Eliciting caregiving behaviour in dyadic human-robot attachment-like interactions

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Based on research in developmental robotics and psychology findings in attachment theory in young infants, we designed an arousal-based model controlling the behaviour of a Sony AIBO robot during the exploration of a children play mat. When the robot experiences too many new perceptions, the increase of arousal triggers calls for attention from its human caregiver. The caregiver can choose to either calm the robot down by providing it with comfort, or to leave the robot coping with the situation on its own . When the arousal of the robot has decreased, the robot moves on to further explore the play mat. We present here the results of two experiments using this arousal-driven control architecture. In the first setting, we show that such a robotic architecture allows the human caregiver to influence greatly the learning outcomes of the exploration episode, with some similarities to a primary caregiver during early childhood. In a second experiment, we tested how human adults behaved in a similar setup with two different robots: one needy, often demanding attention, and one more independent, requesting far less care or assistance. Our results show that human adults recognise each profile of the robot for what they have been designed, and behave accordingly to what would be expected, caring more for the needy robot than the other. Additionally, the subjects exhibited a preference and more positive affect whilst interacting and rating the robot we designed as needy. This experiment leads us to the conclusion that our architecture and setup succeeded in eliciting positive and caregiving behaviour from adults of different age groups and technological background. Finally, the consistency and reactivity of the robot during this dyadic interaction appeared crucial for the enjoyment and engagement of the human partner.

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1. INTRODUCTION

Robots are constantly improving in terms of mechanical skills and their potential for everyday use is therefore increasing. However, potential use in terms of technology does not guarantee actual *usability* in real-world situations. The question of how to design robots that could be integrated in a human social environment, learn from us, and be accepted as social partners, is therefore gaining a growing interest. Among many others, the problems of skill transfer between humans and robots, and how to adapt to new or ever-changing (social) environments needs to be addressed. To that end, some research has been focusing on a *developmental approach* [Lungarella and Metta 2003]. This area of research builds on the concept that the most successful example of adaptation into our social and technological environment, without much prior knowledge, are infants. Following this approach, researchers have for example successfully managed to design robots that use algorithms to learn and adapt to new sensorimotor pairings [Berthouze and Lungarella 2004; Blanchard and Cañamero 2005b; Giovannangeli et al. 2006; Andry et al. 2009; Hiolle et al. 2007]. However, most of these robotic experiments are successful in restricted laboratory settings, and the skill-set the robot develop is limited to one task or a subset of tasks. Other researchers are working more closely to how developmental psychology describes infant development, and investigate how infants explore and discover new features of the environment, particularly through drives like curiosity [Oudeyer et al. 2007] and seeking wellbeing through affect-driven interactions with objects and people [Blanchard and Cañamero 2005a; 2006; Cañamero et al. 2006]. Indeed, the latter contributions are addressing the issue of how positive emotions, and providing comfort can promote a more efficient and consistent learning experience, depending on the environment and the behaviour of the social partner. This area of research seems to be offering a gap to be filled in order to further our understanding of development, and its implications to the synthetic approach roboticists employ to design more adaptive and adapted autonomous robotic systems.

Indeed, human infants grow and discover their new environment most often accompanied by or not far from their mother, or primary caregivers. The skills they learn, the objects and agents they encounter, are surely presented and assimilated within their cognitive and emotional experience with the constant help and assistance of this human beings alongside them. Since the dawn of attachment theory, developed by John Bowlby [Bowlby 1969], and defined as the affectional tie between the infant and its primary caregiver (who provides security and comfort when needed), developmental psychology has been trying to study how this attachment bond affects the cognitive and emotional development of young children. This bond, and the affectional dyad, appear to be crucial and influence the developmental pathway of the infant [Sroufe and Waters 1977].

In the remainder of this paper, we present early research trying to bridge the field of developmental robotics with attachment theory, which besides a thought experiment [Kaplan 2001] and a fairly remote use of the theory [Arkin 1998], has largely remained an unexplored area of research. The main goal is to address how a robotic platform could use the properties of this bond in order to thrive from it, as children most often manage to do. To that end, we present a body of related work that we took inspiration from, then describe what properties of attachment we used and why they are relevant to the design of robotic architectures. We finally present the results of two experiments that bring together our findings, and assess to what extent we improved the state of the art of the field concerned with developing robots and improving human-robot interactions.

2. BACKGROUND AND RELATED WORK

2.1 Attachment in infants

Psychological evidence suggests that caregiver-infant attachment bonds are vital to the cognitive and emotional development of infants [Cassidy and Shaver 2008], especially during the first years of life. Indeed, as John Bowlby [Bowlby 1969] discovered during his studies on mother-infant interactions, the primary caregiver, usually the mother, is utilized by the infant as a **Secure Base** in his/her early life, especially during stressful and/or unusual episodes [Sroufe 1996]. Furthermore, as stressed in [Schore 2001], if caregivers are not being sensitive and responsive enough to the infant's needs, the mental development of the child can be impaired, leading to emotional and cognitive disorders.

Therefore, identifying the factors that are particularly relevant during these interactions, as well as their dynamics, is important to understand how the development of a child can lead to many different and uneven outcomes.
Psychologists developed a procedure to assess how the attachment developed between the child and its primary caregiver [Ainsworth et al. 1978], the *Strange Situation test*. During this procedure, the child would be alternately separated from her primary caregiver (usually the mother), exposed to the presence of a stranger, then reunited with her mother. The reaction at the moment of the reunion would then be observed and analysed, in order to be classified into the following categories: secure attachment, anxious-resistant insecure attachment, anxious-avoidant attachment, and disorganized attachment. This procedure has been the most used to assess attachment in children. However, we believe that the classification in this framework is slighlty rigid for us to take inspiration from it, and leaves aside other potentially important variables, such as the temperament of the infant [Keller et al. 2005; van IJzendoorn et al. 2009] and the cultural background of the dyad. Moreover, from a robotics design point of view, modeling into a robotic architecture such notions as *separation distress*, *fear of strangers*, and *attachment security*, does not appear to be necessary if one would want to study the influence of an adults behaviour in terms of learning experience. However, we can select what we believe are the relevant characteristics of the **Secure Base** paradigm that could be of use to our modeling effort. In a broader view, we can say that, within a secure attachment relationship, the presence and interventions of the attachment figure have the effect of alleviating negative emotions, and induce positive affect in the infant. We therefore looked into other studies, focusing on the role and interplay of positive affect within the mother-infant dyad.

In [De Wolf and van IJzendoorn 1997], the availability of the mother is emphasised as playing a key role in the development of organized or disorganized attachment, being the main difference between the types. The mothers' **sensitivity** (a compound of availability and responsivity) is a key factor in the individual differences of organized attachment. This measure seems more suitable for us to evaluate human's reactions to different behaviours emerging from different organized attachment profiles. On the other hand, as expressed in [Tronick 2007], the dyadic interactions seem to evolve in order for both parties, the caregiver and the infant, to achieve *mutual delight* [Tronick 1989]. This suggests that the dyad is

working together towards increasing and maintaining each other positive emotions such as joy and pleasure, in a mutually regulated process. Therefore, the interaction has to bring to both the infant and the caregiver some amount of pleasure, be that by empathy or a sense of purpose. From the perspective of the infant, this could stem from the satisfaction of learning and verifying newly discovered skills. Moreover, when the dyad is not interacting towards mutual delight, as described in the still face paradigm [Nadel et al. 2005], where mother are behaving as depressed mothers, a significant decrease in the infant's positive emotional response is observed.
In the remainder of this paper, we describe our efforts to apply the notions described above in order for our robotic system to provoke helpful responses from a human partner, that would help its learning experience. The focus is maintained on the interplay between the frequency of caregiving interventions and the learning outcomes for the robot. Additionally, the goal is to address how to obtain such behaviour from non-expert adults (not deeply acquainted with robots), without training or constraints.

2.2 Developmental robotics

As mentioned in section 1, interesting research has been carried out investigating how a robot could use a drive to motivate its exploration and push it towards learning more complex skills [Oudeyer and Kaplan 2004; Oudeyer et al. 2007]. In these contributions, the robot evaluates its *learning progress*, the opposite of the derivative of the prediction error of the next sensorimotor state, in order to choose what new action to perform and predict efficiently the consequences of these actions in a particular sensorimotor context. This architecture explicitly used the notion of betterment of the learnt skill-set to choose what and where to explore, implicitly attributing pleasure to newly discovered correlations, and a negative affect to either well known ones, or unpredictable ones.

Another aspect of interest within the field is the notion of synchrony and rhythm within the interaction. Inspired by [Andry et al. 2001], and developed and tested with adults in [Hiolle et al. 2010], the rhythm of the interaction was used in a simple mirroring interaction game with a humanoid Nao robot. The principle follows the hypothesis stating that a steady rhythm means that the ongoing interaction is going well, therefore reinforcing the current behaviour of the robot, and a break in the rhythm was a negative response. The study showed that human adults implicitly used the rhythm as a reward when they were convinced the robot had child-like capabilities. They behaved in a manner closer to what could be observed whilist interating with childrn, implicitly timing their responses and behaviour according to the success of the game, allowing the robot to learn the correct behaviour to perform. This demonstrates that for humans to behave naturally with a robot, they need a strong belief in the capabilities and limitations of the robot, in order to avoid having them scanning the capabilities and thinking too much about how they should behave. Additionally, other contributions have addressed the impact of the interventions of human partners during sensorimotor exploration and learning. In [Blanchard and Cañamero 2006], the question as to how a robot can use the human's influence to memorise "desired perceptions" depending on specific time horizons is investigated, showing how a simple system can learn and recall sensorimotor associations related to a particular human intervention. Furthermore, whilst implicit, in [Hiolle and Cañamero 2007], the influence of the behaviour of the human partner in an imprinting paradigm is investigated, showing how crucial the issue of timing and synchrony are, even in a simple sensorimotor learning task whereby a robot is able to acquire a following behaviour.

2.3 Towards an attachment model for robots

In order to advance closer to our goal to understand and utilise the attachment bond paradigm towards helping developing robots, we have to select and discard, as previously mentioned, several components of the psychological findings and focus on the potential root of the hypothesised benefit of the paradigm. Therefore, we chose to base our work, and the following architecture, on a main variable, of which the robot would try and maintain the stability. This internal variable need not be related to any artificial physiological needs tied to some resource, but is based on what a developing robot starting with almost no prior knowledge at all should be concerned about, accumulating stable learning experiences to build on. This essential variable is akin to the notion of excitement as defined in [Sroufe 1996], which, in the early months of life, is neither a positive nor a negative emotion or affect, but refers to the level of internal activity and external stimulations experienced by the infant. A high and sustained level is too demanding and challenging, and a low level is not interesting or fruitful at all, therefore it follows that maintaining homeostasis of this variable would be optimal. This internal variable is close to the concept of arousal [Berlyne 1960], within the theory of optimal arousal, and its inverted U-shape hypothesis [Anderson 1990], where higher living mammals try to maintain on average their arousal at a middle level, where their physiology is optimal. Moreover, in our investigation of infant development, the notion of arousal appears even more suited as it is used by psychologist studying newborns in order to assess their emotional intelligence and its development [Brazelton and Nugent 1995]. However, the notion of arousal is often used as a dimension of the two or three-dimensional circumflex model of emotions [Russel 1980] as in [Breazeal and Scassellati 2002]. In these models, the arousal is an orthogonal dimension to the valence of percepts and behaviours, and the model offers a one-to-one mapping from a two dimensional vector from the arousal/valence space to a predefined emotion. In the remainder of this contribution, we do not use the notion of arousal in any way as was done in these models. We use the arousal as a variable of the internal activity, in term of learning experience, which is implicitly tied to the external perceptions, some being more stimulating then other, according to their familiarity and complexity.

3. AN AROUSAL-DRIVEN ARCHITECTURE FOR DEVELOPING ROBOTS

As introduced in the previous section, we took inspiration from developmental psychology and existing work in robotics to design a simplified model based on the notion of arousal, associating the learning experience of the robot, and how stimulating or familiar the experienced environment is. To that end, we designed a model assessing whether the current percepts are being correctly memorised and recalled, which directly influences the arousal level of the robot. The arousal only increases as a result of the changes of the synaptic weights and outupt activity within the learning system of the robot; the only goal of the robot is to learn and discover new percepts and features of its environment. The robot does not have explicit drives or motivations, but its behaviour is regulated by the arousal level. To include the human partner and his influence as a regulator of emotions, the arousal can be decreased by providing comfort to the robot, via direct contact or visual presence. This dynamical system is composed of the essential elements to reflect and test the hypothesis concerning the attachment bond and caregiving behaviour: unfamiliar events and stimuli increase the arousal and induce a state of overexcitment, and the attachment figure can then change this overstimulated state with his presence and physical comfort. Whenever the arousal is low, the infant-robot keeps exploring its environment as long as there are unknown features, in order to further its learning experience.

As described previously, we want the robot to learn incrementally and have its behaviour reflect the current situation in term of learning experience. To that end we have divided the architecture in three main components: the learning system, the arousal system, and the action selection system.

3.1 Learning Systems and their inputs

The learning system is using two well known, off-the-shelf neural network algorithms, that learn and recall, inputs provided by the sensors of the robot. The two learning structures we chose are a Hopfield-like associative memory [Hopfield 1982][Sudo et al. 2007] and a Kohonen map [Kohonen 1997]. These two neural networks provide us with two main characteristics: incremental convergence relative to the closeness and the number of occurrences of the inputs (as opposed to one-shot learning), and a capacity to measure their performance based on variations of the synaptic weights and accuracy of recall. Moreover, these networks demonstrate two main abilities involved in learning: classification for the Kohonen Map, and recall of a complete pattern for the associative memory.

The input to these two neural networks is a 10x10 binary matrix containing all discretized sensors values as described in Fig. 1.

The model used for the associative memory is a modification of the standard Hopfield network, based on models of associative memory described in [Davey and Adams 2004] and [Calcraft et al. 2007]. The network is a two-dimensional grid of N neurons, with a state or output S_i. Every neuron is locally connected to its four nearest neighbours and randomly connected to four other units of the network with a symmetric connection matrix of weights w_{ij}. The connectivity is a blend of the two configurations represented in Fig. 2. In our network, we use asynchronous random-order updates. Then, to learn the presented binary input pattern matrix, we use a modified version of the procedure from [Davey and Adams 2004], described in Alg. 1.

One point in which our algorithm differs from the original [Davey and Adams 2004] is the repetitions until all local fields are correct. During our experiments, the number of steps used to learn the current pattern is fixed (10 steps in the current settings). Therefore, the pattern is learnt correctly and completely if the robot stays in its current position, in front of the sensory input pattern; if all the local fields are correct before ten time steps, the learning stops.

The Kohonen Map algorithm is a traditional implementation of the original one

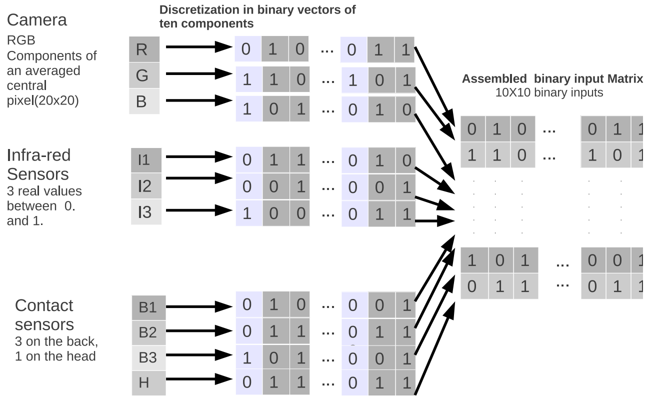


Fig. 1. Processing stages for the construction of the 10x10 binary input matrix.The modalities used are the camera image (from which an average of the centre of the field of view of a 20x20 pixel size, producing one integers per colour channel between 0 and 255), the infra-red distance sensors (3 real floating point values between 0. and 1.), and the 4 contact sensors (4 real floating point values between 0. and 1.). Each of these sensor values is then discretized in a binary vector of size 10. These ten vectors are used to assemble the final binary input matrix, row per row.

and is described in the algorithm 2 . We used a 10x10 two-dimensional map.

3.2 The Arousal Model

To calculate the arousal of the robot we use two different contributions coming from the neural networks reflecting their real-time performances. First, we calculate the discrepancy between the current pattern of stimuli and the output of the associative memory, a value we call surprise $Sur(t)$, since it decreases as a function of the familiarity of the current pattern. Since the associative memory has a fixed number of time steps to learn the pattern, more than one presentation is needed. When a pattern is familiar enough, the network converges fast and the surprise value is close to zero. We calculate this variable as described in the following equation, with X_i being the current perceptual input from Fig. 1, S_i the output activity of the associative memory.

$$Sur(t) = \sum_{i=0}^{N} \mid X_i - S_i \mid \tag{1}$$

We also use Cat_{adj}, a value we call *Categorisation adjustment*, which is the sum of the variations of the weights of the Kohonen map. Since the weights vary proportionally to the distance between the perceptual input vector, this internal variable correlates with the difficulty of the categorisation of the new inputs. Cat_{adj} is calculated as shown in the following equation, with a Kohonen map of N units and an input vector of M dimensions.

$$Cat_{adj}(t) = \sum_{i=1}^{N} \sum_{j=1}^{M} \mid W_{ij}(t) - W_{ij}(t-1) \mid \tag{2}$$

Algorithm 1 Algorithm for the update and learning stages of the associative memory

X_i {Binary Input matrix}
W_{ij} {Initialises weight matrix with zeros}
$P = 8$ {Number of connection per unit}
$N = 100$ {number of units}
$S_i \leftarrow X_i$
$n = 0$
$T = 0.9N$ {learning threshold}
while $h_i \neq X_i$ **or** $n \leq 10$ **do**
  for $i = 0$ to N **do**
    $h_i = \sum_{j \neq i}^{P} w_{ij} S_j$ {Updating all units activity y_i of the map}
    $S_i = \begin{cases} 1 & \text{if } h_i > 0 \\ -1 & \text{if } h_i < 0 \\ 0 & \text{if } h_i = 0 \end{cases}$
  end for
  if $\sum_{i=1}^{N} S_i \cdot X_i \geq T$ **then**
    for $i = 1$ to N **do**
      $\forall i \neq j$
      for $j = 1$ to P **do**
        $w_{ij} = w_{ij} + \frac{S_i S_j}{N}$ {Modifying synaptic weights between units}
      end for
    end for
  end if
  $n \leftarrow n + 1$
end while

At each time step, the arousal of the robot is computed as:

$$A(t) = \frac{Sur(t) + Cat_{adj}(t)}{2} \tag{3}$$

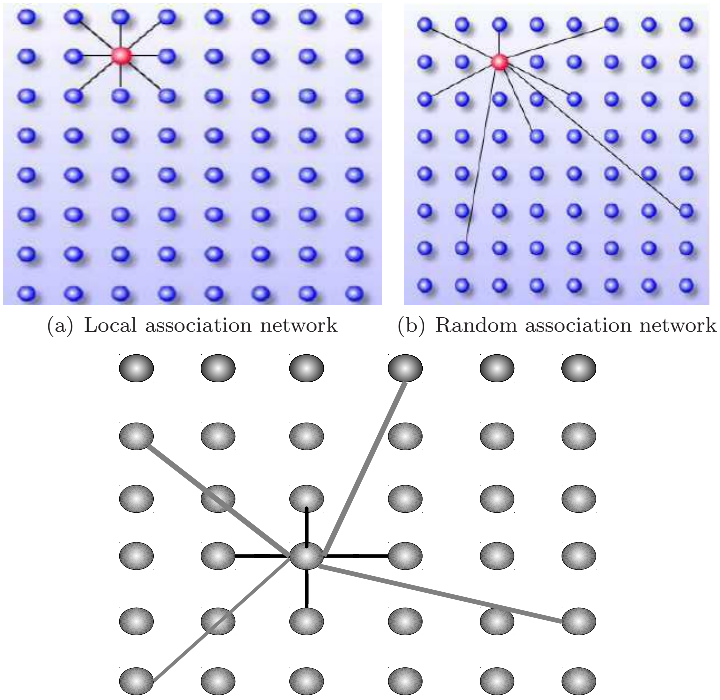
$A(t)$ is then used to compute a smoothed value of the arousal that we call *instantaneous arousal*, as follows:

$$A_{inst}(t+1) = \frac{\tau_a \cdot A_{inst}(t) + A(t+1)}{\tau_a + 1} \tag{4}$$

Here, $\tau_a = 30$ is the time window on which the instantaneous arousal is calculated, as an exponential average of $A(t)$. The intervention of the human partner are summarised in the following variable T_{Care}:

$$T_{Care}(t) = \begin{cases} B_s(t) + V_f(t) & \text{if } B_s(t) > 0 \text{ or } V_f(t) > 0 \\ \beta \cdot T_{Care}(t-1) & \text{otherwise} \end{cases} \tag{5}$$

where $B_s(t) = 0.5$ if robot is being stroked and $V_f(t) = 0.5$ when a face is detected in



(a) Local association network (b) Random association network

(c) Blended connectivity model association networks

Fig. 2. Associative memory network connectivity

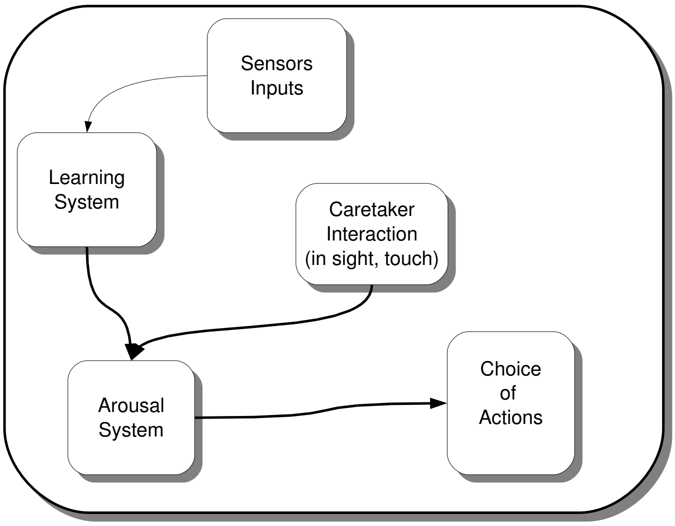


Fig. 3. Entire architecture we endowed our robot with.

Algorithm 2 Algorithm for the update and learning stages of the Kohonen map

$X_i \leftarrow$ Input matrix converted to 1D vector
$N \leftarrow$ Number of units of the Map
$M \leftarrow$ length(X_i) {100 in our experiments}
n {time step}
$\alpha = 0.5$ Learning rate
$h(n)$ {Learning rate as a decreasing function of time}
$nbh(i, j)$ {Neighbourhood function}
$a = 3$
$\kappa = 0.002$ {learning rate decreasing factor}
$end = 20000$
$h(0) = \alpha$
while $n < end$ **do**
  for $i = 0$ to N **do**
    $y_i = \sum_{j=1}^{M} w_{ij} \cdot X_j$ {Updating all units activity y_i of the map. }
  end for
  k $\leftarrow$ getWinner() {Selecting the unit with the highest activity}
  for $j = 1$ to M **do**
    $W_{kj} = W_{kj} + h(n)(X_j - W_{kj})$
  end for
  for $i = 0$ to N **do**
    if $i \neq k$ **then**
      $d(k, j) \leftarrow$Euclidean distance between winner k and neuron i

$$nbh(k, j) = \begin{cases} 1 & \text{if } |d(k, j)| \leq a \\ -\dfrac{1}{3} & \text{if } a < |d(k, j)| \leq 3a \\ 0 & \text{if } |d(k, j)| \geq 3a \end{cases}$$

      for $j = 0$ to M **do**
        $W_{ij} = W_{ij} + h(n)nbh(kj)(X_j - W_{kj})$
      end for
    end if
  end for
  $n \leftarrow n + 1$
  $h(n) = \dfrac{\alpha}{1 + n \cdot \kappa}$
end while

the visual field. Both these values are equal to 0. otherwise. Here, $0 \geq \beta < 1$ is the decay rate of $T_{Care}(t)$, accounting for the duration of the effect of the intervention of the caregiver to diminish the excitment of the robot. This value allows us to modify the robot's response the duration of the relief. $A(t)$ and $T_{care}(t)$ are used to calculate an average of this arousal, called *sustained arousal*,

$$A_{sus}(t) = \begin{cases} \dfrac{\tau_{sus} \cdot A_{sus}(t-1) + A_{inst}(1)}{\tau_{sus}+1} & \text{if } T_{Care}(t) = 0 \text{ and } A_{inst}(t) > 0.01 \\ A_{sus}(t) - \alpha \cdot T_{Care}(t) & \text{otherwise} \end{cases} \tag{6}$$

$\tau_{sus} = 10$ is the time window on which the sustained arousal is calculated, as an exponential average of the instantaneous arousal. α is the decay rate of the sustained arousal when the caregiver is interacting (set to 0.2). Using exponential averages for the instantaneous and the sustained arousal presents two advantages. An isolated non-significant peak in $A(t)$, either due to noise or a really fast change in the input value would not be altering the behaviour unless repeated. Moreover, the cumulative effect of this type of equation allows for a controlled exponential decay following a peak, showing a lasting effect even if the original stimuli has disappeared. This ensures that the threshold basd system we use does not switch too fast which would not appear natural and could cause problems to the robot.

3.3 Entire algorithm and action selection system

The actions the robot takes are based on the levels of both, instantaneous A_{inst} and sustained arousal A_{sus}. The robot can turn to the right to look for new stimuli when the sustained arousal A_{sus} is low and the robot is not stimulated enough. The robot only turns in one direction for two main reasons. First, both the Kohonen Map and the associative memory function better when the sequence of presentation of input patterns is constant. Secondly, this ensures that the robot will not leave the experimental setup, as could be the case with a random walk algorithm. Additionally, when comparing two experimental runs we can assure that the variable assessed is not the trajectory of the exploration of the robot, but the behaviour of the human partner.

If the sustained arousal A_{sus} is neither low nor high, the robot remains still and tries to learn the current pattern of stimuli it is perceiving. If the instantaneous arousal A_{inst} level peaks, the robot barks to communicate that it found something new. If the sustained arousal A_{sus} is high, the robot will keep looking for the caregiver by moving its head from top to bottom and left to right, trying to attract the caregiver closer. The graph in Fig. 4 shows the actions taken based on the two levels of arousal. The overall algorithm is described in Alg. 3.

During the entire experiment, the LEDs situated on the head of the robot were flashing as a sinusoidal wave proportionally to the sustained arousal level(which we use to increase the frequency), slowly not enough stimulated, faster when stimulated, and then flashing fast when overexcited.[1]

4. EXPERIMENTS

4.1 Effects of the behaviour of the human partner

In order to assess if the behaviour of a human partner changed the learning experience of the robot, we designed a first experiment where an experimenter would

[1] A video of the robot capabilities and behaviours can be found here: http://www.youtube.com/watch?v=tndSnyUWqBI

Algorithm 3 Algorithm of the overall architecture

```
n {iteration number}
end = 20000 {end of experiment time step}
LowArousal = 0.2 {Low sustained arousal threshold}
HighArousal = 0.6 {High sustained arousal threshold}
HighInstArousal = 0.8 {High instantaneous arousal threshold}
while n < end do
  X_i ← getCurrentSensors()
  UpdateNetworks(X_i) {update the two networks}
  UpdateSurprise()
  UpdateCategorisationAdjustment()
  UdpateArousalLevels()
  if A_sus(t) ≤ LowArousal then
    Move() {The robot turns to the right for 1 second}
  else
    stop() {The robot stops any movement}
  end if
  if A_sus(t) ≥ HighArousal then
    LookForHuman() {The robot moves its head to find the human partner's
    face}
  end if
  if A_inst(t) ≥ HighInstArousal then
    bark()
  end if
end while
```

behave in two prototypically opposite ways towards the robot. Since the robot would be aroused and overwhelmed when having been exposed to too many new features in the environment, in one set of the experiment, the experimenter would behave as a dedicated caregiver and respond to every single call for attention from the robot. In the other set of the experiment, the experimenter would simply give the robot a few strokes at the beginning, as it is the most exciting time of the experiment (every single perception is new to the learning systems of the robot), then leave the robot on its own to cope with the situation.
Our hypothesis is that the robot being cared for would learn faster and in a more consolidated way. As we can observe in Fig. 5, we used a Sony AIBO robot on child play mat. We chose an AIBO robot because the quality and reliability of the robot itself would later allow us to let non-expert human subjects use the setup without having to train them or restrict their behaviour.

We put colourful objects and toys on it for the robot to observe and learn. For the perceptual capabilities of the robot, we used the average of the RGB values of the pixels located in the centre of its visual field, and the distances that can be measured by its infra-red sensors located on the chest of the robot.

We ran the experiment ten times for each stereotypical style of caregiving of the experimenter. Every run lasted ten minutes. We recorded the data concerning the arousal levels of the robot, and the two values we described previously named

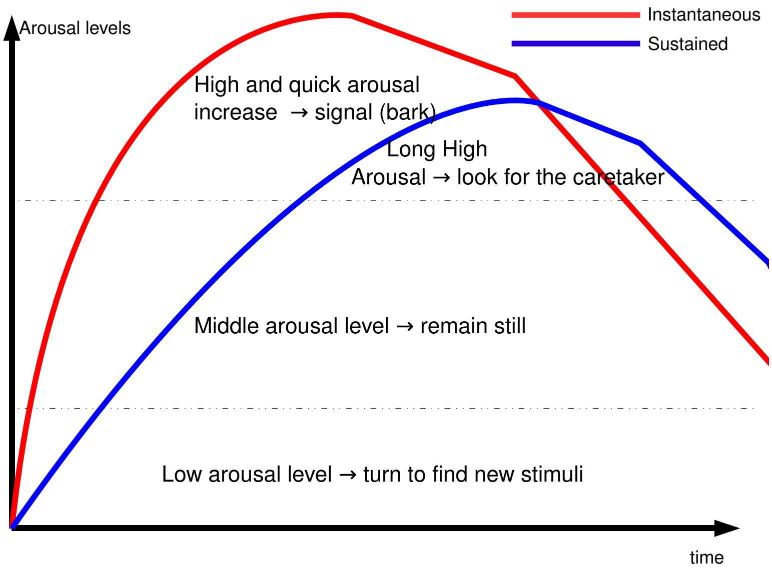


Fig. 4. Actions based on the arousal levels

Fig. 5. Our experimental setup. We used an Aibo robot on a child play mat where several toys can be presented to the robot.

Table I. Results for 10 runs for each caregiving style. ($p < 0.05$)

Style	Cat_{adj}	$\sigma(Cat_{adj})$	Sur	$\sigma(Sur)$
Caring	0.5987	0.0355	0.3456	0.0565
Not Caring	0.6427	0.0407	0.6455	0.0324

Categorisation adjustment and Surprise, related to the convergence and stability of the neural networks. We can read in table I the means and standard deviations of the Surprise and Categorisation adjustment for each different style of care from the experimenter. It is clear that the behaviour of the experimenter had a significant impact on the learning experience of the robot. Indeed, the values presented in table I are the average of all the runs of the mean of the *Surprise* and *Categorisation* *adjustment*, therefore a higher value demonstrates that the network converged and recalled less successfully. We can therefore say that the robot which was cared for learnt the play mat and its features better than the other robot. This can be explained by the fact that the robot tends to lose focus by whilst calling for attention often, and in turn did not allow its learning structures to converge and stabilise as needed. Moreover, as the robot actually stays and searches for a caregiver when the sustained arousal peaks over the defined threshold, the features of the mat are not presented to the neural networks as often as they are in the other condition. This consistency in the presentation order and frequency is crucial for the networks to form base memories and coherent categories.

4.2 A human robot experiment in-the-wild

Now that we have an architecture that has shown to lead a robot to different learning outcomes depending on the behaviour and attention of a human caregiver, we wished to assess whether such a robot would actually elicit such caregiving responses from human adults. Therefore, we designed two different profiles for the robots. One would exhibit the same dynamics and reactions as in the previous experiment. It would emit a call for attention and look for a human face when its arousal levels are high. In the remainder of this paper, we will call this profile "needy". The other profile requires assistance far less often and will be called independent. This was achieved by changing the arousal dynamics relaxation parameter in order to have the arousal increase more slowly, and the effect of the comfort provided lasting longer ($\beta = 0.995$ and $\alpha = 0.95$ for the independent robot, and $\beta = 0.95$ and $\alpha = 0.995$ for the "needy" robot). Indeed, as the arousal level controls the behaviour of the robot, even if the Sur and Cat_{adj} are high, the arousal will peak far later than in the "needy" case. Therefore, the robot with the independent profile will *appear* not to need attention, as it is not exhibiting any behaviours showing it does. Moreover, as the comfort T_{care} reduces the arousal of the robot for a longer time then in the "needy" case, even a low frequence of contact would lead to a robot with an sustained arousal always below the lower threshold, therefore always looking for new stimuli by turning even with a constant variation of inputs to its sensors.

Our hypothesis is that the "needy" profile would elicit more frequent caregiving-like behaviour from the human subjects, as well as being more engaging and stimulating.

4.2.1 *Experiment Protocol.* We carried the experiments over 3 days at the London Science Museum. Doing this, we successfully recruited subjects with different ages, gender, and familiarity with robots, to interact with the robot "in the wild", outside of a closed environment like a laboratory.

The subjects were given the following text as introduction to the experiment and instructions: *A baby Aibo robot is learning to explore its environment with the help of its caregiver. The Aibo robot will be placed on a children play mat containing toys, and it will explore the objects in this new environment. As in the case of children, encountering new objects can trigger at the same time curiosity, enjoyment, and provoke an overaroused state. When the robot is overexcited by this novelty, it will express this by barking and looking around for a human caregiver,* *to get attention and support. The caregiver can decrease the excitment of the robot via visual or tactile contact, for example by showing it its "comfort" toys and other objects, carrying it to a different area in the play mat, or by patting it on top of the head or on the back.*

The directives given to the subjects were the ones that follow:

—the LEDs on the robot head flash as a function of its stimulation level to provide the human subjects with a visual feedback

—the robot reacts to visual cues, distances of objects and contact on its pressure sensors

—when the robot is overexcited, the LEDs will flash fast, the robot barks, and its head moves from side to side to look for a human face

—overexcitment can be alleviated by stroking the back of the robot or by showing a human face in front of the robot camera

—the robot only moves by turning to the right when its stimulation level is low

—the robot can be picked up and manipulated in any ways the subject wants (within reason)

—the robot does not react to any auditory stimuli

After this briefing, the experiment started with one of the two profiles for the robot. The robot was standing on the child play mat as in Fig. 5. The subject interacted with the robot for 3 minutes, then filled in a questionnaire about the robot, then interacted for another 3 minutes with the robot with the other profile, and then filled in the questionnaire about the last robot.

Half of the subjects interacted with the "needy" robot first and then with the other robot, and half of the subjects interacted with the independent robot first. The subjects were not told the difference between the two profiles of the robot.

4.2.2 *Questionnaire.* After interacting with each robot type, we asked the human subjects to answer the following questions on a five points Likert scale.

Q.1. How did you enjoy the interaction?
The purpose of this question is to obtain a subjective rating of the human partner's enjoyment of the interaction. We hypothesised that the subjects would enjoy the "needy" robot significantly more for two main reasons. First, the robot reacts quicker to newly presented stimuli, which provides a more consistent feedback to the subjects' invitations to interact. Secondly, the robot, even if not explicitly stimulated by the human subject, will ask for attention more often, which in turn stimulates the human to engage in the interaction. Finally, this last property of the robot's behaviour could trigger more positive affect in the human, as the robot seemingly needs their participation and attention.

Q.2. How would you rate the reactivity of the robot? This question is meant to provide us with a subjective rating from the human subjects of the consistency of the timing of the robot. The scale ranges from "not reactive at all" to "extremely reactive". We obviously hypothesised that the "needy" robot would get a higher rating than the other profile, due to the fact that the time constants of the profile were far smaller than the ones of the independent profile.

Q.3. How predictable did you find the robot? This question is meant to provide us with a subjective rating from the human subjects of the predictability of the robot. The ideal rating would have been in the middle, where the robot is rated as not too predictable, therefore easy and interesting to interact with. We hypothesised that the independent robot would get a higher rating, as it does not react often to stimuli, and takes a longer have a new behaviour triggered.

Q.4 How would you rate your willingness to assist the robot? This question is meant to provide us with a subjective rating of the feeling of "need" the human subject felt. As we are trying to assess if the architecture and the setup is sufficient enough to trigger caregiving reactions from the human partners, their inclination to provide assistance to the robot would provide us with a rating of how "needy" they felt the robot was, and in turn how consciously they thought they should take care of it. We hypothesised that the "needy" robot would get a higher rating on this question.

Q.5 How would you rate your ease to interact with the robot? This question is meant to provide us with a rating of how easy the subjects felt the interaction with the robot was. It also offers us an insight about any subjects feeling that they did not know what to do during the interaction. We hypothesised that the "needy" robot would get a higher rating with this question since its reaction time and consistency to new stimuli and change during the interaction would provide a timely feedback to the human subjects' actions, therefore avoiding any unsure or hesitant feeling.

Q.6 How would you rate how autonomous the robot was? This question is meant to provide us with an explicit rating of the autonomy of the robot, which should reflect the opposite of the "needy" quality of the profile of the robot. This question is complementary to the one asking about their willingness to assist, in order to assess if the subjects noticed the difference between the two robot profiles in term of neediness and independence. Naturally, we hypothesised that the independent robot would get a much higher rating than the other robot.

5. RESULTS OF THE EXPERIMENT AT THE MUSEUM

As stated in the previous section, the experiments were carried out in the London Science Museum during a special exhibition dedicated to robots. The experiment was set up in a corner of the main hall in order to limit the interferences from the crowd passing by. It is to be noted that the downsides of this location were first the loud noise and the public watching, which may hinder the freedom of the participants, who may be conscious of other people watching while interacting with the robot. The subjects were sitting on the play mat, where toys and colourful objects had been placed, then briefed as previously described. We carried the experiment with 21 adult subjects (5 males and 16 females), who ranged from 19 to 60 years of age (10 were aged less than 30 y.o., 11 were aged 30 and above). We video recorded the interactions and recorded the real time values of the stimulation from the stimuli the robot experimented, and the comfort provided to it during the interaction.

5.1 General qualitative observations

The following observations were made by the experimenter and give a broad view of what can be witnessed during such interactions. First, all the subjects interacted for 3 minutes with the robots, without wanting to stop the interaction or looking out of place. Secondly, the subjects expressed and exhibited more positivity and engagement during and after interacting with the "needy" robot. This observation is in accordance with our hypothesis that the "needy" profile would be easier to interact with, more enjoyable, and could trigger more positive affect. During the interaction, several strategies were observed. Most subjects would first observe the robot for the first ten to twenty seconds, then increasingly try to interact with it. First by patting the robot to see the effect, and then showing the robot a toy and waiting for a reaction. It was noted that males were more inclined to move the robot to new unexplored spots of the mat, and females more often patted the robot, and offered more physical comfort then males.

5.2 Results of the questionnaire

The analysis of the experimental conditions was carried out using Repeated Measures ANOVA. These results are summarised in Table II, and visually presented in Fig. 6 and Fig. 7. Additionaly, we analysed two values collected from the robot, *Touch*, the sum over the whole interaction of what has been registered by the contact sensors of the robot, and *Stimulation*, which is the sum of the Cat_{adj} and Sur (which are the main contribution to the arousal $A(t)$) as they appear in section 3.2, reflecting the variations of the stability of the neural networks. Both these quantities are then divided by the number of time steps the interaction lasted. *Stimulation* gives us an indication of the quantity of the input patterns fed to the neural systems.

We first report that the presentation order of the two profiles of the robot did not produce any significant effect on any of the measures. The repeated Measures ANOVA did not reflect any confound between subjects having interacted first with the "needy" robot or with the independent one. We can note that the subjective ratings show that the subjects reported a high level of enjoyment overall. However, there is significant difference between the two profiles on this measure ($F(1, 20) = 22.3$, $p < 0.001$). Moreover, the analysis clearly shows that overall, subjects rated the "needy" robot as less autonomous then the independent one ($F(1, 20) = 4.5$, $p < 0.05$), which is in accordance with our hypothesis. This result is supported as well by the significant ratings of the *willingness to assist* ($F(1, 20) = 4.2$, $p < 0.05$) which was designed as a complimentary measurement of the autonomy or independence of the robot. The reported *ease to interact* demonstrate a similar strong effect between the two profiles of the robot ($F(1, 20) = 20.3$, $p < 0.001$), with a rating below average (here 2.09) for the independent robot. The same effect is observed whe considering the *reactivity* rating ($F(1, 20) = 18.6$, $p < 0.001$), which strongly supports our hypothesis that the "needy" robot would be scored higher. The only rating that did not produce a significant effect was the *predictability*.

Table II. Summary of results of the repeated measures ANOVA on the answers to the questionnaire and the data recorded from the robot (N=21). The mean and standard deviation (in parentheses) for the subjective ratings are presented for each robot profile along with the F-score F and partial η^2 size effect measure. We displayed the significance next to the name of the rating (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$).

Dependent variable	Needy Robot	independent robot	Main effect
Enjoyment ***	3.85 (1.01)	2.71 (1.05)	$F(1, 20) = 22.3,\ \eta^2 = 0.53$
Reactivity ***	3.43 (0.98)	2.16 (1.04)	$F(1, 20) = 18.6,\ \eta^2 = 0.48$
Predictability	2.93 (0.92)	2.47 (1.25)	$F(1, 20) = 2.4,\ \eta^2 = 0.109$
Willingness to assist *	3.56 (1.07)	3.00 (1.22)	$F(1, 20) = 4.2,\ \eta^2 = 0.18$
Ease to interact ***	3.45 (1.2)	2.09 (0.99)	$F(1, 20) = 20.3,\ \eta^2 = 0.51$
Autonomy *	2.67 (1.13)	3.55 (1.38)	$F(1, 20) = 4.5,\ \eta^2 = 0.23$
Touch	0.22 (1.13)	0.13(0.06)	$F(1, 20) = 1.43,\ \eta^2 = 0.07$
Stimulation **	0.11 (0.04)	0.21 (0.01)	$F(1, 20) = 12.3,\ \eta^2 = 0.51$

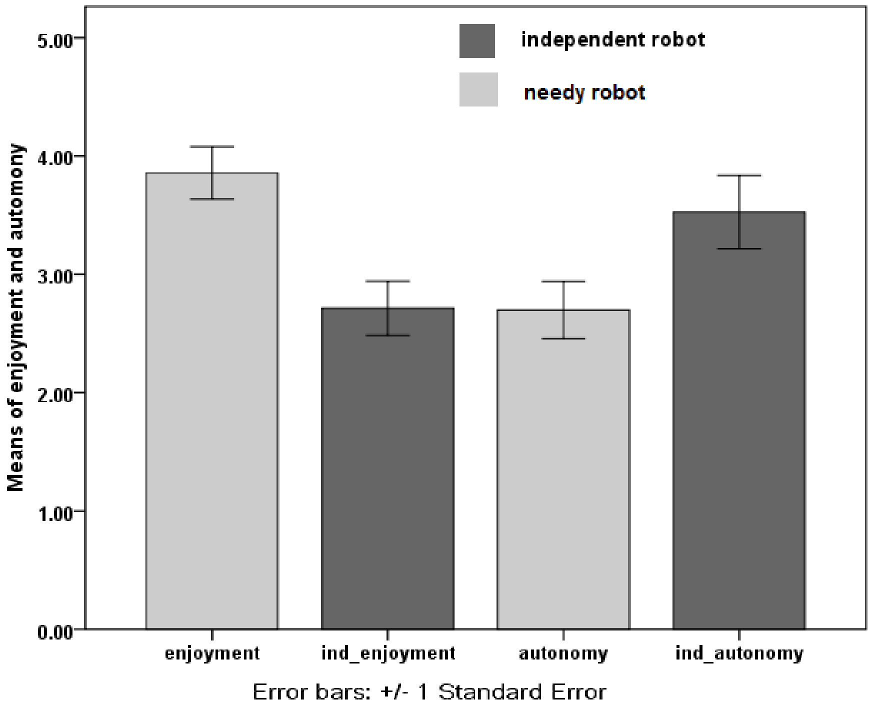


Fig. 6. Summary of the answers of the human subjects to the questions of enjoyment and autonomy (the error bars represent the standard error, and the prefix "ind" has been added in front of the ratings of the independent robot).

The analysis of the data gathered directly from the architecture shows that the subjects did not significantly provide more physical contact (as measured by the sensors on the back of the robot with the variable *Touch*), although the designed profiles would have suggested a stronger value for the "needy" robot. On the other hand, the *Stimulation* measure, the compound of *Surprise* and *Category adjustment*, shows a significative difference with the independent robot, which neural

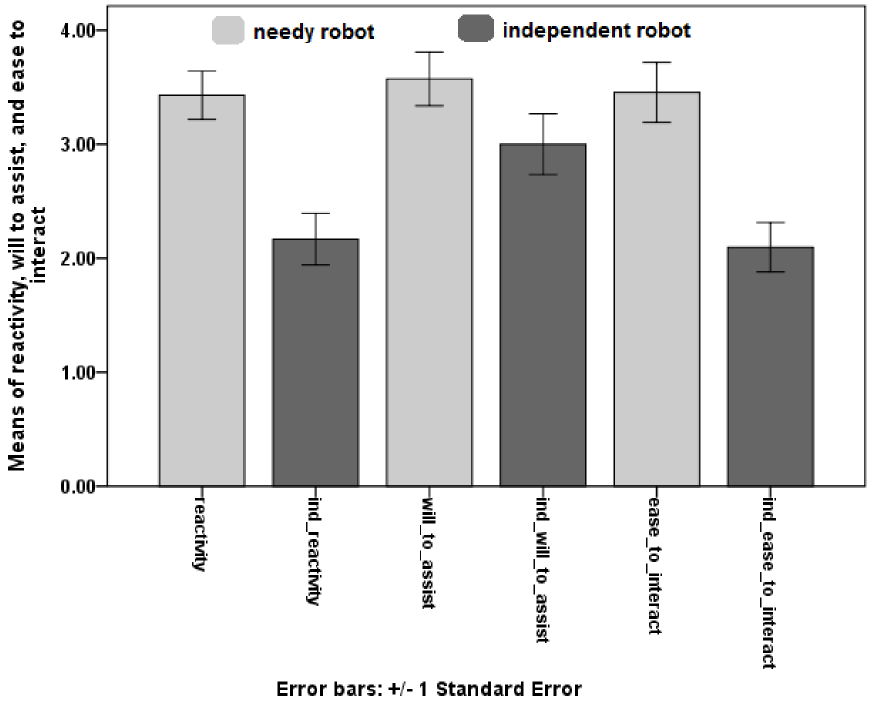


Fig. 7. Summary of the answers of the human subjects to the questions of reactivity, will to assist, and ease to interact (the error bars represent the standard error, and the prefix "ind" has been added in front of the ratings of the independent robot).

systems had to cope with more perceptual information.

5.3 Results per subjects group

T Since we observed different behaviours and dynamics during the interactions with the robot, we investigated if the subjective ratings would vary depending factors like the age group (10 were aged less than 30 y.o., 11 were aged 30 and above), and parenthood (7 of the subjects declared being parents). The repeated measures analysis (ANOVA) shows a significant interaction between the age group and the rating of *autonomy* ($F(1, 19) = 16.1$, $p = 0.001$, partial $\eta^2 = 0.50$). The subjects being 30 years old or more rated both robot profiles similarly ($F(1, 10) = 0, 40$,$p = 0.55$,partial $\eta^2 = 0.05$), in contradiction with the ratings of the younger subjects ($F(1, 9) = 46.58$, $p < 0.001$, partial $\eta^2 = 0.85$) with the general result shown in table II. Moreover, subjects having declared being parents did not show a significant difference in their rating of *autonomy* ($F(1, 19) = 16.0$,$p = 0.022$, partial $\eta^2 = 0.28$). Nevertheless, there was no other significant interactions observed with the other measures presented in the general results.

5.4 Coding of the videos

Additionally to analysing the questionnaire, the video recordings of the experiments were coded, in order to observe any objective features in the behaviour of the subjects. We asked an independent coder to code the videos using the measures described below. The coder had no knowledge of the functioning of the architecture or the research hypotheses.

Indeed, as we are interested in finding out if the profile of the robot influences the engagement and the positive affect in the behaviour of the human partner, we looked for actions and behaviours demonstrating a positive or a negative attitude towards the robot. As for the condition of the video recordings, it has to be noted that only 100 seconds of them were coded as this was the average duration where both the robot and the human subjects were visible. This is the reason why we did not try and code the facial expressions.
We coded the videos and looked for the following specific behaviours. These behaviours have been separated between positive and engaged gestures, and negative or restricting movements.

Affective gestures: These gestures represent playful, gentle, or supportive movement of the hand, head, or body movements, e.g. playful waving the hands like when greeting a child, gesturing with the hands to "come here" or hitting the hands on the floor like when inviting a dog to play.

Affective touch: The human partner strokes the robot. The event starts with a hand moving towards the robot and ends when the hand goes back again. These gestures are the ones showing some kindness and attention as would an adult with an infant or a young puppy.

Restricting touch: This gesture happens when the subject holds the robot in order to limit its movements or covers the head or body. Examples of these behaviours include repeatedly moving the robot back and picking it up in order to see it when the robot continuously moves away or is facing the other direction. The event starts with hands moving toward robot and end with drawing them back.

Aggressive handling: This happens when subject picks up or handles the robot roughly (e.g. turning it upside down, hitting it). This event starts with the hand moving towards the robot and ends when the hand goes back again.

It has to be mentioned that the emotion-relevant behaviours do not include behaviours that are primarily mechanically-based, such as picking the robot up to to inspect it while turning it around, or to touch the robot with the fingertip in order to test if it moves.

Additionally, as we can remark on Fig. 8, where the sums of the behaviours that we qualify as negative are represented, there is a significant difference between the interaction with the two profiles.

sum of negative gestures $F(1, 20) = 5.7$, $p < 0.05$, partial $\eta^2 = 0.241$) sum of positive ones $F(1, 20) = 3.56$, $p = 0.07$, partial $\eta^2 = 0.165$)

6. CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

We have presented two experiments describing and demonstrating how attachment theory phenomenology can be used to investigate the question of how to design developing robots that would trigger caregiving-like responses from adults during

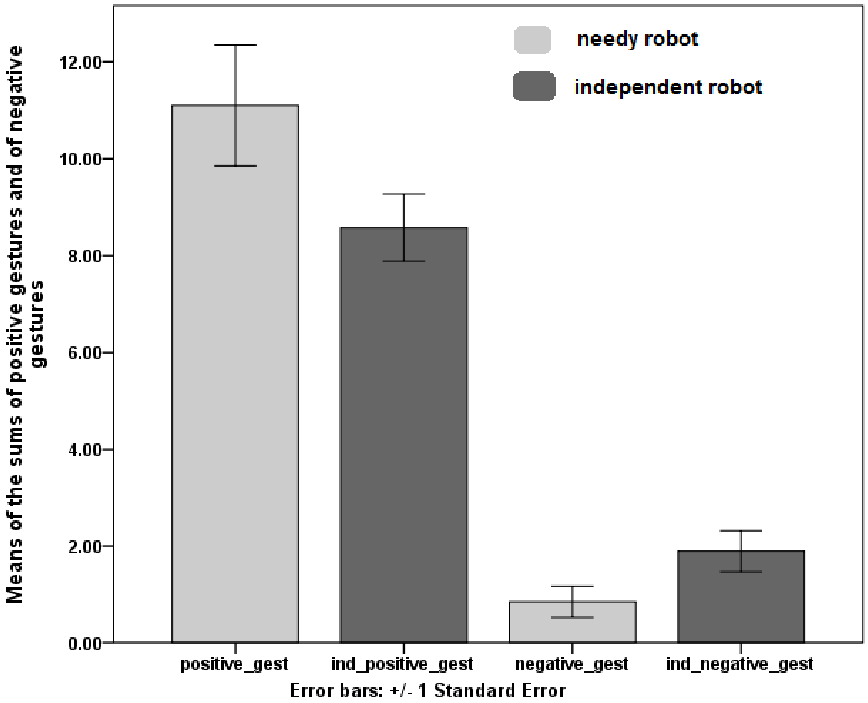


Fig. 8. Results of the sums of the positive and negative gestures from the subjects in the two conditions (the error bars here represent the standard error).

exploration and learning episodes. We used the notion of arousal levels in order for the robot to react based on what it is actually learning in real-time. Following the optimal arousal hypothesis, a low level of arousal triggers exploration in order to find new stimulating percepts, and a high prolonged arousal level, or overexcitment, provokes an orientation response towards an adult figure, in order to get assistance. Physical contact and the appearance of the human partner's face in the field of view would then reduce the arousal, similarly to the calming effect of a mother. In a first experiment, we have shown that this architecture, and its underlying dynamics, produce two different learning outcomes for the robot depending on the interventions of a human partner. If the experimenter intervened as often as the robot requested, the exploration and learning of the percepts was considerably faster than when the experimenter was mostly idle. These results are the direct consequence of the number of presentations and of the focus that the robot has spent observing the various perceptual states available to it. Indeed, the architecture of the robot pushes it to stay in front of a perceptual scene until its learning structures converge to a satisfying level. This effect is only warranted by the slow convergence of the two structures we are using. The Kohonen map and associative memory are well-known for their stability in cases where the patterns are repeatedly presented and can form solid categories and base memories. Our architecture would not produce the observed results if we were using one-shot learning, or other fast adapting algorithms. Moreover, the behavioural response to overexcitment was slighlty detrimental to the learning experience of the robot, diverting it from the play mat and driving to visually explore the upper part of the environment looking for the human partner, therefore adding more percepts to categorise and recall.

In a second experiment, this time "in the wild", we invited adult visitors at the London Science Museum to interact with a robot endowed with a similar architecture. Two different profiles were designed for the robot this time, one "needy" and one independent. These two profiles were created by alterating the dynamics of the original model, and to test whether preferences and behavioral differences would be observed. The results show that subjects were significantly engaged in the interaction, with both profiles, and that a significant preference was shown towards the "needy" robot as reflected in the subjective ratings of *enjoyment* collected using questionnaires. Moreover, subjects rated correctly the profiles of the robot, with two distinct measures (*autonomy* and *willingness to assist*). These two results support our approach in designing robotic architectures susceptible to induce positive emotions and caregiving behaviour in order to facilitate the learning experience of a developing robot. For our subjects who were parents and aged 30 years old and above, the *autonomy* rating was not significantly different between the two conditions, which leads us to believe that either the term itself is too unfamiliar to this population, or the notion of autonomy within this context is interpreted differently than would younger subjects.

Furthermore, the choice of platform and the special context during which the data was gathered could be responsible for some biases in the results and overall behaviour of the subjects. First, the AIBO robot is known to be appealing to most adults, if just by interest for the novelty of the artifact, therefore biasing subjects towards exhibiting more enthusiasm during the interaction. If that would be the case, a possible decrease in the rating of enjoyment could have been observed between the two phases of the experiment. We did not observe such a decrease in the data. Secondly, concerning the data collected following the coding procedures of the video recorded, the range of behaviours an adult can exhibit with such a robot is limited to moving the robot, stroking it or touching its head, and presenting it with object. There is no point in demonstrating skills like stacking or manipulating ojects which could have lead to a richer interaction and a more natural behaviour from the subjects. Yet the results of the coding shows a significant effect of the "needy" robot profile in terms of a reduction in negative behaviours. This result most likely is due to the dynamics of the behaviour of the robot, having been designed as more reactive, and also rated as such by the subjects.

It has to be noted that the results were gathered in a particular setting, the visit of a museum dedicated to science. It is likely that visitors were already keen on discovering and trying out new technologies. Moreover, our data collected was done with a majority of female subjects (14 females against 7 males), who have a different style of interaction then male subjects. Stereotypically, male subjects would leave more space and liberty to explore to an infant or an animal. Furthermore, stroking a robotic artifact in order to to alter its behaviour might provoke an uncanny feeling at first, especially in a public open space.

Nonetheless, keeping these drawbacks concerning the setup into mind, we believe that the observations in term of engagement, positive and affective behaviours displayed, and post experiment feedback comments, make a convincing argument for the pursuit in the development of similar architecture, tailored for human robot interactions. Taking qualitative observations into account as well, we argue that such an architecture succeeded in eliciting caregiving-like responses from adult subjects from various technological and social background, whilst interacting with a robot.

Finally, we can question to what extent the arousal-driven model we developed could serve as a first step towards a biological model of attachment behaviours. A long term goal of the field of developmental robotics is to provide feedback to the fields of behavioral sciences. It is indeed important assess the relevance of the models against the phenomenology that inspired them. In the study presented here, we can argue that we modeled the behaviour of the robot with two phenomena in mind. First, during an exploratory episode, the amount of new information an infant (humans or primates) discovers has an effect on the behaviour and the learning outcome. A low amount drives further exploration, and high amount can be overwhelming. Secondly, the primary attachment figure, or caregiver, has a crucial role in these episodes, and can influence the internal physiology of the infant. The interplay of these two phenomena leads to link the behaviour of the caregiver to the learning efficiency of an infant during a short exploration episode. If we solely compare our model and the behaviours it produces to the phenomena presented, we can argue for the relevance of our model in the sense described in [Webb 2001]. Indeed, we do obtain different learning outcomes depending on the human behaviour. However, this synthetic model uses an abstraction of the underlying physiology responsible for these phenomena. For instance, arousal itself is a measure reflecting the effect of various endogenous and exogenous perturbations. We therefore cannot advocate for a close biological model in terms of realism (using Webb's terminology). Moreover, the learning structures themselves are only classifying and recalling preprocessed input patterns, without any physical interaction with the objects they represent, or active trial and error exploratory approach.

6.2 Future Work

The work presented here can be extended in several interesting ways. In order to further validate our hypothesis that the profile of the robot, and the inherent dynamics of it, is responsible for triggering caregiving-like behaviours –and the positive affect and emotions associated with it– we would like to test a similar setting with a robot with an exploratory behaviour that would follow a random draw as opposed to the arousal levels. This would ensure that the dynamics and the consistency of the behaviour of the robot is key to the response and behaviours observed with the subjects. Moreover, in order to further validate that this kind of architecture, influenced by psychological theories about mother-infant relationships, clearly helps robots to learn in more coherent and efficient ways, we would like to allow our robot to learn slightly more complex skills, and allow it to build on them in order to learn new ones. Indeed, observing such interactions with human adults, actively teaching reusable skills to robots, would help us identify what properties of the behaviours of the human partner is key to accelerate and consolidate the skills of a robot. This theme is deeply related to Vygotsky's *Zone of Proximal Development* [Vygotsky 1967], which was defined as the gap between what a learner has mastered, and what can be achieved with the educational support of the human partner. In our case, for a human to be efficient in teaching reusable and interdependent skills, they would have to understand this concept of proximal development, and therefore demonstrate and teach skills and behaviours that are within the reach of the robot and far enough from what the robot knows as not to be redundant. However, there are tremendous challenges to overcome in order to successfully design such an experiment, such as the length of the experiment –in order to keep the human partner engaged in a long term interaction– and what kind of skills and tasks to propose to a developing robot.

Although we believe that in order to achieve such long term interaction, once more taking inspiration from the mother-infant bond and its properties could be a promising avenue. Indeed, we suppose that if a human teaches skills and behaviours to a robot, there could be ways to have the robot reflect this particular teachings. The robot would behave and respond to stimuli and situations in an adapted manner, and *personalised* to this particular human. We observe this every day with parents. In some ways, although behaving differently and singularly, children do behave like their parents, and react to emotional or non-emotional situation as a product of these dyadic episodes. This does not seem to be a product of direct imitation learning, but a gradual process where behaviours that most children exhibit, were slowly tailored as a product of what they observed in their caregiver, and what they have been directly taught by them. This phenomenon, though loosely defined here, seems to trigger positive emotions in parents and could be a key to keeping the human-robot dyad engaged in long term interactions, and having the robot grow and develop successfully. Of course, in order for this objective to be reached, much progress is needed in the real-time perception of emotional and non-emotional cues in human behaviours, and also the correct identification of the intents and purposes of such behaviours. Possibly a first step towards this end would be for our architecture to be allowed to itself regulate the arousal after repeated exposures to a given stimuli, or set of them. The arousal levels, and the resulting behaviour triggered, could also be slowly shaped as to resemble those of the human partner in the given situation, therefore having a first step toward an empathic acquired behaviour, not imitating the behaviour of the human blindly, but seamlessly being shaped along it.

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