gently, (but with a sufficient pressure).

Moreover, our model for classifying data takes mainly two factors into account: a) the relative magnitude of the frequencies of the Fast Fourier Transform of one vector of sensor data exhibit which frequencies are predominant, which is directly linked to the rhythm of the interaction (e.g duration of touch of sensors, periodicity of touch of the robot on any of her five sensors etc.); b) the FFT respects the linear property. Consequently, if the chin sensor gets activated very often, even with quite gentle touch, then a lot of high values will constitute the input vector and the result of the classification may be affected.

This shows a limitation of our model: the model should be used with caution when integrating boolean sensors. If, for example, there is only one boolean sensor in five and there is a good repartition of activation of sensors, then the classification will work well. But if the boolean sensor is activated too often, it might lead to a wrong classification. Note, it also seems impossible to delimit precisely the border between strong and gentle interaction subjectively.

Experiment 4.
In the present experiment, we decided to avoid the risk of having errors induced by the boolean sensor; consequently, the participant had to respect the constraint of not touching the chin sensor, but she could touch all the four other sensors. The participant could change from one level of interaction to another (gentle, strong) whenever she wanted but she tried to vary the duration of time between the time the Aibo adapted to the current interaction and the time she changed the interaction afterwards.

The idea was to check experimentally that the delay of adaptation was not directly influenced by the rhythm of changes in the subjective interaction. This idea is linked to the fact that we use a finite vector of data to classify the interaction, which means, we take into account only a limited history of the interaction. And since this vector is updated like the process of a sliding window with a stationary length, the duration necessary to classify the interaction should belong to a very short interval of data.

The experiment lasted around seven minutes, alternating longer period for changes in behavior and shorter period for changes. The longest duration of an interaction was 50 seconds, the shortest was 17 seconds. Fig. 8. represents on the x-axis the duration of a level of interaction and on the y-axis the delay of the adaptation to the next interaction level (e.g. length of gentle interaction and delay to adapt to the next kind of interaction which will be strong). The graph shows that there is no linear relationship between the period of changes in behavior and the delay for adaptation.

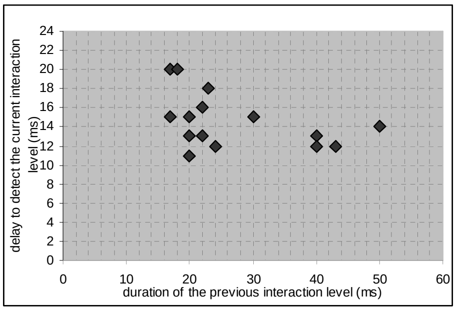

Figure 8: Experiment4 : delay in the process of classification and adaptation and corresponding duration of previous interaction style

6. RELATED WORK

6.1 Educational and therapeutic applications of human-robot interaction

Long-term (therapeutic) studies with Paro. Two studies using the seal robot Paro are particularly relevant for our study since they show that specific everyday life situations exists in which human-robot interaction can have a positive effect on well being of human beings and can even be a significiant factor of performance in therapy. The first long-term study was focusing on elderly people [22], introducing Paro into their everyday life in order to analyse the impacts on their global well being. Paro was introduced daily in two institutions for elderly people, one for 20 minutes every day over 6 weeks and the second one for 1 hour every day over more than one year. Elderly people were free to interact with Paro. Results show that the interaction with Paro improved the mood state of the participants and made the elderly people more active and more communicative with each other and with the caregivers as well.

The second study [13] designed engaging rehabilitation activities that combine physical and cognitive rehabilitation. This experiment lasted three months with a weekly occurrence. The participant was a child with severe cognitive and physical delays. The Paro robot was introduced in the Bobath protocol which is a method used for the rehabilitation of physical functional skills. Results showed that the interaction of the child with Paro seemed to have strengthened the efficacy of the Bobath protocol.

Involving quantitative data in the diagnosis of autism. The goal of this research [20, 21] is to impact the diagnosis of autism by providing the possibility to use quantitative and objective measurements of social responses. Measurements are done through both passive observation (through sensors which record and interpret data during standard clinical evaluations) and structured interactions with autonomous robots. Three criteria are mainly analyzed to distinguish typically developed children from autistic children: gaze patterns, position in the room and vocal prosody. The analysis of gaze tracking is now an integral part of the clinical evaluation. It relies on linear discriminant analysis of autistic and gaze patterns. A pilot study with this analysis has shown that autistic children don't share the same visual strategy as typically developed children and also among themselves. In this study, Scassellati exhibits a very nice application of the analysis of the interaction. He managed to qualify quantitatively criteria of typical human-human interaction through passive sensors and human-robot interaction analysis.

Long-term study on human-robot interaction in the context of dancing. This study [24, 23] aims at finding principles for realizing long-term interaction between a human and a robot. Tanaka et al. decided to run a long-term study with children and the robot QRIO, in a context relevant and frequent during childhood: dancing. This study focussed on the off-line analysis of the interaction, both qualitatively and quantitatively. On the one hand, the study analysed children's behaviour and showed that children tend to adapt their behaviour to the robot over time; e.g. they tend to know the robot is weak and tend progressively to treat QRIO softly. On the other hand, the study points out basic units as requirements for long-term interaction, respectively "sympathy" between human and robot and "variation' in the interaction style.

6.2 Classification of Human-Robot interaction

Different approaches have been used to classify human-robot interaction. More recent ones focus on the use of quantitative data for the characterisation of the interaction.

Links between subjective analysis and quantitative data. Kanda et al. [10] provide an interesting study regarding correlations between subjective evaluation (generally through questionnaires) and quantitative data collected during human-robot interaction. The experimental setup includes a participant interacting with a Robovie robot. Both are equipped with markers and infrared sources are placed in the environment. Through this setup, it is possible to collect, during the interaction, quantitative data characterizing indirectly body movements of both the robot and the subject. After the interaction phase, the individual is asked to specify the interaction subjectively according to some criteria which have been defined during a previous study [11]. The comparison between objective and subjective evaluation of the interaction indicates correlations between both analyses. In this study, Kanda et al. showed the possibility of characterizing quantitatively styles of interaction. Note, analysis of the data is off-line (i.e after the interactions have taken place) and the subjective description of the interaction focusses on the robot's behaviour only.

Salter et al. [17] adopt a different approach to show similarities between objective quantitative data and subjective description of behaviour to specify human-robot interaction. Contrary to Kanda et al.'s study, Salter et al. focus more on the participant's (a child in this study) personality during the interaction rather than on the robot's behaviour and appearance. The subjective evaluation of the children's personality takes place before the interactive phase whereby relatives of the child choose one trait of personality among a predefined list, which best corresponded to the child. The interactive phase is made of dyadic child-robot interaction with a mobile robot called Pekee (Wany Robotics); Off-line clustering analysis of the data show similarities between subjective evaluation and quantitative analysis: a) children which are considered to have the same trait of personality (among the proposed list) show also similar behaviours towards Pekee, and b) children with the same traits of personality tend to activate the same sensors on the robots (same patterns of touch).

Towards quantitative sensor analysis of the interaction. In a further study, Salter et al. [19] enumerate a list of possible states for a mobile robot called Roball and show that it is possible to define each of the states through sensor data analysis only. The four different states are: 'alone', 'interacting', 'carrying' and 'spinning'. The sensor analysis relies on off-line temporal analysis of the sensor data and a 'manual' classification through visual analysis of the sensor data which is not automated.

Automated classification and adaptation. In recent work on an adaptive playground, Derakhshan et al. [8] applied techniques known from robotics, artificial intelligence and multimedia to playgrounds. Their aim was to enable a computerized playground to adapt to children's behaviour in such a way that these children feel encouraged to play. The playground is made of specific tiles and a computer is used to store and process the data When a child is playing, input is provided through tactile sensors on the tiles. By adopting a multi-agent system approach of BDI (Belief Desire Intention) in combination with artificial neural networks techniques (with supervised training) the system learns to recognize various behaviours for either a single child or a group of children playing. Afterwards, the system can identify and adapt autonomously while children are playing. This study is very relevant to our work because it exhibits a different approach to solve the notion of on-line classification and adaptation in a context of human-computer interaction. Our study takes a different perspective though; our model aims at enabling the robotic platform to adapt its own behaviour to the interaction style, in order to a) encourage the child to continue playing, but also b) to enable the robot to influence the child's behavior to reach a specific interaction level. Note, b) is our future goal and only first steps have been taken into this direction.

7. CONCLUSION AND FUTURE WORK

This paper provided a proof of concept of on-line behaviour classification and adaptation of a robot's behaviour according to human-robot interaction styles. Experiments have shown that with our proposed model of classification a) the Aibo is able to classify a dyadic human-robot interaction it is involved in on-line, and b) it can adapt to the interaction by changing its own behaviour and thus changing the interaction with the subject.

The experiments highlighted also some limitations of the model, particularly concerning the involvement of boolean sensors in the process of collecting data. Moreover, a future step in the implementation will investigate running the algorithm on-board and will focus on an optimisation of the delay in the update of the classification of the interaction styles as well.

Concerning the process of the Aibo changing its own behaviour, more investigations needs to be done to define more accurately the different relevant behaviours for the context of child-robot interaction and more specifically for the AuRoRa project, i.e. in a therapeutic context involving autistic children. As already mentioned above, in future work with typically developped and autistic children, the concrete choice of these behaviours will be tailored towards the childrens interests and abilities.

It is hoped that this study represents a step forward in the investigation of 'child's play' with robots, involving both autistic and typically developing children.

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.

8. REFERENCES

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

[2] J.-C. Baillie. Urbi: Towards a universal robotic low-level programming language. In *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2005.

[3] S. Baron-Cohen. *Mindblindness, an essay on Autism and Theory of Mind*. The MIT Press, new edition, 1997.

[4] J. Boucher. Editorial: interventions with children with autism - methods based on play. *Autism, The National Autistic Society*, 17, 2003.

[5] J. Boucher and P. J. Wolfberg. Editorial: Aims an design of the special issue. *Autism, The National Autistic Society*, 7, 2003.

[6] C. Chaillé and S. B. Silvern. *Understanding Through Play.* the British Library - "The World's Knowledge", 1996.

[7] K. Dautenhahn and I. Werry. Towards interactive robots in autism therapy background, motivation and challenges. *Pragmatics and Cognition*, 12, 2004.

[8] A. Derakhshan, F. Hammer, Y. Demazeau, and H. H. Lund. Mapping children playgrounds into multi-agent systems. In *Proc. 11th Int. Symposium on Artificial Life and Robotics (ISAROB)*, 2006.

[9] J. Fourier. *Théorie analytique de la chaleur*. Edition Jacques Gabay, reprinted in 1988, 1822.

[10] T. Kanda, H. Ishiguro, M. Imai, and T. Ono. Body movement analysis of human-robot interaction. In *Proc. Int. Joint Conf. on Artificial Intelligence (IJCAI)*, pages 177–182, 2003.

[11] T. Kanda, H. Ishiguro, T. Ono, M. Imai, and R. Nakatsu. Development and evaluation of an interactive humanoid robot "robovie". In *Proc. IEEE Int. Conf. on Robotics and Automation*, pages 1848–1855, 2002.

[12] T. Kohonen. *Self-Organizing Maps*. Springer, 2001 third Extended extension.

[13] P. Marti, F. Fano, V. Palma, A. Pollini, A. Rullo, and T. Shibata. My gym robot. In *Proc. AISB'05 Symposium on Robot Companion Hard Problem and Open Challenges in Human-Robot Interaction*, pages 64–73, 2005.

[14] B. Robins, K. Dautenhahn, R. te Boekhorst, and A. Billard. Robots as assistive technology - does appearance matter? In *Proc. 13th IEEE Int. Workshop on Robot and Human Interactive Communication (RO-MAN)*, 2004.

[15] B. Robins, K. Dautenhahn, R. te Boekhorst, and A. Billard. Robotic assistants in therapy and education of children with autism: Can a small humanoid robot help encourage social interaction skills? *Universal Access in the Information Society (UAIS)*, 2005.

[16] B. Robins, P. Dickerson, and K. Dautenhahn. Robots as embodied beings - interactionally sensitive body movements in interactions among autistic children and a robot. In *Proc. 14th IEEE Int. Workshop on Robot and Human Interactive Communication (RO-MAN)*, 2005.

[17] T. Salter, R. T. Boekhorst, and K. Dautenhahn. Detecting and analyzing children's play styles with autonomous mobile robots: a case study comparing observational data with sensor readings. In *Proc. of the 8th Conf. on Intelligent Autonomous Systems*, pages 61–70. IOS Press, 2004.

[18] T. Salter, K. Dautenhahn, and R. te Boekhorst. Learning about natural human-robot interaction. In *Robotics and Autonomous Systems*, 2006.

[19] T. Salter, F. Michaud, K. Dautenhahn, D. Létourneau, and S. Caron. Recognizing interaction from a robot's perspective. In *Proc. 14th IEEE Int. Workshop on Robot and Human (RO-MAN)*, pages 178–183, 2005.

[20] B. Scassellati. How social robots will help us to diagnose, treat, and understand autism. In *Proc. 12th Int. Symposium of Robotics Research (ISSR)*, 2005.

[21] B. Scassellati. Quantitative metrics of social response for autism diagnosis. In *Proc. 14th IEEE Int. Workshop on Robot and Human Interactive Communication (RO-MAN)*, 2005.

[22] T. Shibata, K. Wada, T. Saito, and K. Tanie. Human interactive robot for psychological enrichment and therapy. In *Proc. AISB'05 Symposium on Robot Companion Hard Problem and Open Challenges in Human-Robot Interaction*, pages 98–109, 2005.

[23] F. Tanaka, B. Fortenberry, K. Aisaka, and J. R. Movellan. Developing dance interaction between qrio and toddlers in a classroom environment: Plans for the first steps. In *Proc. 14th IEEE Int. Workshop on Robot and Human Interactive Communication (RO-MAN)*, 2005.

[24] F. Tanaka, J. R. Movellan, B. Fortenberry, and K. Aisaka. Daily hri evaluation at a classroom environment: Reports from dance interaction experiments. In *Proc. 1st Annual Conf. on Human-Robot Interaction (HRI)*, pages 3–9, 2006.