Why Should You Care?
An Arousal-Based Model of Exploratory Behavior For Autonomous Robot

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Abstract

The question of how autonomous robots could be part of our everyday life is of a growing interest. We present here an experiment in which an autonomous robot explores its environment and tries to familiarize itself with the features available using a neural-network-based architecture. The lack of stability of its learning structures increases the arousal level of the robot, pushing the robot to look for comfort from its caretaker to reduce the arousal. In this paper, we studied how the behavior of the caretaker influences the course of the robot exploration and learning experience by providing certain amount of comfort during this exploration. We then draw some conclusions on how to use this architecture together with related work, to enhance the adaptability of autonomous robots development.

Introduction

The question of how autonomous robots could be part of our everyday life is of a growing interest. To approach this goal, many questions remain unanswered, from what kind of hardware would be needed, to what kind of architectures would be appropriate in order to promote socially situated robot that would fit in our environment. We are especially interested in the latter issue.

To design such an ideal robot, it is argued that taking an epigenetic approach would be a suited solution (Cañamero et al., 2006). Indeed, this approach would help the robot discover and learn affordances in the environment in which it is situated, including the agents it interacts with, as opposed to an approach where the designed architectures would need prior knowledge about the environment. The concern that arises with this approach is to find what sort of built-in mechanism a robot needs to be able to develop its cognitive and social capacities. To be precise, what are the inner drive(s) and basic principle(s) which will push the robot towards situations in which it will learn what it needs to in order to be fully operational in the given environment. This problem has many of similarities with the development of infants. Psychological evidence suggests that caretaker-infant attachment bonds are vital to the cognitive and emotional development of infants (Hofer, 2006), especially during the first years of life. Indeed, as John Bowlby (1969) discovered during his studies on mother-infant interactions, the primary caretaker, usually the mother, is utilized by the infant as a secure base in his/her early life, especially during stressful and/or unusual episodes. Furthermore, as stressed in (Schore, 2001), if the primary caretaker doesn't act accordingly to the infant's demands in term of interactions, 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.

Our work also took inspiration from work done in the autonomous robotics research area, such as (Avila-Garcia and Cañamero, 2004), for affective (hormonal) modulation of behavior selection in the case of action selection in a competitive scenario; and especially (Blanchard and Cañamero, 2006; Cañamero et al., 2006), modeling the caretaker in the case of a perception used to modulate the robot's affect and thus its behavior. Drawing on these ideas, we have developed a robotic architecture to explore a new environment and learn from it using the robot's caretaker as a secure base, i.e. providing "comfort" to reduce the robot's distress. Numerous scenarios in terms of caretaking style are then possible to try to enhance the robot's experience and especially its learning process.

In the remainder of this paper we introduce an experiment illustrating how a caretaker can help to modulate the arousal of an infant-like robot by interacting with it and providing it with comfort. The architecture used here allows the robot to discover and learn information about its environment, more specifically getting used to meeting certain patterns of stimuli and classifying them in a stable manner. During that exploration, its arousal is stimulated by the novelty and the lack of stability of the patterns it senses. When this arousal level is high, the robot looks for comfort from the caretaker. The arousal thus modulates the behavior of the robot, and the caretaker modulates its arousal.

Robotics Model

Our architecture can be described in three main steps. The robot first learns the features encountered in its exploration of the environment, and gets habituated to them and classifies them. Then the convergence and stability of these structures are evaluated to calculate the arousal level; this arousal level reflects the degree of surprise and mastery of the robot in the current sensorimotor situation. Finally, an appropriate action is selected and executed.

Exploring and Classifying the Environment

To explore and categorize the environment, our architecture uses two different learning systems. First, a Hopfield-like associative memory neural network is used to learn the patterns of stimuli encountered during the experiment. The system is based on models of associative memory (Davey and Adams, 2004). The network is a two-dimensional grid of N binary neurons, with a state or output S_i, locally connected to their four nearest neighbors 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. 1. This model is a modification of the standard Hopfield network. The local field h_i of a unit *i* is given by:

$$h_i = \sum_{i \neq j}^{N} w_{ij} S_j$$

then the next state of the unit i is calculated as:

$$S_i = \begin{cases} 1 & \text{if } h_i > 0 \\ -1 & \text{if } h_i < 0 \\ 0 & \text{if } h_i = \theta_i \end{cases}$$

In our network we use asynchronous random-order updates. Then to learn the presented input pattern vector, we use a modified version of the following procedure from (Davey and Adams, 2004):

Begin with a zero-weight matrix

Repeat either until all local fields are correct or for M time steps

Set the state of the network to one of the input patterns ξ

For each unit i *in turn*

Calculate $h_i \xi_i$

If this is less than a threshold T, then change the weights between unit i and all

other connected units j, according to:

$$\forall j \neq i \quad w'_{ij} = w_{ij} + \frac{\xi_i \xi_j}{N}$$

The point in which our algorithm differs from the original (Davey and Adams, 2004) is the repetition until all local fields are correct. In our experiment the number of steps used to learn the current pattern is fixed (10 steps in the current settings). Therefore, the pattern is learned correctly and completely if the robot stays in its current position, in front of the exact sensory input pattern; if all the local fields are correct before ten time steps, then learning stops as described above.

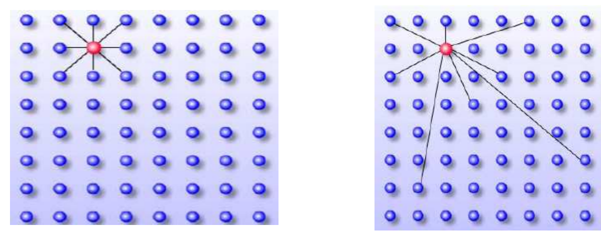

Figure 1: Associative memory network connectivity (locally connected on the left and randomly connected on the right, from (Calcraft et al., 2007))

The second learning algorithm is a classical Kohonen Self-Organizing map (Kohonen, 1997). The goal of this module is to classify the patterns of stimuli encountered during exploration. We used the classical algorithm, but here we don't have a decreasing learning rate or neighborhood size over time; therefore, the map is constantly learning but has nevertheless a satisfying stability for already encountered patterns and keeps its plasticity.

Arousal Model

To compute the arousal of the robot we use two different contributions. First, we evaluate the discrepancy between

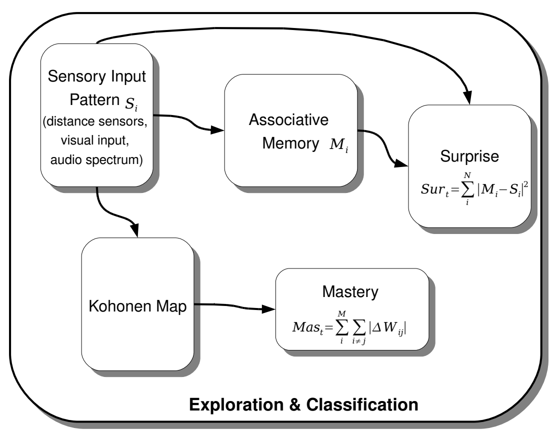

Figure 2: The robot explores and classifies the environment using a Hopfield-like associative memory and a Kohonen Map.

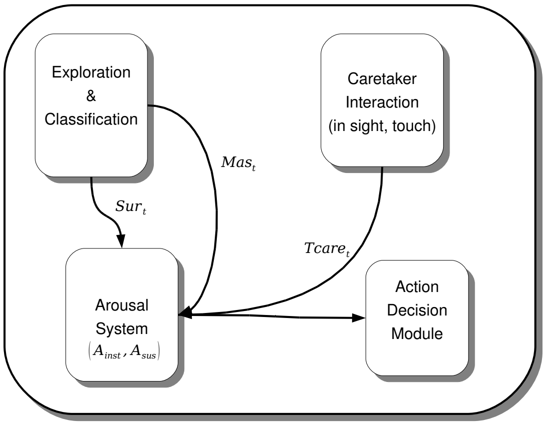

Figure 3: Entire Architecture

Figure 4: Our Experimental Setup

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 of stimuli. Indeed, 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 also use Mas_t, a value we call *Mastery*, which is the sum of the variations of the weights of the Kohonen map. This value shows the ability of the robot to classify the current pattern and how these classes evolve. Formulas of how these values are calculated are displayed in Fig. 2. At each time step, the arousal of the robot is computed as:

$$A_t = \begin{cases} \frac{Sur_t + Mas_t}{2} & \text{if } T_{Care} = 0 \\ A(t-1) - \alpha \cdot T_{Care} & \text{otherwise} \end{cases}$$

where T_{Care} takes the value 0.5 when the caretaker is in sight, 0.8 when he/she touches the back sensors, 1 when both conditions are met, and 0 otherwise. Here α is the decay rate of the instantaneous arousal when the caretaker is interacting (set to 0.2). $A(t)$ is then used to evaluate a smoothed value of the arousal that we call *instantaneous arousal*, as follows:

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

This value allows us to calculate an average of this arousal, called *sustained arousal*,

$$A_{sus}(t) = \begin{cases} \frac{\tau_{sus} \cdot A_{sus}(t-1) + A_{inst}(t)}{\tau_{sus}+1} & \\ \text{if } T_{Care} = 0 \text{ and } A_{inst}(t) > 0.4 & \\ 0 & \text{otherwise} \end{cases}$$

where $\tau_a = 30$ is the time window on which the instantaneous arousal is calculated, as an average of $A_{inst}(t)$, and $\tau_{sus} = 10$, the time window on which the sustained arousal is calculated, as an average of the instantaneous arousal.

Choice of Actions

The actions the robot takes are based on the levels of both, instantaneous and sustained arousal. The robot can turn in only one direction, to discover a new pattern of stimuli when the arousal is low and the robot is in a “bored state”. If the arousal is neither low nor high the robot remains still and tries to learn the current pattern of stimuli. If the arousal level is high, the robot barks to attract the caretaker’s attention, and if the arousal is high and sustained, the robot looks for the caretaker by moving is head from top to bottom and left to right, trying to attract the caretaker in sight. Numerically speaking, the actions described above are taken when the conditions below are met:

$$\begin{cases} \text{if } A_{inst} < 0.25 & \Rightarrow \text{turn to explore} \\ \text{if } A_{inst} > 0.25 \text{ and } A_{inst} < 0.7 & \Rightarrow \text{stay still and learn} \\ \text{if } A_{inst} > 0.7 & \Rightarrow \text{bark to attract attention} \\ \text{if } A_{inst} > 0.7 \text{ and } A_{sus} > 0.6 & \Rightarrow \text{search for the caretaker} \end{cases}$$

Experimental setup and Results

In our experiments we used an Aibo robot on play mat, adding three cylindrical objects of different colors, as shown in Fig. 4. The robot uses three sensory modalities: color (the main color in the center of its visual field projected into the RGB color space), distance (the distance measurements provided by three distance sensors located in front of the robot), and contact (from one contact sensor on the top of its head and three on its back). Each sensor value (including the 3 RGB components of the color of the centre of its visual field) is discretized and projected into a vector containing ten binary elements. To summarize, the robot has to habituate to a vector aggregating all the element of the sensory space, i.e. 100 binary elements (30 for the color, 30 for the distance sensors, 30 for the back sensors, and 10 for the head sensor). The caretaker can provide comfort to the robot either by appearing in its visual field and staying in sight or by touching the sensors on its back. The robot recognizes the caretaker

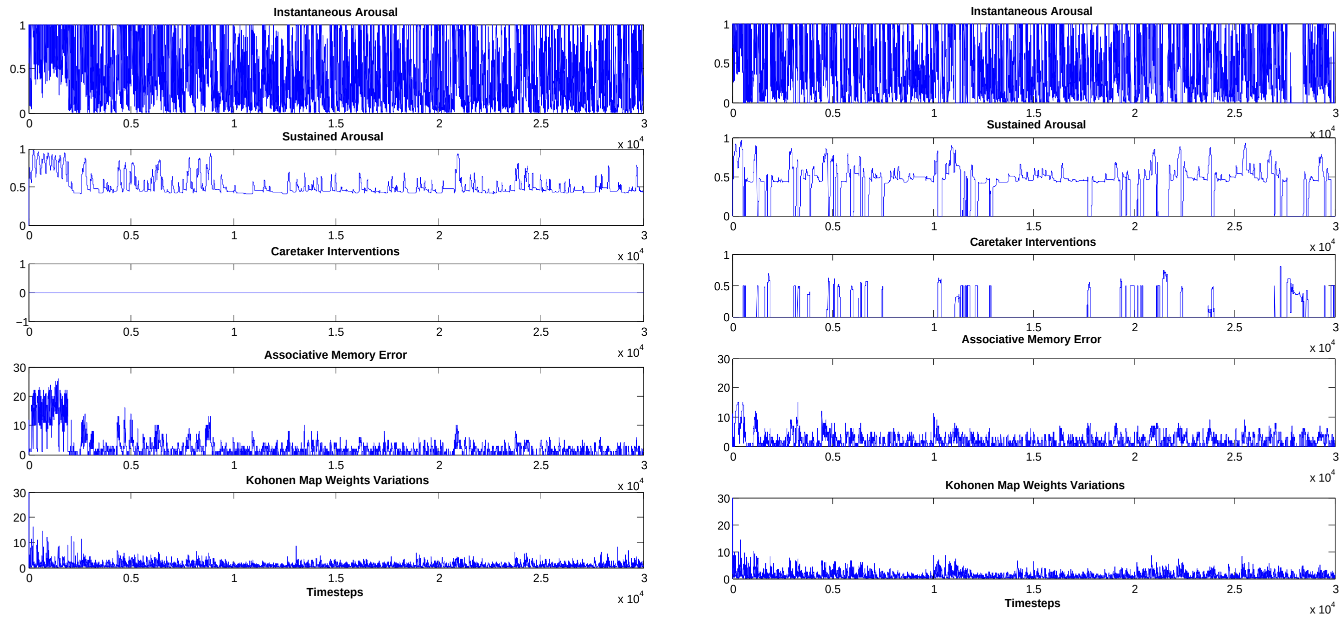

Figure 5: Evolution of (from top to bottom): instantaneous arousal, sustained arousal, caretaker interventions, associative memory error, and variations of the Kohonen map's weights. The graphs on the left-hand side correspond to an experiment with a caretaker only available at the beginning of the experiment whereas the ones on the right-hand side correspond to an active caretaker often providing comfort to the robot.

using the color of its clothes (this is hardcoded in this experiment, the caretaker is wearing a black top as it is the only color absent from the experiment room). At every time step, we recorded the values described in the model section, namely instantaneous arousal, sustained arousal, caretaker interventions, associative memory error, and variations of the Kohonen map's weights.

We have represented the results of two typical experiments in Fig. 5 with two different caretaking styles: an active caretaker, responding almost constantly to the robots demands (results on the right-hand side of the figure), always staying on the right of the robot to appear in sight every time the robot is looking for him/her, and a caretaker who only interacts at the beginning and then leaves the robot on its own and only intervenes few times (once every two minutes). The beginnings of both experiments are the same. When the robot is put on the play mat, it is almost instantly asking for the caretaker, since all the features are new and highly stimulating its arousal. Then the caretaker appears in sight and touches its back sensors to calm it down. We can observe on the graphs that for both caretaking styles, the Mastery value and Surprise value are high and sustained in the case of the non-caring caretaker, since the "non-caring" caretaker then backs away immediately after putting the robot down. Whereas for the other type of caretaking, the experimenter stays close during the whole experiment. In the case of the

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

Table 1: Results for 10 runs for each caretaking style

non-intervening caretaker, the robot is surprised and quickly stimulated by the new environment, and the levels of arousal (sustained and instantaneous) urge it to look for the caretaker quickly. By doing this, the robot actually sees the colors of the upper environment, which are novel stimuli, and tries to learn them, and this results in an even higher increase of its arousal levels. As for the experiment with an active caretaker, since he interacts and provides comfort, the arousal levels are lower and the robot can explore without . To find out how the two different caretaking styles differ, in terms of stability and performance of the exploration and classification system, we ran our experiment 10 times for each of the scenarios. The results for the average values and standard deviations for Mastery (Kohonen Map weights variations), Surprise (associative memory error)and Sustained arousal for the entire experiment are presented in Table 1. These values are used as a measurement of the quality of the learning process, to evaluate how each caretaking style affect the learning experience of the robot. Each run lasted 50,000 timesteps and started from the exact same position. We can see that in terms of the Kohonen Map stability (the Mastery value), the caring caretaker behavior does not outperform the non-caring one by a large difference. However, there is a large difference in terms of Surprise (the associative memory's performance) between the different caretaking styles. The sustained arousal gives coherent results since the robot without the caretaker has to deal on its own to reduce its arousal by mastering the situation and getting habituated to the patterns. We can only conclude with this small sample that both behaviors are not optimal and that finding the correct trade-off between staying close and not caring needs further investigations. As an end result, in all our runs the robot had learned and classified all the encountered patterns meaning therefore its arousal always remained under the lowest threshold and kept turning fast in the arena in the "bored state", looking for new features to learn.

Discussion

The architecture we used in our experiment allows a robot to explore an unknown environment as a function of the dynamics of its interactions with the caretaker and the behavior of this latter. We have seen that even using such a simple architecture, the outcomes of every experiment are different depending on the type of interactions. The developmental approach we have followed reproduces mother-infant interactions. However, what needs to be underlined is the difficulty experienced during tuning the parameters of the architecture, namely the decay rates of the arousal levels. Indeed, to obtain a behavior oscillating between exploring, learning, and demanding the caretaker's presence, we needed to explore several configurations of the parameters. Nevertheless, these results show how using the caretaker as an arousal — and indirectly as a behavioral— modulator is actually possible without having a complex architecture. Furthermore, apart from these two opposite caretaking styles, our architecture allows to actively choose whether a situation, pattern of stimuli, has to be learned or avoided. Indeed, if the caretaker wants the robot to really learn the pattern, he/she can provide a small amount of comfort for the robot to have its instantaneous arousal in the middle level, between the two thresholds. This way the robot remains in its current position, without looking for the caretaker or moving away. In the opposite case, the caretaker can provide comfort to the robot so that it continues to look for another situation, keeping the instantaneous arousal below the lowest threshold, so that the robot does not learn one situation that is judged irrelevant by the caretaker.

As for the related work, a comparable model of arousal modulation and mother-infant interaction, although, not applied to robotics, can be found in (Smith and Stevens, 1996, 2002). In these contributions, the authors used a similar approach to modulate arousal based on neurophysiological data (Hofer and Sullivan, 2001) regarding how endogenous opioids modulate arousal in infants. However, their architecture did not have any cognitive system related to the interactions and their qualities, but was focused on the dynamics of the dyadic interaction. Another contribution can be related to this work. In (Likhachev and Arkin, 2000), the notion of comfort and object of attachment is used by a robot to remember its "comfort zones". What differs between the work presented here is that the object is a person, and also the comfort of the robot is not a function of the distance between the robot and the object of attachment.

Finally, in (Thomaz and Breazeal, 2007), an interesting experiment is described showing how a human can help a robot learn a certain task. In this contribution, a robot can explore and learn on its own but has also the opportunity to use human guidance to adapt to new tasks, changes in the environment, and to generalize one task to similar ones. The robot communicates its internal state with basic facial expressions and gestures. This "Socially Guided Exploration" presents similar features with the work presented here; in both experiments the interactions with a human are used to enhance the learning process, and also in both cases the human teacher/caretaker has to pay attention to the feedback from the robot in order to intervene to help and guide the robot. However, what differs between the two experiments is the modalities the human uses to interact with the robot. In the experiment presented in this paper, the human caretaker orients the robot's behavior by touching its back sensor to reduce its arousal level in order for the robot to move to another sensorimotor context, or appear in sight, whereas in the contribution discussed here, the human teacher can either point with his/her finger to a certain region of the environment or even give verbal instructions to the robot. We argue that the simple non-verbal way of interacting we used in our experiment is sufficient to bias the behavior and improve the learning process of an autonomous robot.

Conclusion and Future Work

In the experiments described above, we have shown how it is possible to modulate the exploratory behavior of an autonomous robot using notions like surprise and mastery to take into account its cognitive development, and especially using a caretaker as a secure base to provide comfort and reduce its arousal. To provide a more autonomous and adaptive solution, we could use material from previous work, modeling the imprinting phenomenon, using a perception or a compound of them as "desired perceptions" (Blanchard and Cañamero, 2005; Hiolle et al., 2007). These perceptions could be the voice of the caretaker and his/her face. We could then to add to our architecture the possibility for the robot to learn how to attract the attention of the caretaker and keep him/her close enough, as has been done in (Hiolle and Cañamero, 2007). However, finding the correct parameters for the architecture to obtain a balanced behavior was not easy and we experienced what was stressed in (Kaplan, 2001):"Fixing the satiation level and the speed of decay in order to obtain the right behavior remains the tricky thing". We think that using even earlier experiences of the robot could help evaluate these parameters. Using this as grounding for an early shaping of the personality of the robot would help us build a more realistic robot, and assess its attachment style using an Ainsworth-like Strange Situation Test (Ainsworth, 1969). To improve the autonomy of our robot's development, adding a curiosity drive (Oudeyer et al., 2007) would guide the robot's exploration towards more interesting situation, acting in order to increase its "learning progress". Another possibility would be to modify our architecture using the arousal, or a variable related to it (first derivative for instance), to directly modulate the cognitive abilities of the robot. More precisely, this value could modulate the learning rate, and/or the neighborhood of the Kohonen map. The robot could then exhibit various behaviors depending on the situation, and the dynamics of the system would certainly be different, perhaps closer to what happens with infants. On another level, what also needs to be done is to come up with accurate and consistent metrics to qualify and even quantify the behavior of the caretaker. We would also like to measure how a caretaker is interacting and possibly assess the effects of the different caretaking styles. We could then even point out what definitely should not be done based on the behavior and personality of the robot. We would also like to investigate how a robot could develop bonds with several caretakers and exhibit preferences for a given caretaker as a function of the given context or situation.

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