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A Robot that Uses Arousal to Detect Learning Challenges and Seek Help

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Abstract

In the context of our work on dyadic robot-human (caregiver) interaction from a developmental robotics perspective, in this paper we investigate how an autonomous robot that explores and learns novel environments can make use of its arousal system to detect situations that constitute learning challenges, and request help from a human at points where this help is most needed and can be most beneficial. In a set of experiments, our robot learns to classify and recognize the perceptual properties of various objects placed on a table. We show that the arousal system of the robot permits it to identify and react to incongruent and novel features in the environment. More specifically, our results show that the robot identifies perceived outliers and episodic perceptual anomalies. As in the case of young infants, arousal variations trigger regulatory behaviours that engage caregivers in helping behaviors. We conclude that this attachment-based architecture provides a generic process that permits a robot to request interventions from a human caregiver during relevant events.

Introduction

Since the pioneering work of John Bowlby regarding the role and the dynamics of *attachment* behaviors in development of infants from an early age (Bowlby, 1969), much research work in Developmental and Comparative Psychology has been devoted to address the impact of attachment dynamics on the socio-cognitive and emotional development of infants, both in human and non-human primates (see e.g., (Cassidy and Shaver, 2008; Bard et al., 2014)). As Bowlby highlighted following his observations of behaviors and affective displays in infants, a primary attachment figure – often the mother – plays a central role in regulating and orienting the infant during stressful periods, and during play- and learning-oriented interactions. Bowlby developed a control systems theory of this aspect of social interaction, where proximity-seeking regulatory behaviors are produced by the infant as a response to the distress felt. These proximity-seeking behaviors serve to attract and maintain the attention of the caregiver, and also help to regulate the developing emotions of the infant (Sroufe and Waters, 1977). The strategies employed by infants to attract and maintain the attention of the caregiver and for emotion regulation are different in their nature and time line, and have been classified into different types of attachment profiles (Ainsworth and Bell, 1970). Bowlby introduced the notion of *Secure Base* to reflect the role that caregivers play in grounding the exploratory behaviors of infants, qualifying the attachment figure as an affective safe haven from which to explore (Bowlby, 1988) and develop social, affective and cognitive skills in a successful manner. Since then, much work has been devoted to the study of the factors responsible for the emergence of these patterns of behaviors, and the impact of the behavior of the attachment figure in their development (Mikulincer et al., 2003). Particular attention has been paid to the notions of *Sensitivity* – the ability to correctly interpret the behavior and demands of the infant – and of *responsiveness* – the timeliness of the responses of the caregiver – which have been related to presence or absence of physical and emotional availability of a caregiver, and are thought to be determinants of the affect of the infant (Field, 1994).

The notion of *arousal* has been used in psychology to measure and quantify states of heightened activity, alertness, and attention, and was originally believed to reflect the activation of part of the central nervous system. This notion lead Hebb to propose a theory of drives based on an arousal system (Hebb, 1966). Moreover, arousal (together with valence) is considered one of the core dimensions of emotions (Russel, 1980). Alongside Hebb's work on the relationship between arousal, drives and goal-oriented behaviors, Berlyne postulated in his theory of curiosity (Berlyne, 1969) that low levels of arousal trigger exploratory behaviors whereas internal conflicts between expectations and the stimuli perceived give rise to a higher level of arousal. He added that the exploratory behaviors serve to promote a medium-to-optimal level of arousal. Berlyne hypothesized that arousal was a construct relating to "collative variables" and related them to exploratory behaviors as follows: "... [but] the paramount determinants of specific exploration are, however, a group of stimulus properties to which we commonly refer by such words as 'novelty', 'change', 'surprisingness', 'incongruity', 'complexity', 'ambiguity', and 'indistinctiveness'." (Berlyne, 1965, page 245). Furthermore, Berlyne formulated the notion of arousal as "all the stimulus properties that go to make up arousal potential, including the "collative" properties, e.g., novelty, variability, surprisingness, complexity, and ambiguity." (Berlyne, 1969, page 1068).

Our work in the area of developmental robotics has used the concept of collative variables to drive and regulate robot behaviours using variants of an architecture inspired from attachment theory. In previous studies, we showed how humans interact with a robot endowed with such architecture (Hiolle et al., 2012), and in more recent work (Hiolle et al., 2014), we demonstrated that the parameters of the architecture yield different patterns of exploration depending on the complexity of the environment. While these previous studies focused on global behavioural consequences of the use of collative variables regulated by human interactions, in this paper, we investigate in which specific situations these variables provide meaningful information and reflect the potential need for a human intervention. As these variables reflect the real time novelty or ambiguity of a given perceptual context, we need to be able to sample the realm of contexts and time span in which these variables are meaningful. More precisely, during an exploration and knowledge gathering episode, we investigate how and when does the dynamics of these variables offer an opportunity for a human to help development and learning. As our results suggest, human help can for example be useful to indicate to the robot whether to discard or attend to the current object of attention, or to provide physical assistance (e.g., moving the objects to help disambiguate perceptions) if the current situation is beyond the capabilities of the robot.

Related Work in Robotics

Arousal. Arousal has been used in artificial and robotic systems for different purposes. It has for example been used as a parameter to control the emotional displays of a robot as a function that reflects the levels of external stimulation received by an agent (Breazeal, 2003). Ogino and colleagues (Ogino et al., 2013) propose a motivational model of early parent-infant communication. Their model is based on the need for relatedness and its relationship to the dynamics of the pleasure and arousal in face-to-face interactions. They tested their architecture using a virtual robot on a computer which interacted with a human playing the role of the parent. To that end, their model includes a two-dimensional vector of pleasure and arousal following the circumplex model of emotions introduced by Russel (1980). The arousal of the agent is computed with respect to measures of novelty, stress and the perceived arousal of the human. The pleasure varies proportionally to the pleasure perceived, the relatedness, and the expectancy of the perception of some emotion in the human. Their study intended to reproduce the phenomenology observed during mother-infant interactions and especially during still face episodes (Nadel et al., 2005). These episodes are characterized by a decrease in pleasure and positive emotions when the attachment figure stops responding to the infant's positive signals, such as gazing and smiling. The results they present show that this model reproduces the typical drop in positive affect following a still-face episode. Although the architecture based its novelty on a predictive system learning the likeliest next action the caregiver would produce, the interplay between the behavior of the caregiver and the exploratory behavior and learning of the robot were not studied.

The Attachment System. In the few studies trying to model the attachment system and its dynamics, the behaviors related to attachment and their occurrence are studied in isolation from other important facets of (infant) development. Typically, the socio-cognitive development is left aside, the attachment subsystem is considered on its own, and the analysis is solely concerned with the success or failure of a coping strategy or a regulatory behavior. For instance, Petters Petters (2006) presents simulations of caregiver-infant interactions using several control architectures based on attachment theory. The main goal of these simulations of artificial agents interactions was to model the relationships between the goals and behaviors observed in young infants. The resulting architectures were tested in unsafe or safe (secure or insecure) scenarios. Depending on parameters relating to the sensitivity of the caregiver of the infant agent, the behavior of the infant would vary. Specifically, the architectures comprised several main components inspired by the literature on Attachment theory. First, an Anxiety internal variable increases when the perceptual appraisal of the situation was deemed unfamiliar or unsafe. A Warmth internal variable was introduced to evaluate the positive interactions with the caregiver as hypothesised in the Secure Base paradigm. Based on these internal variables and the current perceptions, the action selection system assigns weights to the current goals and a winner-take-all approach is used to trigger the behavior associated with the most active one. Several variations of this architecture have been tested to include learning and adaptation from previous interactions. This adaptation was based on the success or failure to regulate the internal variables.For instance, the agent tries to approach its caregiver when the Anxiety variable is high, and the responsiveness or sensitivity of the carer (a built-in constant in the simulation) defines if the carer will provide Warmth and relieve the Anxiety. The reported results clearly show some emergent categories which are believed to correspond to the ones Ainsworth brought to light (Ainsworth et al., 1978). However, the attachment behavior itself is considered aside from the exploration and its potential consequences on development. In contrast with the models developed and tested in simulations in various studies concerning the emergence of attachment patterns (Petters, 2006; Stevens and Zhang, 2009), we have studied the dynamics of the dyadic interactions in a robot-centric manner. Our main aim is to improve the adaptivity of autonomous robots in order to, on the one hand, support their autonomous learning as a function of its interactions with the physical and social environment, and on the other hand improve the affective experience of the human in human-robot dyadic social interactions. However, despite the differences with the other body of work that models attachment dynamics and arousal modulation, we share the common view of the basic interplay between caring styles and behavior variations in affective adaptation.

Exploration, Curiosity and Intrinsic Motivation. A growing body of work in the robotics research community has focused on applying Berlyne's concept of curiosity as an intrinsic motivation for developing skills in robots. Following the encouraging results from the "playground experiment" from Oudeyer et al. (2007) and the advances in self-assessment measures related to novelty and learning progress (Şimşek and Barto, 2004), research has been devoted to the improvement of exploratory behavior and self-development of autonomous agents and robots. Most often these architectures use some evaluation of the progress of the agent in terms of learning, computed as the decrease of the prediction error of the Learning System of the robot (Kaplan and Oudeyer, 2005). Typical architectures modeling curiosity aimed at guiding the exploration of a developing robot often focus on specific task learning problem (Kaplan and Oudeyer, 2005; Luciw et al., 2011) and do not take advantage of the potential availability of humans. However, this principle has also been successfully applied to influence and help a robot in navigation tasks (Jauffret et al., 2013). In this contribution, the authors use self-evaluation measures of success and failure for the robot to express its "frustration" and trigger the help from a human when frustration is too high. They show how this strategy can help the robot subjectively identify deadlock situations, and be assisted in solving a given problem with the help of a human. In a similar fashion, a Surprise-based learning architecture was used to help a robot autonomously and incrementally build logical rules concerning the perceptions it meets in its environment (Ranasinghe and Shen, 2009).

Robot Architecture

In our previous experiments (Hiolle et al., 2012) an Aibo robot had to explore and learn the objects present in an environment consisting of toys and objects of different colors, shapes and sizes placed on a children's playmat inspired by the playground experiment (Oudeyer et al., 2007). The objects were a source of arousal for the robot as a function of their novelty. The level of arousal interacted with the parameters of the learning system, also influencing the observable behavior of the robot, particularly the time it would spend

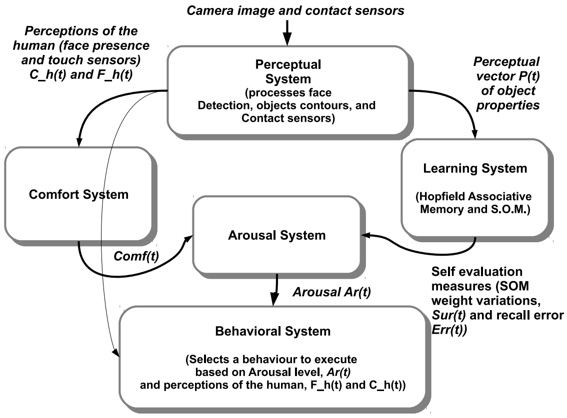


Figure 1: Components of the robot architecture used in the experiments. The Perceptual System processes the perception into a binary perceptual vector to be learned by the Learning System. We then evaluate the Stimulation as in Eq. 1, which is used with the *comfort* (Eq. 3) to compute the Arousal level in Eq. 2. The *arousal* level is used by the Behavioral System to choose the action to be performed.

in front of an object while learning it. In the experimental setup used in the study reported in this paper, the "task" of the robot was similar – exploring and learning novel objects in an environment, for which it can "solicit" (or not) the attention of a human carer as a function of its level of arousal caused by the exploration of the environment, and the carer can provide "comfort" via the visual (by showing his / her face) or tactile (patting the robot on the touch sensor placed on its head) modalities – but have we varied the previous setup as follows. We have used an Aldebaran Nao robot controlled using the architecture in Fig. 1 described in details below. The robot is placed in front of a table on which several colored objects (toy rubber cubes and balls) are placed as depicted in Fig. 2a. Following the previously presented body of work on attachment and exploratory behaviour for autonomous robots, we attempt to validate our architecture for attachment and dyadic exploration. We wish to evaluate when and how specific arousal variations occur and to which event they correspond to. In turn, this study will inform us on the specific helping behaviour a human can provide in this context, helping to generalize the results to different exploration and learning scenarios.

Perceptual System. The Perceptual System of the robot uses the image from the camera and the contact sensors located on the head of Nao to process information about the objects and humans around it. Perceptions feed into two different components of the architecture – the Comfort System and the Learning System. Perceptions about objects are extracted from the camera image and provide input to the Learning System. To perform visual perception of objects, the Perceptual System extracts the contours in the image for the robot to learn features of the visual scene. To this end, we have used available visual processing tools from the OpenCV library. Our algorithm then selects the three largest closed contours using a Canny filter and extracts the following information from them. For each contour, the following properties are calculated to construct a binary vector $P(t)$. The size of the area enclosed in the contour is measured as an integer in the interval $[0, 5000]$, the length of the perimeter of the contour is evaluated as an integer in the interval $[0, 1000]$, the average of the three colour channels in the RGB colour space is computed for the enclosed area of the contour, resulting in 3 floating point values in the range $[0, 255]$. The five values resulting from the previous steps are then normalised and discretized into 50 bins to construct a vector of 250 binary components $P(t)$ which is used as input to the Learning System. Perceptions concerning human interventions might come from the camera or the contact sensors and provide input to the Comfort System and the Learning System. To be able to process the input from the human, the Perceptual System contains variables related to the presence of a face in the visual field ($F_h(t)$), and the values of the contact sensors ($C_h(t)$) located on the head of Nao. The presence of the face is a binary signal updated using the available face detection algorithm from the OpenCV library. The three contact sensors located on the head of the robot are also binary sensors, and are accessed and read using the URBI middleware.

Learning System and Self-Evaluation Measures. As in the architecture used in our previous work (Hiolle et al., 2012; Hiolle and Cañamero, 2008), the robot learns selected features of the scene using two neural networks – a Hopfield associative memory (Davey and Adams, 2004) and a self-organising map (Kohonen, 1997). These two types of learning algorithms were chosen for the following two reasons: first, their dynamics are well understood, and second, each algorithm provides two different but complementary capabilities associated with the task of learning: classification and recall. The self-organising map tries to classify the current binary vector, and the Hopfield network converges to the pattern closest to the input vector. At every time step, a new perception vector $P(t)$ is presented as an input to the two networks, and an iteration of update and learning is performed by both neural networks. A real-time measure of the performance of the two networks is produced and stored as an internal variable named *Stimulation*, $Stim(t)$ in equation 1, which is used to increase the level of arousal. *Stimulation* is computed as the half of the sum of the discrepancy between the pattern recalled by the Hopfield network $Err(t)$ (recall error), and the sum of the variation of the weights of the self-organising map $Sur(t)$.

$$Stim(t) = \frac{Err(t) + Sur(t)}{2} \tag{1}$$

$$\text{with} \begin{cases} Err(t) = \sum_{i=1}^{N} \mid S_i - P_i \mid \\ Sur(t) = \sum_{i=1}^{M} \sum_{j=1}^{N} \mid w_{ij}(t) - w_{ij}(t-1) \mid \end{cases}$$

In equation 1, the intermediate variable $Err(t)$ is the discrepancy between all N components of the recalled pattern from the Hopfield network (S_i) and the current pattern (P_i), N is the number of components of the input vector, and M the number of units in the self-organising map. The value of $Err(t)$ indicates how novel the current perception $P(t)$ is for the memory, since the more novel it is, the higher the recall error $Err(t)$ will be. The second term, $Sur(t)$, is the sum of the variations of the synaptic weights of the Kohonen map. This "surprise" value reflects how far the current synaptic weights of the winning unit are from the current perception. This measure also reflects the novelty of the current perceptions $P(t)$. These two measures are related to the prediction error used in other systems for self-evaluation (Weng, 2002).

The Arousal System and the Comfort System. The arousal model is an adaptation of the model described and studied in previous work (Hiolle et al., 2012). The arousal level increases as a function of the *Stimulation* perceived, to reflect the cognitive effort demanded by the current situation and the familiarity of the current perceptual vector $P(t)$. The arousal is modeled as a smooth average of the *Stimulation* (see Eq. 1), which is a real-time evaluation of the recall error of the associative memory and the variation of the synaptic weights of the self-organising map. Additionally, in the same way as arousal and distress are modulated by the attachment figure in infants, the robot's caregiver can decrease the arousal via tactile contact or by presenting his/her face in the visual field, using the *comfort* computed from Eq. 3.

$$Ar(t) = \begin{cases} \dfrac{\tau_{ar} \cdot Ar(t-1) + Stim(t)}{\tau_{ar} + 1} & \text{if } Comf(t) \leq 0.1 \\ Ar(t-1) - \alpha_{ar} \cdot Comf(t) & \text{otherwise} \end{cases} \tag{2}$$

As we can see in Eq. 2, the arousal level is a scalar value computed as an exponential average of the stimulation perceived when no comfort $Comf(t)$ is perceived. Exponential averaging is used to prevent sudden changes that could lead to abrupt changes in the behavior of the robot. The window parameter τ_{ar} controls the influence that the current *Stimulation* has on the arousal, thus defining its slope; it is a smoothing factor that biases this influence either towards "the past" (a larger τ_{ar} that produces smoother behavior) or towards "the present" (a smaller τ_{ar} that gives rise to more reactive behavior), as a function of the variability of the *Stimulation*.

$Comf(t)$ is the internal variable evaluating the influence of the human, i.e., the comfort provided through the two available modalities, which are the perception from the head contact sensors ($C_h(t)$) and the perception from the face detection module ($F_h(t)$). $Comf(t)$ is calculated as follows:

$$Comf(t) = \begin{cases} \dfrac{Comf(t-1) \cdot \tau_h + C_h(t) + F_h(t)}{\tau_h + 1} \\ \text{if } C_h(t) > 0 \text{ or } F_h(t) > 0 \\ \beta_h \cdot Comf(t-1) \text{ otherwise} \end{cases} \tag{3}$$

The trace rate β_h controls the rate at which the past comfort subsists in the system and provides the architecture with a means to vary the duration of the effect of human intervention. τ_h controls the weight given to past perceived comfort as it defines the time window on which the comfort value is updated. Both parameters were used in our previous HRI study (Hiolle et al., 2012) to define the two robot profiles that react differently to human interventions.

Interactions between the Arousal System, the Comfort System and the Learning System. The interaction between the arousal-comfort interplay and learning are as follows. Following the models previously discussed, a moderate level of arousal fosters learning, while extreme (high and low) levels of arousal hinder learning. An excessively high level of arousal reflects lack of "stability" in the underlying neural networks, leading the robot to stop in front of the stimulus currently perceived (the source of arousal) and "call for help" (look for a human). An excessively low level of arousal reflects "boredom" (lack of stimulation, lack of novel input to the networks) that leads the robot to divert attention away from the current stimulus and explore in search of new ones. The fact that the level of arousal descends from high to medium (when the decrease is not directly produced by human comfort) indicates that the robot is learning new, "interesting" things, and in fact a medium level of arousal following a high level is a sign that the robot has learned something new. The fact that the level of arousal descends from medium to low indicates that the robot is perceiving stimuli that are already familiar and have low "interest".

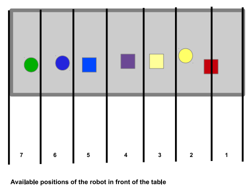
Action Selection and the Behavioral System. The Behavioral System, takes inspiration from behavior-based-robotics approaches, particularly (Brooks, 1986; Arkin, 1998; Avila-Garcia and Cañamero, 2004) and contains a set of predefined behaviors to be executed depending on the current perceptions and the arousal level. Each behavior possesses its own activation level, which reflects the relevance of that behavior for the current situation and is computed based on the Arousal level and behavior-related perceptual information. In a similar vein to (Avila-Garcia and Cañamero, 2004), our simple architecture implements in effect a two-resource action selection problem. Our robot must choose between two activities, "Explore-and-Learn" and "Find-a-Human" using a Winner-take-all action selection algorithm. The activation of these behaviors only depends on the level of arousal. If the arousal is greater than or equal to a given threshold (which here we have chosen to set to a high level, $Highthresh$), the behavior "Find-a-Human" will be executed. These two main behaviors can trigger other simpler behaviors, also following a Winner-take-all policy. The "Explore-and-Learn" behavior selects whether to attend to and learn the current stimuli ("Learn" behavior), or to move away from it and explore other elements of the environment ("Explore" behavior). The regulatory behavior "Find-Human" can either trigger the appetitive behavior to search for a face by moving its head (and therefore the camera located on its head), or the consummatory behavior of tracking a face (using the location of the face in the visual field provided by the perceptual system).

Experiments and Results

Experimental Setup

Arena. The arena used to carry our tests is shown in Fig. 2. Colourful objects are placed on a table covered with a black cloth to facilitate the extraction of the contours of the objects. The robot can then step laterally to change the view of the scene, and move the robot incrementally from one index position to the next. At the end of the table, the direction of the movement is changed, and it then starts moving in the other direction.

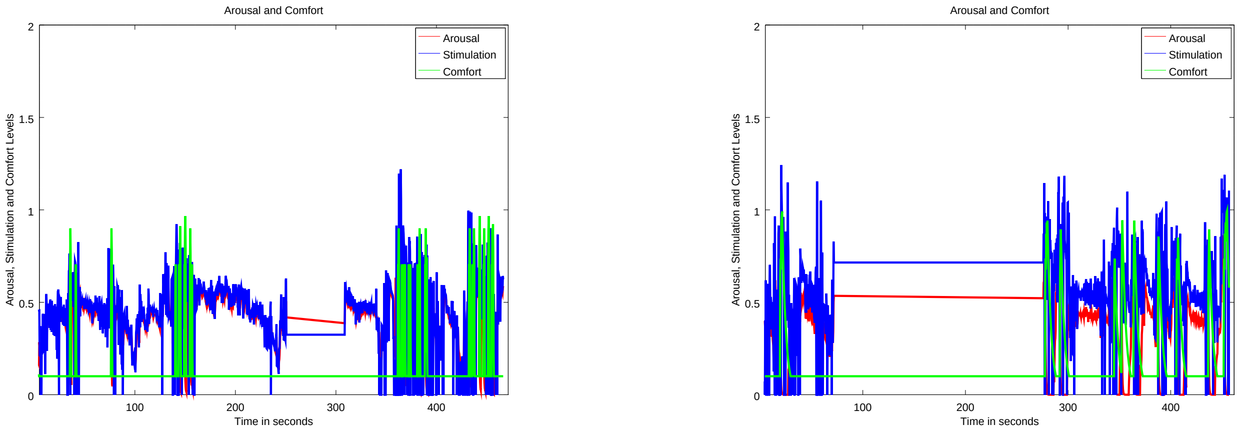
(a) Top view of the table and the robot during the experiment



(b) Schematic of the top view of the table and the robot during the experiment with the possible positions and their labels

Figure 2: Experimental setup used with the Nao robot.

Caregiver Responses. In order to examine the architecture and the dynamics it produces in a systematic way, we designed an automated system to produce the responses of the caregiver. A "caregiving" response is produced every time the behavior "Find-Human" is activated and *arousal* is above the higher threshold, precisely one second after the behavior is activated, which is a good approximation (empirically established) to the time a human present by the setup takes to respond to the robot. The mechanism to produce



(a) (b)

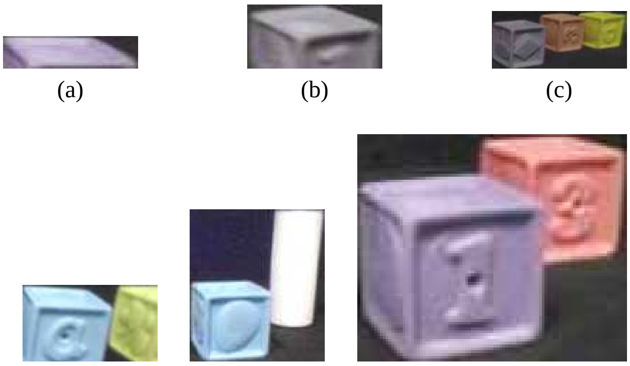
Figure 3: Graphs of the levels of Arousal, Comfort, and Stimulation during 2 typical runs (Arousal in red, Stimulation in blue, and Comfort in green). The robot is exploring the objects on the table, moving from position 1 to 7, and then back. After the robot has achieved this exploration twice, the experimenter swaps the objects for different ones (note that on both graphs, this corresponds to the time period where the values represented are constant). We can observe that during both these runs, once the objects were swapped, high arousal levels and more frequent comfort requests are recorded. This demonstrates how the system reacted to the modification of the environment.

this "caregiving" response consists of modifying the variables that monitor the presence of a human face ($F_h(t)$) and contact on the touch sensor on the head ($C_h(t)$), and hence to produce *Comf*. We summarise this process in Eq. 4.

$$\begin{cases} Req(t) = Req(t-1) + 0.1 & \text{if } Ar(t) > HightThresh \\ Req(t) = \alpha_c \cdot Req(t-1) & \text{otherwise with } \alpha_c = 0.1 \\ \text{if } Req(t) > 0.5 & F_h(t) = C_h(t) = 1 \end{cases} \tag{4}$$

Tests and Results

The experimental runs unfolded as follows. First, the robot is placed standing in front of the table on the position labelled 1 in Fig. 2b. After the system is started the robot will attend current stimuli until the arousal felt drops below the low threshold. The robot will then move to the next position by stepping to the side. After the robot has walked in front of all the object twice, the experimenter pauses the system, and swaps the objects for new ones. The new objects vary from the initial ones either in shape or colour, for instance, blue cubes are replaced by purple cubes, and the small white cans are replaced by bigger ones. The robot's system is then resumed, and the robot continues its exploration and learning episode. During each run, we recorded all internal variables such as Arousal, Comfort, Stimulation, responses from the two neural networks (winner of the Kohonen Map, and recall error from the Hopfield associative memory). We also recorded all images used by the robot to extract the contours of the objects, and each contour was also recorded as an individual image to allow us to relate high Arousal episode to what the robot was perceiving and extracting at the time. Every run lasted between six and ten minutes. The parameters used in the experiment were the following: $\alpha_{ar} = 0.6$, the decay rate of Arousal, $\tau_{ar} = 5$, the time window for Arousal, $\tau_h = 3$,the time window for comfort, $\beta_h = 0.8$, the trace rate of comfort, $HighThresh = 0.6$, the higher threshold for Arousal, and $LowThresh = 0.4$, the lower threshold for Arousal . As we can observe in Fig. 3, when no comfort is provided, the Arousal level follows the trend of the perceived Stimulation, being computed as an average thereof. The first exploration of the table leads to high arousal episodes since the robot just discovers new objects after the other. Then, as can be seen in Fig. 3a after approximately 150 seconds, the arousal remains below the High threshold, when the robot has experienced the available features often enough. The same can be seen in Fig. 3b, after 60 seconds approximately. It has to be noted that the two presented runs are different in their timing, one robot took 200 seconds to go twice over the whole setup whilst one only took about 80 seconds. This can be due to a more favourable initialisation of the Kohonen Map synaptic weights and associative memory connectivity. Additionally, during the run presented in Fig. 3b, the robot faced less ambiguities and outliers (as can be seen in Fig. 4) than during the other run. After the objects were swapped, both runs show how differently the robot reacts (in terms of arousal felt and comfort requested) than in timesteps preceding the swap. The system reacts to these changes as expected when facing new objects and perceptual features, slowing down its exploration and learning further.



(a) (b) (c) (d) (e) (f)

Figure 4: Samples of various outliers identified by the system. The following contours have been extracted following a high level of arousal during the experimental runs. We can see that these are examples of “failures” of the perceptual system in correctly extracting the contour of an object. Some of these examples include multiple objects extracted as on contour. These anomalies happen either when the objects are placed too close together or when the lighting conditions are less ideal. The algorithm might also extract the upper part of a cube if the light intensity is different between the upper and the frontal part of the object.

We show in Fig. 4 typical ambiguous perceptions that gave rise to high Arousal levels during the previous two runs. We can see that these cases mostly concern extracted contours that did not include a single object or highlighted some part of an object only. For instance, Fig. 4a and 4b show contours extracted that concern only the upper part of one of the rubber cubes on the table. These cases can happen due to changing lighting condition (when light is coming from above). Another common occurrence is several objects being extracted as one contour. This can be due to their too close positioning and having similar colours when represented in gray scale, which the algorithm for contour extraction uses. Moreover, this case would be occurring even more frequently if the robot were to try and manipulate the objects. When faced with these outliers, the robot triggers a regulatory behaviour to request help from a human. In a human-robot interaction, the human could choose to manipulate the objects to disambiguate the situation, for instance moving the object away from each other when they are too close together, or moving one object slightly closer of further so that the light is more evenly distributed on it. In this case, the human need not know which ambiguity stemmed the request, since he/she would not be able to know if the robot is perceiving only the upper part of the object, or if objects are too close. A natural –or common– behaviour observed in human is to move and shake objects in front of infants which in the case we present would be sufficient to solve the problem. Alternatively, the human could choose to make use of the comfort system, providing comfort via tactile interaction, and therefore lower the arousal and pushing the robot to explore further, discarding the current situation.

Conclusions and Perspectives

We have presented an architecture inspired from models of attachment that allows an autonomous robot to learn and classify perceptions of available objects and measure their relative novelty based on past experience. Based on these measures, the robot may trigger requests for help from a human in order to disambiguate or determine whether a situation is new and worth learning, or if some physical manipulation is needed from the human. The experimental results were gathered in a simple setting, where the robot was learning the features of colourful objects placed on a table in front of it. Furthering on results from previous studies, in this paper we have shown how and why a robot familiarizing itself with novel objects available in the environment would experience specific high arousal episodes, and how they related to the novelty of the environment and to specific ambiguities which arise in real-world interactions. We showed how the robot reacted to novel objects when the experimenter swapped the objects for new ones. In this instance, the robot reacted more strongly to these objects than previously, exhibiting more frequent regulatory behaviours. This type of regulation can be useful to notify the human that the environment or the current interaction has changed substantially, and giving the human the opportunity to pay closer attention and help the robot if needed, or intervene in order to solve a potential conflict that arose from the robot interacting with the environment. Alternatively, the human may also choose to redirect the robot’s attention by providing comfort which promotes further exploration. The case highlighted in this study showed that the robot’s perceptual system sometimes selected parts of objects or even multiple objects as contours to learn. These ambiguities could have arisen from how the robot manipulated the objects, variations in lighting conditions, or some other external influence, such as another human interfering with the setup. We therefore argue that this attachment-based system provides useful signals and ensuing behavioural dynamics for an autonomous robot engaged in exploration and learning. Exhibiting regulatory behaviours following these ambiguities could speed up the development and learning of the robot by making use of the human – her knowledge and help – in a timely fashion.

In the future, we plan to use of proprioception for the robot to explore its own capabilities and skills by touching and manipulating the objects, as a step towards engaging in physical interaction with the objects it learns.

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References

Ainsworth, M. and Bell, S. (1970). Attachment, exploration, and separation: Illustrated by the behavior of one-year-olds in a strange situation. *Child development*, pages 49–67.

Ainsworth, M., Blehar, M. C., Waters, E., and Wall, S. (1978). *Patterns of attachment: A psychological study of the strange situation.* Hillsdale, NJ: Lawrence Erlbaum.

Arkin, R. (1998). *Behavior-Based Robotics*. The MIT Press.

Avila-Garcia, O. and Cañamero, L. (2004). Using hormonal feedback to modulate action selection in a competitive scenario. *From animals to animats*, 8:243–252.

Bard, K., Bakeman, R., Boysen, S. T., and Leavens, D. A. (2014). Emotional engagements predict and enhance social cognition in young chimpanzees. *Developmental science*.

Berlyne, D. (1969). Arousal, reward and learning. *Annals of the New York Academy of Sciences*, 159(3):1059–1070.

Berlyne, D. E. (1965). *Structure and direction in thinking*. New York: John Wiley and Sons, Inc.

Bowlby, J. (1969). *Attachment and loss*, volume 1: Attachment. New York : Basics Books.

Bowlby, J. (1988). *A secure base: Parent-Child Attachment and Healthy Human Development* . Basic books.

Breazeal, C. (2003). Emotion and sociable humanoid robots. *International Journal of Human-Computer Studies*, 59:119–155.

Brooks, R. (1986). A robust layered control system for a mobile robot. *IEEE Journal of Robotics and Automation*, 2(1):14–23.

Cassidy, J. and Shaver, P., R. (2008). *Handbook of attachment: theory, research, and clinical applications*. Guilford Press.

Davey, N. and Adams, R. (2004). High capacity associative memories and connection constraints. *Connection Science*, 16(1):47–65.

Field, T. (1994). The effects of mother's physical and emotional unavailability on emotion regulation. *Monographs of the Society for Research in Child Development*, 59(2-3):208–227.

Hebb, D. (1966). Drives and the cns (conceptual nervous system). *Brian Physiology and Psychology*, pages 67–83.

Hiolle, A. and Cañamero, L. (2008). Why should you care? an arousal-based model of exploratory behavior for autonomous robots. In Bullock, S., Noble, J., Watson, R., and Bedau, M. A., editors, *Artificial Life XI: Proc. of the 11th Int. Conf. on the Simulation and Synthesis of Living Systems*, pages 242–248. MIT Press, Cambridge, MA.

Hiolle, A., Cañamero, L., Davila-Ross, M., and Bard, K. A. (2012). Eliciting caregiving behavior in dyadic human-robot attachment-like interactions. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 2(1):3.

Hiolle, A., Matthew, L., and Cañamero, L. (2014). Arousal regulation and affective adaptation to human responsiveness by a robot that explores and learns a novel environment. *Frontiers in Neurorobotics*. *Submitted*.

Jauffret, A., Cuperlier, N., Tarroux, P., and Gaussier, P. (2013). From self-assessment to frustration, a small step towards autonomy in robotic navigation. *Frontiers in Neurorobotics*, 7(16).

Kaplan, F. and Oudeyer, P.-Y. (2005). The progress-drive hypothesis: an interpretation of early imitation. In Dautenhahn, K. and Nehaniv, C., editors, *Models and Mechanisms of Imitation and Social Learning: Behavioural, Social and Communication Dimensions*. Cambridge University Press.

Kohonen, T. (1997). *Self-Organizating Maps*. Springer-Verlag.

Luciw, M., Graziano, V., Ring, M., and Schmidhuber, J. (2011). Artificial curiosity with planning for autonomous perceptual and cognitive development. In *Development and Learning (ICDL), 2011 IEEE International Conference on*, volume 2, pages 1–8. IEEE.

Mikulincer, M., Shaver, P. R., and Pereg, D. (2003). Attachment theory and affect regulation: The dynamics, development, and cognitive consequences of attachment-related strategies. *Motivation and emotion*, 27(2):77–102.

Nadel, J., Soussignan, R., Canet, P., Libert, G., and Gérardin, P. (2005). Two-month-old infants of depressed mothers show mild, delayed and persistent change in emotional state after non-contingent interaction. *Infant Behavior and Development*, 28:418–425.

Ogino, M., Nishikawa, A., and Asada, M. (2013). A motivation model for interaction between parent and child based on the need for relatedness. *Frontiers in psychology*, 4.

Oudeyer, P., Kaplan, F., and Hafner, V. (2007). Intrinsic motivation systems for autonomous mental development. *IEEE Transactions on Evolutionary Computation*, 11(2):265–286.

Petters, D. (2006). *Designing agents to understand infants*. PhD thesis, School of Computer Science, The University of Birmingham.

Ranasinghe, N. and Shen, W.-M. (2009). Surprise-based developmental learning and experimental results on robots. In *IEEE 8th Int. Conf. on Development and Learning, 2009. ICDL 2009*, pages 1–6. IEEE.

Russel, J. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39:1161–1178.

Şimşek, Ö. and Barto, A. (2004). Using relative novelty to identify useful temporal abstractions in reinforcement learning. In *Proceedings of the twenty-first international conference on Machine learning*, page 95. ACM.

Sroufe, L. and Waters, E. (1977). Attachment as an organizational construct. *Child development*, 48:1184–1199.

Stevens, G. and Zhang, J. (2009). A dynamic systems model of infant attachment. *Autonomous Mental Development, IEEE Transactions on*, 1(3):196–207.

Weng, J. (2002). A theory for mentally developing robots. In *Proceedings of the The 2nd International Conference on Development and Learning*, pages 131–140. IEEE.