A Developmental Approach to the Study of Affective Bonds for Human-Robot Interaction

Antoine Hiolle

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Antoine Hiolle

Abstract

Robotics agents are meant to play an increasingly larger role in our everyday lives. To be successfully integrated in our environment, robots will need to develop and display adaptive, robust, and socially suitable behaviours. To tackle these issues, the robotics research community has invested a considerable amount of efforts in modeling robotic architectures inspired by research on living systems, from ethology to developmental psychology. Following a similar approach, this thesis presents the research results of the modeling and experimental testing of robotic architectures based on affective and attachment bonds between young infants and their primary caregiver. I follow a bottom-up approach to the modelling of such bonds, examining how they can promote the situated development of an autonomous robot. Specifically, the models used and the results from the experiments carried out in laboratory settings and with naive users demonstrate the impact such affective bonds have on the learning outcomes of an autonomous robot and on the perception and behaviour of humans. This research leads to the emphasis on the importance of the interplay between the dynamics of the regulatory behaviours performed by a robot and the responsiveness of the human partner. The coupling of such signals and behaviours in an attachment-like dyad determines the nature of the outcomes for the robot, in terms of learning or the satisfaction of other needs. The experiments carried out also demonstrate of the attachment system can help a robot adapt its own social behaviour to that of the human partners, as infants are thought to do during their development.

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Chapter 1

Introduction

Most robotic architectures and control systems have to go through a thorough phase of "hand design", where they are programmed and fine-tuned to suit a particular task or specific environmental constraints. This process differs depending on several factors such as the capacities of the embodiment (perception, energetic autonomy, navigation, communication interfaces, computing power), the dynamic nature of the environment and the agents populating it.

To tackle these shortcomings, an increasing amount of research has been devoted to the study and development of adaptive capabilities for autonomous robots. The principles motivating this research are rooted in observations and theories from life sciences, regarding the capacities of living systems to adapt to their environment and its dynamic nature. One main strand of research along these lines has been focusing on the study and modelisation of the development of infants. Its main goal is to understand the factors and phases that contribute to the (healthy) development of a baby into a functional adult. Indeed, developmental robotics can be defined as the field of research bridging developmental sciences and robotics (Lungarella, Metta, Pfeifer and Sandini 2003). Its origins also stemmed from the interest of roboticists and engineers to find new ways to design robotic architectures that would foster an adaptivity and efficacy similar to those observed in living systems, in particular infants. This interdisciplinary endeavour is meant to be beneficial for developmental sciences as well. The implementation and in-field testing of theoretical models of phenomena under investigation provides insights into their plausibility and dynamics. This developmental approach to robotics is currently applied to a large body of phenomena ranging from perceptual development (Schlesinger, Amso and Johnson 2011), symbol grounding (Cangelosi and Riga 2006), motor skills acquisition (Demiris and Hayes 1999, Andry, Gaussier and Nadel 2003, Berthouze and Lungarella 2004), "low-level" imitation in social interactions (Blanchard and Cañamero 2006b, Andry, Garnault and Gaussier 2009, Cañamero, Blanchard and Nadel 2006, Blanchard and Cañamero 2007) and to "higher order" cognitive processing such as "conscious-like" systems (Shanahan and Baars 2005).

Another major key component of the adaptive capabilities of humans and other animals has been linked to the use of affective processes such as emotions and motivations. Affect and emotions help living systems to make fast and efficient decisions based on the perceived situation, assessing their needs and objectives. The main principle of this approach states that living systems such as mammals utilise affective appraisal in order to maintain homeostasis on key internal variables relating to their survival. Motivations aid an agent –biological or artificial– to select a behavioural strategy in order to satisfy a need, or reach a goal, for instance foraging for food and then consuming it when hunger is felt (Frijda 1986, Frijda 2010). On the other hand, emotions are involved in prompting adaptive behaviours based on the internal state of the agent and the salient perceptions from the environment (Damasio 1994). These emotional behaviours help the agent communicate its internal state and intentions as well. Recent progress in the modelisation and use of affect based architectures for artificial agents have shown how to devise simple motivation systems based on the embodiment and environment (Cañamero 1997, Cañamero, Avila-Garcia and Hafner 2002, Aylett 2004, Cañamero 2005, Cañamero and Avila-García 2007, Malfaz, Castro-González, Barber and Salichs 2011), and which kind of adaptive properties it provides to the agent. Additionally, motivation and emotion based decision system have been employed to facilitate non-verbal communication between humans and robots (Breazeal and Scassellati 1999, Breazeal 2001, Breazeal and Scassellati 2002).

1.1 Motivations, Scope, and Problem Statement

Alongside the technological advances, a real need is felt in multiple applicative domains to have autonomous robots helping humans. Robots do not tire as humans do and are suited for repetitive tasks. They appear as powerful tools to help humans in a variety of contexts. From assistive carers helping autistic children train and acquire socio-cognitive skills (Robins, Dautenhahn, Te Boekhorst and Billard 2004) or elderly patients (Broekens, Heerink and Rosendal 2009), to help the motor skill rehabilitation of stroke victims (Loureiro, Amirabdollahian, Topping, Driessen and Harwin 2003, Amirabdollahian, Loureiro, Gradwell, Collin, Harwin and Johnson 2007), and industrial production, successful robotic systems have increased the impatience and eagerness of the professionals working in these domains.

One of the main issues with such systems is to endow them with appropriate adaptive capacities. In the absence of suitable adaptation skills, technically skilled operators are required to tune and adapt the parameters and functions of the system depending on the variability of the environment, including the human users. Comparatively, humans require far less time to adapt and learn renewable skills in new or varying environments. Indeed, humans have a natural capacity to explore the environment and acquire or adapt skills to suit their needs and goals. This skill is present since early infancy and is at the core of our socio-cognitive and physical development. Moreover, from the early months of life, infants are constantly stimulated and exposed to new contexts and challenges and this helps them train and diversify their cognitive and social capacities in terms of perceptual accuracy, motor skills and social interactions. Psychological literature suggests that the successful development of infants into mature and capable adults is strongly correlated with the frequency and quality of their interactions with their parents, or primary caregivers (Bowlby 1969, Sroufe and Waters 1977, Waters, Crowell, Elliott, Corcoran and Treboux 2002). The framework provided by attachment theory postulates that the interplay between the exposure to new situations, the availability of the caregiver(s), and the exploratory behaviours of infants shapes the development of their socio-cognitive skills (Schore 2001). The early interactions with a primary caregiver are the first instances of interpersonal relationships and are believed to be at the core of the functional and healthy organisation of behaviour.

Available psychological models of infant-caregiver relationships are based on the following principles. First, a "bond" between the infant and its primary caregiver(s) develops in the early months after birth. This bond is characterized by specific behaviours of the infant oriented toward one or several specific individuals (Bowlby 1969, Keller, Voelker and Yovsi 2005). These individuals are the ones the infant interact the most often with, the mother in most cases in the western culture but it can be a group of carers in some other cultures (Keller et al. 2005). These behaviours, qualified as regulatory behaviours, are triggered by the attachment subsystem when the infant experiences a state of negative affective. For instance, an infant meets a new person for the first time, feels fear towards the new individual, and calls or clings to his caregiver. In turn, the caregiver decreases the child's discomfort, or negative affect, with comfort via contact by holding the child, or with a soothing voice until the child settles (Sroufe 1995). The negative affect results from an overwhelming autonomic activation of the child's nervous system, which has been linked to psychological constructs of excitement or arousal (Hebb 1966, Berlyne 1969, Sroufe 1995). These constructs do not carry any valence, positive or negative benefit to the infant, but their intensity and duration are linked to the affective state of the infant and to the nature of behaviour they promote. Low arousal promotes exploratory behaviours and the search for new experiences, whereas high arousal episodes reflect an over-activation of the nervous system and an inability of the infant to cope with the current situation. The caregiver's comfort externally regulates the negative affect of the child, and within the arousal construct hypothesis, lowers the arousal state of the child to promote exploration episodes (Tronick 2007b). The caregiver can then be thought of as an external means to evaluate the current situation, whom the child uses when its own evaluation capacities and behavioural system fails to return the child to a positive or at least neutral affective state.

Drawing on these ideas, this dissertation endeavours to study, model and assess the benefits of the attachment based dynamics of dyadic regulation for a human-robot dyad. In effect, the research work carried out assesses how and when an autonomous robot could benefit from a human's interventions as an external affective regulator as young infants do in their early years. In other words, the main goal is to use a bottom-up approach to evaluate and quantify the positive effects of low level dyadic regulation of affect in an autonomous robot. The focus of the research presented here is centred on the modeling of robotic architectures and their use in a robot-centric manner using theoretical models from psychology and the latest advances in robotic architectures. The main goal is to explore and select potential useful mechanisms of the mother-infant dyad, model and implement them in a robotic architecture and assess the benefits and limitations they bring to the robot.

The research question addressed in this thesis thus focuses on the use of affective bonds to regulate affect and behaviour of an autonomous robot. It can be stated as follows: "Can a robot use regulatory effects of human interventions similar to those of affective bonds to organise and adapt its behaviour, if so how, and in which situations and contexts?"

Particular aspects of this investigation can be summarised with the following questions:

- What are the requirement to design a minimal attachment system for human-robot interaction? (Chapters 2, 3 and 4)
- What are the benefits and limitations of the dyadic regulation of affect in a human-robot interaction? (Chapters 4, 5, 7, and 8)
- At which level of the control system –emotional, motivational or behavioural– should the intervention and influence of the human caregiver be modeled? (Chapters 4 and 8)
- How do humans engage and reciprocate in these dyadic regulation interactions? (Chapter 6)
- Does this affective mechanism provide additional benefits or emergent properties depending on the environment and the behaviour of the human? (Chapters 5, 7 and 8)
- How can the robot continuously measure the regulation "success" from the human and adapt to the variations in his/her behaviours? (Chapters 7 and 8)

1.2 Outline of the Thesis

This thesis is structured as follows:

- Chapter 2: In this chapter, a review of psychological findings on attachment theory is presented to describe the main principles underlying the dyadic regulation in caregiver-infant interactions and the potential benefits such a system can have for a robot;

- Chapter 3 presents a view of the affective components needed for the attachment system. Relevant architectures for robotic systems and software agents are described focusing on the principles and mechanisms of interest to the modeling and functioning of affective dyadic interactions. The chapter highlights which of their components and properties are relevant for designing a dyadic regulatory system for autonomous robots.

- Chapter 4 presents the design steps to develop a model of attachment for a developing robot. It compares the model devised to an existing one, and ends by proposing a complete architecture containing the minimal features identified;

- Chapter 5 presents the first evaluation of the architecture with a SONY AIBO robot. The robot explored the features of a simple environment with three types of caregiver. The results show how this dyadic regulation system provides different behavioural and learning outcomes depending on the behaviour of the human in terms of responsiveness.

- Chapter 6: Based on the results of the previous work on the dyadic regulatory system, this chapter presents a human-robot interaction study with non-expert users who interacted with the robot endowed with the regulatory architecture presented in Chap 5.The architecture allows for different dynamics of the regulatory effects of the human intervention (intensity and duration of the effects of the "social comfort") two interaction profiles were designed to assess how users would perceive and interact with them. The subjects interacted once with a robot with a "needy" profile, triggering regulatory behaviours often, and once with an "independent" robot, which requires less human support. The results show how non-expert humans adequately perceive the robot in terms of the behaviour profile and on average engage and behave positively with the robots.

- Chapter 7: This chapter present a set of experiments where the two profiles developed in the previous chapter are confronted to two different environmental settings to assess the influence of the profiles on the exploration experience. The architecture was tested on an Aldebaran NAO robot which is discovering and learning object properties on a table in front of it. Using an automated caregiver acting as the human, therefore providing both profiles with a similar "responsive caregiver", the robot is confronted by a simple and low density environment and then an environment with a higher density. The results show how the profiles designed produce different behaviours and explorative patterns for an equal regulation effort from the human, however only clearly in an environment with a high density of objects. In addition, an adaptive mechanism was developed for the robot to autonomously vary its interaction profile along a continuum between the "needy" and "independent" settings. The mechanism reacts to variations of the "responsiveness" of the human. The results demonstrate how and when this mechanism is beneficial and provides a means for the robot to organise its behaviour as a result of the interactions with the human and the environment.

- Chapter 8: This chapter examines how to integrate the model of the dyadic regulatory system in a motivation-based action selection system for an autonomous robot (Lewis and Cañamero 2014). In this more complex architecture, the robot has several needs and goals to satisfy, and the conceptual model of dyadic regulation is rooted in the social drive and motivation of the robot. The adaptation to the "responsiveness" of the human is also integrated and helps to regulate the social drive and the behaviours it motivates based on the interaction history.

- Chapter 9: This chapter provides a summary of the theoretical and experimental findings presented in this thesis, and offers perspectives on the theoretical and practical extension of this research.

- Appendix A: This appendix presents the publications and dissemination events consequential to the research carried out in this thesis.

- Appendix B: This appendix presents the material and documentation from the human-robot interaction experiment presented in chapter 6.

1.3 Contributions to Knowledge

The work presented in this thesis brings the following contributions:

1. A review of the literature on the psychology of mother-infant attachment and the existing artificial affective systems leads to the selection of requirements to design a minimal model of human-robot dyadic regulation. This model aims at operationalizing the principles of attachment for the robot to use the human as an external resource for affect regulation.

2. A dyadic regulation architecture based on the construct of arousal was developed, implemented and tested on two robotic platforms to evaluate the benefits and limitations of the attachment system for a robot learning features of a new environment. Key features of the architecture have been identified to lead to different outcomes and behavioural profiles. This is the first operationalisation of an attachment system for a developing robot. The evaluation of the architecture provides evidence for the differential effect of the behaviour of the caregiver on the development of the robot as

predicted by attachment theory. Although the robot is executing simple tasks, this evidence can be used as a basis to further the research in more complex architectures or learning tasks.

3. A set of experimental setups have been designed offering simple test beds for the extension of the attachment model, and its comparison to other systems which may aim to use the human as a resource for developing robots.

4. A mechanism is proposed to adapt the regulation profile of the robot based on the responsiveness of the human, a measure used in attachment interaction in psychology. This mechanism was illustrated in two experiments where the human responsiveness varied and provoked an *affective adaptation* of the robot. Considering the current state of the art, this is the first time that such a measure is used to adapt the social behaviour of a robot in real-time. This dissertation provides further evidence of the benefits of this mechanism depending on the task of the robot (foraging for food or learning perceptions of a new environment).

5. The attachment system was integrated in a motivation-based action selection architecture, thus providing evidence of its transferability by selecting its core features. This provides a roadmap to integrate the attachment system into other architecture or control systems that wish to use this minimal approach to human-robot social interactions.

6. Finally, a set of tools has been developed for human-robot interaction experiments with naive users. Although they were tested on a relatively small sample, the questionnaire and the behavioural grid can be of use for researchers assessing the perception of their robot control system in terms of attachment interaction.

1.4 Research Projects

This dissertation is the product of 8 years of research while I participated in two interdisciplinary European funded projects. I present below a short description of both these projects as well as the relationship between the work reported here and the objectives of the projects.

1.4.1 The FEELIX GROWING Project

FEELIX GROWING (`http:\\www.feelix-growing.org`) is a European funded project under the sixth framework programme which ran between December 2006 and July 2010. The project's main goal was to investigate socially situated development, develop and integrate robotic systems following the underlying principles of this development in order to augment the adaptive capabilities of robots. The FEELIX GROWING project took an interdisciplinary approach combining theories, methods, and technology from developmental and comparative psychology, neuroimagery, ethology, and autonomous and developmental robotics. To achieve this general goal the following objectives were set out for the project:

- Identification of scenarios presenting key issues and typologies of problems in the investigation of global socially situated development of autonomous (biologically and robotic) agents.

- Investigation of the roles of emotion, interaction, expression, and their interplays in bootstrapping and driving socially situated development, which includes implementation of robotic systems that improve existing work in each of those aspects, and their testing in the key identified scenarios.

- Integration of (a) the above capabilities in at least 2 different robotic systems, and (b) feedback across the disciplines involved.

- Identification of needs and key steps towards achieving standards in: (a) the design of scenarios and problem typologies, (b) evaluation metrics, (c) the design of robotic platforms and related technology that can be realistically integrated in people's everyday life.

The project has yielded interesting results in the domains of human-human imitation, human social interactions, great apes social behaviours, human assisted robot learning, and robot emotional expression. Within this project, I designed and implemented the attachment model which is the core of this dissertation. This work was undertaken with the collaboration of Prof. Kim Bard and Dr. Marina Davila-Ross from Portsmouth University, who provided help in the early stages in order for me to understand properly the psychological theories involved. Their help was also valuable during the preparation and analysis of the human-robot experiment presented in Chapter 6.

1.4.2 The ALIZ-E project

ALIZ-e is a European funded project under the seventh framework programme which ran between March 2010 and August 2014. The project set out to develop robotic control systems for small social robots such as the Aldebaran's Nao to interact with young children. The project's work was also directed at specific end users: children with diabetes between the ages of 7 and 11. At this age, children with diabetes are meant to start to learn to manage their condition themselves. To that end, they often spend a week in a hospital or clinic, where they are taught how to measure their glycaemia and other physiological variables and to choose whether to eat or inject insulin depending on these measures and how they feel. This transition to self-management of this life-long condition is often reported as stressful for the children.

One of the ambitious goals of the project was to try and design scenarios and AI based architectures for long term child-robot interactions.

In addition, the project aimed at tackling the following issues:

- Robust "any-depth" interaction. Robustness against low-quality perception and interpretation
- Out of the lab into the real world: the robot will be evaluated in paediatrics department
- Long-term memory and self-sustained long-term interaction. Key to long-term interaction is having a personalised adaptive memory storing experiences and interaction episodes
- Analysis and synthesis of emotion and affect in human-robot interaction
- Pervasive machine learning and adaptation. Learning experiences will be unstructured. Learning will rely on an array of different approaches
- Cloud computing as computational resource on autonomous systems

Within this project, I participated in the control system for NAO's real-time non-verbal behaviour production (especially real time emotional body poses), work which is not directly related to this thesis. The main input from the research presented in this dissertation to the project is reported in chapters 7 and 8, where the attachment system is used to regulate the social interaction profile of the robot depending on the behaviour of the partner. This work has been carried out by myself and the team at Hertfordshire University, as is acknowledged in each chapter concerned.

Chapter 2

Attachment Theory and Affective Bonds: The Caregiver as an External Regulator of Affect

2.1 The Origins of Attachment theory

The Attachment Theory framework originated from the pioneer work of Sir John Bowlby (Bowlby 1969, Bowlby 1958) following observations of children being separated from their parents due to their deaths or a long term hospitalisation. Bowlby observed the damaging effects of these episodes, and postulated a theory which is now at the base of most research in the early development of infants. Being deeply influenced by the work of Charles Darwin and Sigmund Freud, this seminal work resulted from a careful interdisciplinary approach, bringing together psychoanalysis, ethology, control theory and evolutionary perspectives. Within the theoretical framework he developed throughout the years, Bowlby places the mother, or primary caregiver, at the centre of the development of the infant. Moreover, the role emphasised in the theory goes beyond the previous views concerning the tie between a child and his mother, believed to be conditioned by the need for nourishment. As Harlow demonstrated in (Harlow 1958) and (Harlow and Harlow 1969) when faced with a stressful stimulus (like loud noises or a stranger approaching them), rhesus monkeys would choose to cling to an artificial surrogate "mother" which did not provide any nourishment. They would also spend more time holding the surrogate while resting.

The human playing this role in the life and development of the infant is referred to as the attachment figure. Again according to behavioural observations, the bond between the infant and the attachment figure starts developing in the early months after birth, and becomes more obvious to an observer around the ninth month, when the infant begins to exhibit fear towards strangers.
The behaviour of the infant is then shifted more often towards this attachment figure. The infant displays a marked preference towards this mother-figure and uses her as a comfort provider and stress reliever depending on the situation.

2.2 Development of the Bond between the Infant and the Attachment Figure

According to Bowlby, the development of the attachment behaviours of the infant goes through the following four phases (Bowlby 1969):

Phase 1: Orientation and Signals with limited discrimination of figure.

During this phase, the infant exhibits orientation behaviours towards most human partners. The discrimination capabilities of the infant are believed to be mainly olfactory and auditory. The relief of negative (crying or distressed) episodes can be achieved by providing comfort to the infant, using a calming voice and physical contact. The baby usually then displays positive social signals such as smiling, clinging, and grasping. Such episodes are believed to engage and reinforce the adult caring behaviours, giving positive feedback from simple positive behaviours. This phase lasts approximately twelve weeks.

Phase 2: Orientation and Signals directed to One or More Discriminated Figures.

During this phase, the overall behaviour of the infant is similar to phase 1, although more marked towards the main carer of the infant. For example, longer attention and more orientation behaviours will be produced following the intervention of the attachment-figure. This phase lasts approximately until six months.

Phase 3: Maintenance of Proximity to a Discriminated Figure by Means of Locomotion as well as Signals

During this phase, the infant uses his new repertoire of responses, including crawling and more refined mobile behaviour, to display increased preference towards the attachment figure. The infant would follow the mother-figure following departure, and come to greet her upon reunion. In addition to these changes, the infant shows increased caution towards strangers, and longer exposure and interaction with them will trigger withdrawal and distress. This phase starts around the sixth month and lasts throughout the second and into the third year.

Phase 4: Formation of Goal-Oriented Partnership.

During this phase, the infant now treats the attachment figure as an independent object, that he can use towards achieving certain goals. For instance, when exploring a new situation, the infant would gaze towards the mother-figure and time his advances based on his/her signals. The infant will seek guidance and encouragement from the attachment figure. As a consequence, the development of his skills will be highly dependent on the behaviour of the attachment figure, be they social, motor, or cognitive.

As mentioned in Bowlby's work the timing of these stages depends on the frequency and stability of the interaction with the attachment figure. The description of these phases brings to light several main characteristics of the attachment bond. First, it does not seem that the infant develops a bond towards a more "capable" carer. Indeed, as an evolutionary trait, the attachment bond is vital to the survival of the infant. Logically, it follows that bonding even with a less capable carer is preferable than to none. The infant therefore does not discriminate on the quality of the interactions but on their frequency, with the bond being mature when the infant can successfully recognise his carer in a multimodal way, and exhibit a full repertoire of social and motor responses to use the attachment figure. From a dyadic point of view, Bowlby's description of the development and the changes in the behaviour of the child suggests that the signals that the infant emits also serve as a reinforcer for the behaviour of the adults. Indeed, positive social signals, like smiling and physical contact are likely to promote caring behaviour and bonding. Even without a biological tie to the infant, many carers, nannies and adopting parents, will attest of an intense bond with the infant they are raising or taking care of. These phases are concurrent with other developing capabilities of the infant. Indeed, the discrimination of visual stimuli, faces in particular, will develop fully during the first year of life. As a process, Shaver and colleagues describe the dynamics of the dyad and of the reactive attachment system as depicted in Fig. 2.1.

2.3 The Caregiver as a Secure Base and its Role in the Regulation of the Affect of Infants

Following the work of John Bowlby, Mary Ainsworth attempted to categorise patterns of attachment in infants (Ainsworth, Blehar, Waters and Wall 1978). For that purpose, she developed an experimental setup named the *Strange Situation Procedure*. The aim of the test is to induce a mild stress to the infant, and observe how the mother-infant dyad copes

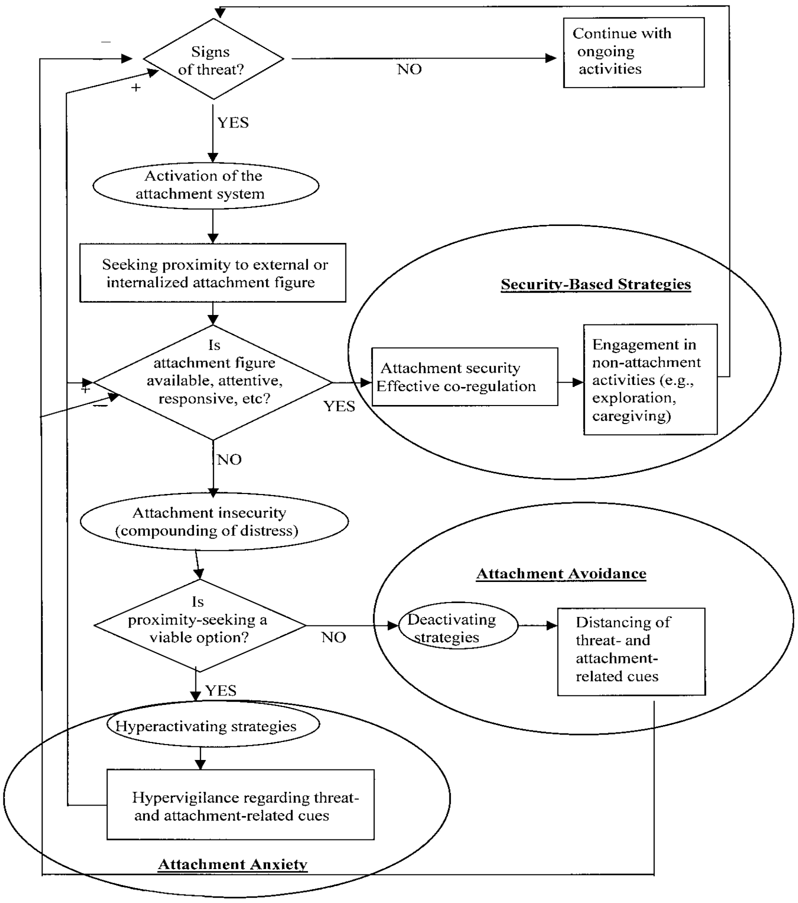


Figure 2.1: An integrative model of the activation and dynamics of the attachment system (from (Shaver and Mikulincer 2002))

with this situation. During this experiment, the mother-infant dyad would go through the following procedure:

1: The mother (or other familiar caregiver) and the baby enter a room. The mother sits quietly on a chair, responding to the infant only if he seeks attention.

2: A stranger enters the room, and talks to the mother. The stranger then approaches the infant with a toy.

3: The mother leaves the room.

4: The stranger leaves the infant playing unless he is inactive and then tries to interest the infant in toys.

5: Mother enters and waits to see how the infant greets her.

6: The stranger leaves the room and the mother waits until the infant settles. She then leaves the room again.

7: The infant is left alone in the room. The stranger comes back and repeats episode 4.

8: The mother returns and the stranger leaves the room.

The observed behaviour at the moment of the reunion was analysed and then classified into one of the following categories: secure attachment, anxious-resistant insecure attachment, anxious-avoidant attachment, and disorganized attachment. The secure attachment category includes infants that would explore and interact with the environment for a significant period of time even when the attachment figure has left. It is hypothesised that they are confident in the return of the mother in times of need. Infants belonging to the insecure categories display negative behaviours or at least no positive ones during the reunion. Some avoid eye contact with the mother-figure, and resist physical contact.

When left alone, they exhibit more wariness towards strangers and explore or interact less with the available objects.
The classification in this framework appears rigid and leaves aside other potentially important variables such as the temperament of the infant and the cultural background of the dyad. This classification has then been challenged by other research (Keller et al. 2005, van IJzendoorn, Bard, Bakermans-Kranenburg and Ivan 2009) claiming that different style of behaviours in terms of use of the attachment figure by the infant can also lead to a healthy development and that the golden standards proposed by this classification cannot be applied to all dyads.

To account for the broader spectrum of responses, researchers have tried to design tools for the analysis and evaluation of parenting and caring style with a less strict categorisation (Harris 2002, Mikulincer, Shaver and Pereg 2003). In (De Wolf and van IJzendoorn 1997), the availability of the mother is emphasised as playing a key role in the development of organized and disorganized attachment. The mothers' sensitivity to the infant signalling and her responsiveness to the requests of the infant have been identified as key factor in the individual differences of organized attachment. The responsiveness is defined as the timing and quality of the responses from the mothers or primary caregivers to the distress signals of the infants (Feldman 2003). A responsive caregiver was estimated to be the soothing or comforting the infant following distress signalling within a 30 second time frame (Bornstein and Tamis-Lemonda 1997). This measure seems more suitable to evaluate human reactions to different behaviours emerging from different organized attachment profiles. On the other hand, as suggested by Tronick in (Tronick 1989), the dyad interacts in order for both parties, the caregiver and the infant, to share moments of **mutual delight** and reciprocity. These episodes are characterised by "reciprocal positive exchanges in which interactive errors are readily repaired" (Tronick 1989, Tronick 2007a).

Further evidence suggests that a caregiver-infant attachment bond is vital to the cognitive and emotional development of infants (Cassidy and Shaver 2008), (Zimmermann 1999), especially during the first years of life. Indeed, as John Bowlby emphasised, that the primary caregiver, usually the mother, is utilized by the infant as a **Secure Base** in his/her early life during stressful and/or unfamiliar episodes (Sroufe 1995). Furthermore, as stressed in (Schore 2001, Lyons-Ruth, Alpern and Repacholi 1993), 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.

This suggests that the dyad is working together towards increasing and maintaining each other's positive emotions such as joy and pleasure, in a mutually regulated process. Therefore, the interaction has to bring to both the infant and the carer some amount of pleasure, be that by empathy (Preston and De Waal 2002) (as a shared positive emotion from the mutual enjoyment of the interaction) or a sense of purpose. From the perspective of the infant, in a non-threatening scenario 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, Soussignan, Canet, Libert and Gérardin 2005), during which mothers are behaving as depressed mothers, a significant decrease in the infant's positive emotional response is observed.

2.4 The Neurophysiology of Mother-Infant Affective Interactions

A strong body of evidence suggests that the neurophysiological basis for infant attachment and distress responses is regulated by the release of endogenous opioids such as oxytocin (Gray, Watt and Blass 2000, Weller and Feldman 2003, Nelson and Panksepp 1998). The stress responses of the infant are correlated with increase in the level of cortisol level (Liu, Diorio, Tannenbaum, Caldji, Francis, Freedman, Sharma, Pearson, Plotsky and Meaney 1997), and in turn the opioid system can reduce these levels. The consensus on the dynamics of the physiological substrates of attachment and mother-infant interactions is that the comfort provided by a caregiver promotes the release of opioids which in turn calm and soothe the infant by inhibiting the effect of the cortisol on physiological arousal. The lack of release of these endogenous opioids would trigger what Bowlby designated as the attachment system, and therefore the behaviours aimed at regulating this imbalance by involving the caregiver would be performed. As emphasized in (Smith and Stevens 1996, Stevens and Zhang 2009), the regulatory processes involved in this can be modeled as differential equations including the effects of the endogenous opioids in intensity and duration, the responsiveness of the caregiver, and the frequency of the interactions. Their work was aiming at simulating the Strange Situation procedure and its effects on arousal and negative affect depending on the sensitivity of the simulated agent to opioids and cortisol. These sensitivity parameters determined the rate at which the opioids level inhibits the arousal and therefore influences the timing and duration of the regulatory behaviours triggered when the arousal is high. This modelisation bears similarity with the one used in the work carried out throughout the thesis. First, a comfort variable (mediated by opioids) is used to decrease the arousal of the robot in a similar dynamic manner as the authors proposed. Second, the sensitivity parameters they used to modulate the influence of the opioids on endogenous arousal is meant to reflect the responsiveness of the caregiver, a measure that has been developed and used to modulate the regulatory behaviour of the robot in chapters 7 and 8.

2.5 Artificial Models of Mother-Infant Attachment

In the few studies trying to model the attachment system and its dynamics, the behaviours 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 behaviour. For instance, Petters Petters (2004) presents simulations of caregiver-infant interactions using several control architectures based on attachment theory (Petters 2006). The main goal of these simulations of interactions between artificial agents was to model the relationships between the goals and behaviours observed in young infants. The resulting architectures were tested in safe or unsafe (secure or insecure) scenarios. Depending on parameters related to the sensitivity of the caregiver of the infant agent, the behaviour of the infant would vary. Specifically, the architectures comprised several main components inspired by the literature on Attachment theory. First, the value of an internal variable called Anxiety increases when the perceptual appraisal of the situation was deemed unfamiliar or unsafe. A internal variable called Warmth 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 behaviour 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, with similar dynamics to the Animat approach to motivational systems (Cañamero 1997, Avila-Garcia, O. and Cañamero, L. 2004, Cañamero and Avila-García 2007). 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 show some emergent categories which are believed to correspond to the ones Ainsworth brought to light (Ainsworth et al. 1978).

2.6 Summary

This chapter provides an overview of the main principles behind attachment theory and the affective nature of the interactions between an infant and its primary caregiver. These principles can be summarized as follows:

1. The infant uses the attachment figure when negative affect or distress is felt and exhibits regulatory behaviours to seek proximity to the caregiver and receive comfort to alleviate this negative affect

2. A responsive and sensitive caregiver responds to these bids in an adequate and timely manner maximizing the infant's positive experience

3. Responsive and sensitive caregivers are believed to lead to a healthier development and more exploratory behaviours

4. The interplay between negative affect of the infant and the intervention of the primary caregiver can be modelled as the interaction between a stress hormone (cortisol) and opioids

5. The dynamics of these physiological substrates can be modelled as interconnected dynamical equations where the responsiveness of the attachment figure and the sensitivity to the comfort determine behavioural patterns

These principles provide a global framework to guide the design of a model of affective bond for an autonomous robot. In order to do so, the model needs to contain a real time model of affect, and means by which a human can exert effect on it in order to regulate the behaviour of the robot and examine the consequences of these interactions. The following chapter will therefore examine existing research in the modelisation of affect in autonomous robots as well as models exhibiting exploratory behaviours.

Chapter 3

Affective Processes and Interactions for Autonomous Robots

3.1 Affective Processes: Motivations and Emotions in Humans and Other Animals

As was highlighted in the previous chapter regarding the principles of attachment interactions, a crucial aspect of the mother-infant dyad is the regulation of negative affective and the promotion of positive emotional experiences. To clarify what this entails, a short introduction to affective processes and their components is presented.

3.1.1 Definitions and functions of affect and emotions

Following Darwin's studies (Darwin 1872/1965), and the common evolutionary history of humans and other animals, it is accepted that the organisation of behaviour is deeply influenced by affective processes such as emotions and motivations. The function served by affective processes is believed to facilitate adaptation to changing environmental conditions and therefore promote the survival of the individual. In other words, as supported by Scherer, emotions “facilitate our adaptation to events that are important to our wellbeing” (Scherer 2005, p. 706), and serve “the preparation of action tendencies (fight, flight), recovery and reorientation (grief, work), motivational enhancement (joy, pride), or the creation of social obligations (reparation)”. For instance, a fearful or angry emotional response prepares the body for a fight or flight response when confronted by a potentially dangerous stimuli (spotting a snake or seeing a cliff). Joy, or happiness, expand the focus of attention and communicates the willingness to engage in more pleasurable experience (Fredrickson 1998). An emotion, as a process, is often quantified by its duration and intensity (or emotional arousal), and pleasurable nature (or valence) (Russel 1980, Russell and Barrett 1999, Russell 2003). Moreover, emotions are a short lived process which can be quantified by their onset, peak, and offset phase, lasting a few seconds (Ekman 1989, Ekman 1992) to minutes or even hours (Verduyn, Van Mechelen and Tuerlinckx 2011). One important aspect of emotions is their communicative function. In addition to preparing the body for situations or event specific action tendencies, emotions convey the internal state of one individual to others through facial expressions, body postures, vocalisations, and tone prosody (Ekman 1992). These communicative behaviours have evolved to serve this specific purpose and help one individual evaluate events and situations by processing the emotional signalling of other individuals (De Gelder and Vroomen 2000, Parkinson 1996). On the other hand, following Hull’s theory (Hull 1943), motivations arise as a result of the lack of satisfaction of one individual’s biological needs such as hunger and thirst. The deviation from the ideal homeostatic level of the needs gives rise to behavioural drives urging the agent to act to return to an ideal level of satisfaction. He proposed a theory of behaviour based on the reduction of such drives. He stated that the body motivates organised responses towards the reduction of the drive until the needs reach a satisfactory level. A simple illustration of these motivated behaviours is for instance the sequence of foraging for food and then eating when one is hungry. In addition, to the reduction of drives, Hull proposed that individuals are also motivated when they perceive a stimulus that can help satisfy their needs. For instance, individuals are often motivated to eat when they see available food. He labelled these stimuli as incentive cues which predict the reduction of a drive.

3.1.2 Emotional Arousal

Throughout the years, the notion of *arousal* has been used in psychological theories to measure and quantify states of heightened activity, alertness, and attention, and was originally believed to represent 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). He stated that an optimal arousal level is sought in order to balance the activity of the central neural system. Low arousal pushes the organism to seek new stimuli and take risks via exploration, while high arousal levels reflect the fact that the central nervous system is actively engaged, for instance, in learning or trying to satisfy a physiological need. Alongside Hebb's work on the relationship between arousal, drives and goal-oriented behaviours, Berlyne postulated in his theory of curiosity (Berlyne 1954, Berlyne 1960) that low levels of arousal trigger exploratory behaviours whereas internal conflicts between expectations and the stimuli perceived give rise to a higher level of arousal. He added that the exploratory behaviours serve to promote a medium-to-optimal level of arousal. Berlyne hypothesized that arousal was a using "collative variables" and related them to exploratory behaviours as follows:

> "The probability and direction of specific exploratory responses can apparently be influenced by many properties of external stimulation, as well as by

> many intraorganism variables. They can, no doubt, be influenced by stimulus intensity, color, pitch, and association with biological gratification and punishment, ... [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). Arousal has also been investigated in terms of optimal functioning during knowledge acquisition and retention. A debate has grown centred on the "Inverted U-Shape hypothesis" (Anderson 1990, Baldi and Bucherelli 2005), which posits that physiological and cognitive functions are influenced by the arousal level in a non-linear manner, and that an optimal medium level exists at which optimality can be attained for memory and physical tasks. These theories on the role and the components of arousal support the idea that arousal reflects the intensity of the engagement of the individual in a task, be it exploring new situations and stimuli, or satisfying a physiological need. Moreover, these early low-level views on arousal also focus on the fact that arousal determines behaviour based on several internal factors such as the evaluation of novelty or incongruity of perceptions. Both these notions are operationalized in the model of attachment used throughout this dissertation (in chapters 4, 5, 6 and 7).

3.1.3 Affective Components for the Attachment System

As was emphasized in the previous chapter, the affective interactions between an infant and the attachment figure balance the behaviour of the infant between safe exploration and proximity seeking. In terms of the affective processes described previously, it can be said that the distress of the infant triggers a motivation for proximity seeking. This emotional distress can be likened to a high and sustained arousal resulting from the exposure to uncanny, novel or fearful stimuli. When this is not the case, the arousal of the infant is low and therefore motivates exploratory behaviours for the arousal to return to a medium or high level. In essence, the attachment figure or caregiver can be thought of as an external regulator of the arousal of the infant. This view is supported by the work of Feldman and colleagues Feldman (2003) who showed that the co-regulation of positive arousal between mother-infant and father-infant displayed cycles between low and medium levels, or high and medium levels, depending on the style and gender of the caregiver. This reinforces the view that infants are subject to these cyclic arousal fluctuations. Moreover, these cycles seem to occur fast and reflect a real-time state of the interaction.

3.2 Affective Interactions and Exploration for Autonomous Robots

Several research works in robotics and human-robot interactions have designed and tested components which are of interest to the modelling of the affective interactions system inspired by mother-infant attachment interactions. No work has been solely focused on an attachment system itself though and especially not on the interaction between arousal and comfort provided by a human caregiver during exploration and learning of new situations. However, to help the modelling of such a system, this section presents the main ideas and systems that have been developed which have been later included or adapted in the modelling and implementation of such a system.

3.2.1 Artificial Affective Systems for Human-Robot Interactions

Cynthia Breazeal used the concept of arousal in the design of the control system of her social robot Kismet (Breazeal and Scassellati 1999, Breazeal 2003). This robot was designed to integrate various properties of social interactions, such as emotional communication using facial expression and tone prosody. Based on earlier work from Velásquez and Maes (1997), the architecture uses a selection of drives to be regulated during the interaction. The drives are represented by continuous values which can reflect three states: overwhelmed when high, homeostatic within a satisfactory range, and underwhelmed. These drives were "Stimulation" which requires the robot to interact with objects, "Social", which pushes the robot to seek face-to-face interactions, and "Fatigue", which pushes the robot to rest when overstimulated. The arousal of the robot is related to the state of these drives, high when a drive is overwhelmed, medium when the drive is in homeostatic regime and low when a drive is underwhelmed. Although the arousal itself does not drive the robot's behaviour as Hebb's model would suggest, it reflects the ongoing internal activity of the system, and is then used to influence which emotional facial expression would be displayed. In essence, the arousal controls the nature of which communicative display will be exhibited (in an attempt) to regulate the internal emotional state of the robot. For instance, when the robot is overstimulated, high arousal would help exhibit an angry facial expression, and therefore communicate to the human interactant to stop stimulating the robot, regulating and alleviating the arousal of the robot as a result. This facet of the work deeply relates to the modelling of the behaviour of infant proposed in the literature on mother-infant interactions. Indeed, based on the real time values of the internal needs and the activity of the robot, the social requests and communicative behaviour towards the human are adapted in order to regulate the arousal of the robot. A similar approach is used throughout this dissertation. A high level of arousal of the robot is used to trigger regulatory behaviours to encourage the human to intervene and regulate the interaction, and in turn decrease the arousal of the robot. One main difference between the two approaches is that the work presented in this thesis explicitly uses the comfort provided by the human to alleviate the arousal, which then regulates the behaviour. Such a difference derives from the minimal approach to the modelling of the mother-infant interaction dynamics carried out in this dissertation, where the comfort from a human source directly modulates the arousal of the robot.

Another relevant instance of human-robot interaction is the work by Ogino, Nishikawa and Asada (2013) who 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 pleasure and arousal in face-to-face interactions. The relatedness measures the contingency between which emotion the robot displaying and which one the human is conveying. They tested their architecture using a virtual robot on a computer which interacted with a human playing the role of the parent. 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 (Tronick, Als, Adamson, Wise and Brazelton 1979, Adamson and Frick 2003, 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 behaviour of the caregiver and the exploratory behaviour and learning of the robot were not studied. However, they do emphasize the importance of the role of the synchrony between the caregiver and the infant during the affective exchanges and how they influence the affective state of the agent.

3.3 Exploration and Comfort Systems for Autonomous Robots

3.3.1 Robotic Comfort Zones

One of the first occurrences the use of some tenets of the attachment paradigm to robots can be found in (Likhachev and Arkin 2000). Within this contribution, the authors attempted to use the notion of comfort and attachment to particular objects in order to bias the exploratory behaviour of an autonomous robot. The authors used simulations of an agent exploring an environment based on the level of comfort a specific place produced within the architecture. The comfort function they used had the following properties. The landmark can induce increases of comfort, no contribution, or a decrease thereof. They propose a comfort function that decreases linearly with the distance from the object of comfort. The robot can then navigate to the closest safe place it has memorised, or avoid the non-comfort ones while navigating to a specific location.

3.3.2 Bottom-up Approach to the Imprinting Phenomenon

Blanchard and Cañamero developed and improved a bottom-up architecture inspired by the imprinting phenomenon (Blanchard and Cañamero 2006a, Blanchard 2007), a mother-following behaviour emerging after the hatching of nidifugous birds. This phenomenon was studied at length since its discovery by Konrad Lorentz (Lorenz 1935), showing that these birds (mainly with geese), could be “imprinted” to any person or object depending on the timing, frequency, and duration of the presentations of the person or object. Amongst attachment related phenomena to model and study, imprinting has the advantage of simplicity in terms of observation and production of the behaviours involved. Indeed, imprinting is modeled as a preferential orientation and ensuing following behaviour of a particular person or object. Its evolutionary benefits are numerous, since young chicks will have a higher chance of survival if they cling to their mother, and will in turn be exposed to useful contexts, such as where to find food, shelter, or even a future sexual partner. From a robotic architecture design standpoint, as was done by Blanchard and his colleagues, one can use associative learning to pair a perception (the imprinted object), and a behaviour or motor primitive such as moving forward. This work modeled the sensor representation of the imprinted object as a “desired perception”, which a homeostatic dynamical system would use to regulate the behaviour (i.e. the robot would produce the action leading to the decrease of the discrepancy between the current perceptual state and the desired perception). Extensions of the work allowed the robot to learn several desired perceptions by associating them to a level of comfort which was provided by a human caregiver (Blanchard and Cañamero 2007). The robot would then move between these desired sensation depending on an internal level of affect based on the history of the comfort perceived. When the comfort felt in the recent history was high, the robot would be motivated to explore further its environment, however, when no comfort is found, the robot would fall back to the closest desired sensation it can reach. This work relates to the work carried out in the modelling of mother-infant attachment in the sense that the robot would seek novelty when a high level of comfort was felt, but retreat to previously known comfortable situation when too much novelty was met and no comfort was provided. This principle is followed in the later modelling of the arousal/comfort interactions and the ensuing behaviours of the robot in such situations.

3.3.3 Exploration, Novelty, and Curiosity

Some relevant implementations of robot exploration and novelty detection are relevant to the design of the attachment system and particularly for the exploration behaviour of the robot and the estimation of the arousal in a novel environment. For instance, Vieira Neto and Nehmzow (2007) developed and tested a robotic system where the robot would first explore the environment to estimate a degree of normality using a Grow When Required network (Marsland, Shapiro and Nehmzow 2002). This specific type of self-organising map (Kohonen 1997) permits to add nodes to a network which represents an input pattern previously met. When a new input pattern is presented to the network, a new node may be added to the network depending on the estimated novelty of the input pattern. The novelty of the input pattern is determined using the distance between this pattern and the closest learned pattern in the network, and a habituation term from the node representing the pattern in the network. They applied this system for a robot to first acquire a degree of normality from the visual field, and then detect anomalies and later changes in the environment. In this thesis, a similar approach is used to estimate the novelty of a pattern of stimuli the robot perceives, however using the synaptic variations of a traditional Self-Organising Map which translates into the effort a learning system makes to adapt to a new pattern of stimuli. This measures is used to help compute the level of arousal of the robot, in line with Hebb's and Berlyne's view on the arousal construct.

Another interesting instance of a novelty detector was proposed by Crook and Hayes (2001). They used the energy measure of a Hopfield auto-associative network (Hopfield 1982) to estimate the novelty of a visual pattern of stimuli for a robot to inspect a "image gallery". This fully connected network functions as a content addressable memory, and can converge to a known pattern from a partially known one. The novelty of an input pattern can be estimated either using the recall error of the Hopfield network (the discrepancy between the input pattern and the recalled pattern) or the energy of the network. The novelty detection system used to stimulate the arousal level in this thesis uses a similar process but focuses on the recall error instead of the energy. This was chosen since the Hopfield model used was altered to use an asymmetrical and sparse connectivity matrix for which the energy measure does not apply.

A growing body of work in the robotics research community has focused on applying Berlyne's concept of curiosity as an intrinsic motivation for exploration and the development of skills in robots. In (Oudeyer and Kaplan 2004), the authors describe an architecture allowing the robot to exhibit a "curious" behaviour using an intrinsic motivational system. The system was designed to enable the robot to choose to explore and experience increasingly complex sensorimotor pairing. The approach was based on the principle that infants and other biological systems employ adaptive heuristics in order to choose what and where to explore and try to fill knowledge gaps. They tested their system in an infant-like setup, the playground experiment, where a Sony AIBO robot (a robot dog later described in chapter 5) explores a children play mat and discovers contingencies in its sensorimotor repertoire. The robot was guided by the principle of minimization of the learning progress. Essentially, the robot performs actions which are believed to reduce the error of its own developed sensorimotor learning system. Following the encouraging results from the playground experiment 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 behaviour 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 2004). 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, Graziano, Ring and Schmidhuber 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 (Hasson and Gaussier 2010, Jauffret, Cuperlier, Tarroux and Gaussier 2013). In these contributions, 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 the 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. However, their model takes for granted the immediate presence and responsiveness of a human, and do not assess the implication of the variations in his/her behaviour.

3.4 Summary and Proposed Methodology for the Design and Operationalization of a Minimal Attachment System

To summarize, this chapter presented a set of important principles and research work relevant to the design of a dyadic regulation system based on attachment interactions for an "infant" robot. First, a minimal model requires the following components:

1. Human and infant exploration can be modeled and driven by an arousal level which can be evaluated through measures of novelty and satisfaction of needs

2. Such measures can be obtained online using existing learning systems and their respective performance measures

3. Arousal can be modeled as a drive which low level promotes exploration and high

level triggers behaviour aiming at regulating it (Hebb 1966, Velásquez and Maes 1997, Breazeal 2003)

4. Comfort can be modeled after distal (Likhachev and Arkin 2000) or proximal interactions (Blanchard and Cañamero 2007) with the human caregiver which influences the affect of the robot and therefore its behaviour

From a methodological point of view, the goal of this thesis will be attained by first designing a minimal model of the robot-caregiver interactions based on the theories and relevant work presented in the previous and current chapters. Then, a scenario to test the dynamics of the system and the behaviour of the robot should be devised. Then, we need to assess the influence of the factors highlighted by the theories on mother-infant attachment. These factors are the responsiveness of the behaviour of the caregiver and the properties of the environment regarding arousal inducing stimuli. As a first step, the following chapter will present the design of the attachment system for dyadic regulation of arousal and its components for an autonomous robot.

Chapter 4

A Model of Attachment-based Regulation of Affect for Autonomous Robots

4.1 Outline

This chapter presents the design steps for the development and implementation of a dyadic regulation system based on the attachment system presented in previous chapters. The model is based on the interactions between an arousal level and the comfort provided by a human caregiver.

The design of the level of arousal followed the principles derived from Hebb's Conceptual Nervous System (Hebb 1966) and Berlyne's view on arousal and exploratory behaviour (Berlyne 1969). The level of arousal increases proportionally to novelty measures and decreases with comfort. The model for the estimation of the arousal is then compared to a later model used in simulation by Stevens and Zhang (2009) to expose its main similarities and differences in their dynamics. Then, the use of two learning systems is put forward with tailored performance measures in order to provide the arousal system with a real-time value of the novelty and learning performance of a robot exploring a new environment. The chapter ends by proposing a robotic architecture for attachment-based human-robot interactions composed of the arousal system and the learning systems proposed. This architecture was used in three human-robot experiments assessing the influence of the attachment model and the behaviour of the robot depending on the behaviour of a human caregiver and the environment in which the robot is exploring and trying to learn perceptual features.

4.1.1 Contributors and Funding Bodies

The work reported in this chapter was carried out by myself under the supervision of Lola Cañamero. It is part of the work reported in the FEELIX GROWING project for the workpackage "FEEL" aiming at modelling minimal social interactions and their influence on development and behaviour.

4.2 Adaptation of the Paradigms and Mechanisms of the Attachment System

In order to understand and operationalise a minimal attachment system for autonomous robots, several components of the psychological findings have to be selected and adapted from the existing affective interaction systems for artificial agents. As was presented in the previous chapters 2 and 3, the role of the caregiver in a dyad can be summarized as a regulating the negative affect of the child through comfort when regulatory behaviours are performed. The negative affect –in its simpler form– corresponds to a high level of arousal or excitement (Sroufe 1995). Hebb (Hebb 1966) and Berlyne's (Berlyne 1960, Berlyne 1969) views on arousal as a drive for behaviour support the following hypotheses. First, the arousal reflects the level of internal evaluation of "collative variables" (such as novelty, surprise, complexity, or incongruity) based on the perceptions and expectations of the organism (an infant in our case). Second, the arousal level itself can be seen as a drive for two type of behaviours. A low arousal level promotes the execution of exploratory behaviours which, in turn, help to increase the arousal and therefore regulate its level upward. These exploration episodes are meant to increase the level of stimulation of the organism, and to increase the arousal. When the level of arousal is high and sustained due to fearful stimuli, or a fast variability of the environment which does not allow the organism to process properly the perceptions, the organism will seek to lower its arousal, trying to avoid the noxious stimuli. In these high arousal situations, infants seek the comfort of their caregiver in an effort to decrease their level of arousal. Therefore, an arousal drive can be modeled based on the amount of stimulation the organism perceives, which includes an estimation of novelty and/or a commitment of resources (cognitive or physical). This drive would then control which types of behaviours are executed with the goal of regulating the arousal.

4.3 The Dyadic Regulation Model for Attachment: Interactions between Arousal and Comfort

This section presents the modelling steps for the design of an arousal drive based on the principles of attachment theory and the considerations from early psychological models of exploratory behaviours from Hebb (1966) and Berlyne (1960). The value of the arousal is based on an evaluation of the stimulation of the agent (based on the perceived novelty or complexity of the current perceptions of the environment). Thus, the desired properties of the model are the following:

- The level of arousal should reflect the properties of the environment perceived and how the robot relates to them: this will be achieved through a variable called "Stimulation";
- The arousal of the robot "drives" its behaviour: a low level promotes further exploration and high level triggers behaviours aimed at reducing the arousal, such as the regulatory behaviours described in the literature on attachment;
- Comfort provided by an external source, such as a caregiver, produces a decrease in arousal, and thus promotes exploratory behaviours;

4.3.1 Arousal as an Average of the External Stimulation

In the models used throughout this dissertation, the arousal is defined as a continuous floating point variable belonging to the range [0.0 ; 1.0]. The arousal is modeled as a smooth average of a quantity of Stimulation $Stim(t)$. In addition, the arousal is divided in two variables: an *instantaneous* value and a *sustained* value. The instantaneous arousal is used in an experiment with the AIBO robot to trigger barking sounds in order to warn the caregiver of a rising high level of stimulation (see Chap. 5). The sustained arousal is used to drive the other behaviours of the robot. A low level triggers exploratory behaviours, and high level provokes a regulatory behaviour aimed at finding the human caregiver and obtain comfort. $Stim(t)$ is used to compute a value of the *instantaneous arousal*, as follows:

$$A_{inst}(t+1) = \frac{\tau_{inst} \cdot A_{inst}(t) + Stim(t+1)}{\tau_{inst} + 1} \tag{4.1}$$

The sustained arousal is computed as another smooth average of the instantaneous arousal A_{inst}.

$$A_{sus}(t+1) = \frac{\tau_{sus} \cdot A_{sus}(t-1) + A_{inst}(t+1)}{\tau_{sus} + 1} \tag{4.2}$$

The values of the two time windows to process the two arousal levels ($\tau_{inst} = 30$ and $\tau sus = 10$) correspond to the values used in chapter 5, when the arousal and behaviours of the robots were updated at a 10 Hz frequency. These values are chosen in order for the behaviour of the robot to reflect the past stimulation perceived and were empirically defined. In the case presented in chapter 7, only A_{sus} was used to drive the behaviour, and a time window $\tau_{inst} = 5$ was used due to a slower update cycle at 3 Hz. $\tau_{sus} = 10$ is the time window on which the sustained arousal is calculated, as an exponential average of the instantaneous arousal. Using exponential averages for the instantaneous and the sustained arousal presents two advantages. An isolated non-significant peak in $Stim(t)$, either due to noise or a really fast change in the inputs value would not be altering the behaviour unless repeated or lasting. 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 based system here used does not switch too fast between behaviours which would not appear natural, and could cause problems to the robot. In figure 4.1, we can see how both the instantaneous arousal and the sustained arousal vary depending on the shape of the stimulation in terms of frequency. For instance, the first peaks of the stimulation function start from timestep 7 until timestep 20. The duration of the peaks of stimulation (10 timesteps) is low enough so that the levels of arousal do not increase higher than 0.2. If their duration increases as between timesteps 500 and 900, the arousal levels have values oscillating around 0.7. If the stimulation is a longer lasting square function (from timesteps 1000 to 1200), the arousal levels rise above an 0.7 limit in 50 timesteps. A triangular function gives a delayed peak of arousal by approximately 60 timesteps.

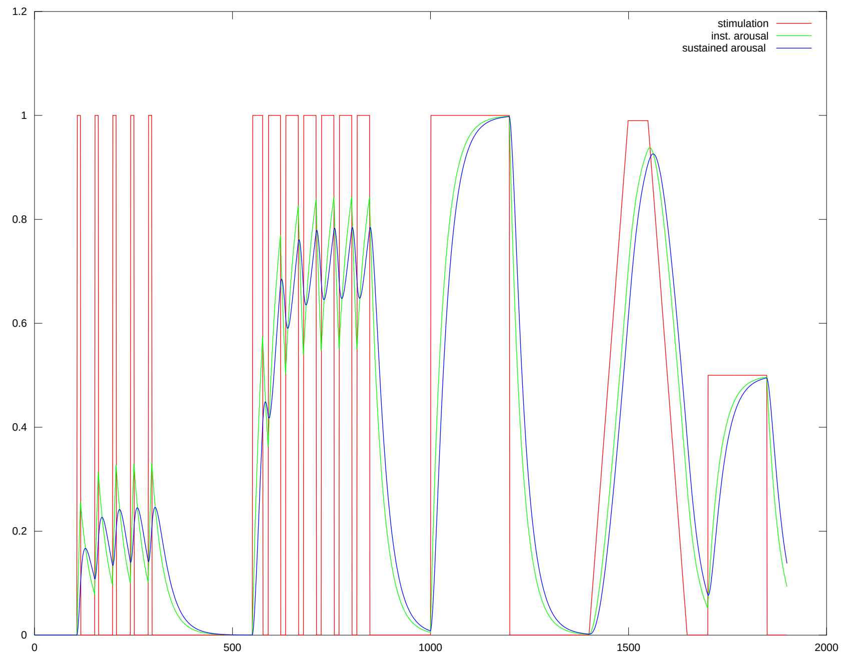


Figure 4.1: Dynamics of the arousal system depending on the shape of the stimulation (with $\tau_{inst} = 30$ and $\tau sus = 10$). A higher frequency of stimulation leads both the arousal to rise higher, with the instantaneous arousal rising earlier. The shape of the stimulation function determines when and how high the arousal levels will peak.

Using exponential averages for the levels of arousal was inspired by Oudeyer, Kaplan and Hafner (2007) and the manner in which they use a similar function to evaluate the prediction error of the robot in order to compute the learning progress in one sensorimotor region. Averaging the prediction error, or in this case the stimulation, provides an overview of the range of the value of the variable and is also more robust to outliers and sudden variations. They used this value to decide which action the robot should perform depending on an estimation of the current progress in the current situation. This dynamic is adapted to the arousal drive since is designed to balance the behaviour of the robot between exploration and regulatory behaviours depending on the past stimulation experienced. However, as the authors noted, using an exponential average provokes delays depending on the time windows used. In their system, it meant that the robot's behaviour was guided by a value of learning progress that allowed the robot to confirm what has been previously learned, instead of orienting the robot towards situations where a lot of progress could be achieved. For the case of the level arousal described here, as seen in figure 4.1, the arousal levels take a considerable amount of time to relax to the real value of the stimulation (200 timesteps to decay from 1.0 to 0. for instance). Therefore, depending on which arousal level the exploratory behaviour and the regulatory behaviour react, they might not truly reflect the situation in terms of the perceived stimulation.

4.3.2 Evaluation of the comfort

The intervention of the human partner are summarised in a variable $Comf$ which belongs to the interval [0.0 ; 1.0]. The comfort variable is proportional to distal (perception of a face in the later experiments) and proximal (using of contact sensors) modalities of the human caregiver. The comfort value is calculated as followed in Eq. 4.3:

$$Comf(t) = \begin{cases} C_h(t) + F_h(t) & \text{if } C_h(t) > 0 \text{ or } F_h(t) > 0 \\ \beta_{comf} \cdot Comf(t-1) & \text{otherwise} \end{cases} \tag{4.3}$$

where $C_h(t) = 1.0$ if proximal comfort is provided (i.e. the robot is being touched or patted). $F_h(t) = 0.2$ accounts for distal comfort (i.e. when a human face is detected in the visual field). Both these values are equal to 0 otherwise. Here, $0 < \beta_{comf} < 1$ is the decay rate of $Comf(t)$, accounting for the duration of the effect of the intervention of the caregiver to diminish the excitement of the robot. The value of this decay rate controls the duration of the relief the robot after some comfort was provided, the higher the β_{comf} the longer one intervvention lasts in the system. Figure 4.2 shows the dynamics of the comfort depending on the decay rate β_{comf}. A longer lasting comfort correlates with a higher value of β_{comf}. As will be emphasized in chapters 5, 6, and 7, this parameter is important as it

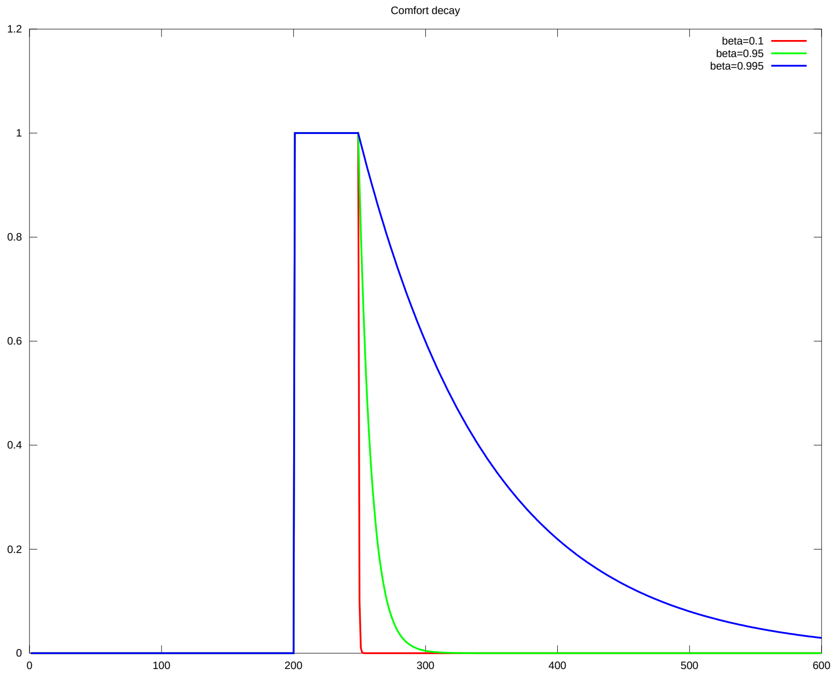


Figure 4.2: Dynamics of the comfort depending on the shape of the decay rate β_{comf}. Three different values are used (0.1 in red, 0.95 in green, and 0.995 in blue). The higher the decay rate, the slower the decay of the comfort. This provides a means to have the effect of the caregiving intervention last longer.

defines the frequency of the occurrence of the regulatory behaviour of the robot when the environment is highly stimulating.

For instance, with a value of 0.1, the comfort decays to 0 in a couple of timesteps. A value of 0.95 leads to a decay lasting approximately 50 timesteps and the last 0.995

makes the comfort last over 500 timesteps. This last two values will be used in chapter 6 to define two regulatory profiles, one "needy" (low β_{comf}) and one "independent" (high β_{comf}). Within the setup described in this chapter (with 10 Hz update rate), the first profile leads to a robot exhibiting regulatory behaviours every 10 seconds, while the other profile only exhibits them every 50 seconds.

Moreover, as proposed and tested in chapter 7, a real time tuning of this parameter depending on the responsiveness of the human allows the robot to adapt its "social or regulatory profile" to the availability and capacity of the human to regulate the arousal of the robot. A_{sus} decreases as a function of the variable $Comf(t)$ as follows:

$$A_{sus}(t) = A_{sus}(t) - \alpha_{care} \cdot Comf(t) \tag{4.4}$$

α_{care} is the decay rate of the sustained arousal when the caregiver is providing comfort ($\alpha_{care} = 0.2$).

In figures 4.3 and 4.4, we can observe the effect of the parameter α_{care}. A high value (0.2 in figure 4.3) reduces the sustained arousal quickly (in 5 timesteps) whereas a lower value acts much more slowly. This parameter influences the dynamic of the effect of the intervention of the caregiver. In all instances of the model in this thesis, the parameter was set to $\alpha_{care} = 0.2$, for a quick relief of the arousal. This was decided so that the weight carried out by the intervention was constant and kept the same fast dynamic. The questions later addressed focus on the frequency and occurrences of the intervention and not their duration or intensity (hence, the use of a square function for the simulation). With this parameter, punctual and lasting interventions lower the arousal to its minimum quickly, and therefore change the behaviour of the robot quickly too. However, for the completeness of the model and its potential extension to other questions related to arousal regulation, one has to keep in mind that this parameter determines the shape of the offset

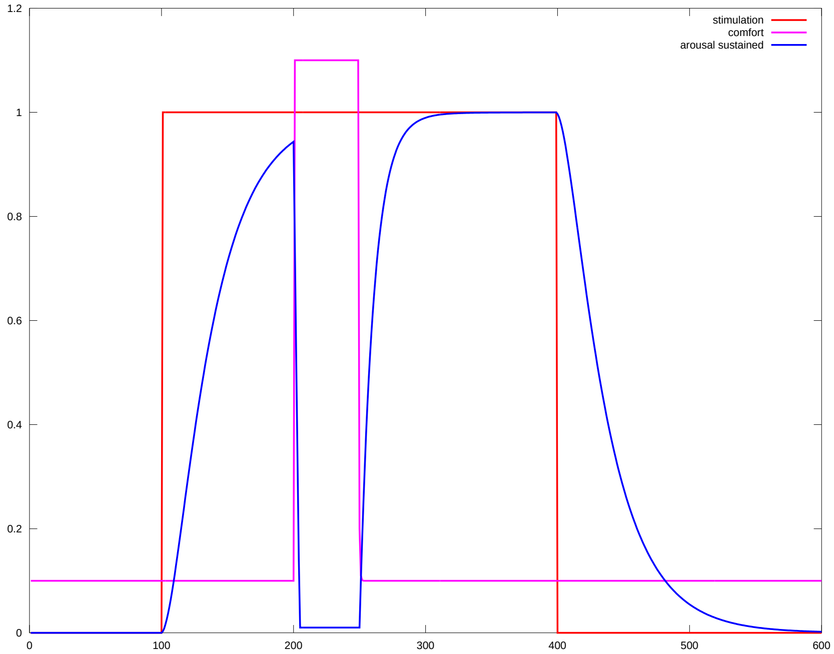


Figure 4.3: Dynamics of the arousal when comfort is provided while the stimulation is high. With $\alpha_{care} = 0.2$ the arousal decays in a few timesteps when comfort is provided (the level of comfort was raised by 0.1 to ease the reading of the plot).

of the arousal and therefore can be manipulated depending on the goals of the integration of the model. For instance, as we will see in the comparison with another model presented below, this parameter can be used to determine the pace of the regulation of the arousal by simulated endogenous opioids.

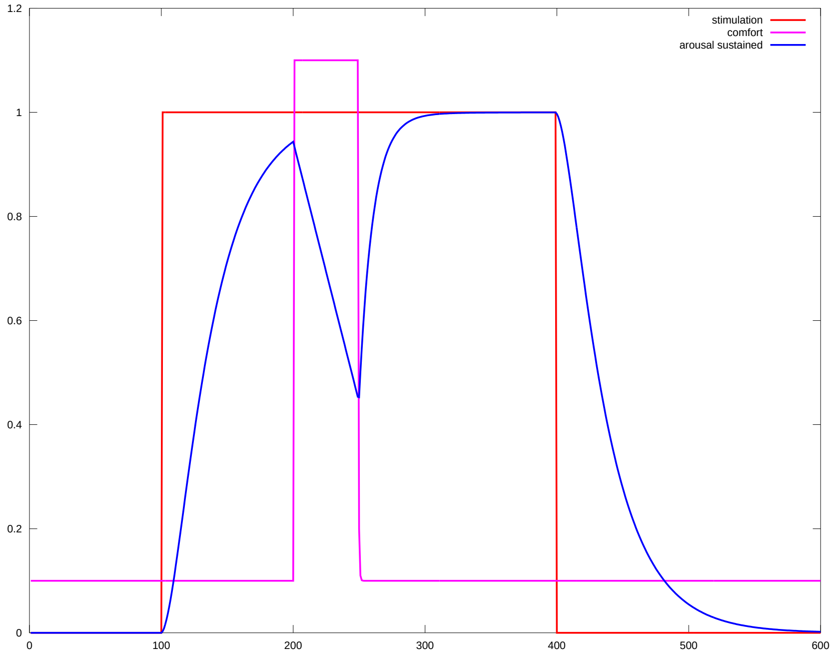


Figure 4.4: Dynamics of the arousal when comfort is provided while the stimulation is high with a lower decay rate. With $\alpha_{care} = 0.01$ the arousal decays much more slowly and is not fully reduced to 0 with the comfort provided (once more the comfort value was raised by 0.1 for ease of viewing).

4.4 Comparison of the Attachment Model to the Simulation Model of Stevens and Zhang

As introduced in chapter 2, a model of the interaction of the arousal from externally stimulating stimuli and the comfort provided by a caregiver with comparable dynamics was proposed by Stevens and Zhang (2009). Their model was designed to simulate the interactions between physiological substrates of arousal (serum cortisol level) and caregiving from the attachment figure (opioids such as oxytocin). This model endeavours to reproduce characteristic patterns of "negative reactivity" in a simulated stressful scenario comparable to the Strange Situation procedure from Ainsworth et al. (1978).

This model has been re-implemented in simulation and can be described as follows. The graphs and data presented here come from an implementation of their model as described in Stevens and Zhang (2009). The arousal level increases proportionally to a measure of arousing stimuli N which would correspond to the level of stimulation. A self-regulation factor μ which makes the arousal level decay over time. A level of opioids O which corresponds to the value of comfort also contributes to decrease of the arousal. These three contributions are computed as shown in equation 4.6.

$$\frac{dA}{dt} = -\lambda O(t-1) - \mu A(t-1) + p_a N(t) \tag{4.5}$$

In this equation, λ reflects the rate at which the arousal level (or cortisol serum level) is soothed by the opioids. μ controls the relaxation time of the arousal, and p_a was defined as the sensitivity of the arousal level to externally arousing stimuli represented by N.

Unfolding this equation as an iterative formula as used in the evaluation of arousal proposed in section 4.3.1, we obtain the following formula:

$$A(t) = -\lambda O(t-1) + (1-\mu)A(t-1) + p_a N(t) \tag{4.6}$$

whereas an equivalent version of Eq. 4.4 would be:

$$A(t+1) = -\alpha_{care} O(t-1) + \frac{\tau_{sus}}{\tau_{sus}+1} A(t) + \frac{1}{\tau_{sus}+1} A_{inst}(t) \tag{4.7}$$

We can see that this equation closely resembles Eq. 4.7. The λ parameter is equivalent to the α_{care} and is responsible for the rate of soothing of the caregiving interventions on the level of arousal.

In the absence of comfort, the equation becomes similar to the one proposed in the sense that the arousal increases proportionally to p_a and the intensity of the arousing stimuli which is equivalent to $\frac{1}{\tau_{sus}+1}$ and A_{inst}, respectively.

In the absence of comfort and arousing stimuli, the arousal level decays with the exponential decay constant $1-\mu$ (assuming $\mu < 1.$, for the arousal level to remain ≥ 0), which corresponds to $\frac{\tau_{sus}}{\tau_{sus}+1}$ in the equation proposed in section 4.3.1.

The level of opioids O is also calculated using a dynamical equation depending on a relaxation parameter λ, the level of arousal A, and the intervention of a caregiver to regulate distress M, as can be seen in equation 4.8.

$$\frac{dO}{dt} = -\lambda A(t-1) - \mu O(t-1) + p_c M(t) \tag{4.8}$$

One main difference in comparing this equation to the one proposed in section 4.3.2 is that the level of opioids O is influenced by the level of arousal. In the equation proposed in section 4.3.2, the comfort is not meant to be considered as a level of substrate of comfort, but an actual reflection of the intervention of a caregiver. The level of arousal does not influence this variable at all. Figure 4.5 provides a simulation of their model. First, both arousal and opioids values start at a 0.5 level. At timestep 10, an arousing input (N) appears which produces an increase in arousal A. Then, a caregiving intervention (M) occurs at time step 20 and lasts longer than the arousing input. When both N and M are present, the arousal and comfort values stabilize. This is due to the fact that both have a similar $\mu = 0.1$ value and the input weights (p_a and p_c) of the external contributions M and N are also both equal to 1. When the arousing stimuli N disappears, the arousal decays to 0 due to the lasting effect of the intervention of the caregiver and the inhibiting

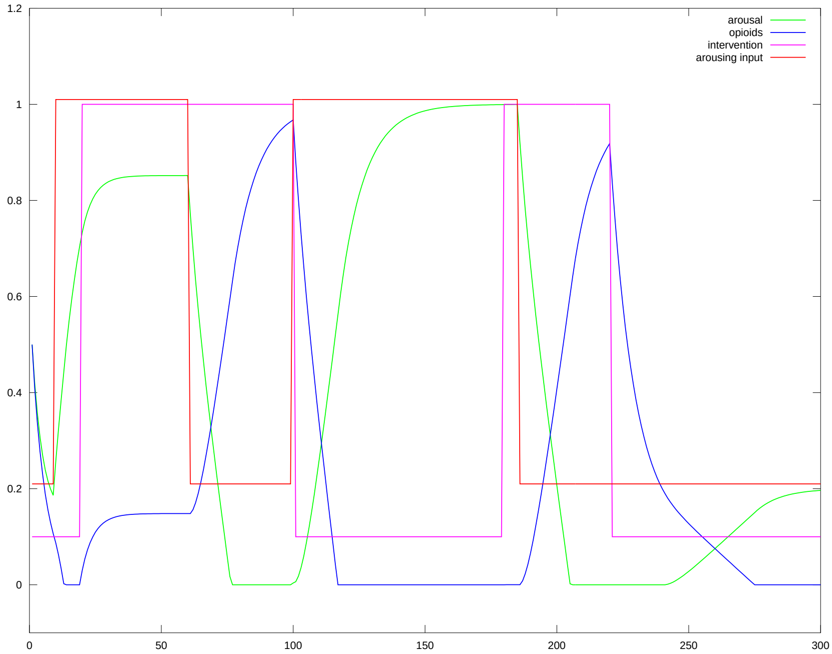


Figure 4.5: Simulation of the arousal/opioid interactions from the model of Stevens and Zhang. The levels of arousal (A in the equations, in green in the graph) and opioids (O in the equation and in blue in the graph) reflect the opposing effect of each quantities when an arousing stimuli is present (N in the equation, and in red in the graph, and raised by a 0.01 value for reading ease of the graph), and an intervention of the caregiver (M in the equation, and in pink in the graph).

effect of the opioid level. When a later arousing input is present at timestep 100, the arousal increases slower than in the first occurrence due to the lasting effect of the level of opioids.

One main important difference between the two models resides in the different inhibition dynamics between the arousal and the comfort (or substrate of it). The model presented here does not decrease the level of perceived comfort ($Comf$ in the model of this chapter and O in the model of Stevens and Zhang) depending on the level of arousal. In the model proposed, the arousal is computed differently when comfort is perceived than when it is not. This choice was made as an interpretation of the calming effect of the comfort on arousal from the literature. Indeed, if the caregiver is modeled as a secure base (Bowlby 1988), the comfort provided should always succeed in alleviating the discomfort, or high level of arousal, and from this observation came the two equations presented above. Moreover, the goal of the investigation is to assess the effect of the model on behaviours such as exploration and learning and evaluate the consequences of the behaviour of the human and the complexity of the environment. The addition of this internal competitive mechanism would add to the complexity of the model which is not the main goal here. The model proposed by Stevens and Zhang however aims at simulating the actual physiological substrates and their antagonistic effects, which explains their choices. From the level of arousal and opioids, they propose to simulate the intensity of the negative reactions – or regulatory behaviours – following the following equation 4.9:

$$B = s_A A - s_C O \tag{4.9}$$

Where s_A and s_C are the sensitivities to the arousal and opioids respectively. B is the magnitude of the negative reaction (a continuous positive value). Their study which aimed at reproducing the patterns of attachment proposed to use this variable to differentiate between the patterns. Figure 4.6 shows the variation of the negative reactivity in three cases. First, in the case of equal sensitivities s_A and s_C (set to 1). Then, in the case of a higher sensitivity to arousal with $s_A = 2s_C$, and then in the opposite case where the sensitivity to comfort (or its opioids substrate) is higher than the sensitivity to arousal ($s_C = 2s_A$). These graphs were produced using the same dynamics of the arousing stimuli N and the intervention of the caregiver M. We can see that a high sensitivity to arousal produces a higher intensity of negative responses as well as longer lasting ones. An equal sensitivity leads to a stabilization of the intensity of the negative reaction (time steps 20 to 60 for instance) until the arousing stimuli have disappeared.

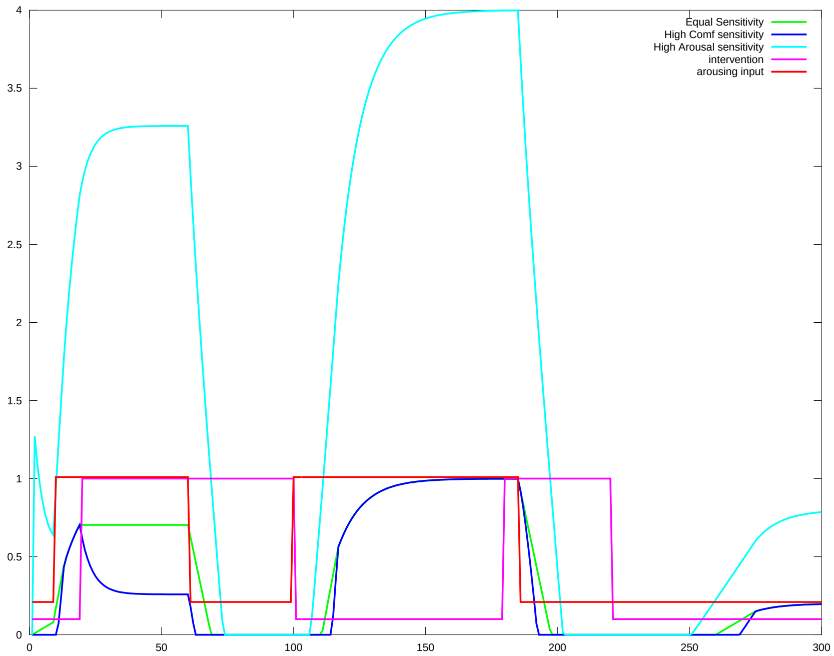


Figure 4.6: Negative reactivity variation from the model of Stevens and Zhang depending on the sensitivity to the arousal and opioids. The higher sensitivity to arousal is plotted in red, an equal sensitivity is in green, and a lower sensitivity to arousal is in blue. The input A and O have the same values as was used previously in figure 4.5.

4.5 Novelty and Learning Accuracy as Sources of Stimulation for the Arousal of a Learning Robot

As was highlighted in the previous chapter, an attachment-based dyadic regulation system contains at least three main components: a set of regulatory behaviours, an affective evaluation system, and an interface through which the human can provide comfort and relieve negative affect. The affective evaluation system in this chapter is designed to reflect the perception of the novelty and stability of the environment. Within the dyadic regulation model, this measure acts as the infant's distress (usually resulting from meeting a stranger) which triggers regulatory behaviours and promote the help of the caregiver. In comparison to psychological experimental setup with infants and their caregiver, the distress arises from the perception of the environment and the way the robot's internal learning structures react to them. This section presents two neural network-based learning systems that were adapted in the following chapters for a robot to learn perceptual features and use evaluation measures tailored for these two systems to provide inputs for the arousal level. The properties that guide the selection of the components learning system are the following:

- The components of learning system should learn incrementally, and react according to the familiarity of the inputs provided to them
- The lack of accuracy or progress of the learning system can be measured and used in a variable to provide input for the stimulation used in the arousal system
- These measures should decay over time when the perceptions are familiar and increase when novel perceptions are encountered

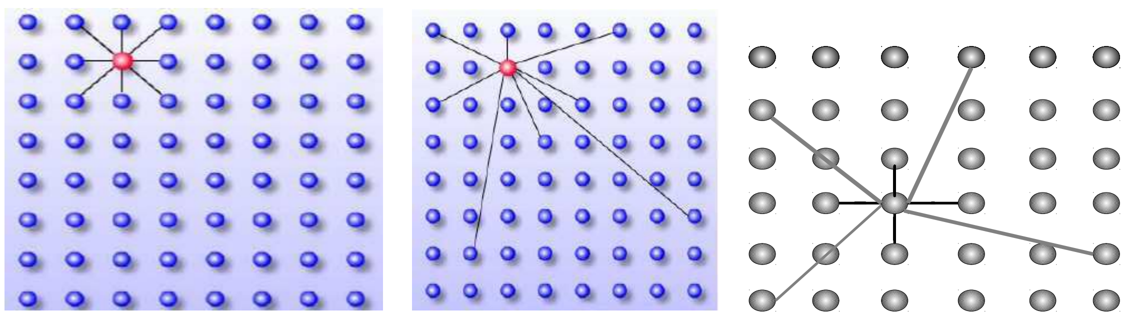
For these reasons, the two learning systems selected were an auto-associative memory and a Kohonen Self-Organising Map.

The sections below explains their functioning and what measures can be used to assess their performance in real-time.

4.5.1 The Auto-Associative Memory

The model used for the auto-associative memory is a modification of the standard Hopfield network (Hopfield 1982), based on models of associative memory described in (Davey and Adams 2004, Calcraft, Adams and Davey 2007). Functionally, this neural network has the ability to store binary patterns that are presented to it. The patterns are stored using associative synapses between neural units. The size of the network is the same as the binary input pattern. When a new pattern is presented, the network uses it as an input P and the network runs through iterations of updates and learning steps in order for its neural unit to converge to the input pattern. When the learning step is omitted, the network converges to the learned pattern closest to the input one, providing a degree of familiarity with the input when compared to it.

The network used is a two-dimensional square 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. 4.7 which help increase the capacity of the network (Davey and Adams 2004).



(a) Local association network. (b) Random association network. (c) Blended connectivity model association networks.

Figure 4.7: Associative memory network connectivity.

The network uses asynchronous random-order updates. Then, in order to learn the presented binary input pattern matrix, the system uses a modified version of the procedure from (Davey and Adams 2004), described in Alg. 1. The main modification resides in the use of an upper limit to the number of iterations for the network to converge (the constant $n = 10$ in the algorithm). This upper limit was chosen for the network to output a pattern $S(t)$in a fixed amount of time. Therefore, once integrated in the robot control system, the learning system update and learning step would finish within a defined period of time, and the arousal can be computed with a constant frequency. To measure the performance of the auto-associative memory, the recall error is used. It is computed as the Hamming distance between the current pattern from the perception ($P(t)$ in the algorithm), and the output of the memory $S(t)$. As can be seen in the algorithm, the recall error is computed as in equation 4.10:

$$Err(t) = \sum_{i=1}^{N} \mid S_i - P_i \mid \tag{4.10}$$

Theoretically, this value can range from 0 to N since the input and output are binary. N corresponds to a completely incorrect output, and 0 to a perfect recall. The figure below 4.8 shows the recall error for a set of 10 new patterns presented to the system. Each pattern is presented 3 times, then another pattern is presented. This loop iterates 5 times. After this period, another set of 10 different patterns is presented to show how the recall error reacts to change (at time step 150). As can be seen in figure 4.8, when the first set of patterns is presented, the recall error takes approximately 2 presentations of the whole set (i.e: 60 timesteps) to relax to values close to 0. When a new set of pattern is presented, although the magnitude of the recall error is not as high as the initial one, the recall error relaxes to a value close to 0 at time step 220, which illustrates the time the network takes to learn appropriately (with a 1% maximum recall error) a new set of 10 oscillating patterns only

```
P(t) ; /* Binary Input Perceptual Vector */
w_ij ; /* Initialises weight matrix with zeros */
C = 8 ; /* Number of connection per unit */
N = 100 ; /* number of units */
S(t) ← P(t) ; /* Each state of unit receives input vector value */
n = 0; /* Update and learning step */
T = 10 ; /* Learning threshold */
h(t) ; /* Vector containing the activation of the local fields of all
units */
repeat
    for i = 1 to N do
        h_i = Σ_{j≠i}^{C} w_ij S_j;
        S_i = { 1    if h_i > 0
              { −1   if h_i < 0
              { S_i  if h_i = 0
    end
    if Σ_{i=1}^{N} S_i · P_i < T then
        for i = 1 to N do
            foreach w_ij do
                w_ij = w_ij + S_i S_j / N; /* Modifying synaptic weights */
            end
        end
    end
    n ← n + 1;
until S(t) = P(t) or n = 10 ;
Err(t) = Σ_{i=1}^{N} | S_i − P_i | ; /* Compute Recall Error */
```

Algorithm 1: Algorithm for the update and learning stages of the auto-associative memory. At every time step t, a binary pattern $P(t)$ (once transformed to the $[-1, 1]$ value range required by the associative memory system) is fed to the network in order to be learned. The memory iterates until the all local states $S(t)$ are equal to $P(t)$ or after 10 iterations. After this phase, the recall error $Err(t)$ is computed.

presented for 3 timesteps. If the duration of the presentation of each pattern increases, as would be the case for a robot attending a stationary pattern, the recall error presents a different dynamic, as we can see in figure 4.9. The main difference in the shape of the

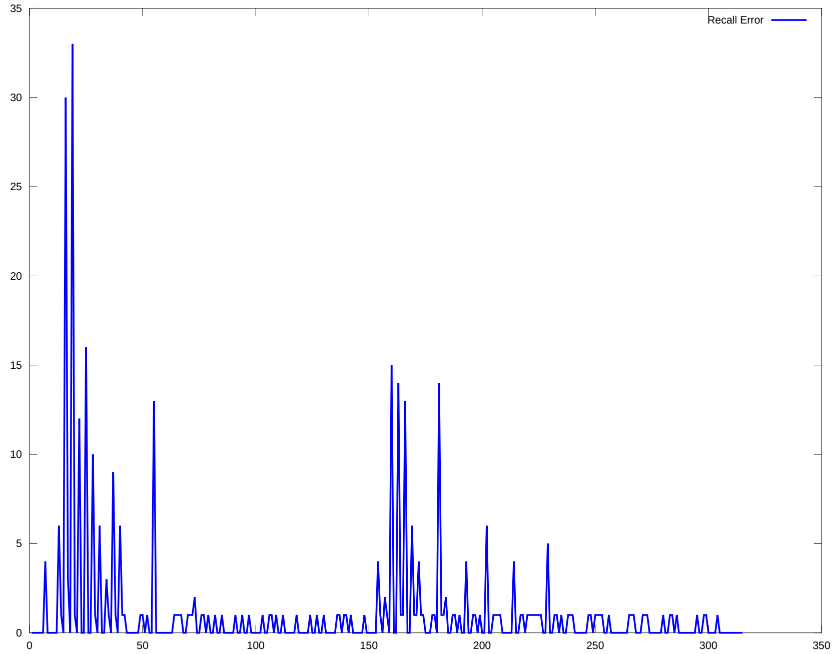


Figure 4.8: Variation of the recall error of the auto-associative memory with a 3 timesteps presentation time. Two different sets of 10 patterns are presented. The first one at time step 0 and the next one at timestep 150.

recall error here is the amount of time the recall error is close to zero. Since the patterns do not vary as fast as in the previous case, the recall error in between pattern presentation is equal to 0 or 1 most of the time. If we use both these examples to compute an $A_{sus}(t)$ level following the previous equations we obtain the following comparison in figure 4.10, where the stimulation feeding the arousal only takes the recall error as input.

Figure 4.10 demonstrates the dynamics of the arousal sustained depending on the variability of the patterns presented. These two extreme scenarios will help define the boundaries

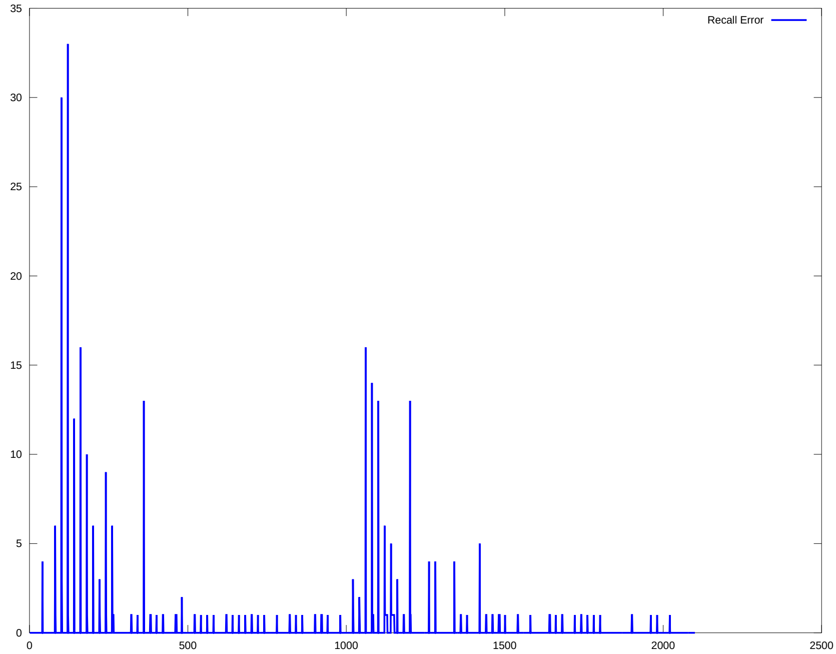
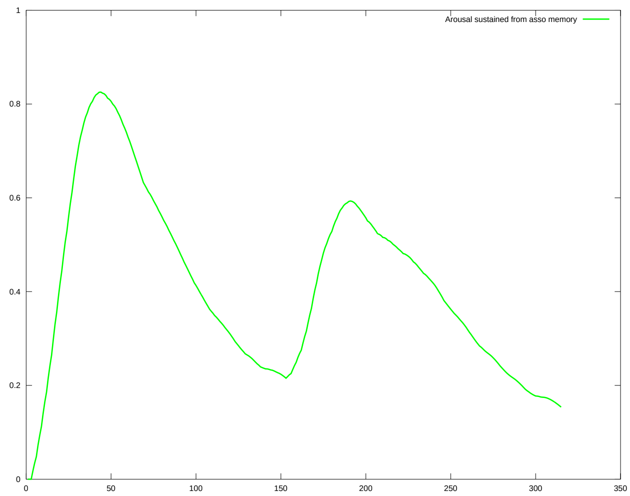


Figure 4.9: Variation of the recall error of the auto-associative memory. Two different sets of 10 patterns are presented. The first one at time step 0 and the next one at timestep 1000.

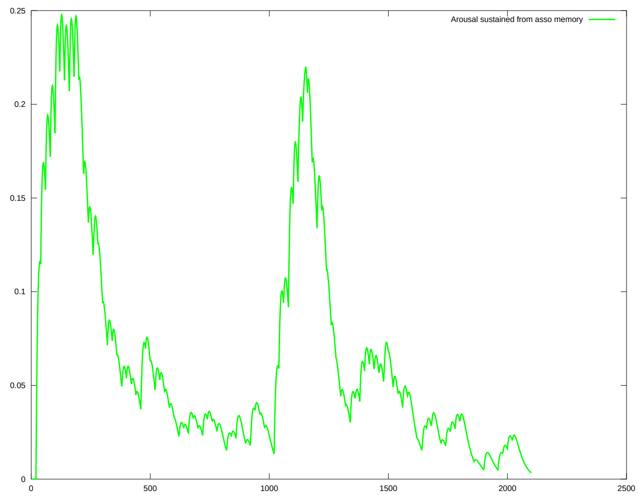
between what is considered low arousal and high arousal which should trigger a regulatory behaviour.

4.5.2 The Self-Organizing Map for the Categorisation of Perceptual Features

The Kohonen Map algorithm is an adapted implementation of the original from Kohonen (1997) and is described in the algorithm 2. The implementation used in this dissertation is a two-dimensional grid of size 10x10.



(a) Arousal sustained from the recall error with 3 timestep presentation.



(b) Arousal sustained from the recall error with 20 timestep presentation.

Figure 4.10: Comparison of the arousal sustained level based only on the recall error. The magnitude of the arousal sustained is lower for the case when patterns are presented for 20 timesteps (maximum at 0.25). The case where patterns oscillate every 3 timesteps leads to a higher arousal with the first and second set of patterns (maximum at 0.8 then 0.6).

```
P(t); /* Binary input vector of size M */
N = 100 ; /* Number of units of the map */
n = 0 ; /* time step of the entire experiment */
α = 0.5; /* Initial learning rate */
h(t) ; /* Learning rate as a decreasing function of the time step t */
nbh(i,j) ; /* Neighbourhood function */
a = 3 ; /* Neighbourhood size */
κ = 0.0002 ; /* Learning rate decreasing factor */
w_ij = rand(0.01); /* SOM map weight initialised to a small random value */
h(0) = α;
h(t) = α / (1 + t·κ); /* Update the learning rate */
for i = 1 to N do
    y_i = Σ_{j=1}^{M} w_ij · P_j ; /* Updating all units activation y_i of the map */
end
k ← getWinner() ; /* Selecting the unit with the highest activation */
for j = 1 to M do
    w_kj = w_kj + h(t)(P_j − w_kj)
end
for i = 1 to N do
    foreach k ≠ i do
        d(k,i) ←Euclidean distance between winner k and neuron i
```

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

```
    end
    for j = 1 to M do
        w_ij = w_ij + h(t)nbh(k,j)(P_j − w_ij);
    end
end
/* Computing the sum of the variations of the synaptic weights */
```

$$Cat(t) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} \mid w_{ij}(t) - w_{ij}(t-1) \mid;$$

$t \leftarrow t + 1;$

Algorithm 2: Algorithm for the update and learning stages of the Self-Organising map

The algorithm functions as follows. For a given input vector P, the algorithm selects the neural unit i with a set of synaptic weight w_{ij} the closest to the input vector. Once selected, the synaptic weight are modified using the following learning rule, in equation 4.11:

$$w_{ij} = w_{ij} + h(t)nbh(k,j)(P_j - w_{ij}) \tag{4.11}$$

In this equation, $h(t)$ is the learning rate which decays with time, and $nbh(k,j)$ is a neighbouring function which selects which other units will be updated. In the implementation of this algorithm, the learning rate decays very slowly to allow the robot to still learn throughout the experiment. The neighbourhood function is also constant over time, for similar reasons. This adaptation allows the evaluation of the variation of the synaptic weights in order to feed the stimulation value for the levels of arousal. As pointed out by Kohonen (1997), such an implementation does not guarantee convergence of the map to a optimal representation of the input patterns. However, this is not the goal of this algorithm. This algorithms provides an iterative learning process, where the weights of the neural units converge slowly to the input they react to. The variation of the weights is relative to the distance between the input pattern P and the weights of the winning unit and of its neighbours. These variations are summarised in the Cat variable which reflects the adjustment of the category using equation 4.12:

$$Cat(t) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} \mid w_{ij}(t) - w_{ij}(t-1) \mid \tag{4.12}$$

The Cat variable varies in a similar manner as the recall error with a higher value for novel stimuli than for familiar ones. It is the average per neural unit of the synaptic weight variation. In figure 4.11, we can see how this variable reacts to the presentation of 10 patterns for 3 timesteps as in the previous section, and then how it reacts to 10 new patterns presented after 150 timesteps. In figure 4.12, we can see how this variable reacts

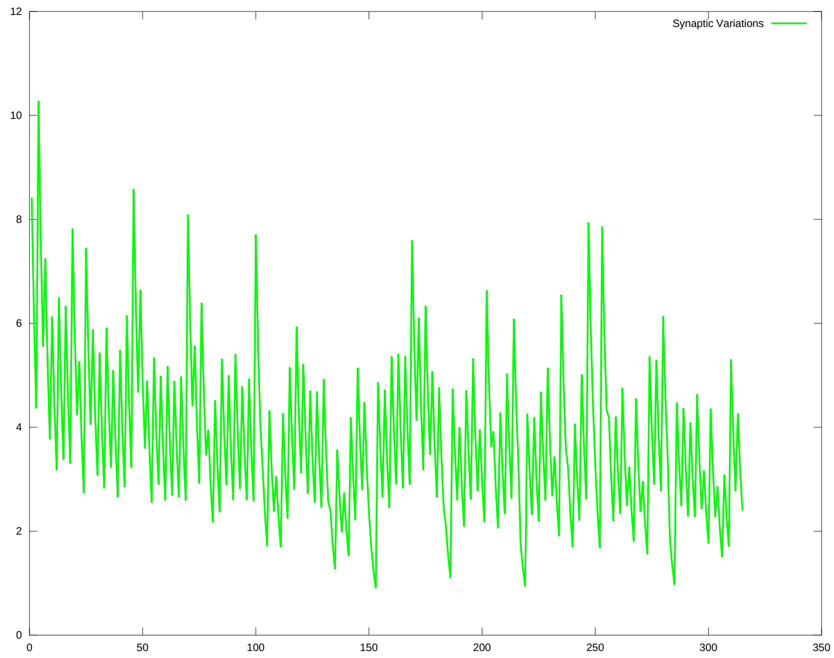


Figure 4.11: Dynamics of the variation of the synaptic weights of the SOM with a 3 timesteps presentation time. Two different sets of 10 patterns are presented. The first one at time step 0 and the next one at timestep 150.

to the presentation of 10 patterns for 20 timesteps as in the previous section. One main difference between the two conditions is that when the patterns are presented for longer, the value of the synaptic variation has time to decay close to zero, bringing the synapses of the winning unit closer to the value of the input P. The synaptic variation peaks are of the same magnitude but last longer for the condition where the patterns vary faster. This also translates in a smaller average distance between the winning unit and the input

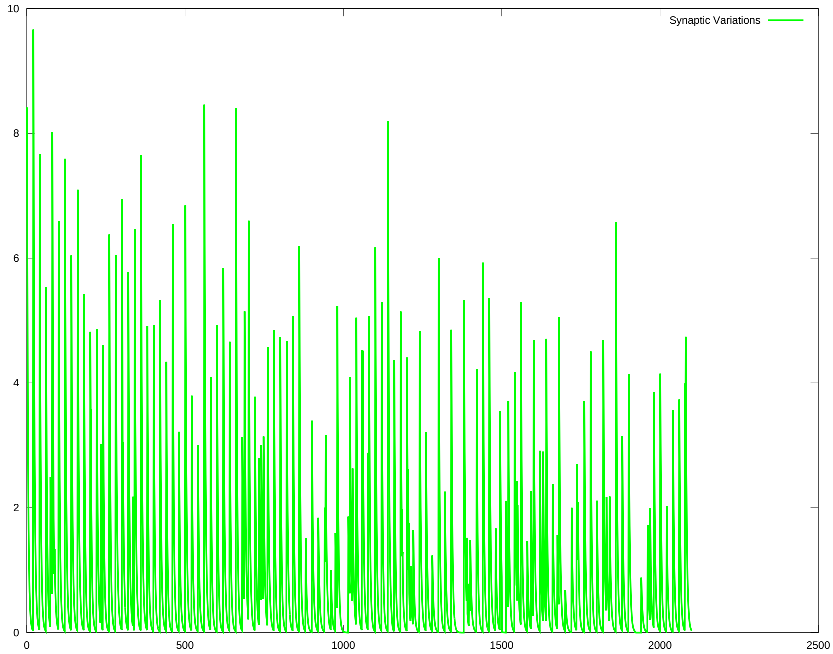


Figure 4.12: Dynamics of the variation of the synaptic weights of the SOM with 20 timesteps presentation time. Two different sets of 10 patterns are presented. The first one at time step 0 and the next one at timestep 1000.

pattern. This value is calculated in equation 4.13:

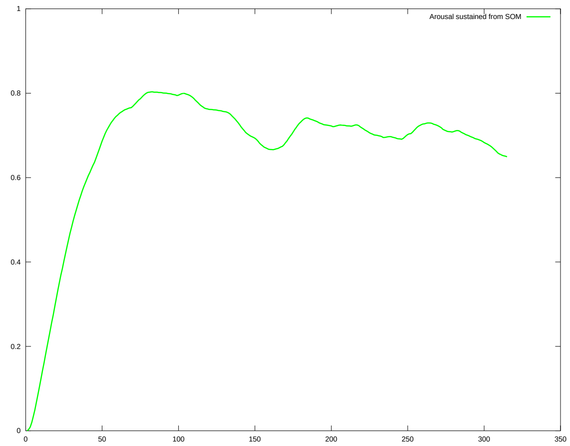
$$WinDist = \sum_{j=1}^{N} \mid w_{ij}(t) - P_j \mid \tag{4.13}$$

Where i is the index of the winning unit. Between the two conditions presented above we obtain $WinDist = 0.24$ for the first condition, where the patterns lasted 3 timesteps, and $WinDist = 0.04$ for the second condition where the patterns lasted 20 timesteps. This quantity reflects the adequacy of the neural unit to represent the input pattern and can be used as a measure to assess the learning accuracy of the robot. This measure will be used in the following chapter 5 to differentiate the effect of different caregiving styles on the learning of the robot. Figure 4.13 shows the variation of the level of arousal sustained A_{sus} in the two conditions. A main difference is the high and sustained level of the arousal when patterns vary often (3 timesteps presentation). In opposition to the recall error in the fast varying pattern condition, when the arousal uses the synaptic weights variations as input it does not decay and stays stable. Again, these two extreme cases help decide on the threshold to be placed on the arousal level, and then to be tested in a real setup.

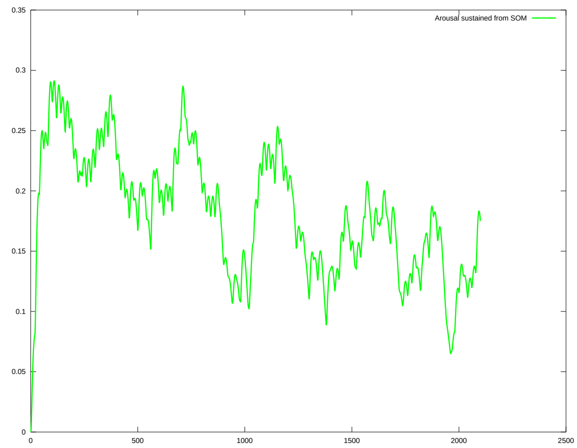
4.6 Robot Architecture with the Attachment System

This section presents the final architecture that was used in the experiments presented in chapters 5, 6 and 7. The architecture is divided into five main components as depicted in Fig. 4.14. The Perceptual System computes the perceptions based on the sensors used from the robot. In chapters 5 and 6, the Aibo robot is used and these sensors include the camera image, infrared distance sensors, and contact sensors. In chapter 7, where the Aldebaran Nao robot is used, these sensors include the camera image and the contact sensors located on the head of the robot.

A selection of these perceptions (about the human and the other features of the environment) serve as the input $P(t)$ to the Learning System. The Learning System contains the two learning algorithms presented above, the self-organising map and the auto-associative memory. This allows the robot to try and learn the current features of the environment and permits the evaluation of the novelty of these features. The evaluation measures from the Learning System are fed into the Arousal System using the $Stim(t)$ variable, which in the current version of the architecture reflects the dynamics of learning and perceptual novelty. This provides real time arousal levels which, in the absence of any human intervention,



(a) Arousal sustained from the synaptic variations with 3 timestep presentation



(b) Arousal sustained from the synaptic variations with 20 timestep presentation

Figure 4.13: Comparison of the arousal sustained level based only on the synaptic variations. The magnitude of the arousal sustained is lower for the case when patterns are presented for 20 timesteps (maximum 0.28 and minimum at 0.1). The case where patterns oscillate every 3 timesteps leads to a higher arousal sustained and an almost constant level (between 0.6 and 0.8) with the first and second set of patterns.

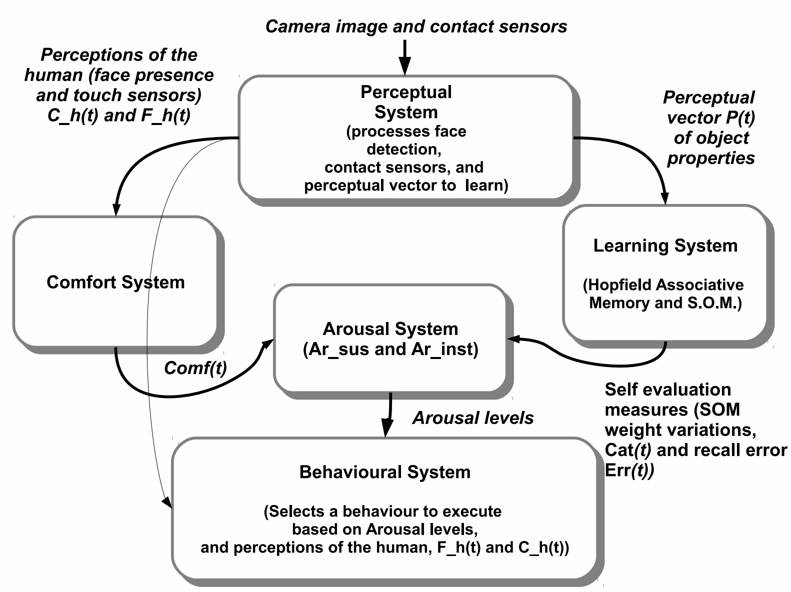


Figure 4.14: Components of the robot architecture with the arousal based attachment system. The Perceptual System processes the image from the camera and the contact sensors. In turn, a binary perceptual vector $P(t)$ containing the perceptions to be learned is used as input for the Learning System. The Perceptual System also computes the perceptions related to the human: the presence and location of a human face in the visual field, and the perception from the contact sensors of the robot. The self-evaluation measures from the two neural networks in the Learning System regarding the current perception $P(t)$ are used to compute the level of arousal of the robot and are fed to the Arousal System, presented in section 4.3.1. The Comfort System uses the tactile and visual perception of the human ($C_h(t)$ and $F_h(t)$, respectively), and the comfort evaluated is used to decrease the arousal level. The Behavioral System uses the *arousal* level and the perceptions related to the human to trigger either requests for assistance when the arousal level is high (i.e., looking for a human and gazing at him/her), walking away in order to explore further when the arousal is low, or remaining still attending to and learning the current perceptual pattern when the arousal is at medium level.

correlates with the subjective novelty and complexity of the current situation. Based on the two variables Cat (the variation of the synaptic weights of the SOM) and Err (the recall error), the stimulation is calculated following equation 4.14 and used int equation

4.1.

$$Stim(t) = \frac{Err(t) + Cat(t)}{2} \tag{4.14}$$

The stimulation is thus an average of both evaluation measures of the Learning System.

Perceptions related to human interventions (distal or proximal), such as the presence of a human face in the visual field or tactile contact on the head sensors, are passed on to the Comfort System, presented in section 4.3.2. The Comfort System inputs to the Arousal System to decrease the arousal level of the robot in a way akin to the soothing and regulatory effect that the comfort provided by a human caregiver has on an infant (Feldman 2003). The algorithm executed by the architecture is summarised in Alg. 3.

```
t = 0 ; /* Experiment time step                                    */
end ; /* End of experiment time step                               */
LowArousal = 0.4 ; /* Low sustained arousal threshold              */
HighArousal = 0.6 ; /* High sustained arousal threshold            */
/* Initialization of the internal variables to 0.                  */
Stim(0) = 0 ; /* Stimulation                                       */
Err(0) = 0; /* Associative memory recall error                     */
Sur(0) = 0; /* Variation of the weights of the SOM                 */
Comf(t) = 0; /* Comfort value                                      */
while n < end do
    /* Reads the sensors and updates perceptions P(t), C_h(t), and F_h(t)
       */
    (P(t), C_h(t), F_h(t)) ←processPerceptions() ;
    /* Evaluates the comfort value Comf(t) using (C_h(t), F_h(t))  */
    Comf(t) ←processComfort(C_h(t), F_h(t));
    /* P(t) used as input of the learning system, both execute their
       update and learning algorithms                              */
    (Stim, Err(t), Cat(t)) ←updateLearningSystem(P(t)) ;
    /* Compute arousal level                                       */
    (A_inst(t), A_sus(t)) ← updateArousal(Stim(t), Comf(t));
    /* Updates the activation of behaviors and executes winner     */
    updateBehavioralSystem(A_inst(t), A_sus(t), C_h(t), F_h(t));
    t ← t + 1;
end
```

Algorithm 3: Algorithm for the entire architecture with the attachment system

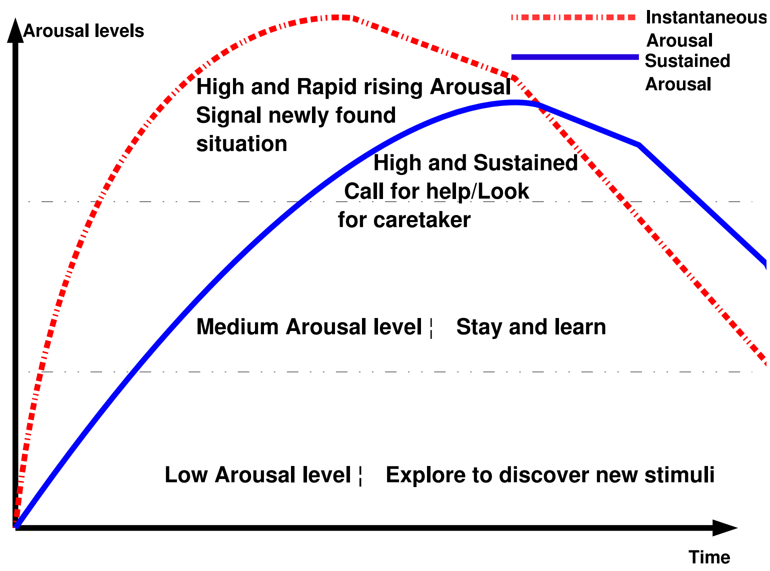


Figure 4.15: Dynamics of the behaviours of the robot based on the levels of arousal. A high instantaneous arousal provokes behaviour such as vocalisation to attract the attention of the human and a high sustained arousal pushes the robot to look for the caregiver.

The arousal level is then used by the Behavioral System as input to perform behaviour selection and decide whether to explore the environment, remain focused on the current perceptions, or trigger a regulatory behaviour to obtain help from the human. The Behavioral System is responsible for which action to perform depending on the level of arousal. This system uses thresholds in order to do so as depicted in figure 4.15. These thresholds are $As_{low} = 0.4$ for the lower threshold. Values of arousal below this threshold corresponds to a low stimulation and were chosen based on the work carried out in section 4.5. When the arousal sustained is below this threshold, the robot will trigger exploratory behaviours to look for more stimulation. A high threshold $As_{high} = 0.6$ was chosen to qualify arousal levels which reflects a high degree of the perceived novelty and should trigger regulatory behaviours such as looking for the human in order to receive comfort. A threshold $Ai_{high} = 0.7$ was chosen to trigger the vocalisations based on the level of instantaneous arousal of the robot for the work reported in chapters 5 and 6. Levels of arousal sustained between these two thresholds trigger no behaviour, the robot remains still and tries to learn the pattern it perceives.

4.7 Summary

This chapter presented the design steps for the development of an attachment system based on the construct of arousal. The arousal reflects the stimulation of the robot and development its behaviour. The model has been divided in five main components. First, the Perceptual System is responsible for the processing of the perceptions of the robot. The Learning System then receives the input pattern from the Perceptual System and tries to learn the pattern using two neural network algorithms. The evaluation of the performance of these networks provides a stimulation value for the arousal system. In addition, the perceptions of the human behaviour are used to assess a level of comfort in the Comfort System. The Arousal System then evaluates the levels of arousal depending on the comfort and the stimulation. A Behavioral System then decides based on two thresholds whether the robot should remain still, signal to the caregiver, look for the caregiver, or explore more.

A comparison to an existing model (Stevens and Zhang 2009) was provided. Their model was designed for a different purpose from the one proposed here, the reproduction of the infant attachment patterns (Ainsworth et al. 1978) using a simulation of interaction between neural substrates of arousal and comfort. The main difference between the models is that the one from this thesis presented in this chapter treats the influence of comfort differently. The comfort is not related to the arousal level whereas their model uses this property. Moreover, they propose to analyse negative responses from the infant depending on their intensity. The arousal model developed in this chapter solely aims at controlling the behaviour of the robot, and not the intensity of any responses. Both these models seem to have been developed concurrently see (Stevens and Zhang 2009) and (Hiolle and Cañamero 2008b, Hiolle and Cañamero 2008a). The arousal model developed and described in this chapter was later used in researcher modelling infant attachment behaviour using neural networks in simulation by Cittern and Edalat (2014).

Chapter 5

An Artificial Arousal System for Robot Exploration

5.1 Outline

This chapter presents a series of experiments using the architecture proposed in chapter 4 with the Sony AIBO robot "dog". The robot endowed with this architecture was placed in a small arena with objects of different size and colours. The Learning System of the robot then tries to learn the features of the perceptions based on raw sensor data (distance sensor, main colour and touch sensors). When too much novelty is felt through the stimulation and then in levels of arousal, the robot barks and searches for a human. A human experimenter played the role of the caregiver to respond to these regulatory behaviours and provide comfort to the robot by appearing in the visual field and/or patting the sensors on the back of the robot. The variable in the experiments was the behaviour of the experimenter in terms of responsiveness. A highly responsive caregiver would answer the calls of the robot immediately, and provide comfort often. A less responsive caregiver seldom responds to the calls of the robot. The results show how this variation in the behaviour of the human provides a different learning outcome in the robot and a different exploratory dynamic in the environment.

5.2 Contributors and funding bodies

The work presented in this chapter was achieved during the EU funded FP6 FEELIX-GROWING project (FP6 IST-045169), under the work package "FEEL". The modelling was achieved by myself with the support from Lola Cañamero and our partners in Portsmouth University represented by Pr. Kim Bard. The design of the architecture, its implementation, and the experimentations were executed by myself under the supervision of Lola Cañamero.

5.3 The Robotic Platform used: The Sony AIBO ERS-7 Robot

The AIBO (an acronym for Artificial Intelligence Robot) ERS-7 robot (see Fig. 5.1) is the third generation of robot "dogs" designed by Sony. The commercialisation of this robot was an attempt by Sony to introduce robot companions into people's homes. However, researchers in robotics realized that this robotic platform was a relatively affordable alternative to bespoke robotic systems and it was thenr used in several experiments pertaining to sensorimotor exploration and learning (Oudeyer et al. 2007), robot acceptance by humans (Weiss, Wurhofer and Tscheligi 2009), and was also the standard platform between 1999 and 2007 for the Robocup (http://www.robocup.org/robocup-soccer/), a competition for robotic football teams. AIBO is 32 cm long, 18 cm wide and 28 cm high. It weighs 1.65 kg. The robot uses a MIPS R7000 @ 576 MHz 64 bit processor, with 64 MB of RAM. The robot also has a slot where a Flash memory card can be inserted. This allows developers

Figure 5.1: The AIBO ERS-7 robot by Sony

to run their own software. Additionally, the robot is equipped with an on-board Wi-Fi card to remotely control the robot. The robot possesses 18 degrees of freedom enabling control of the legs, head, neck, mouth, and tail. A 350 000 pixel camera is located above its mouth, and two microphones are located on both sides of its head. A speaker was placed on the chest of the robot allowing to play sound files. The robot's battery allows for approximately 1.5 to 3 hours of autonomy depending on the use of the robot.

5.3.1 Software interface

Sony provided a software development kit in 2003, named Open-R. This C++ based toolkit allows access to the low level hardware components. Although this SDK is not widely used any more, comprehensive information concerning this programming framework is still available (Serra and Baillie 2003, Rico, Gonzalez-Careaga, Cañas Plaza and Matellan-Olivera 2004). A more flexible alternative to control and program the AIBO robot is to use the URBI middleware (Baillie 2005) which was designed as a unified robot programming language. Jean-Christophe Baillie and colleagues built this middleware on top of the Open-R toolkit for AIBO and it provides a scripting language to control the robot and all its actuators.

Actuators

As can be seen on Fig. 5.1, the AIBO robot has an embodiment designed after a small dog. It possesses 3 degrees of freedom per leg, 2 degrees of freedom for its head, 1 on its neck and two on its tail. This embodiment allows the robot to lie down, sit, walk and move its head. Table 5.1 shows the actuators of the robot.

Table 5.1: List of the actuators and their ranges on the Sony AIBO ERS-7 robot accessible via the URBI middleware

Name	Range (in degrees)	Description
legRF1	-134.0 to 120.0	right fore leg
legRF2	-9.0 to 91.0	right fore leg
legRF3	-29.0 to 119.0	right fore leg
legRH1	-134.0 to 120.0	right hind leg
legRH2	-9.0 to 91.0	right hind leg
legRH3	-29.0 to 119.0	right hind leg
legLF1	-120.0 to 134.0	left fore leg
legLF2	-9.0 to 91.0	left fore leg
legLF3	-29.0 to 119.0	left fore leg
legLH1	-120.0 to 134.0	left hind leg
legLH2	-9.0 to 91.0	left hind leg
legLH3	-29.0 to 119.0	left hind leg
neck	-79.0 to 2.0	angle between the neck and z-axis
headTilt	-16.0 to 44.0	vertical orientation of the head
headPan	-91.0 to 91.0	head rotating around z-axis (neck)
tailPan	-59.0 to 59.0	rotation around y axis (wagging)
tailTilt	2.0 to 63.0	rotation around x axis
mouth	-58.0 to -3.0	opening of the mouth

Sensors

The AIBO ERS-7 robot has contact sensors on his back and the top of its head, 3 distance sensors (infra-red) on its chest, and touch sensors under its "paws", and 3 acceleration sensors. Additionally, the robot provides a camera image (camera located on the tip of the "nose" of the robot) and two microphones located in the robot "ears" on each side of its head.

Table 5.2: List of the sensors and their ranges on the Sony AIBO ERS-7 robot

Name	Range	Description
pawLF	0.0 to 1.0	binary contact sensor (left fore leg)
pawRF	0.0 to 1.0	binary contact sensor (right fore leg)
pawLH	0.0 to 1.0	binary contact sensor (left fore leg)
pawRH	0.0 to 1.0	binary contact sensor (right hind leg)
distance	19.0 to 90.0	infra-red distance sensor on the head
distanceNear	5.7 to 50.0	infra-red distance sensor on the head
distanceChest	20.0 to 150	infra-red distance sensor on the chest
headSensor	0.0 to 35.0	pressure Sensor on the head of the robot
backSensorF	0.0 to 60.0	front pressure Sensor on the back of the robot
backSensorM	0.0 to 60.0	middle pressure Sensor on the back of the robot
backSensorR	0.0 to 60.0	rear pressure Sensor on the back of the robot
accelX	-19.6 to 19.6	acceleration sensor (front-back)
accelY	-19.6 to 19.6	acceleration sensor (right-left)
accelZ	-19.6 to 19.6	acceleration sensor (up-down)
camera	N/A	240 by 60 RGB image
mic	N/A	interleaved stream of 1048 bits from the right and left microphones

5.3.2 Perceptions used in the experiment

The Perceptual System used in the experiment is responsible for producing the input vector to the Learning System and to the Comfort System. The Learning System needs a pattern of stimuli $P(t)$ to learn and then evaluate their novelty. The Comfort System needs to process the perception of the human caregiver to calculate the level of comfort.

Perceptions for the Learning System

In these experiments, the perceptions to be learned come from the following sensors:

- The 3 distance sensor values: distance, distanceNear, and distanceChest. These sensors react to the closeness of objects
- The 4 contact sensors of the robot: headSensor, backSensorF, backSensorM and backSensorR.
- The average colour channels (R, G, B) of the centre of the camera image, defined as a 20 by 20 square in the centre.

All these sensor values were normalised using the ranges in table 5.2 for the distance and contact sensors. The colour channels were normalised over 255 since they belong to the range [0 ; 255]. These normalised values are then discretized over 10 bins as presented in figure 5.2. The values of these sensors are acquired in real time using the URBI middleware and the handles provided in the table of the sensors 5.2.

These sensors were chosen because they provide a raw global perception of the environment that AIBO is in. Distance sensors give information about the distance of objects in front of the robot, and the colours of the image provide another property that varies when the robot moves or explore. It was decided not to use the microphones of the robot since the robot itself makes a lot of noise when moving, even if just the head is moving[1]. These

[1] An earlier implementation of the system used the microphones and processed a fast Fourier transform to identify the main fundamental frequency in the last sound heard. As a result, when the robot would start moving to explore it would immediately stop due to the noise the joints produce when moving.

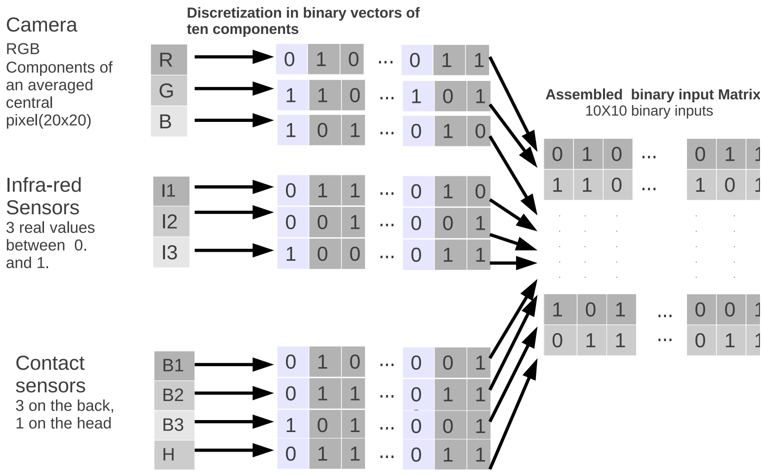


Figure 5.2: Processing stages for the construction of the 10x10 binary matrix of the sensor inputs. The input used for the modalities are the image from the camera (from which the means of the three colour channels within square of 20x20 pixels located at the centre of the field of view is calculated, producing one integer 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.

choices provide features that can be easily manipulated in the environment by putting different coloured objects at various distances of the robot.

The binary matrix $P(t)$ from the processing described in figure 5.2 is used by the Learning System as presented in section 4.5 in chapter 4.

Perceptions for the *comfort*

The Comfort System receives two different inputs: the value of the sensors on the back of the robot (to evaluate $C_h(t)$, the amount of proximal comfort), and the presence of a face in the visual field (to evaluate $F_h(t)$, the distal comfort). The proximal comfort is evaluated using the three sensors on the back of the robot: backSensorF, backSensorM and backSensorR. Then, $C_h(t)$ is set to 1.0 whenever one of these sensors is active.

The detection of a face requires the camera image and the use of a dedicated face detection algorithm. The algorithm used was implemented using the OpenCV library, and is one of their example algorithms [2]. This OpenCV module uses an algorithm developed by Viola and Jones (2001). The algorithm is fast and runs on a usual normal specification computer in under 100 millisecond for an image the size of the one provided by AIBO. The OpenCV module returns a Boolean f signifying the presence of a face, and two (x, y) $((0,0) being the center of the image)$ coordinates in the image if a face is detected. In addition, the size of the face relatively to the size of the image can be estimated. In this implementation and in the experiment, only the Boolean was used. When $f(t) = 1$ then the variable $F_h(t)$ is set to its non-zero value, which was set to 0.2 (see section 4.5 in chapter 4). This value, lower than the one for the proximal comfort, is set so that the robot would stop searching for a face and return to attending the stimuli.

5.3.3 Regulatory and Exploratory Behaviours

A small set of behaviours were implemented for AIBO robot. Following the requirements of chapter 4, the robot needs to be able to look for the caregiver and signal high arousal levels with vocalisations (See 4.6). To that end, simple two regulatory behaviours were designed.

- "Bark": the robot plays a wav file "bark.wav" (provided with the Urbi middleware) using every(5s): speaker.play("bark.wav")
- "Search Face": the head of the robot pans the upper region using the following Urbi command: headTilt.val= 30 time:0.5s; headPan.val= -20 sin:10s ampli:90;

[2] See the OpenCV tutorial on object detection http://docs.opencv.org/doc/tutorials/objdetect/cascade_classifier/cascade_classifier.html

The "Bark" behaviour is active when the instantaneous arousal is higher than the threshold $Ai_{high} = 0.7$. The robot then "barks" every 5 seconds to attract the attention of the caregiver. The "Search Face" behaviour scans the upper region of the visual field so that the robot can find the human even if he/she is standing. The head moves from right to left with a 10 seconds period. This speed allows for the robot not to miss the face and for the image to still stay stable for the face detection algorithm to function properly. This behaviour is active when the sustained arousal is higher than the predefined threshold $As_{high} = 0.6$.

The exploratory behaviour designed makes the robot turn to the right on the spot. This was chosen so that the robot goes through a cyclic exploration of the environment, and that the perceptions it processes are similar in all conditions, as opposed to using a random walk. The behaviour uses a primitive from the URBI middleware, $turn(time)$, where $time$ is the duration of the movement. In the experiments presented below, the robot would turn for 1.5 seconds every two seconds. This allows the robot a 0.5 to assess the perceptions in front of it. When the levels of arousal of the robots are neither higher nor lower than the defined thresholds, the robot interrupts the ongoing behaviours and remains still.

In addition to these behaviours, during the entire experiment, the LEDs situated on the head of the robot were flashing according to a sinusoidal wave proportionally to the sustained arousal level (which is used to modulate the intensity of the LED), slowly when not stimulated, faster when stimulated, and then flashing fast when the robot is overexcited [3].

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

5.4 Experiments

5.4.1 Experimental Setup and Research Hypotheses

During the experiments, the robot was placed in the middle of a wooden arena on a children's play mat as can be seen in figure 5.3. Several large and colourful objects were placed so that the robot can react to their features. The robot was connected via WIFI

Figure 5.3: The experimental setup. An AIBO robot was placed on a children's play mat in a wooden arena where several toys and large objects can be perceived.

to a nearby computer to process the perceptions and for the control system to send the behaviour to be executed. The whole algorithm was bounded to run in 100 ms per iteration. All the perceptions and variables of the system are then updated at a rate of 10 Hz. In addition, both neural network algorithms were initialized with the same random seed for their initial synaptic weights to guarantee that this parameter in the architecture is constant. Every run presented below unfolded in the same manner. The robot would start from the same initial position in the arena in front of the big red cylinder. The robot triggers regulatory behaviour since the perception is new to the Learning System. The human experimenter then soothes the robot a first time until it starts exploring. After this first intervention, the experimenter only responds depending on the "caregiving" style based on the responsiveness. During different runs, the experimenter changed its response time in relation to the requests of the robot. It has to be noted that the parameter of the Comfort System β_{comf} was set to 0.1 during these experiments. The other parameters of the model are the ones presented in chapter 4: $\tau_{inst} = 30$, $\tau_{sus} = 10$, $As_{high} = 0.6$, $As_{low} = 0.4$, $Ai_{high} = 0.7$.

The main hypothesis to be tested was that the responsiveness of the human has a measurable influence on the learning outcome and the exploration pattern of the robot. The experiments carried out aimed at assessing how the behaviour of the robot varied depending on the responsiveness of the human and how the learning algorithm reacted to these different caregiving styles. To assess this hypothesis, the following variables of the architecture were logged for analysis:

- The arousal levels of the robot A_{sus} and A_{inst};
- The Stimulation $Stim$, and the evaluation measures: the recall error Err and the synaptic variation Cat;
- The distance $WinDist$ between the synaptic weights of the winning neural unit of the SOM and the current perceived pattern from equation 4.13;
- The instantaneous variation of the pattern of input $P(t)$ (i.e.: $\Delta_P = P(t) - P(t-1)$)
- The patterns P to account for the number of uniquely different patterns the robot perceives $Unique(P)$
- The behaviours executed by the robot to evaluate the amount of exploration (Exp),

regulatory behaviour (*Search*), and attention to the current pattern of stimuli (*Attend*) each as a percentage of time over the whole run

- The intervention of the human through C_h and F_h (the values of the proximal and distal comfort)

All the runs presented below lasted 5 minutes, during which the experimenter tried to respond to the requests of the robot with an even response time.

5.5 Results of the Variation of the Responsiveness of the Caregiver

5.5.1 High Responsiveness

The run presented here features the interaction previously described with the experimenter displaying a high level of responsiveness. To behave so, the experimenter stays in front of the robot almost constantly and immediately responds to any regulatory behaviour such as "Bark" and "Search Face".

Figure 5.4 shows the variations of the arousal sustained, instantaneous arousal, and comfort during the run. We can see that the comfort plot shows a very high frequency and that the arousal oscillates extremely fast. Figure 5.5 shows the behaviours produced during the run. We can see the rapid interventions of the caregiver, where every "search" behaviour is quickly followed by some contact. Moreover, we can see how quickly the robot switches between the three types of behaviours at first, and then spends more time "Attending" to the pattern which indicates that the robot has become more familiar with the patterns and that some do not elicit so much novelty. During this run, the average levels of the measures described above were the following:

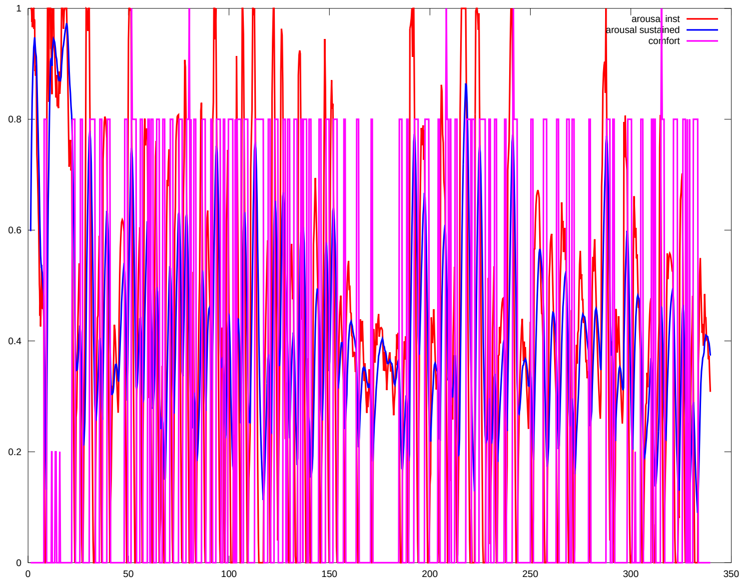


Figure 5.4: Arousal levels and Comfort variations of the robot during an interaction with a caregiver with a "high responsiveness"

- $A_{sus} = 0.422$
- $A_{inst} = 0.421$
- $Comf = 0.3$
- $Stim = 1.38$
- $Err = 1.44$
- $Cat = 0.091$
- $WinDist = 0.12$
- $\Delta_P = 0.042$

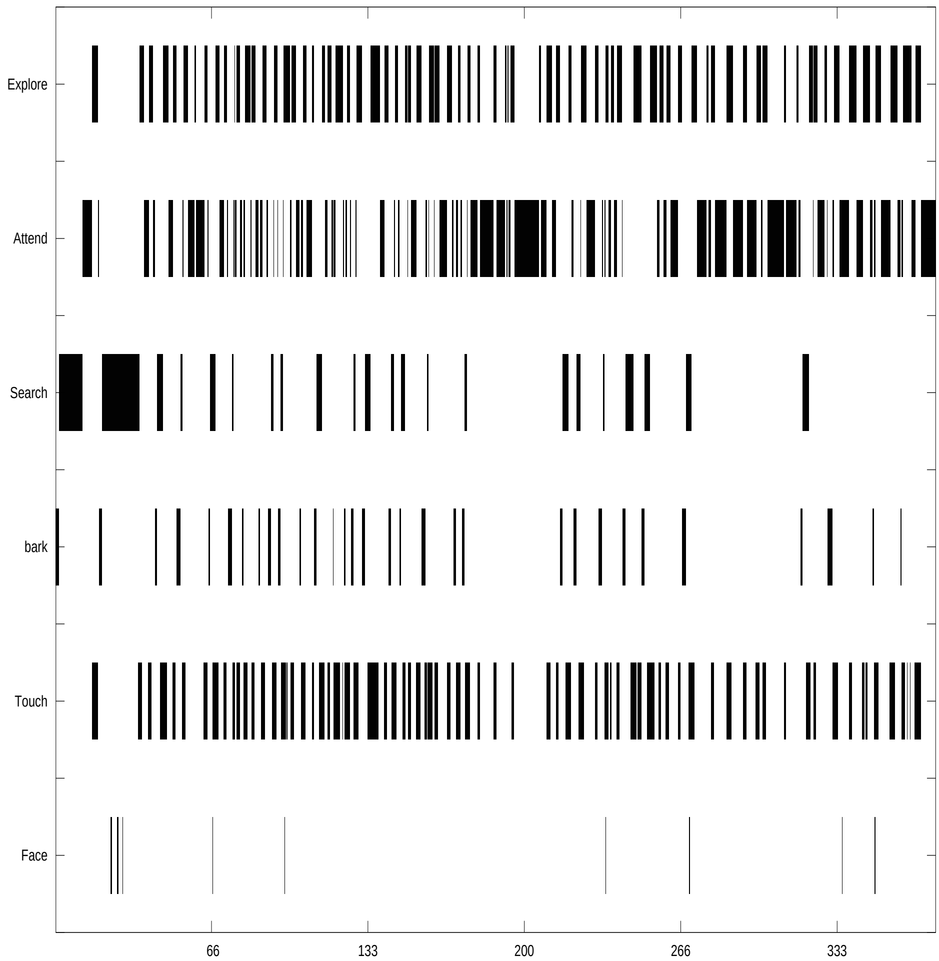


Figure 5.5: Behaviours produced by the robot during an interaction with a caregiver with a "high responsiveness", touch and face presence

- $Search = 0.16$
- $Expl = 0.35$

- $Attend = 0.39$
- $C_h = 0.32$
- $Unique(P) = 771$

These values show that the robot spent almost a similar amount of time between exploring and attending to stimuli ($Expl = 0.35$ and $Attend = 0.39$), and 15% of its time looking for the caregiver. The other quantities will be compared to runs with a different responsiveness.

5.5.2 Medium Responsiveness

The run presented here features the interaction previously described with the experimenter displaying a lower level of responsiveness. To behave so, the experimenter replied less often and less quickly to the requests of the robot.

Figure 5.6 shows the variations of the arousal sustained, instantaneous arousal, and comfort during the run. We can observe the diminished frequency of the occurrence of comfort. Figure 5.7 shows the behaviours produced during the run. We can see the rapid interventions of the caregiver, where every "search" behaviour is quickly followed by some contact. We can also see that the robot spends more time "Attending" than in the previous run, which is confirmed by the measurement of the behaviour. During this run, the average levels of the measures described above where the following:

- $A_{sus} = 0.48$
- $A_{inst} = 0.47$
- $Comf = 0.12$
- $Stim = 0.9$
- $Err = 1.01$

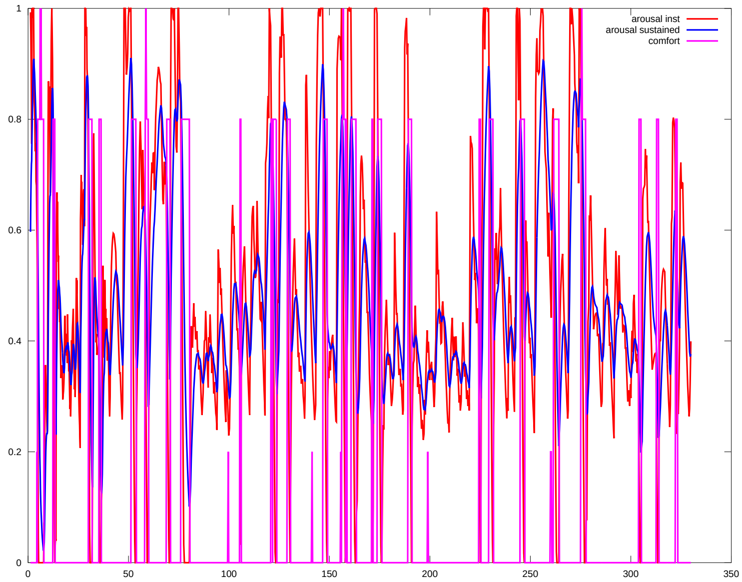


Figure 5.6: Arousal levels and Comfort variations of the robot during an interaction with a caregiver with a "medium responsiveness "

- $Cat = 0.0072$
- $WinDist = 0.029$
- $\Delta_P = 0.040$
- $Search = 0.21$
- $Expl = 0.22$
- $Attend = 0.58$
- $C_h = 0.21$
- $Unique(P) = 541$

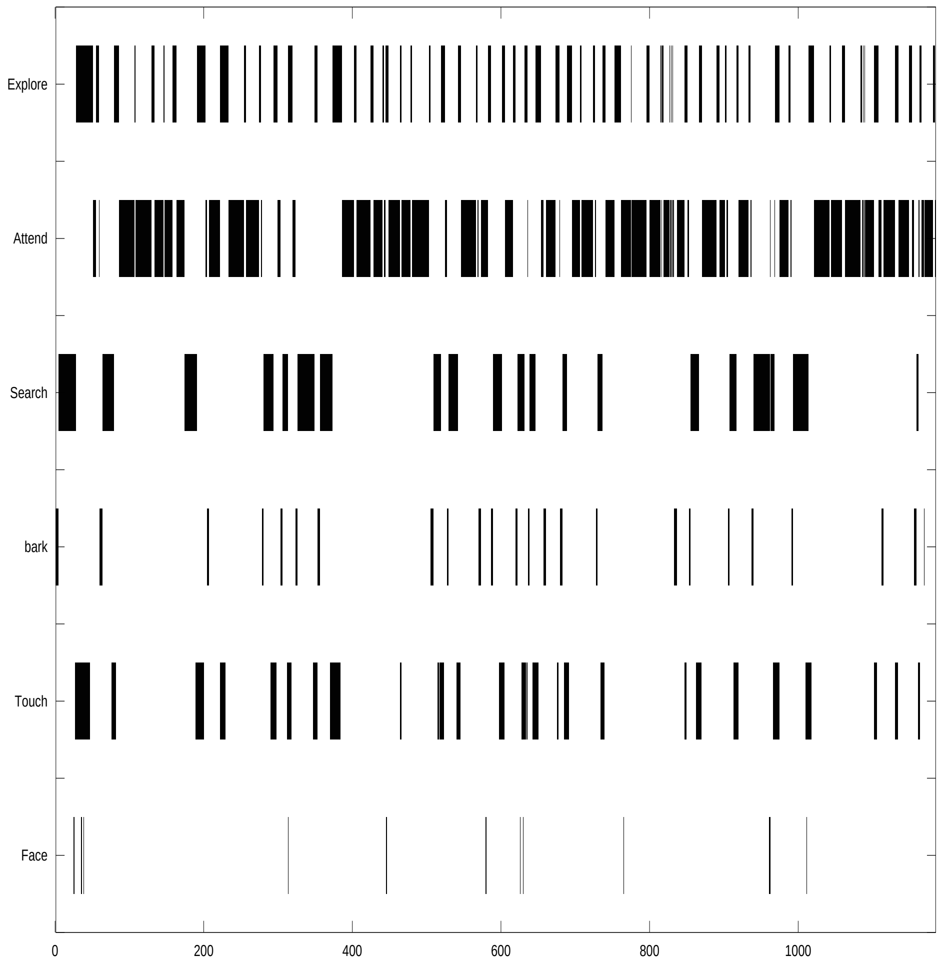


Figure 5.7: Behaviours produced by the robot during an interaction with a caregiver with a “medium responsiveness ”, touch and face presence

One main difference is first in the behaviours ($Expl = 0.22$ and $Attend = 0.58$), where the robot spend the majority of its time attending to patterns in specific locations, and spent 21% of its time looking for a caregiver. Moreover, the robot has perceived fewer unique patterns (541 in this run against 771) than with the highly responsive caregiver. This also leads to a lower distance $WinDist$ (0.029 in this run against 0.12 with the highly responsive caregiver). The robot also experienced a higher level of arousal though not a higher level of stimulation. The average recall error Err and Cat values are also lower than in the run with the caregiver a high responsiveness. The instantaneous variation $\Delta = 0.04$ is marginally lower than in the case of the highly responsive caregiver too.

5.5.3 Low Responsiveness

The run presented here features the interaction previously described with the experimenter displaying a very low level of responsiveness. To behave so, the experimenter seldom responded to the requests of the robot. The experiment would intervene after a very long period if the robot would not move on to explore on its own. Figure 5.8 shows the variations of the arousal sustained, instantaneous arousal, and comfort during the run. We can observe the seldom occurrence of comfort. Figure 5.9 shows the behaviours produced during the run. We can observe that the robot spends longer periods of time looking for the caregiver and long periods where it attends to the stimuli. During this run, the average levels of the measures described above where the following:

- $A_{sus} = 0.57$
- $A_{inst} = 0.57$
- $Comf = 0.019$
- $Stim = 0.71$
- $Err = 0.84$
- $Cat = 0.059$

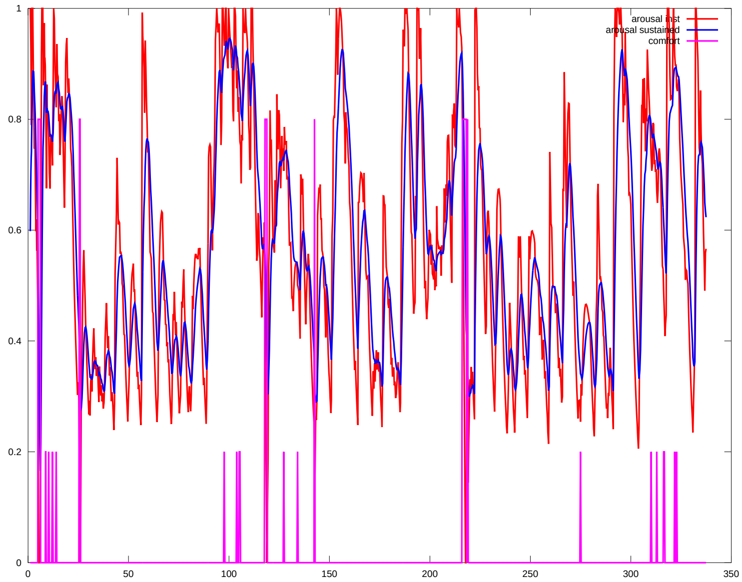


Figure 5.8: Arousal levels and Comfort variations of the robot during an interaction with a caregiver with a "low responsiveness "

- $WinDist = 0.064$
- $\Delta_P = 0.038$
- $Search = 0.39$
- $Expl = 0.11$
- $Attend = 0.45$
- $C_h = 0.020$
- $Unique(P) = 374$

Again, the time spent in each behaviour is different ($Expl = 0.11$ and $Attend = 0.45$), where the robot spends again the majority of its time attending to patterns in specific

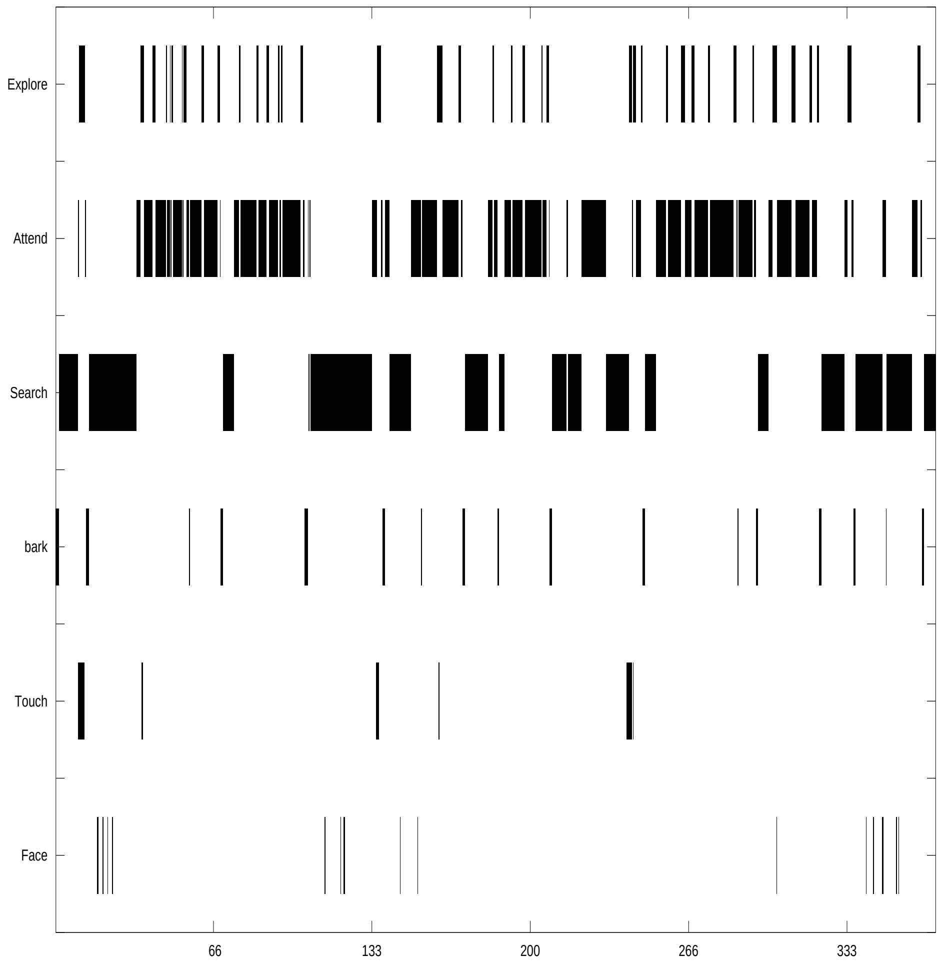


Figure 5.9: Behaviours produced by the robot during an interaction with a caregiver with a “low responsiveness ”, touch and face presence

locations, and spent 39% of its time looking for a caregiver. Moreover, the robot has perceived even fewer unique patterns than in the two previous runs (374 in this run against 771 for the high responsiveness caregiver, and 541 for the medium one). However, the distance between the SOM winning node and the perceived pattern $WinDist$ is higher than in the medium responsiveness case and lower than the high responsiveness one (0.064 for low responsiveness against 0.029 for the medium one and 0.12 with the highly responsive caregiver). It also met less stimulation than in the previous two cases.

5.6 Discussion

The architecture used in this experiment allows a robot to explore an unknown environment as a function of the dynamics of its interactions with the caretaker and the behaviour of this latter. Using such a low-level architecture, the outcomes of every experiment are different depending on the responsiveness of the human.

The results show that the "responsiveness" of the human has a differential measurable effect first on the behaviour of the robot. This is partially a consequence of the design of the model and the selection of the behaviours. Indeed, in the case of a highly responsive caregiver, the robot will meet a new pattern of stimuli or a sequence of them while exploring, then trigger a regulatory behaviour. The time spent exploring, attending to a pattern and searching for a human are consistent with the behaviour of the human. A higher responsiveness leads to more exploration episodes and also encountering more varied and unique patterns. This caregiving style also leads to a higher level of stimulation as a consequence of the fast alternation between exploration, attending and short periods of regulatory behaviours. This caregiving style leads to a more varied learning experience in terms of number of patterns encountered, however, it leads to less depth in the learning outcome of the SOM, as the $WinDist$ measure shows. If the caregiver intervenes immediately, the robot spends less time learning the pattern, hence the higher $WinDist$ value for the interaction with highly responsive caregiver. This leads to a cycle of what can be called a more shallow learning, and in itself drives the robot to more frequent regulatory behaviours in the long run. Since the patterns are not learned in depth, the next time they will be presented to the robot they will most likely increase the arousal level enough for another regulatory behaviour to be triggered.

The $WinDist$ measure was the lowest in the case of a caregiver with a medium responsiveness style. This can be explained by the fact that the amount of time the robot spent in front of some stimuli was sufficient for the SOM to adapt its weights almost fully. Therefore, the winning neural unit was more adapted to the pattern than with the two other caregiving styles. The interaction with a caregiver with a lower responsiveness resulted in a higher value of this measure. This is probably due to the longer duration of the "Search" behaviour, where the robot would scan the upper visual field to look for the human. Since the head of the robot is constantly moving, the pattern it tries to learn varies frequently and therefore does not allow the SOM to learn these new patterns deeply.

The use of the two levels of arousal A_{inst} and A_{sus} can be put in question. During the experiments, the barking of the robot would occur slightly earlier (a couple of seconds) than a "Search" behaviour. The behaviour and the two arousal levels have been kept for the study with naive users presented in chapter 6 since this study was organised closely to the completion of the work presented here. However, in chapter 7, where the architecture was used on an Aldebaran NAO robot learning features of objects on a table, the arousal system only used the A_{sus} variable to control the "Search" behaviour. Vocalisations were not needed due to the face-to-face nature of the setup.

Concerning the behaviours the robot uses, the regulatory ones implemented present some benefits and limitations. First, the behaviour "Search" is rarely successful at finding a face in the visual field as we can see in the logs of the behaviours. This is due to the actual behaviour of the experimenter, the fact the robot only scans in front of it and does not walk or turn in case this search fails. This behaviour was still kept as such in the following chapters. First, in chapter 6, adult subjects interacted with the same architecture in a freer setting. They could lift and move the robot and the feedback of the robot stopping to search when it faces the human could be beneficial. Second, in chapter 7, the setting itself is designed for the robot to face the human, if he/she is present. The robot is placed in front of a table and the human is standing or sitting on the other side.

Additionally, we can question to what extent this arousal-driven model of attachment interactions 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 behavioural sciences. It is indeed important to assess the relevance of the models against the phenomenology that inspired them. In the study presented here, it can be argued that the behaviour of the robot was designed 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. Second, 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. Comparing the model and the behaviours it produces to the phenomena presented, it can be argued for the relevance of our model in the sense described in (Webb 2001). Indeed, the model yields 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. The results do not support a close biological model in terms of realism (using Webb's terminology (Webb 2001)). Moreover, the learning structures themselves are only classifying and recalling preprocessed input patterns, without any physical interaction with the objects they represent, or any active trial and error exploratory approach.

5.7 Summary

This chapter presented a series of experiments with an autonomous robot endowed with the architecture presented in chapter 4. The robot tried to learn the features of the perceptions of the environment and exhibited regulatory behaviours when its arousal levels were high and sustained. The architecture was evaluated with the experimenter playing the role of the caregiver, and displaying three different caregiving styles based on the variation of his responsiveness. The evaluation of the results supports the initial hypothesis that the behaviour of the human partner influences the learning outcome of the robot. The following conclusions can be reached from this experiment.

- A caregiver with a high responsiveness drives the robot to learn more varied patterns but in a more shallow manner than with a less responsive caregiver;
- An extremely low responsive caregiver leads the robot to encounter less varied stimuli and it does not learn them as deeply as with a caregiver with medium responsiveness;
- The model of attachment designed and operationalized in the architecture produces patterns of behaviours consistent with the behaviour of the human in terms of responsiveness;

Therefore, this architecture and the model its derived from can offer benefits to a human-robot dyad where a robot is learning about its environment. First, the human can control when and what the robot learns by either letting the robot attend some situation longer, or by providing comfort quickly so the robot explores some new area of the environment. Extending the interaction to a more capable robot in terms of locomotion and learning capacities, this model could lead to some implicit personalisation of the development of the robot. Indeed, a human caregiver might be more inclined to let the robot cope with a situation he/she wants the robot to learn or master, and may provide earlier comfort and promote earlier withdrawal from situations of either low or no interest to him/her.

The following chapter will endeavour to assess how naive adults subjects perceive and interact with the AIBO robot endowed with this architecture.

Chapter 6

Human-Robot Caregiving Interactions with Naive Users

6.1 Outline

This chapter presents a human-robot interaction study conducted at the London Science Museum with "naive" (or non-expert) adult subjects. The aim of the study was to assess how adults interact and perceive the AIBO robot endowed with the architecture presented in Chap. 5. The subjects interacted twice with the robot, once with a robot with a "needy" regulatory profile, and once with an "independent" regulatory profile. These two profiles were presented in a counter-balanced manner. The evaluation of the interaction was achieved through feedback questionnaires after each interaction, and analysis of the video recordings. To evaluate if the regulatory profiles of the robot were perceived for what they were designed, the questionnaires recorded the subjective ratings of autonomy of the robot, enjoyment and ease of interaction. To assess whether the regulatory profiles elicited different behaviours or caregiving styles, the annotation of the videos focused on the affective behaviours produced by the subjects. The results suggest that the subjects all enjoyed and were engaged in the interaction. The subjects also reported preferring to interact with the "needy" robot, which timely behaviour was more coherent with the interaction. The results show no major negative behavioural tendencies, indicating that the architecture and its dynamics was acceptable and useful in fostering a similar interaction than the one where an in-lab experimenter played the role of the caregiver.

6.2 Contributors and funding bodies

The work reported in this chapter was part of the FEELIX GROWING project for the second workpackage "FEEL". The experimental protocol, questionnaire, and video annotation were done with the help of Prof. Kim Bard and Dr. Marina Davila-Ross from Portsmouth University, and with the supervision of Lola Cañamero. The experiment was carried out in the London Science Museum, with the help and coordination of Louis Buckley to whom I am indebted. The logistics of the experiments were also supported by Sven Magg and Nicolas Oros. The experiments were carried out by myself.

6.3 Experimental Setting for Caregiving Interactions

As seen in chapters 4 and 5, the architecture provides a means to vary the effect the comfort produces on the arousal of the robot, therefore varying the frequency of the regulatory behaviours depending on the novelty and stability of the perceptions of the environment. To provide us with two clearly different regulatory profiles, the decay rate of the comfort β_{comf} and therefore the lasting decreasing effect of the comfort on the arousal sustained can be manipulated. The following equations from chapter 4 were used again:

$$Comf(t) = \begin{cases} C_h(t) + F_h(t) & \text{if } C_h(t) > 0 \text{ or } F_h(t) > 0 \\ \beta_{comf} \cdot Comf(t-1) & \text{otherwise} \end{cases} \tag{6.1}$$

$\beta_{comf} = 0.995$ and were chosen for the "independent" robot, and $\beta_{comf} = 0.95$ for the "needy" robot. Their dynamics can be seen in chapter 4, section 4.3.2. With a 10 Hz update cycle, the "needy" profile will exhibit at most a regulatory behaviour every 10 seconds, while the "independent" profile will request help only every 50 seconds. Therefore, the robot with the "independent" profile will *appear* not to need attention. Since the comfort $Comf$ reduces the arousal of the robot for a longer time than in the "needy" case, even a low frequency of contact would lead to a robot with a sustained arousal always below the lower threshold, therefore looking for new stimuli by turning even with a constant variation of the inputs to its sensors.

6.3.1 Research Questions, Hypotheses, and Measures

The experiments carried out with naive users aimed at assessing how humans engage with the robots and perceive them depending on their profile. Additionally, this experiment allows insights on the metrics that can be used to evaluate such interactions. Since no similar experiments were carried out before, a dedicated questionnaire was designed providing subjective ratings of the perception of the robot. This exploratory study permits to assess the suitability of such a questionnaire for human-robot caregiving interactions. In addition, a set of behaviours related to the affective interactions of the humans with the robot were selected. Their purpose is to evaluate how the perception of the robot and the actual behaviours observed are distinctively different with each interaction with a different profile. The following hypotheses were assessed:

- The main 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. If true, this difference should be reflected by the rating from the subjects and the observations of the behaviours produced by the human

- The "needy" profile should be rated as requiring more help than the "independent"
- During interactions with the "independent" robot, less positive affective behaviours from the human should be observed, and less comfort provided

6.3.2 Experimental Setup and Protocol

The experiments were carried out over 3 days at 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 the loud noise and the public watching, which may hinder the freedom of the participants who may be self-conscious of other people watching while interacting with the robot. The subjects were sitting on the play mat, on which toys and colourful objects had been placed, then briefed as described below. The group of subjects consisted of 21 adult (5 males and 16 females), aged between 19 to 60 years ($mean = 33.4$ and $std = 11.7$). The interactions were video recorded, and as well as the data related to the real time values of the stimulation (*Surprise* and *Categorisation adjustment*) the robot experienced, and the comfort provided to it during the interaction. The subjects were of different ages, gender, and self-rated parenting experience. The demographic data from the recruited subjects (age group, gender, parenting, and self-rated experience with children) can be found in the table B.1 in appendix B.

The experiment received favourable approval from the University of Hertfordshire ethics board, under approval number 0809/107. After signing an informed consent form, the subjects were given the following text as an 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's 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 over aroused 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 excitement 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 additional directives given to the subjects concerning the capabilities of the robots were the following:

- the LEDs on the head of the robot 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
- over-excitement 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 of the robot. The robot was standing on the play mat as in Fig. 6.1. 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 filled in the questionnaire about the last robot. The presentation of the profile of the robot was counter-balanced. Half of the subjects interacted with the "needy" robot first and then with the other robot. Half of the subjects interacted with the "independent" robot first. The subjects were not told the difference between the two profiles of the robot. Instead, they were told that the robots had different characters, as different infants or animals might.

Figure 6.1: Experimental setup at London Science museum. The AIBO robot was placed on the play mat in the foreground and the subjects were sat on it whilst interacting with the robot. The objects and toys were used by the subjects to stimulate the robot.

6.3.3 Questionnaire

After interacting with each robot, the subjects answered the following questions using a five points Likert scale. The questionnaire used can be found in appendix B and the questions are presented below.

Questions and Associated Hypotheses concerning the profiles

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. The hypothesis is 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". It was 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. The hypothesis is 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. 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. The hypothesis is 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 feeling arising if they did not know what to do during the interaction. The hypothesis is 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 terms of neediness and independence. Naturally, the hypothesis is that the “independent” robot would get a much higher rating than the other robot. The questionnaire was tailored especially for the interaction designed and therefore was not inspired by the literature. However, the questionnaire presents some similarities to the one described developed and used by Bartneck and Forlizzi (2004). The authors endeavoured to use this questionnaire to guide the design of social robots, and to be used as a framework to classify and compare them. They used five properties: form, modality, social norms, autonomy, and interactivity. All properties are presented on a continuum with three word anchors, one at the lowest extreme, one in the middle of the continuum, and one at the other extreme. The property of form ranged from “abstract”, “biomorphic” to “anthropomorphic”. This property is not of strong interest to the investigation since the study does not provide alternative embodiments. However, one interesting conclusion of the authors’ work is that the form of the robot should match its capabilities. The experimental setup conforms with this requirement in the sense that the AIBO robot is dog-shaped and therefore should not be expected to interact verbally or exhibit complex cognitive capabilities. The second property they investigate is the “modality”, defined as the number of communication channels the robot can use to and ranges from unimodal to multimodal. The third property is the one of “social norms”, measured from “no knowledge of social norms”, “ minimal knowledge” to “full knowledge”. Both these properties are interesting for the design of social robots however do not bear importance to the assessment of the interaction and acceptance of the regulatory profiles designed. The authors describe autonomy as “having the technological capabilities to act on behalf of humans without direct input from humans.”. Autonomy is measured on a continuum from no autonomy, some autonomy, to fully autonomous. In the questionnaire used in the study presented in this chapter, autonomy was rated on a five point Likert scale ranging from very needy to very independent. Also, the rating of autonomy used in the study presented in this chapter is used to assess how the subjects perceived how the robot was able to cope on its own, and not act on behalf of a human. As this point could be ambiguous, the question added concerning the willingness to assist was designed to offer another alternative to rate the autonomy of the robot from the perspective of the human. The rating of the subjects' willingness to assist reflects the subjective feeling of the need to intervene, therefore can be seen as a second rating of some other form of autonomy or independence. This item should be inversely correlated with a level of the reliance on the human which corresponds more to the "needy" profile.

6.4 Results

6.4.1 Results from the questionnaires

This section presents the results of the questionnaires filled in by the subjects after each interaction. The following tables 6.1 and 6.2 summarise the answers to the six questions presented above for the "needy" and the "independent" one respectively, and present the mean and standard deviations of each ratings.

Table 6.1: Frequencies of each responses item to the questionnaire for the robot with the "needy" regulatory profile, mean and standard deviation.

Dependent variable	1	2	3	4	5	mean	std
Enjoyment	0	3	3	**9**	6	3.86	1.01
Reactivity	0	4	**7**	**7**	3	3.43	0.98
Predictability	0	**8**	**8**	3	2	2.90	0.88
Willingness to assist	1	3	3	**11**	3	3.57	1.08
Ease to interact	1	4	5	**6**	5	3.47	1.21
Autonomy	2	**8**	5	4	1	2.67	1.06

The presentation order of the two profiles of the robot did not produce any significant effect on any of the measures. The analysis of the experimental conditions was carried out using the Wilcoxon signed rank test, as is appropriate for ordinal data of paired samples from questionnaires using a Likert scale. The analysis of the effect of the order did not reflect any confound between subjects having interacted first with the "needy" robot or

Table 6.2: Frequencies of each responses item to the questionnaire for the robot with the "independent" regulatory profile, mean and standard deviation.

Dependent variable	1	2	3	4	5	mean	std
Enjoyment	2	**8**	6	4	1	2.71	1.06
Reactivity	6	**9**	2	4	0	2.17	1.04
Predictability	3	**12**	2	1	3	2.48	1.25
Willingness to assist	3	4	**6**	**6**	2	3.00	1.22
Ease to interact	6	**9**	5	0	1	2.09	0.99
Autonomy	2	2	5	4	**6**	3.57	1.29

with the "independent" one. The results of the statistical anaysis are summarised in Table 6.3.

Table 6.3: Summary of the statistical analysis of the results of the questionnaire. questionnaire and the data recorded from the robot (N=21). The analysis was performed using the Wilcoxon signed rank test.

Dependent variable	"Needy" robot	"Independent" robot	Z score and significance
Enjoyment	3.86 (1.01)	2.71 (1.06)	$Z = -3.46,\ p = 0.001$
Reactivity	3.43 (0.98)	2.17 (1.04)	$Z = -3.13,\ p = 0.002$
Predictability	2.90 (0.89)	2.48 (1.25)	$Z = -1.44,\ p = 0.150$
Willingness to assist	3.57 (1.08)	3.00 (1.22)	$Z = -1.82,\ p = 0.069$
Ease to interact	3.48 (1.21)	2.09 (0.99)	$Z = -3.35,\ p = 0.001$
Autonomy	2.67 (1.06)	3.57 (1.29)	$Z = -2.24,\ p = 0.025$

As can be seen in the results of the questionnaire, four of the six questions yielded significantly different results between the two conditions. First, the subject rated their enjoyment higher after interacting with "needy" robot compared to the "independent" robot (3.86 for the "needy" against 2.71 for the "independent", $Z = -3.46,\ p = 0.001$). This rating confirms the hypothesis that interacting with the robot with the "needy" profile would be more enjoyable. Concerning the properties of the robot, all ratings besides the one concerning the autonomy are higher for the robot with "needy" profile, which confirm the all but one initial hypotheses concerning the rating of both profiles. However, some of them do not reach statistical significance after analysis.

Each measures compare as follows in the two conditions:

- The reactivity of the robot was rated higher for the "needy" robot than the "independent" one (3.43 for the "needy", and 2.17 for the "independent" $Z = -3.13,\ p = 0.002$). The hypothesis concerning this item is thus confirmed by the data analysis.
- The predictability was rated higher for "needy" robot, which contradicts the initial hypothesis. It was hypothesized that the "independent" profile would rate higher since it mainly explores the environment and requires little interaction, however the analysis reveals that there is no statistical difference between the two profiles (2.90 for the "needy" against 2.48, with $Z = -1.44,\ p = 0.150$).
- The willingness to assist was rated higher for the "needy" robot however not reaching statistical significance (3.57 for the "needy" against 3.00 for the "independent", with $Z = -1.82,\ p = 0.069$)
- The ease to interact measure was rated significantly higher with the "needy" robot as hypothesized (3.48 for the "needy" and 2.09 for the "independent", with $Z = -3.35,\ p = 0.001$)
- The autonomy of the robot was rated significantly lower for the "needy" robot, confirming the initial hypothesis about the profiles designed (2.67 against 3.57 with $Z = -2.24,\ p = 0.025$)

6.4.2 Results per Subjects Group

This section provides the results of the investigation of variations of the subjective ratings depending on factors like the age group (9 were aged less than 30 years old, 12 were aged 30 years old and above), parenthood (7 of the subjects declared being parents), and gender. The data was analysed using the Mann-Whitney test as is appropriate for comparing ordinal data against an independent variable. The self-rated experience with children measure did not yield any significant difference. Below are the results for each group which yielded any statistically significant difference:

- Gender (5 males, and 16 females): two measures showed significant differences depending on the gender of the participant. First, the enjoyment during the interaction with the "needy" robot shows a statistically different interaction (mean for females: 3.6, and for males: 4.6, $U = 17.5$ and $p = 0.049$). During the interaction with the robot with the "independent" profile, males rated the reactivity of the robot lower than females (mean for females 2.37, and for males 1.4, with $U = 15.5$ and $p = 0.033$). Finally, the predictability of the "independent" robot was rated higher by male subjects (mean for females: 2.15 and for males: 3.6, with $U = 18.$ and $p = 0.043$). This results should be taken with caution since the sample was clearly imbalanced concerning this factor.

- Age group (subjects split between younger than 30 or not; 12 older and 9 younger than 30 years of age): This factor only influenced the ratings of the "independent" robot. First, the reactivity of the robot was rated higher by subjects older than 30 years of age (mean for older subjects: 2.41 and 1.77 for other subjects, with $U = 27.0$ and $p = 0.043$). Younger subjects rated its predictability higher than older subjects (mean for older subjects: 1.91, and 3.22 for younger subjects, with $U = 28.0$ and $p = 0.040$). Finally, the autonomy of the "independent" robot was rated significantly lower by older subjects (mean for younger subjects: 4.33 and 3.00 for older subjects, with $U = 21.5$ and $p = 0.017$).

- parenthood (7 subjects declared being parents, 14 did not): Once more, only the measures concerning "independent" showed any significant interactions. Subjects being parents rated the reactivity of the robot higher than the other subjects (mean for parents: 2.71, others: 1.85, with $U = 22.00$ and $p = 0.033$). The autonomy of the "independent" robot showed a barely significant difference (parents' mean: 2.71, others 4.0, with $U = 23.5$ and $p = 0.05$).

Statistical differences in group ratings mostly concerned the "independent" robot besides a lower enjoyment reported by female subjects with "needy" robot. The data does suggest that the "independent" profile was perceived differently depending on age, gender and other factors. A point which will be later discussed.

6.4.3 Comfort and Stimulation of the Robot

In addition to questionnaires, the Stimulation and Comfort received by the robot were recorded. Both these values are averaged over the whole duration of the interaction. Both quantities were significantly different between the two conditions following the Wilcoxon test results. First, the comfort received by the robot was higher in the condition were the subjects interacted with the "needy" robot than the "independent" one (mean and standard deviation for "needy": 0.22 (0.32); for the "independent": 0.12 (0.06), with $Z = -2.33$ and $p = 0.02$). On average the "needy" robot received more comfort than the "independent" robot. As for the Stimulation, the average between the synaptic variation of the SOM and the recall error of the associative memory, the "independent" robot on average received more stimulation (mean and standard deviation for "needy": 0.11 (0.12); for the "independent": 0.21 (0.17), with $Z = -2.63$ and $p = 0.01$).

6.4.4 Annotation of the video recordings

In addition to the analysis of the questionnaire, the video recordings of the experiments were coded, in order to observe any objective features in the behaviour of the subjects.

An independent coder analysed the videos using the measures described below. The coder had no knowledge of the functioning of the architecture or the research hypotheses. This analysis of the behaviour of the subjects attempts to show objectively if the profile of the robot influences the engagement and the positive affect the human partner. 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 due to the interaction being located in a corner and only one camera could be set up. This is the reason why facial expressions of the subjects could not be coded. 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, 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 the 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.

Table 6.4 summarizes the descriptive statistics concerning the behaviours observed during interactions with the “needy”robot, while table 6.5 shows the ones for interactions with the robot with the “independent” profile.

Table 6.4: Results from the annotation of the videos of the interactions with the “needy” robot. For each behaviour, the table presents the mean, standard deviation, minimum and maximum of the number of occurence of each behaviour. Additionally, the last two measures are the sum of each affectively positive (affective touch and gesture) and negative behaviours (restricting touch and aggressive handling) respectively.

Behaviour	Mean	std	Minimum	Maximum
pickup	0.35	0.59	0.00	2.00
affective gesture	2.10	2.53	0.00	8.00
affective touch	8.65	4.57	3.00	22.00
request making	2.40	2.23	0.00	7.00
request with toys	2.90	2.17	0.00	8.00
restricting touch	0.50	0.88	0.00	3.00
aggressive handling	0.35	0.67	0.00	2.00
sum positive	11.10	5.59	3.00	24.00
sum negative	0.85	1.42	0.00	5.00

As can be seen in table 6.6, after carrying out the Wilcoxon statistical test on all the behaviours, no sginificant difference was obeserved between the conditions. However, when the coded behaviours were grouped in either positive or negative ones (i.e. affective gestures with affective touch, and restricting touch with aggressive handling), in the last two variables of the tables (sum positive and sum negative), a significant effect between the

Table 6.5: Results from the annotation of the videos of the interactions with the "independent" robot. For each behaviour, the table presents the mean, standard deviation, minimum and maximum of the number of occurence of each behaviour. Additionally, the last two measures are the sum of each affectively positive (affective touch and gesture) and negative behaviours (restricting touch and aggressive handling) respectively.

Behaviour	Mean	std	Minimum	Maximum
pickup	0.58	0.77	0.00	2.00
affective gesture	1.47	1.43	0.00	5.00
affective touch	6.53	2.83	0.00	11.00
request making	2.26	1.91	0.00	6.00
request with toys	2.79	2.32	0.00	8.00
restrictive touch	1.42	1.39	0.00	5.00
aggressive handling	0.42	0.69	0.00	2.00
sum positive	8.58	3.02	3.00	13.00
sum negative	1.89	1.85	0.00	7.00

Table 6.6: Statistical analysis of the observed behaviour of the subjects with the two regulatory profiles. The tables presents the mean and standrad deviation for each profiles, and the results of the analysis, whichs was ran using the Wilcoxon signed rank test.

Behaviour	"needy"	"independent"	Z-score and significance
pickup	0.35 (0.59)	0.58 (0.77)	$Z = -1.02$ $p = 0.30$
affective gesture	2.10 (2.53)	1.47 (1.43)	$Z = -1.18,\ p = 0.23$
affective touch	8.65 (4.57)	6.53 (2.83)	$Z = -1.57,\ p = 0.11$
request making	2.40 (2.23)	2.26 (1.91)	$Z = -0.22,\ p = 0.82$
request with toys	2.9 (2.17)	2.79 (2.32)	$Z = -0.14,\ p = 0.88$
restrictive touch	0.50 (0.88)	1.42 (1.39)	$Z = -2.65,\ p = 0.01$
aggressive handling	0.35 (0.67)	0.42 (0.69)	$Z = -0.33,\ p = 0.73$
sum positive	11.10 (5.59)	8.58 (3.02)	$Z = -2.12,\ p = 0.03$
sum negative	0.85 (1.42)	1.89 (1.85)	$Z = -2.43,\ p = 0.01$

conditions was found. During the interactions with the "needy" profile more positive behaviours were observed than with the "independent" one (means of 11.10 for the "needy" against 8.58 for the "independent" with $Z = -2.12$ and $p = 0.03$). Overall only a few negative behaviours were observed but during interactions with the "independent" profiles more of them were observed (0.85 for the "needy" and 1.89 for the "independent" with $Z = -2.43$ and $p = 0.01$).

6.5 Discussion

In this experiment carried out at the London Science Museum, adult visitors were invited to interact with a robot endowed with the attachment system presented in chapter 4 where the robot could exhibit two opposite profiles, one designed to appear "needy" and one "independent". The evaluation aimed at assessing whether the subjects would interact and perceive the profiles according to their stereotypically opposite design. In addition, it tried to assess whether the items chosen for the questionnaires are suitable to assess such interactions. The results show that subjects were significantly engaged in the interaction following the results of the self-rated enjoyment, with both profiles, and that a significant preference was shown towards the "needy" robot. Moreover, subjects rated correctly the profiles of the robot, significantly with one measure of autonomy, and without significance with the item "willingness to assist" of the questionnaire. On average, they also provided more comfort to the "needy" robot than the "independent" one which can be qualified as a suitable behaviour since it corresponds to what the profiles are designed to elicit. The stimulation measure show that the "independent" robot received on average more stimulation than the "needy" one which is again what the profile was designed for. Finally, the sum of the positive behaviour coded from the video indicate a significant difference between the positive and negative behaviours exhibited, all in accordance with the hypothesis that the "needy" should elicit more positive and caring behaviours. These results support the approach in designing robotic architectures susceptible to induce positive emotions and caregiving behaviour in order to facilitate the learning experience of a developing robot. However, the choice of platform and the special context during which the data was gathered could be responsible for some of 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 artefact, 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. No such decrease was observed in the data. Second, 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 objects to it. Some items of the questionnaire did not confirm the initial hypotheses with statistical significance. The “willingness to assist” was used in order to complement the autonomy rating and did not provide a statistical difference. This might be due to the low size of the sample or because of the phrasing of the question. Therefore, this item might need to be rephrased depending on the setting and the objective of a future experiment. Additionally, the “predictability” item gave results opposite to the predictions. This item was designed to reflect the predictable behaviour of the “independent” robot, which explores for long periods of time whereas the needy robot reacts often to new stimuli and solicits help. However, it seems that subjects interpreted it as correlated with the predictable behaviour of the “needy” robot, which explores for short periods of times then barks and looks for the human.

Some demographic factors played a role in the differences of the ratings of the robot. Considering the size of the sample they also have to be considered with caution. Males tended to rate the profile in a more pronounced way than females concerning the “independent” profiles. No hypothesis concerning this observation was made beforehand, but as indicated in (Feldman 2003), males tend to promote faster arousal cycles, alternating between high stimulation and low ones quickly. This might be a reason why they rated the “independent” profile far less reactive than females and also rated it as more predictable. Older subjects and parents rated the “reactivity” of the “independent” robot also higher than other subjects. Either the item is not interpreted in the same manner or these demographic factors influence the expectation of these subjects. This suggests that some boundaries in the rhythm of interaction that the robot demands could be correlated with these factors. However, a study with a larger sample and possibly a modified setup would be needed to assess this question.

6.5.1 Summary

This chapter described a human-robot study where naive users interacted with robots having 2 different regulatory profiles. On average, subjects interacted appropriately with each profile as reflected by the behavioural observations and their ratings through the questionnaire. To summarise, the model and the ensuing results presented here can be of worth to roboticists and researchers dealing with human-robot interactions during which incremental learning and adaptation to the user's behaviours are desired. For instance, within the field of assistive robotics, such an architecture that facilitates the interaction by providing frequent timely feedback can be helpful to trigger and maintain engagement.

The results support the following hypotheses:

(a) naive (i.e. non-expert) human adults engage positively in such caregiving interactions, if only for a short period of time

(b) the two regulatory profiles lead human adult subjects to engage in caregiving interactions according to the needs and dynamics of the profile

(c) the subjects explicitly recognised and rate the regulatory profiles according to their designed features ("needy" against "independent")

(d) The questionnaire designed can be a useful tool for qualifying such interactions, but its validity needs to be assessed against a larger sample of adults, and probably a longer interaction

This chapter assessed the reactions and perception of adults subjects to the profile of the robot, however, the profiles of the robot were not evaluated in terms of their dynamics depending on the learning task and the complexity of the environment. The following chapter endeavours to evaluate the differences in behaviour they yield depending on the environment and its variability.

Chapter 7

Regulatory Profile Influence on Exploration and Learning

7.1 Outline

This chapter presents the study of the influence of the regulatory profiles of the robot on the exploration and learning experience of a new environment. The robot is endowed with the same regulatory system developed in chapter 4 and with two regulatory profiles inspired by the ones tested with human subjects in 6. Here, the evaluation of the system has been carried out on an Aldebaran Nao robot, a humanoid robot the size of a toddler with similar capabilities than the AIBO robot. This robot complies with the requirements of the ALIZ-E project in terms of robotic platform, and provides an easier embodiment to interact with. In comparison to chapter 5, instead of trying to learn and categorise raw perceptions, the robot is now learning properties of objects presented on a table in front of it. This provides an easier setup to vary the complexity and relative novelty of the features learned by exchanging the objects with more or less similar ones. Moreover, the caregiver can manipulate the objects and therefore the environment. In addition, to isolate the effect of the regulatory profiles from the behaviour of the caregiver, in one set of experiments the interventions of the caregiver are now produced automatically in reaction to the request of the robot. This modification offers an equal responsiveness of the caregiver during the experimental runs as opposed to what was evaluated in chapter 5. First, the activation of regulatory behaviours by the robot will coincide with variations in the perceptual features in the environment and provide an opportunity for the caregiver to either regulate the arousal through comfort, or manipulate the environment. Second, assuming equal responsiveness of the caregiver, a "needy" robot would explore and learn the environment more slowly than an "independent"robot, since it would need the caregiver to provide comfort for the robot to explore further depending on how many novel or conflicting features it perceives.

7.2 Contributors and funding bodies

The work presented in this chapter has been carried out under funding of the ALIZ-E project. The implementation and experimental design were carried out by myself under the guidance of Lola Cañamero and Matthew Lewis.

7.3 The Robotic Platform Used: Aldebaran's Humanoid Robot NAO

The work presented in this chapter uses a different robotic platform than the two previous experimentation in chapters 5 and 6. The Aldebaran NAO robot was chosen for the following reasons. First, it is the platform used during the ALIZ-E project and this work was carried out for this project and to study dyadic affective regulation interactions in human-robot interactions. The appealing appearance of the robot and its capabilities were key arguments in choosing this platform to undertake the research. Second, this platform is becoming a standard in human-robot interaction and most robotics laboratory own and use NAO. Therefore, an argument can be made for the easier reproduction of the research and its adaptation to other experimental setup using this robot. Finally, the size of the robot and its capabilities are more suited for the interaction presented in this chapter. Indeed, the robot was used standing in front of a low table and the human experimenter was standing opposite to it. Compared to the AIBO robot, his child-like size allows for interactions closer to the ones reported in attachment scenarios.

The NAO robot also possesses similar capabilities than the AIBO robot. Its specifications are described below.

- Height: 58 cm
- Weight: 4.3 kilograms
- Processor: Intel Atom 1.6 GHz
- Sensors: two HD cameras, four microphones, sonar rangefinder, two infrared emitters and receivers, inertial board, nine tactile sensors (with three on the head), eight pressure sensors
- Actuators: 25 degrees of freedom
- Programming: C++, Python, Java, MATLAB, URBI, C, .Net

In the work reported in this chapter, and in the ALIZ-E project, the programing of the robot was done again using the URBI middleware, which was a contractual requisite of the project. However, this allowed for an easier integration of the architecture developed in the research project of this dissertation. The URBI middleware again allowed to manipulate

Figure 7.1: The Aldebaran NAO Robot

each actuators and all sensors that were necessary. Moreover, it provides higher primitives such as walking, turning and side stepping which were used in this chapter and in chapter 8.

7.4 New Experimental Setup and Research Questions

7.4.1 Research Questions

The work presented in this chapter aims to evaluate the influence of the profiles used in chapter 6 on the exploration and regulatory behaviours with regards to the complexity of the environment. The robot uses the same architecture described in chapter 4. The two profiles used in this chapter are inspired by the "needy" and "independent" profiles previously used. The "needy" profile triggers regulatory behaviours more often due to a faster decay of its comfort using the variable $\beta comf$ introduced in chapter 4. The "independent" profile requires less support from the human caregiver since its $\beta comf$ is higher, and therefore the internal perception of the comfort provided in the Comfort System lasts longer.

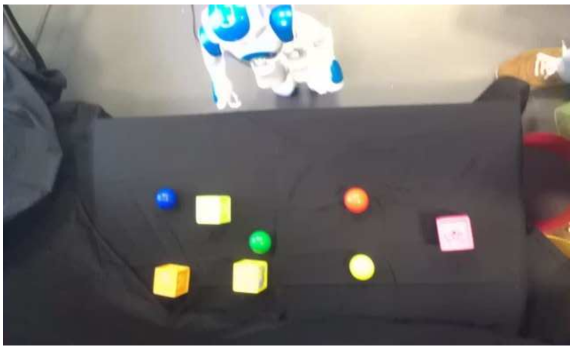
The research questions addressed in this chapter are the following.

- How does each profile react to change in the environment in terms of regulatory behaviours and exploration?
- How does each profile behave depending on the amount of different perceptions from different objects in the environment in terms of regulatory behaviours and exploration?

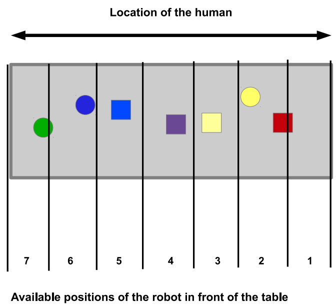
All these questions are later addressed using an equal high responsiveness from the caregiver. This was achieved using an simulated system which provides comfort automatically at a fixed time after a regulatory behaviour, therefore keeping this factor constant in the evaluation. A final question addressed is "How can the robot adapt its profile in real time if the human responsiveness is variable?".

7.4.2 The Experimental Setup

The new experimental setup uses the NAO robot learning the features of objects placed on a table. The robot is placed in front of a table on which several coloured objects (toy rubber cubes, coloured plastic balls, varied sized cans covered in white paper) are placed as shown in Fig. 7.2a.



(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 7.2: Experimental setup used with the Nao robot. 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 the perceptual inputs to be learned. These steps move the robot incrementally from one index position to the next. When the robot reaches the end of the table, the direction of the movement is changed, and it then starts moving in the other direction.

To explore the objects in this environment, the robot moves laterally along the table by stepping first to its left and then to its right. The maximum number of steps in each direction is limited to six, providing the robot with seven different views of the scene as can be seen in Fig. 7.2b. The position of the robot at a given time step can be accurately recorded, which was not easily possible in the setup used in chapter 5. At every time step, the following internal values used by the architecture were logged: *Stimulation*, *Arousal*, *Position*, *Behaviour produced*, and *Comfort*.

The robot is connected via Ethernet to a computer where visual processing and learning are performed, and communicates with the computer using the URBI middleware (Baillie 2005). The Arousal and Comfort System are running on board using the Urbiscript language. Each iteration of the perception-action loop lasts 300 milliseconds on average, the robot transmits the image from the camera to the computer, where the perception system extracts the contours from the image, transmits them to the Learning System, and then the *Stimulation* value is computed. This value is then sent to the robot to compute the arousal level.

7.4.3 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. As in chapters 4, 6, and 5, 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, available visual processing tools from the OpenCV library were used. The algorithm then selects the three largest closed contours using a Canny filter, as depicted in figure 7.3, 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 $[0, 1000]$.
- The length of the perimeter of the contour is evaluated as an integer in the interval $[0, 1000]$.

- The location (x, y) of the centroid of the contour is calculated as vector of two integers in the interval $x \in [0, 320]$ and $y \in [0, 240]$.
- 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 seven values resulting from the previous steps are then normalised and discretized into 50 bins to construct a vector of 350 binary components $P(t)$ which is used as input to the Learning System.

One main difference between this Perceptual System and the one in chapter 5 is that each component of the perceptual input P is discretized into 50 bins and not 10. This value was chosen empirically after testing the Learning System with various objects. 50 bins lead to a possible discrimination between all objects presented to the system.

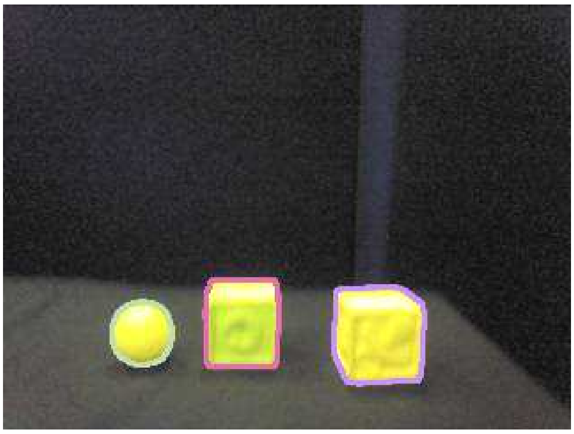


Figure 7.3: Contours of objects extracted from a camera image from the Nao robot. The extraction algorithm uses a Canny filter as implemented in the OpenCV library (version 2.4).

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, as in chapter 5, 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 (Baillie 2005).

7.4.4 The Arousal System

The arousal model is an adaptation of the model described 4. The main difference is that only the arousal sustained is used, since the vocalisations of the robot were not used, and considering the limited benefits the two level of arousal provided (See the discussion of chapter 5). The arousal level (now referred to as variable $Ar(t)$) 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*, which is a real-time evaluation of the recall error of the associative memory Err and the variation of the synaptic weights Cat of the self-organising map.

$$Ar(t) = \begin{cases} \dfrac{\tau_{sus} \cdot Ar(t-1) + Stim(t)}{\tau_{sus} + 1} & \text{if } Comf(t) \leq 0.1 \\ Ar(t-1) - \alpha_{ar} \cdot Comf(t) & \text{otherwise} \end{cases} \tag{7.1}$$

As we can see in Eq. 7.1, 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 behaviour of the robot. The window parameter τ_{sus} 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_{sus} that produces smoother behaviour) or towards "the present" (a smaller τ_{sus} that gives rise to more reactive behaviour), as a function of the variability of the *Stimulation*. A threshold on the effect of the comfort has been used and set to 0.1. The arousal uses the comfort to decrease only when the comfort value is equal or above 0.1. This change was made since the comfort of the "independent" profile decays slowly and asymptotically towards 0, and the comfort has no effect when the value is below this threshold.

7.4.5 Action Selection and the Behavioral System

As in chapter 5, the robot possesses one exploratory behaviour, side stepping to a new position (called 'Explore-and-learn"), and one regulatory behaviour "Find-Human", which is the same as the "Search" behaviour in chapter 5.

The activation of these behaviours only depends on the level of arousal. If the arousal is greater than or equal to a given threshold, Ar_{high}, the behaviour "Find-a-Human" will be executed. These two main behaviours can trigger other simpler behaviours, also following a Winner-take-all policy. The "Explore-and-Learn" behaviour selects whether to attend to and learn the current stimuli ("Stay and Learn" behaviour), or to move away from it and explore other elements of the environment ("Explore" behaviour). The regulatory behaviour "Find-Human" can either trigger the appetitive behaviour to search for a face by moving its head (and therefore the camera located on its head), or the consummatory behaviour of tracking a face (using the location of the face in the visual field provided by the perceptual system). The behaviour "Gaze-at-human" lets the robot stare at the human until its arousal drops below the high threshold on the arousal.

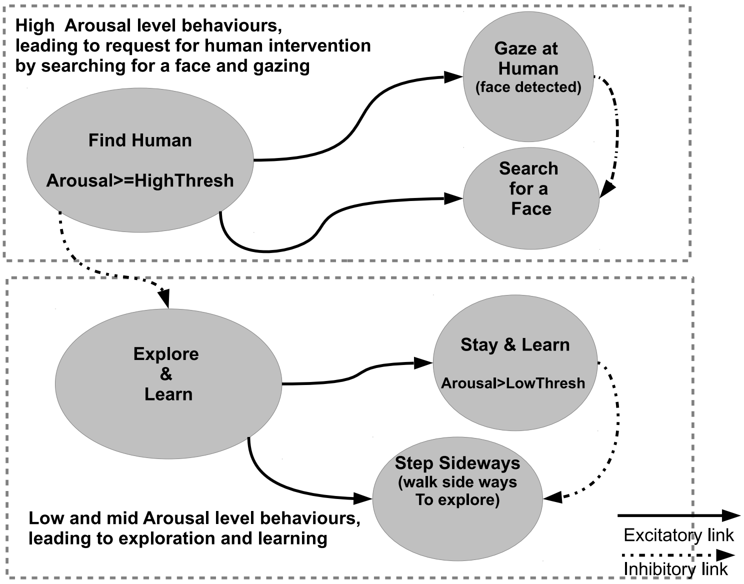


Figure 7.4: Behaviours used and their connectivity. The two behavioural systems "Explore-and-learn" (exploratory behaviour) or the "Find-Human" (the main regulatory behaviour) are mutually inhibiting. If the Arousal level is above than Ar_{high}, the regulatory behaviour is activated and in turn inhibits the exploratory behaviour. The "Explore-and-learn" behaviour, when active, activates the two connected behaviours "Stay-and-Learn" and "Step-Sideways"'. The activation of the behaviour "Stay-and-Learn" is modulated by the Arousal level. If the Arousal level is above Ar_{low}, the behaviour "Stay-and-Learn" maintains a high activation level and inhibits the "Step-Sideways" behaviour. If the Arousal level is lower, the activation of the behaviour "Stay-and-Learn" is null, and the behaviour "Step-Sideways" is not inhibited and therefore executed. In a similar process, the regulatory behaviour "Find-Human" either searches for a face when the face detection algorithm does not detect one, or tracks a face and gaze at the human. The perception of a face in the visual field modulates the behaviour "Gaze-at-human", which inhibits the behaviour "Search-Face".

7.4.6 Caregiver Responses for Equal Responsiveness

In order to compare the two profiles and the dynamics they produce in a highly controlled and systematic way, an automated system to produce the responses of the caregiver was implemented. A "caregiving" response is produced every time the behaviour "Find-Human" is activated, precisely one second after the behaviour 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 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*. In essence, $C_h(t)$ is set to 1 when this mechanism fires a second after the execution of a regulatory behaviour. This time of 1 second was chosen empirically after testing. Because of the nature of the setting, when the robot looks for the caregiver it removes its gaze from the setup and therefore the arousal starts decreasing. The robot stares back at the setting and either the arousal spikes once more or the stimulation decreases and the arousal as well, leading the robot to starts exploring again. If the spike of arousal is high enough or if the perceptions of the contour are again promoting a high Stimulation, the behaviour lasts longer than a second and a simulated comfort response is provided.

Although this system can generate any caregiving profile between the two extremes of constant responsiveness and non-responsiveness, or between constant presence and total absence, only an immediately responsive caregiver (which responds to each request from the robot) was used for these evaluations, since this is the profile that modulates the arousal to a greater extent. However, that immediate responsiveness can give rise to two different caregiving styles when interacting with different robot profiles, and that match them: a constantly present caregiver when interacting with the needy robot, and a more "relaxed" or "hands-off" caregiver when interacting with the independent.

7.4.7 Two Robot Profiles

As in chapter 6, the evaluation used two different robot behavioural profiles, varying in the way they regulate high levels of arousal: a "needy" and an "independent" robot, borrowing the terminology commonly used in attachment theory regarding regulatory behaviour.

From a behavioural perspective, the "needy" robot "solicits" human attention often, whereas the "independent" robot seldom does it. From an architecture viewpoint, these profiles process the interventions of the human, and therefore the comfort provided, with different temporal dynamics. In terms of the architecture, the profiles vary in terms of the temporal parameters used to compute the variable *Comf*, namely the length of the time window τ_h, and the trace rate β_{comf}. The "needy" profile uses a short time window τ_h and a low trace rate β_{comf} as in Eq. 6.1. Having low values for these two parameters leads to a shorter-lived *Comf*. This in turn means that the robot will call for assistance often and therefore fits with the "needy" characteristics in terms of attachment behaviour. Higher values for these parameters, implemented in the "independent" profile, produce fewer calls for attention and a longer effect of the comfort on the level of arousal. From an observer's point of view, naive humans interacting with this robot also tend to qualify it as being more independent 6. The parameters used for the two profiles are presented in Table 7.1. The time window $\tau_{sus} = 6$ for the arousal is far lower than the one used in chapter 5. This is due to the slower update cycle in this setup.

Table 7.1: Parameters used in the experiment for the "needy" and the "independent" robot profiles

Parameter name in the model	"needy" profile value	"independent" profile value	Description
α_{ar}	0.6	0.6	Decay rate of the arousal
τ_{sus}	5	5	Time window for the level of Arousal
β_h	0.7	0.95	Trace rate of the comfort
Ar_{high}	0.6	0.6	Higher threshold for the level of Arousal
Ar_{low}	0.4	0.4	Lower threshold for the level of Arousal

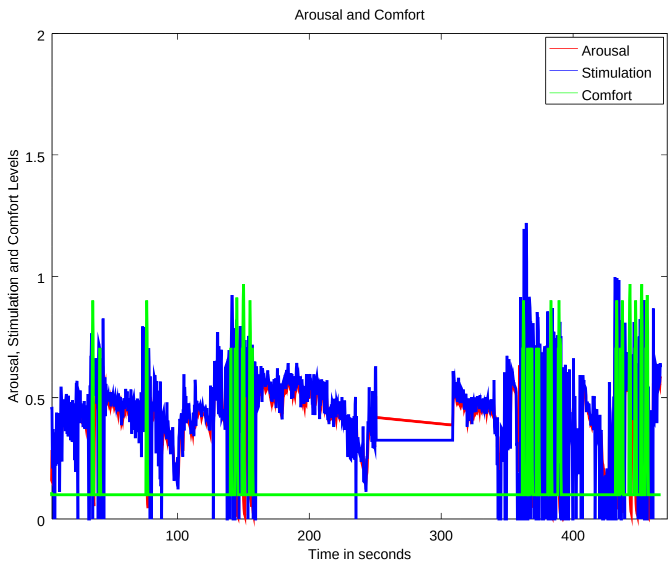


Figure 7.5: Evolution of the Arousal, Stimulation, and Comfort levels (Arousal in red, Stimulation in blue, and Comfort in green) for the robot with the "needy" regulatory profile.

7.5 Results

7.5.1 Reaction to a global change in the environment

This section shows the results of two runs with the proposed setup where the robot explored and learned the features of the objects on the table using the "simulated" caregiver with a high responsiveness. At the middle of the run, the experimenter would pause the algorithm, and change the objects for different ones. 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 "flat line"). During this run, 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. Figure 7.5 shows how the “needy” profile reacts to such a change in the environment. We can see that after the change, more frequent regulatory behaviours are produced (as attested byt the comfort provided by the automated system). This change in the environment drives the “needy” robot on alert the “caregiver” often. Comparing to a run with the robot with the “independent” profile, we can see that the

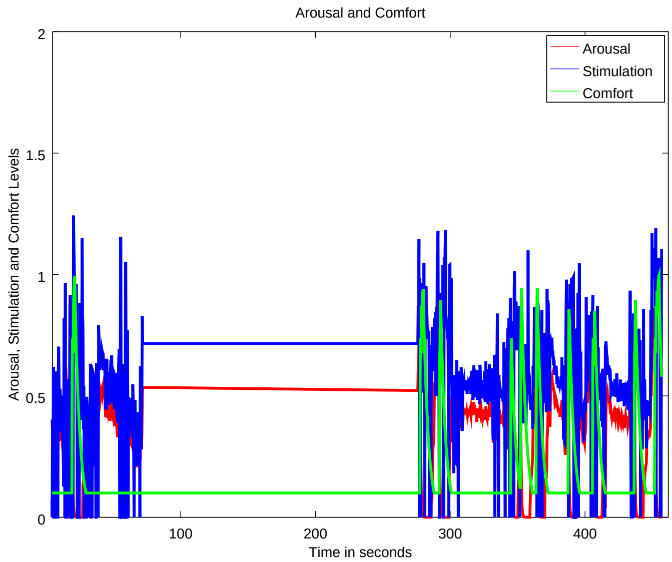
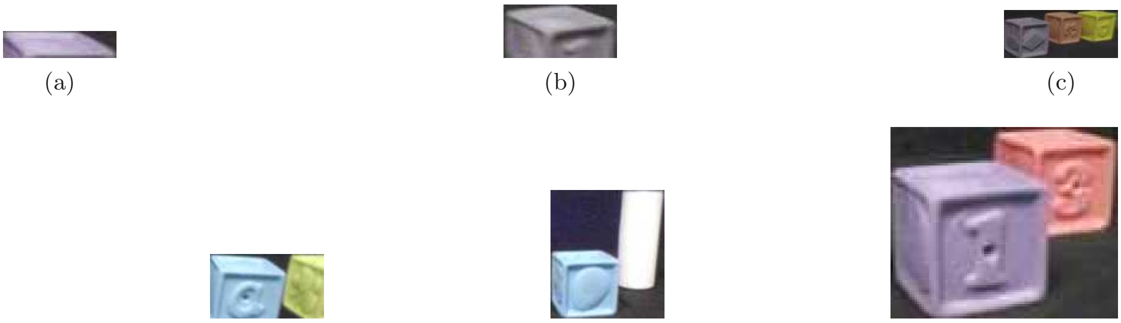


Figure 7.6: Evolution of the levels of Arousal, Comfort, and Stimulation (Arousal in red, Stimulation in blue, and Comfort in green) for the robot with the “independent” regulatory profile.

this profile triggers less regulatory behaviours for a similar change, but their frequency increases.

7.5.2 Local sources of Arousal increase

This section shows which perceptual features the Arousal System reacts to in the current system. Figure 7.7 shows examples of “failures” of the perceptual system in correctly extracting the contour of an object. These samples have been extracted from sample runs



(a) (b) (c)

(d) (e) (f)

Figure 7.7: Samples of various outliers identified by the system. The following contours have been extracted following a high level of arousal during the experimental runs.

and correlate with a high arousal and the occurrence of a regulatory behaviour. Some of these examples include multiple objects extracted as one contour. These anomalies happen either when the objects are placed too close together or when the lighting conditions are not 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. When the objects are too close together, the human caregiver can either move them apart or provide comfort to the robot for it to move to another position. Therefore, the architecture and its dynamics provide opportunities for the human to intervene in different ways. It has to be noted that the human does not know why the robot is exhibiting a regulatory behaviour.

7.5.3 Effect of the Profiles in the Exploration in a Simple Environment

The two robot profiles were tested in a simpler and stable environment, with only a few objects placed on the table as can be seen in Fig. 7.8.

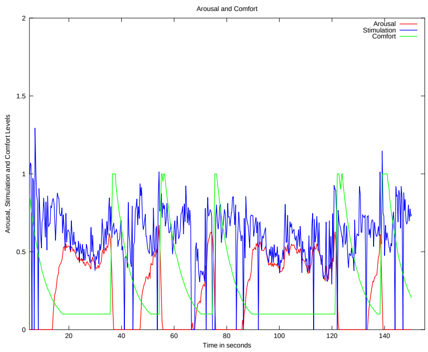
Each profile was tested in 10 runs (thus giving a total of 20 runs in this environment) using the automated "responsive" caregiver profile that responded to each request from the robot. For each profile, results and overall duration were very similar across all runs. Here

Figure 7.8: The simpler environment used in the initial tests of the robot profiles.

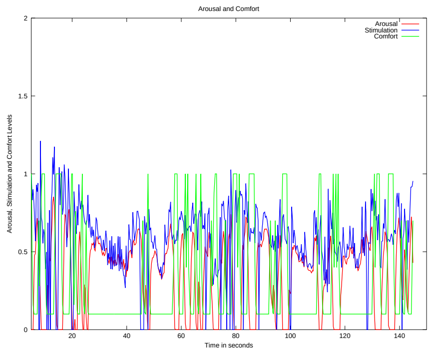
are the results from a representative example.

The results for each robot profile in a run of 150 seconds are displayed in Fig. 7.9. As we can see in Figs. 7.9a and 7.9b, the main difference between the profiles is the amount of comfort that each robot requested. In these figures, this difference is illustrated by the number of peaks in the *Comf* (in green) which are much more numerous in for the "needy" profile, as predicted by the model. We can also see on the graphs for the "independent" robot the difference in the lasting effect of the value of *Comf*, showing a trace lasting up to 10 seconds. This effect reduces the arousal to a low level, and this drives the robot to move and explore. In terms of exploration, the lasting effect of the comfort provided increases exploration time since the robot stops to attend to the stimuli after longer periods of exploration, i.e., it stops less often than under high arousal. During exploration periods, the stimuli perceived (the contours of the available objects) vary faster in their location in the visual field, their subjective size (area and length of contour perceived), and most likely their colour in the RGB space as the angle of view differs.

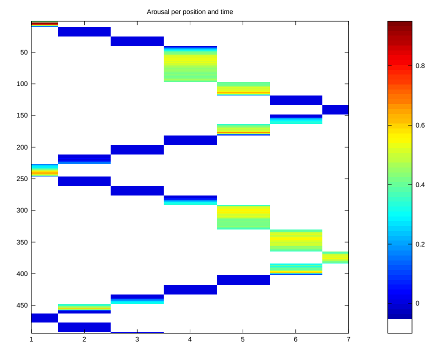
The "Temperature" plots in Fig. 7.9d and 7.9c represent the arousal level against time and position in the setup. They show how long each robot profile spent at each position in the setup. In these figures, we can see that, on average, both profiles go through the setup at a similar pace. Starting from the first position (labelled 1), they reach the end of



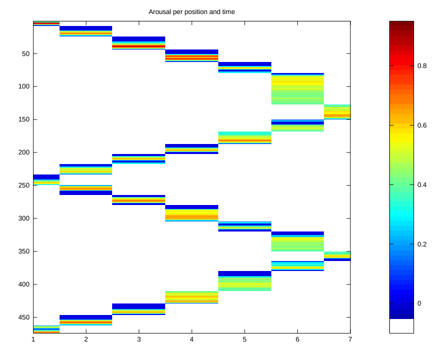
(a) Evolution of the Arousal (red), Comfort (green), and Stimulation (blue) for the "independent" robot



(b) Evolution of the Arousal (red), Comfort (green), and Stimulation (blue) for the "needy" robot



(c) Temperature plot representing the level of arousal as a function of time (y axis measured in timesteps) and position (x axis) for the "independent" robot



(d) Temperature plot representing the level of arousal in function of time (y axis measured in timesteps) and position (x axis) for the "needy" robot

Figure 7.9: Summary of the main variables of the architecture from experimental runs in the simple environment for both profiles of the robot. The top figures 7.9a and 7.9b display show the arousal variations and the variables used to compute the arousal level. The two bottom figures 7.9c and 7.9d show the arousal of the robot against time for each position that the robot can reach in the environment. The main differences between the two profiles reside in the *arousal* level and *comfort* level. Since the "independent" profile has a lower trace factor of the comfort, its arousal level is then reduced for a longer period of time when it receives comfort. Consequently, it can go through the several positions faster than the "needy" robot.

the table around time step 160 (approximately 50 seconds), and come back to the other end of the table by time step number 250 (approximately 83 seconds). This shows how the parameters of the model processing the *comfort* level in *each of the two profiles require a different amount of caregiving in order to obtain a comparable exploration dynamics.*

In the figures, we can also observe that the "needy" profile shows more frequent episodes of medium arousal (for instance in time step 50 to 100, and again at time step 300) than the "independent" one. The "independent" profile shows these episodes less often since the longer lasting effect of the comfort provided reduces its arousal to a low level for longer. The next experiment in a more complex environment aimed to investigate the potential implications of this difference.

In conclusion, while both robot profiles took approximately the same time to walk through the environment, their regulatory behaviours and patterns of exploration were different. While the "needy" robot needed frequent comfort from the caregiver to be able to learn and progress, the "independent" robot used less comfort to learn and progress the same amount. Therefore, to achieve a similar exploration dynamic in this simple environment, the "needy" would need a caregiver with a higher frequency of responses, whereas the "independent" would cope with a less responsive caregiver.

7.5.4 Effect of the Profiles in the Exploration in a more Complex Environment

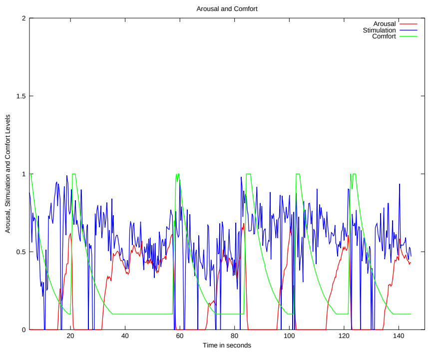
This experiment aimed at testing how the same robot profiles, with access to the same highly "responsive" automated caregiver as previously, would cope with their arousal levels and explore and learn the environment under more challenging conditions. To achieve this, the setup was filled with a higher number of objects to increase the complexity of the exploration and learning task (see Fig. 7.10). This modification of the setup permits to assess, for each robot profile and with equally responsive caregivers as previously, how the dynamics of the exploration/learning and generally the behaviour of the robot is influenced by the increased density of new percepts in the environment, and hence by the arousal and its differential processing in each profile.

Each profile was again tested in 10 runs using the automated "responsive" caregiver profile that attended to each request from the robot. For each profile, results were very similar for all runs as was the overall duration. These results are from a representative run that lasted approximately 160 seconds.

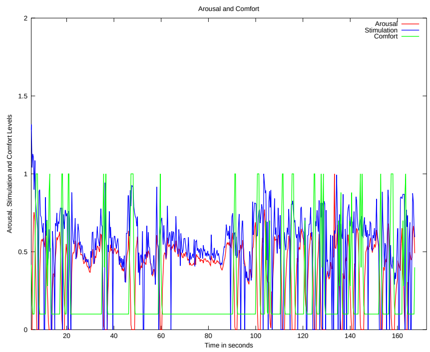
Figure 7.10: The more complex environment used in the second set of tests of the robot profiles. More objects that vary in shapes and sizes were placed on the table.

Comparison to the simpler environment

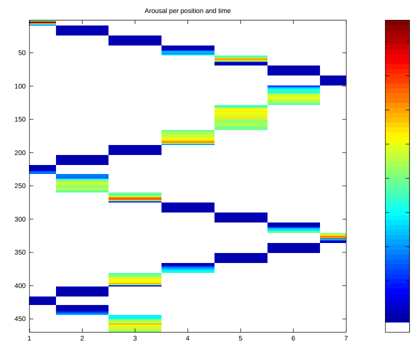
In comparison to the simpler environment, the increased complexity of this environment had a higher impact on the "needy" than on the "independent" robot, both in terms of the trade-off between learning and exploration and in terms of the regulatory behaviours produced. We can observe in Fig. 7.11 that the "needy" robot explored the setup at a considerably slower pace than it did in the simpler environment over the whole run, since it was confronted with more situations where the stimulation (and hence the arousal) increased due to the novelty of the perceived objects and their properties. The "independent" robot also showed more periods of high arousal (time step 170 and 270) and longer periods of medium arousal than it did in the simpler setup (cf. Figs. 7.9c and 7.11c). In terms



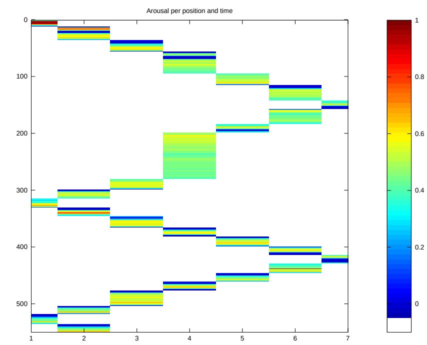
(a) Evolution of the Arousal (red), Comfort (green), and Stimulation (blue) for the "independent" robot



(b) Evolution of the Arousal (red), Comfort (green), and Stimulation (blue) for the "needy" robot



(c) Temperature plot representing the level of arousal as a function of time (y axis measured in timesteps) and position (x axis) for the "independent" robot



(d) Temperature plot representing the level of arousal as a function of time (y axis measured in timesteps) and position (x axis) for the "needy" robot

Figure 7.11: Summary of the main variables of the architecture from experimental runs in the more crowded environment for both robot profiles. The top figures 7.11a and 7.11b show the variations in arousal and the variables used to compute the arousal level. The two bottom figures 7.11c and 7.11d show, for each robot profile, the arousal of the robot at each time for each position of the setup the robot can reach.

of *Comf* needed, the "independent" profile did not solicit the attention of the caregiver more often than in the simpler environment. Once more, the longer-lasting effect of the comfort appears to have been sufficient for the robot to go through this setup in a similar manner as through the simpler one. For the "independent" profile, the simpler and more complex setup were equivalent in terms of exploratory behaviour, since the longer-lasting effect of the comfort provided made the robot move and explore. On the other hand, the "needy" profile produced more regulatory behaviours than in the previous scenario, as expected by the increased density of available objects. Despite receiving the more frequently requested comfort, due to the effects of more demanding setup, the "needy" robot also showed longer periods of medium arousal than before since even the increased comfort was not sufficient to decrease the arousal below medium levels, i.e., to the low threshold that fosters exploration.

Comparison between the two profiles

A comparison of both profiles in this more complex environment given similar responsiveness from the caregiver (responsiveness to every request from the robot for both profiles, following the same responsiveness pattern as in the simpler environment) shows additional differences than those found in the simpler environment. Differences between the two profiles were found in terms of exploratory behaviour and learning dynamics. Due to the higher density of objects and features, again in this environment the "needy" robot requested assistance more often than the "independent" and therefore remained in the same position for longer (even after comfort was provided) due to the interplay between the stimulation perceived and the comfort provided. However, contrary to what happened in the simpler environment, both profiles explored this more complex environment at different paces. The "needy" robot explored this time at a slower pace than the "independent": while the "independent" robot took 140 seconds to walk through the setup twice, the "needy" took 170 seconds to do the same.

Contrary to what might seem on a first approximation, these results do *not* suggest an advantage of the “independent” profile over the “needy”, besides one of speed of exploration. They merely indicate a *difference* in the way both robots explore and learn. Due to the differential interactions between arousal levels, the comfort provided, and the learning system, the fact that the “needy” robot spent prolonged periods in front of a novel stimulus, and that its arousal descended from high to medium levels while doing so, means that it spent more time learning and that it learned “more carefully” and deeply the features of the novel objects (the learned patterns were better consolidated in the underlying neural networks). The longer-lasting effects of human-provided comfort on the “independent” robot generally kept its level of arousal in the medium-low range, fostering exploratory behaviour to the detriment of time spent learning objects. In other words, confirming incidental observations that our previous work had suggested, in this experiment while the “independent” robot explored more, the “needy” robot spent more time trying to learn. Neither robot profile is at an absolute advantage with respect to the other. From the point of view of the robot (e.g. in terms of performance or task-execution) both, a more exploration-oriented and a more learning-oriented behaviour, can present advantages and disadvantages depending on the specific circumstances or the task to which the robot is confronted. From the point of view of human-robot interaction, both profiles are also equally valid and potentially useful, since each might better suited to different types of human profiles and preferences. The results show that different types of interaction and “caregiving styles” affect differentially the regulatory, exploratory and learning patterns of the two robot profiles. The interaction dynamics between the immediate responsiveness of the caregiver and each profile gave rise to a responsive and constantly present caregiver in the case of the “needy” robot, and to a responsive but more “hands off” caregiver in the case of the “independent” robot. The profiles of the robots and the caregiving styles matched to give rise to different but equally valid regulatory, exploratory and learning patterns.

Ideally, a robot should be able to behave according to both profiles in an adaptive way that is appropriate for the task, the environment, or the human user concerned. The next experiment was designed to test a mechanism to permit switching between profiles to adapt to a human as a function of his/her interaction preferences, and assess the implications of this adaptation for the robot and the dyadic human-robot interaction. This would allow the robot to react to a decrease in the responsiveness of the human but also to an increase in the complexity of the environment.

7.5.5 Experiments with Varying Responsiveness of the Caregiver: Affective Adaptation

As the results previously presented show, the exploration and learning of the robot are influenced both by the behaviour of the caregiver, and by the parameters used to compute the comfort level and its influence on the arousal level. The experiments conducted in 5 tested "idealized" categories of caregiving styles showing clearly defined profiles at different points of the "responsiveness" dimension. However, in real-world interactions with humans, those clear "typical" profiles tested are unlikely to be found: people are more likely to show a profile somewhere between those extremes, and the same person might also change his/her *responsiveness* over time. At the same time, people might vary in their preference for a more "needy" or a more "independent" robot at different points in time. A robot interacting in the real world should thus be able to adapt its behaviour to the changing interaction styles (in the case concerned in this paper, in terms of responsiveness) and preferences of the human. The adaptation here is a case of *affective adaptation* that relies on the assessment of the behaviour of the caregiver when help and attention are requested.

The next step was thus to endow the robot architecture with adaptation capabilities – in this case, permitting the robot to assess the *responsiveness* of the human to the robot's regulatory behaviours (requests for attention and help), and vary those regulatory behaviours (in terms of "independence" or "neediness") as a function of the responsiveness of the human.

This new element was inspired by the literature on parental caring style and the dimensions used to assess it (De Wolf and van IJzendoorn 1997). The notion of *responsiveness* has been linked to a carer's ability to attend to an infant's demands in a timely and accurate manner. The model of the formation of patterns of attachment (Ainsworth et al. 1978) postulates that infants adapt to the interactive style of their caregiver and their "trust" in the caregiver's ability to soothe them influences their behaviour.

In essence, in this new condition the architecture correlates the activity of the regulatory behaviour of the robot (finding a human by looking for a face) with the comfort received. This correlation is reflected in a new variable *responsiveness*, $Resp_h(t)$ (with $0 < Resp_h(t) < 1$), which increases when the robot receives comfort after having made a request. The *responsiveness* is computed as shown in Eq. 7.2 only when the behaviour "Find-Human" is active:

$$Resp_h(t) = \begin{cases} Resp_h(t-1) + \alpha_{resp} \cdot (1 - Resp_h(t-1)) & \text{if } Comf(t) > 0.1 \\ \\ Resp_h(t-1) - \alpha_{resp} \cdot (1 - Resp_h(t-1)) & \text{otherwise} \end{cases} \tag{7.2}$$

The parameter controlling the dynamics of the comfort $Comf(t)$, β_{comf} (cf. Eq. 6.1), is adapted as follows[1]:

$$\beta_{comf} = 0.7 + (1 - Resp_h) \cdot R_{\beta_{comf}} \tag{7.3}$$

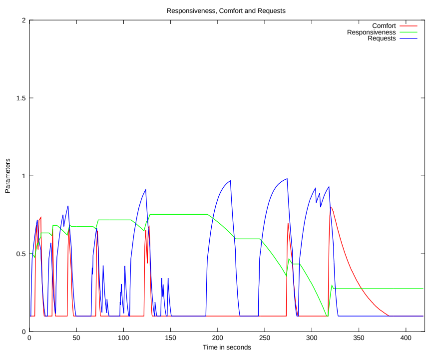
[1] A version of this mechanism was published in (Hiolle, Lewis and Cañamero 2014a), where the comfort used another parameter τ_h to average the input of C_h and $F_h(t)$. After further investigation, this parameter had very little influence on the dynamics and is therefore omitted in this version of the algorithm.

As we can see in Eq. 7.3, the decrease of the parameter β_{comf} is proportional to the calculated *responsiveness*. The constant $R_{\beta_{comf}}$ determines the range of variability of β_{comf}. This adaptive architecture mechanism was tested in the same setup used in the second experiment (Section 7.5.4) for a total of five runs. However, this time a real human (the experimenter) played the role of the caregiver. To assess the dynamics of the adaptation and its effect on the regulatory and exploratory behaviours of the robot the robot, the experimenter alternated periods of extreme *responsiveness* and periods of low *responsiveness*. The parameters used are presented in Table 7.2.

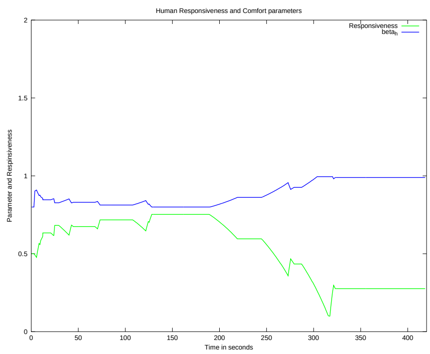
Table 7.2: Parameters used in the adaptive regulation experiment

Parameter name in the model	Value	Description
α_{ar}	0.8	decay rate of the arousal
τ_{sus}	3	time window for the level of arousal
β_h	0.7	initial trace rate of the comfort
α_{resp}	0.03	variation constant for the responsiveness
$Resp(0)$	0.5	initial responsiveness level
$R_{\beta_{comf}}$	0.3	range of variation of the comfort trace rate
Ar_{high}	0.6	higher threshold for the level of Arousal
Ar_{low}	0.4	lower threshold for the level of Arousal

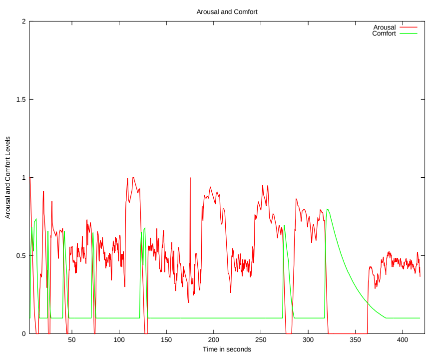
The results from a typical run of the experiments testing the adaptive architecture are presented in Fig. 7.12. The top left of Fig. 7.12a shows how the evaluated *responsiveness* varied in time depending on the responses of the human caregiver. As we can see from the start of the run, when a request was made, the evaluated *responsiveness* started decreasing since the caregiver had not yet responded. At every peak of the *comfort* level, as projected from the model, the evaluated *responsiveness* steadily increased (approximately from second 5 to 140). In turn, the parameters used to evaluate the *comfort* level, and therefore to lower the level of *arousal* were updated and decreased. The profile of the robot slowly developed towards a more "needy" one, since the human caregiver responded at every call of the robot. After 150 seconds, the experimenter stopped responding to the demands



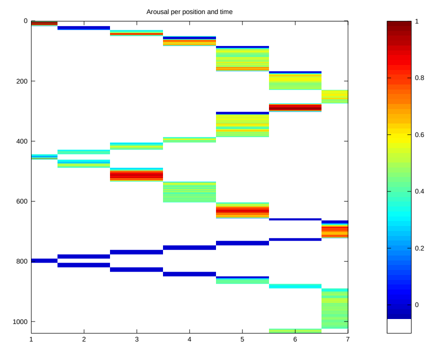
(a) Variations of the *comfort* sensed (in red), the evaluated *responsiveness* (in green) of the human caregiver, and the requests of the robot (in blue)



(b) Variations of the parameter of the *comfort* evaluation (the trace rate β_{comf}) and the evaluated *responsiveness* of the human



(c) Variations of the *comfort* (in green) and the *arousal* level of the robot (in red)



(d) Temperature plot of the Arousal level of the robot as a function of time and the position of the robot

Figure 7.12: Effects of the adaptive controller based on the *responsiveness* of the human caregiver.

of the robot. We can see that during the next two displays of regulatory behaviour (at approximately 170 seconds and 240 seconds), the *responsiveness* decreased as a result of the failed attempt to obtain attention. Consequently, as modeled, the *Comfort* parameter varied towards the more “independent” profile. At the end of the run, both in Figs. 7.12c and 7.12d, we can clearly see the difference in the lasting effect of the comfort provided by the experimenter (at approximately 320 seconds). The level of arousal decreased to a low level, driving the robot to explore more.

7.6 Summary

This chapter presented an adaptation of the robot architecture using the attachment system in an exploration and learning scenario. The experiments assessed the interplay between affective variables – namely the level of arousal of the robot as a function of the novelty and complexity of the environment and the comfort provided by a caregiver to help regulate that arousal – in dyadic robot-(human) caregiver interactions and their effects on the exploratory, learning and regulatory behaviours of the robot.

The evaluation assessed independently the differences between two "idealized" robot profiles – a "needy" and an "independent" robot – in terms of their use of a caregiver as a means to regulate the "stress" (arousal) produced by the exploration and learning of a novel environment, depending on its variability and complexity. In addition, a step further was taken by having the robot adapt its regulatory behaviour along the "needy" and "independent" axis as a function of the varying responsiveness of the caregiver. The initial evaluation demonstrates how the model reacts to the new perceptions to be learned, depending on their variability and the quality of the extraction of the perceptual features. The arousal level correlates with the apparition of outliers and unusual contours of objects. Moreover, the mode also clearly provokes a variation in the frequency of the regulatory behaviours when the objects of the environment were changed for others. An experiment in which each of the robot profiles had to explore and learn a simpler environment with a few objects on the table was carried out to examine potential differences between the profiles in terms of exploratory and regulatory behaviours. The "independent" profile needed less interaction with the human caregiver to progress in its exploration. Every time that the caregiver provided comfort to the robot, its longer-lasting effect in the architecture led the robot to progress faster and farther in the setup. In contrast, for the "needy" profile to progress with comparable dynamics, the caregiver needed to have almost constant presence to respond to the demands of the robot. The results thus showed that, to achieve the same results with the two robot profiles, different caregiving styles are needed.

In a second set of experiments the perceptual complexity of the environment was increased, affecting the dynamics of arousal increase and regulation. The two robot profiles showed different patterns of exploration and learning dynamics depending on the perceptual complexity of the environment. The results also showed that the two profiles exhibit different behavioural dynamics as a function of their different processing of the comfort provided by the caregiver. The exploration dynamics of both robots produced a different learning "experiences" for the two robot profiles. The "needy" profile stopped more often and spent more time learning than the "independent" one. The "independent" profile showed longer exploration episodes following the relief due to the comfort provided lowers the level of arousal for a longer time.

The results from these two sets of experiments show that the architecture can allow a human interacting with the robot to influence and even decide on the granularity of the exploration. Adapted to the difficulty of the learning task at hand, the amount of comfort provided by the human can lower a high level of arousal to a medium level, causing the robot to focus on the stimulus it is currently attending to. If even more comfort is provided, the level of arousal will drop below the low threshold, triggering an exploratory behaviour that drives the robot to move away from the stimulus it was attending to. The results also show that different types of interaction and "caregiving styles" affect differentially the regulatory, exploratory and learning patterns of the two robot profiles. The interaction dynamics between the immediate responsiveness of the caregiver and each profile gave rise to a responsive and constantly present caregiver in the case of the "needy" robot, and to a responsive but more "hands off" caregiver in the case of the "independent" robot. The profiles of the robots and the caregiving styles matched to give rise to different but equally valid regulatory, exploratory and learning patterns.

Taking a developmental approach, this robot architecture and its close interrelation with the behaviour of and interaction with a human "caregiver" can provide a basis for the *personalization* and *adaptation* of the behaviour of the robot to the interaction profile of the human, based on the features of the environment or on the specific contexts in which the caregiver interacted the most with the robot. Through his/her interventions, the human can decide when closer attention has to be paid to specific aspects of the environments and when to discard the current perceptual context, biasing the learning of the robot in a way that meets his/her preferences or needs.

In addition to the comparison of the two stereotypically designed "idealized" profiles, an additional mechanism was added to the architecture to make the affective regulatory behaviour of the robot *adaptive* to the *responsiveness* of the human. This component was inspired by the literature on parental caring style and the dimensions used to assess it (De Wolf and van IJzendoorn 1997). The notion of *responsiveness* has been linked to a carer's ability to respond to an infant's demands in a timely and accurate manner. The hypotheses on the formation of patterns of attachment (Ainsworth et al. 1978) postulate that infants adapt to the interactive style of their caregiver and their "trust" in the caregiver's ability to soothe them biases their behaviour. In a similar manner, this adaptive element was introduced in the architecture to provide the robot with a tool to cope with real-time variations in the caregiver's availability to respond to regulatory behaviours. The architecture modulates the effect of the comfort provided by the human by modifying the parameter used to process the comfort provided. The robot can therefore in turn modify its own profile autonomously along the "needy" and "independent" dimensions. The more comfort is provided to the robot, the more the robot leans towards the "needy" profile. When requests are not responded to, the behaviour of the robot moves towards a more "independent" profile. In a real-world scenario, this adaptivity should help a robot tune the quantity and frequency of its affective regulatory behaviour to the behaviour of the human it interacts with.

Chapter 8

Attachment and Dyadic Regulation in Motivational Systems

8.1 Outline

This chapter presents the work carried out to adapt the attachment and dyadic regulation system in a motivation-based action selection architecture. Using a similar modelisation of the interaction between the negative affect and the production of regulatory behaviours as was used in the previous chapters, an existing control system for an autonomous robot was modified to use the attachment system to drive the social behaviours of the robot. The originally developed architecture and scenario (Lewis and Cañamero 2014, Cañamero 2014) were used here as a test bed for the evaluation of the dyadic regulation system and its adaptive effect on the behaviour of the robot in a more complex setting than the "exploration and learning" used in the previous chapters. To that end, starting from original model and architecture, this chapter demonstrates how to adapt the "social" motivation of the robot to reflect the need of the robot for help to regulate its affect and currently unsatisfied needs. The adapted attachment system uses a two-step approach to produce regulatory behaviours. In a first step, unsatisfied needs lead the arousal level to increase, and in a second step the arousal level induces an increase in the social motivation of the robot. This motivation drives the robot to search for the human caregiver and get help. In addition, the mechanism to adapt the dynamics of the regulatory behaviours introduced in chapter 7 was adapted to modulate the social motivation. The robot can evaluate the responsiveness of the human and adapt the timing and duration of its social requests. The architecture was evaluated in an adapted scenario where the robot tries to satisfy its need for food with the help of the human. The system was evaluated against two factors: the actual responsiveness of the human and the estimated responsiveness used by the robot. A mismatch between this two factors leads to poorer results in the ability of the robot to satisfy its need for food. The results also demonstrate how the dyadic regulation and the adaptation to the responsiveness of the caregiver affects the behavioural organisation in terms of the reliance to the human caregiver depending on the recent history of the interaction and the current needs of the robot. Moreover, the modelisation of the robot's regulatory behaviours being motivated by a drive for social interactions leads to patterns of behaviour that have a closer relationship to some of the original patterns of attachment uncovered by Mary Ainsworth (Ainsworth and Bell 1970).

8.1.1 Contributors and funding bodies

The work presented in this chapter was part of the ALIZ-E project. Among the various components which were used in the work reported in this chapter, Matthew Lewis and Lola Cañamero designed the motivation-based action selection system. Matthew Lewis implemented the motivation system and the behaviours of the robot, and then tested the whole system including each specific behaviour, motivation and their parameters, to suit the needs of the end users and the requirements of the experiments with the children (see (Lewis and Cañamero 2014, Cañamero 2014)). Their work is referred to as the original model or control system in this chapter. My contribution focused on the development of the attachment system added to this motivation-based architecture. This work first includes the modelisation of the arousal based on the needs of the robot and the comfort provided by the human. A second step was to adapt the "social" motivation to produce the regulatory behaviours based on the level of arousal and the previous history of interaction. The principle of adaptation to the responsiveness of the human was then designed to influence the dynamics of the social motivation of the robot. The design, implementation, and evaluation of the attachment system in the motivation system were done by myself under the supervision of Matthew Lewis and Lola Cañamero.

8.2 The Diabetic Robot Toddler

8.2.1 Paradigm and Interactive Scenario

This section summarizes the work of the initial model and scenario as described in (Cañamero 2014) that has been used and adapted for this chapter. The robot toddler system has been designed for the Aldebaran Nao robot to interact with children with diabetes aged between 8 and 11 years old (Lewis and Cañamero 2014, Cañamero 2014). The robot control system is fully autonomous in the sense that no experimenter or "wizard" was needed to control it. The scenario is centred around the principle that children with diabetes interacting with a robot showing similar diabetic symptoms can improve their *self-efficacy* in managing their own condition (Bandura 1977, Bandura 1997, Lewis and Cañamero 2014). To that end, the robot is modeled after a toddler, therefore implicitly needing more care and attention than a pre-adolescent child. The robot is also only pre-verbal, it can express its internal states and current needs through vocalizations, however it does not have any capacity to understand vocal commands or expressions. The environment in which the robot was situated is a toddler's playroom populated with objects that permit it to satisfy its needs: feeding, drinking, playing, resting, socializing, and correcting its glucose levels (since the robot has its own diabetes condition) either with insulin in the case of hyperglycaemia, or by doing corrections with appropriate foods. To satisfy some of these needs, and notably to correct its glucose levels, robot – called Robin in the project – needs the help of a human. For the robot, from an action selection perspective, the child is a "resource", a provider of physical wellbeing, pleasure and social comfort in the form of, for example, stroking the head of the robot, and Robin's social behaviours (approaching, and vocalizing) can be viewed as appetitive behaviours designed to elicit social responses which reduce the homeostatic deficit.

To guide and select its behaviour, the robot uses a motivational system based on the work of Avila-Garcia, O. and Cañamero, L. (2004) but extended to a more complex decision making system. The level of the robot's needs motivate the robot to perform appetitive (searching for relevant stimuli such as food) and consummatory behaviours (such as reaching and eating). The action selection architecture for the robot was developed following an embodied cognitive science and robotics approach. This architecture makes the robot motivationally autonomous – autonomous in the sense that the resulting behaviour is a consequence of the current motivational state of the robot, which is calculated as a function of the current internal deficits of its homeostatic variables (related to bodily needs) and its external perceptions. The robot's motivational state changes as a function of its interactions with its physical and social environment, and the strength or intensity of the different motivations are constantly re-assessed, producing changes in the priorities of motivations whenever appropriate. The intensity values of the motivations are then used as the activation levels of corresponding behaviours (perception-action loops) with other behaviours for fall recovery and vocalizations. The action selection mechanism then selects for execution behaviours that best satisfy the current needs. The action selection mechanism allows the simultaneous execution of multiple behaviours. This permits simple behaviours, such as gazing, walking and reaching, to run at the same time, meaning that a wide variety of full-body motions and behaviours are generated from a small number of simple (and simpler to create than full-body animations) behaviours. Such a system is appropriate for the larger number of degrees of freedom found in a humanoid robot and for richer social interactions. From a technical standpoint, the robot's control system and its parameters were set to allow an 8 Hz update cycle. This frequency was chosen taking into account the reactivity of the robot and the necessary computing time required for processing the perceptions of the robot and the resulting activation of the behaviours.

8.2.2 Principles for the Adaptation of the Attachment System to the Scenario and the Motivational System of the Robot

The control system used in this original scenario (Lewis and Cañamero 2014) (depicted in Fig. 8.1) as well as the experimental setup itself provide a suitable test bed to assess the relevance and potential of an adaptation of the attachment model developed and operationalized in this dissertation. The following reasons motivate the use of this setup and the adaptation of the motivational system:

- the robot toddler needs human assistance by design, at least for regulating its "condition".
- its set of needs such as the need for food requires to be maintained within satisfactory levels. If the robot cannot manage to regulate its needs on its own, this failure in regulation can be likened to a state of distress or high arousal.

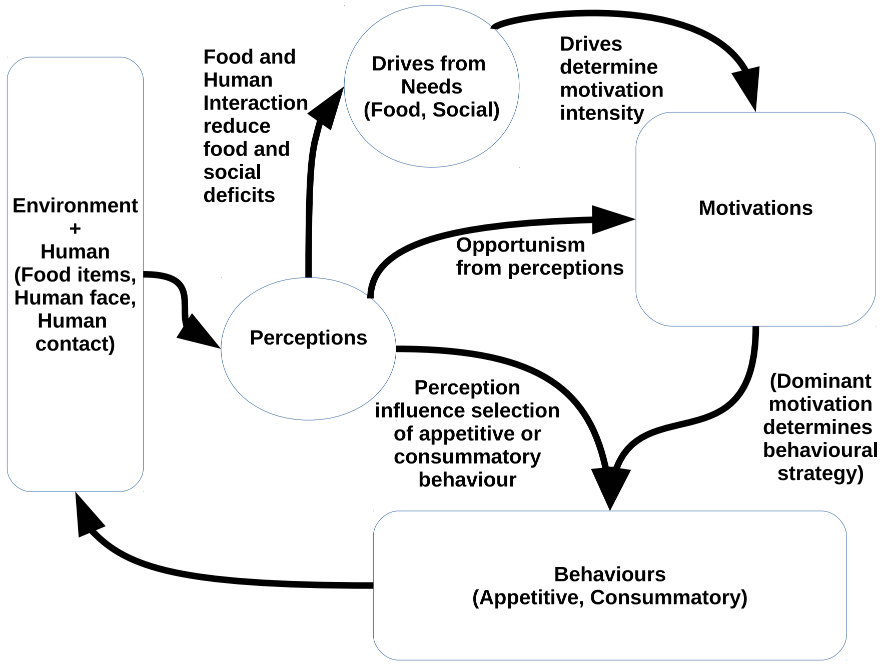


Figure 8.1: Original model of the interactions between the deficits, motivations, and behaviours (Lewis and Cañamero 2014, Cañamero 2014)

- following the attachment system paradigm, this distress should lead to the production of regulatory behaviours aimed at the human in order to get help. This can be interpreted as activating the "Social" motivation and triggering its behaviours to attract the attention of the human when the arousal is high. Such behaviours are directed at attracting the attention of the human and foster a caring behaviour and are therefore akin to the notion of regulatory behaviours used in the literature of attachment and in the model used in this dissertation.

The modification of the dynamics was therefore performed in order to have the social motivation reflect the internal distress of the robot, which results from active motivations not being satisfied. In essence, when a need of the robot is high, for instance the need for food, the arousal of the robot would increase to reflect this lack of satisfaction. In turn, the arousal would increase the social need and therefore motivation. When the social motivation reaches a higher value than the motivation for food, the behaviour of the robot would be shifted from searching for food to searching for the human. When the human responds to the bids of the robot and approaches it, he/she would provide the robot with comfort to alleviate the distress which in turn reduces the need for social interaction. This would lead the robot to resume its search for food, which the human can then assist by feeding the robot by hand or moving it where some food is located. The control system with the adapted attachment system is depicted in figure 8.2. We can see the components of the attachment system and their interactions with the drives/deficits, the social motivation, and the perceptions. The social drive and its motivation are influenced by the affective components identified in the attachment model: the arousal and the comfort.

In order for the robot to adapt its regulation dynamics to the system, evaluating the responsiveness of the human can be an asset. As was proposed in chapter 7, the responsiveness of the human can be evaluated using the correlation between the occurrence of comfort and the activation of regulatory behaviours. Adapting this mechanism to the present scenario means to adapt the timing and frequency of the social behaviours of the robot. First, the responsiveness can be used to influence the rate at which the social motivation increases when the robot is in a state of high arousal and has a high social motivation. If the responsiveness is high, the robot would switch from the food motivation to the social one faster as a result of successful regulation of previous episodes. If the responsiveness is low, the social motivation would rise more slowly, and the robot would spend more time searching for food and therefore behaving in a more independent manner. A second factor that the responsiveness can modulate is the influence of the perceptual incentive on the value of the motivation as theorized by Hull (1943). A high responsiveness would increase the value of the perceptual incentive for the social motivation –the face of

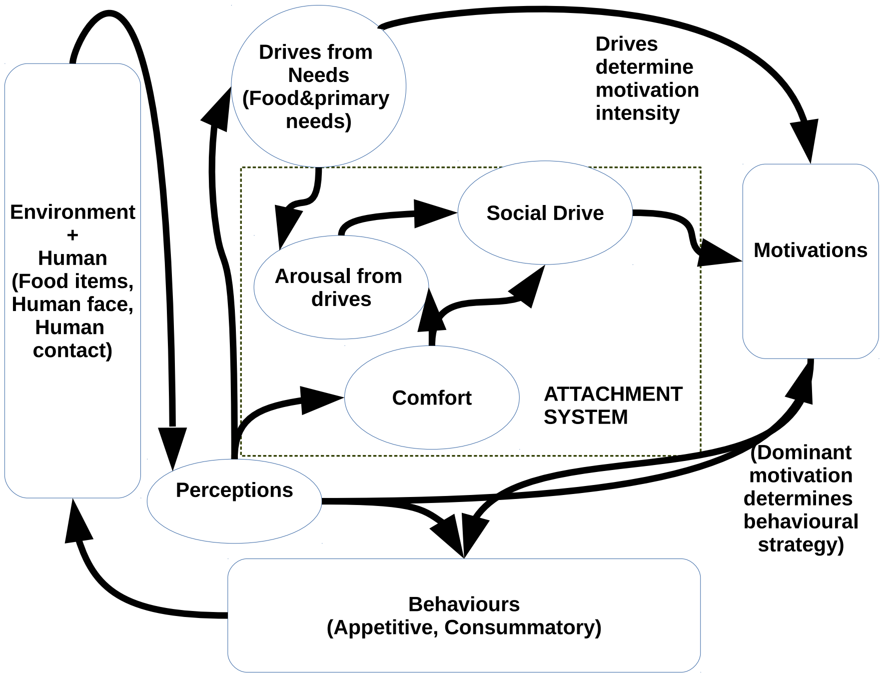


Figure 8.2: Adapted model of the interactions of the deficits, motivations, and behaviours, with the newly developed and integrated attachment system located in the square containing the arousal, comfort, and social drive. In comparison to the original model, the social deficit and motivation are driven by the level of arousal and comfort, and all belong to the attachment system. The social motivation is processed differently than other needs, as is put forward in models of attachment systems.

the human in this scenario– and provoke earlier opportunistic regulatory behaviours from the robot when it perceives it. Opportunistic behaviours occur when the social deficit associated with the social motivation is not the highest (compared to the food one) and therefore the motivation to produce these behaviours stems from the perception of the stimuli, in this case the face of the human. In the case of a low responsiveness, the influence of the perception of the face of the human would be weaker and the robot would end up exhibiting less opportunistic behaviour, relying less on the help of the human.

To summarize, the main differences between the original control system (Lewis and Cañamero 2014) and the adapted system used in this chapter with the attachment system lie in the modified processing of the social motivation. In contrast with the original system, and other motivation-based system such as was done by Velásquez (1998) and Breazeal and Scassellati (1999), the social motivation – and the drive or deficit it is based on– is a reflection of the current affective state of the robot in terms of satisfaction of the needs. Whereas these other works treated each motivation and drives on their own, having social interaction stemming from a long period of "loneliness" or "boredom", this model derived from principles of the attachment system, proposes that the social motivation –and the interactive behaviours it triggers – originates from the need to regulate the affect here represented by the arousal. This model is meant to essentially focus on the occurrence of the social interactions during periods of high needs of the robot.

In comparison to the model of attachment and dyadic regulation previously tested in the previous chapter, this model separates the affective component (the arousal) and the drive that motivates the social and regulatory behaviours of the robot. Where the previous model used the arousal level to trigger regulatory behaviour when it was high, therefore being the drive and motivation for social interaction, here the level arousal produces a social deficit, which in turn motivates social interactions. This leads to the following questions:

- "What differences in the behaviour of the robot does this new attachment model and motivations bring in comparison to the arousal only driven model?".
- " What are the main differences stemming from the social profiles? How do they influence the interaction and the success of the regulation of the needs of the robot depending on the behaviour of the human?"

The evaluation reported later in this chapter attempts to address both these questions using the responsiveness of the human as a influencing factor, and the estimated responsiveness used by the robot to adapt the dynamics of its social drive and motivation.

8.3 Subset of the Architecture used for the Attachment System

This section presents the features of the original model that were used or adapted in the evaluation of the attachment system.

The main components that are of interest are the following:

- the dynamics and nature of the behaviours involved in the satisfaction of robot's need for food
- the dynamics and nature of the behaviours involved in the satisfaction of the social motivation
- the evaluation of the social deficit of the robot
- the calculation of the value of the motivations of the robot based on the deficits and current perceptions of the robot

The main motivations used within the system that are important to the adaptation of the attachment model are the motivation for food and the social motivation. In the original system (Lewis and Cañamero 2014), the motivation for food is relative to the number of "food items" the robot has consumed in the recent past. When the robot "eats" a food item, its need – or deficit– for food is instantly reduced by a set amount, reflecting a fuller stomach. The food is then "digested" following a linear function.

8.3.1 Perception of the Human Caregiver and Social Motivation

From the original implementation of the perceptual system (Lewis and Cañamero 2014), the robot can perceive interactions with the human caregiver using its camera image and the touch sensors located on the top of its head as was done in chapter 7. The same OpenCV based face detection algorithm is used to detect a face from the camera image of the robot. This sensor returns the position of the face in the image, and the size of the detected face. The size of the face is a normalised value relative to the size of the image, and therefore theoretically contained within the interval $]0.0\ ;\ 1.0]$, However, most values are within a $[0.2; 1.0]$ range, since the smallest face that can be detected is only 20 pixels in height and width. This perception is later on used to calculate a perceptual incentive for the social motivation. The closer the face is, the higher the perceptual incentive evaluation will be and the higher the value of the motivation will become. The touch sensor on the top of Nao's head provides a means to evaluate the comfort provided by the human. Within the system, a binary variable $Touch(t)$ is set to 1 when the human strokes the robot's head. This permits to evaluate the comfort as the frequency of touches or strokes on the head.

8.3.2 Dynamics of the Motivations

The motivational system is based on the work reported in (Avila-Garcia, O. and Cañamero, L. 2004) and adapted to the diabetic robot scenario in (Lewis and Cañamero 2014). The value or activation of a given motivation is determined by two factors: a deficit or drive stemming from one of the robot's needs, and a perceptual incentive –a stimulus or set of stimuli that precede the reduction of the need. For instance, when the robot is motivated to eat, perceiving a food item in the visual field will increase the motivation intensity. The list of the motivations used in this chapter and the behaviours they activate is provided in

Table 8.1: Motivations used in this evaluation from the robot toddler system

Motivation name	Description	Behaviours involved	Perceptual Incentive
Food	Aims to reduce the food deficit after eating	Searching for food, Reaching and Eating, Vocalize for food	Food item in the visual field
Social	Aims to reduce the social deficit when comfort provided	Search Human, Face Approach, Face Follow, Vocalize for Human	Presence of a face in the visual field

table 8.1.

For a motivation i, its activation value follows equation 8.1:

$$M_i(t) = D_i(t)(1 + \alpha_i I_i) \tag{8.1}$$

Where $D_i(t)$ is the deficit associated to the motivation and I_i is the value of the perceptual incentive (the size of a food item in the image or of a human face). α_i is a coefficient modulating the influence of the perceptual incentive, set to 1 by default. For the social motivation, this coefficient α_{social} is meant to be later modulated proportionally to the responsiveness. It is referred to as the perceptual incentive factor. The food deficit is calculated proportionally to the "fullness" of the stomach, and therefore grows linearly during the digestion of an item. It is also bounded to the interval [0 ; Max_f]. The higher bound Max_{food} reflects the amount the "stomach" of the robot can contain, a constant set to 80 in the experiments. This value is related to the fact that "eating" one food item fills up 60% of the stomach and therefore two items at a time are more than enough for the robot to be satiated (this values were chosen for the original scenario for the robot to alternate between feeding and other activities).

Table 8.2: Subset of behaviours used intg he evaluation of the attachment system

Behaviour name	Description	Activation
Food Approach	Walks towards the food item	Nao perceives food item too far to reach
Reach for food	Right or left arm of the robot reaches	Nao perceives food item close enough to reach
Eat food	Right or left arm of the robot goes to the mouth of the robot	Nao has reached for food item
Search for food	Head pans left to right at head level	Food motivation is dominant
vocalize for food	Robot vocalizes "Hungry"	Food motivation is dominant
vocalize for Human	Robot vocalizes "Approach me"	Social motivation is dominant
Search Human	Robot head pans from left to right and up and down	Social motivation dominant
Face follow	Head stays in the direction of a detected face	Social motivation is dominant and a face is perceived
Face approach	Head stays in direction of a detected face and robot walk towards human	Social motivation is dominant, a face is perceived and further than 50cm away
Explore	Random walk	Default behaviour

8.3.3 Behaviours and Action Selection

Table 8.2 presents all the behaviours that are used in the evaluation of the attachment system which belong to the original architecture (Lewis and Cañamero 2014). The table also summarises when these behaviours are activated depending on the activation of the motivations and the perceptions of the robot.

One of the main aspect to be noted is the difference between the two behaviours “Search for food” and “Search Human”. The foraging behaviour for food only searches the visual field at a predefined height where food items are located in the environment. However, the foraging behaviour searching for a human face scans the visual field of the robot horizontally but also vertically, since the human might be standing up or sitting down in the setup. Therefore, the robot can still find food items while looking for the human caregiver, however, this strategy is less efficient for finding food items.

The action selection developed for the original scenario functions follows a winner-take-all approach (Lewis and Cañamero 2014, Cañamero 2014). The motivation with the highest activity selects which set of behaviours to execute (either food related behaviours or social ones). The behaviours are then executed concurrently whenever possible depending on what the robot perceives and which joints they use. For instance, the robot searches for a human by executing the behaviour “explore” and “search for human” when no face is visible and the social motivation is dominant. If a face is detected, the robot can execute the behaviours "face follow" and "face approach" concurrently. The vocalizations behaviours can be executed at any time, and were designed to be executed at a minimum interval of 5 seconds.

8.4 Influence of the Comfort, Arousal, and Responsiveness on the Social Motivation

This section presents the adaptations made to the original model (Lewis and Cañamero 2014, Cañamero 2014) to use the attachment system. The modifications to integrate an attachment system as proposed in figure 8.2 concern the following points:

- the social deficit is evaluated using the arousal level and the comfort

- the arousal is evaluated based on the level of the deficits and the comfort provided
- the social motivation depends on the social deficit and the perceptual incentive
- the responsiveness is evaluated depending on the comfort provided by the human
- the responsiveness influences the increase rate of the social deficit and the intensity of the contribution of the perceptual incentive used for the evaluation of the social motivation

8.4.1 Social Deficit from Arousal and Comfort

The social deficit varies using the following contributions from the arousal and comfort. High arousal provokes an increase of the value of the social deficit with the rate Inc_{social} which reflects the growing need for social interaction and decreases linearly with a constant decay rate $Decay_{social} = 0.5$. The value of this constant decay was chosen for the social deficit and the motivation to decay in 20 seconds when no comfort is felt and the arousal is low. This parameter controls the offset of the social deficit and therefore the social motivation.

The social motivation decays faster when comfort is provided for the robot to change rapidly the dominant motivation and therefore the behavioural strategy (from looking for the human to foraging for food). This way, after comfort is felt, the robot can implicitly and explicitly communicate its current goal by looking for food or vocalizing for it. The social deficit saturates at an upper limit, which was set to $Max_{social} = 85$ in the original setup (Cañamero 2014), to ensure that it is higher than the maximum value of the food deficit and for the robot to switch its behavioural strategy from searching for food for instance to actively searching and calling for the human caregiver. The calculation of the social deficit is summarized in equation 8.2.

$$\Delta D_{social}(t) = \begin{cases} 0 & \text{if } D_{social}(t) = Max_{social} \\ \\ Inc_{social} & \text{if } Ar(t) > \theta_{Ar} \\ \\ -\beta_{social} & \text{if } Comf(t) > \theta_{comf} \\ \\ -Decay_{social} & \text{otherwise} \end{cases} \tag{8.2}$$

In this equation, we can see that the social deficit saturates at $Max_{social} = 85$. When the arousal is over its high threshold $\theta_{Ar} = 0.9$, the deficit increases linearly by Inc_social. When comfort is provided, when $Comf(t) > \theta_{comf}$, the deficit decreases linearly by a factor $\beta_{social} = 3$. This value guarantees that the social deficit and therefore social motivation drops quickly below the food motivation when comfort is provided. Moreover, at the chosen update rate of $8Hz$, this value makes the social deficit decrease to 0 quickly, under 5 seconds. $Decay_{social} = 0.5$ is the linear decay rate when the social deficit is positive and no other contributions from either the arousal or the comfort of the human are perceived.

8.4.2 Comfort

Similarly to the previous chapters, the comfort increases with human proximal interactions through physical contact. The comfort does not increase when the robot perceives a human face, though, as this would interfere with the approach behaviour of the robot and the opportunistic mechanism. The perception of the face is rather used as the incentive stimulus that increases the motivation for social interaction when a social deficit exists. The comfort uses the touch sensor on the head of the robot and increases proportionnally to the variable $Touch(t)$ presented earlier.

$$Comf(t) = \frac{\tau_{comf} Comf(t-1) + Touch(t)}{\tau_{comf} + 1} \tag{8.3}$$

The comfort is again calculated as a running average of the $Touch(t)$ variable, therefore being higher when frequent strokes on the head are perceived. The parameter τ_{comf} was set to 3, as it results in a peak of comfort after 3 seconds of interaction with the sensor, as we can see in figure 8.3. This also lead to the definition of the threshold $\theta_{comf} = 0.8$ which determines when the comfort decreases the arousal and influences the evaluation of the responsiveness.

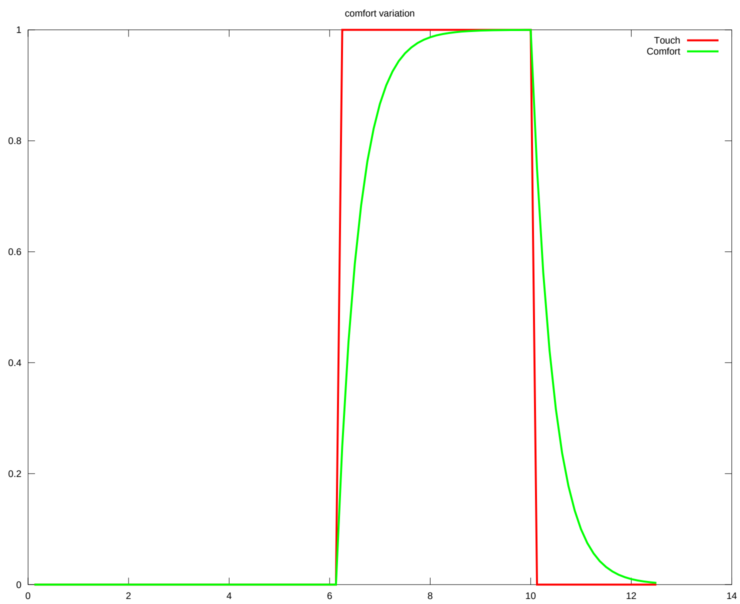


Figure 8.3: Comfort variation with a square input coming from the $Touch(t)$ sensor (x-axis in seconds with an 8Hz update rate)

8.4.3 Arousal

In contrast with the work done in the previous chapters, the arousal level is designed to reflect the satisfaction of the needs. Conceptually, the arousal increases when one or more deficits are close to their maximum level, and decreases when comfort is felt or the deficits decrease. Therefore, in this system the arousal increases as a function of the deficits as follows:

$$Ar(t) = Ar(t-1) + \alpha_{ar}(1 - Ar(t-1)) \text{ card}(D_i > 0.9Max(D_i)) \tag{8.4}$$

Where *card* is the cardinality, i.e. the number of deficits which are above 90% of their maximum value. This equation leads to an arousal level that asymptotically grows to 1.0 when one or more deficits are higher than 90% of their maximum. The arousal grows faster if more deficits are in this high region.

The arousal decreases when deficits decrease, accounting for a relief of distress associated with the current need being satisfied.

$$Ar(t) = Ar(t-1) - \alpha_{ar} Ar(t-1) \text{ card}(\frac{dD_i}{dt} < 0.0) \tag{8.5}$$

Finally, the arousal also decreases when comfort is perceived, following the equation 8.6:

$$Ar(t) = Ar(t-1) - \alpha_{comf} Comf(t) \text{ when } Comf(t) > \theta_{Comf} \tag{8.6}$$

This implementation of the regulation system offers two different ways through which the arousal can decrease, one using the caregiver through comfort, the other using the dynamics of the reduction of the deficits.

Therefore, the arousal reflects the subjective discomfort of the robot, either through the lack of comfort, or lack of satisfaction of the needs. The parameter α_{ar} determines the rate at which the arousal increases and decreases depending on the level of the needs. A value of 0.2 was chosen for this parameter. This value produces a dynamic where the arousal rises to over its threshold $\theta_{Ar} = 0.9$ in 2 seconds. When one deficit decreases, the arousal drops to 0 in less than 2 seconds. In figure 8.4, we can see the rate at which the arousal varies

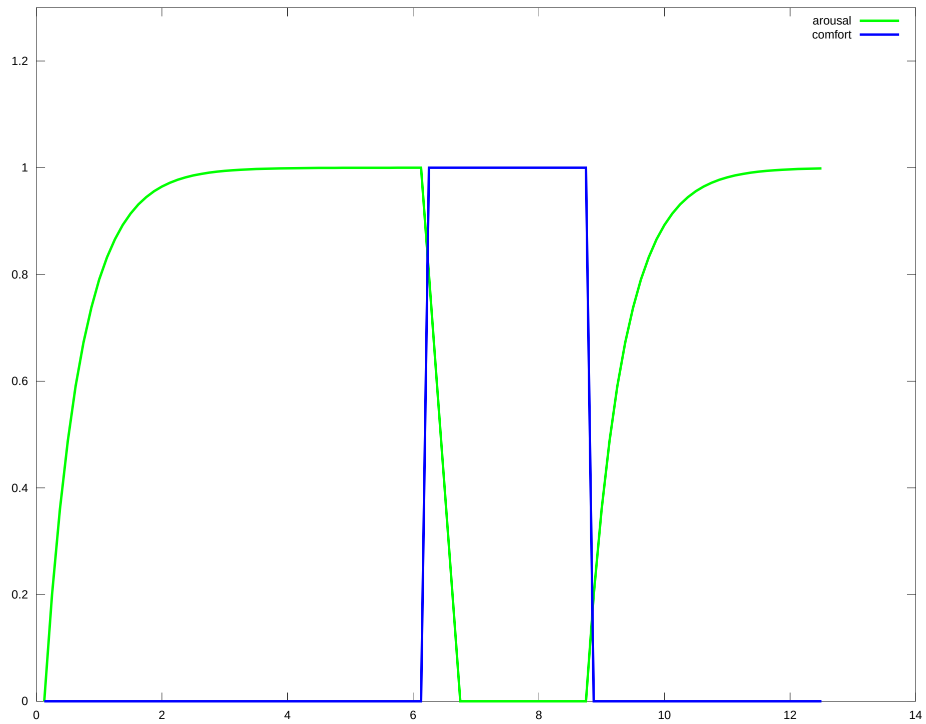


Figure 8.4: Variation of the arousal when deficits are high (0 to 6 seconds), and when comfort is provided (6 to 8 seconds) (x-axis in seconds with an 8Hz update rate)

when the deficits are at their critical value, and how it decreases when comfort is provided. The arousal peaks in approximately two seconds and can be alleviated by comfort in one second.

These parameters permit a fast transition between motivations and a quick soothing when the robot is in need. A quick soothing of the arousal when comfort is provided stops the increase of the social motivation and therefore keeps the robot focused on its current need. The second fast peak of the arousal exemplifies how the arousal reacts if its needs are still not satisfied. To keep the arousal low, the human caregiver needs to keep comforting the robot and help satisfy the current need which gave rise to arousal and therefore the motivation for social interaction.

8.4.4 Adaptation to the Responsiveness of the Human

As in chapter 7, the responsiveness is used to modulate the timing of the requests to the human when the robot is in need of help. Within the system presented in this chapter, this equates to the modulation of the parameters responsible for the dynamics of the social motivation, which in turn, provokes an earlier onset of the behaviours soliciting requests to the human (searching for the human, vocalizing, following the face, and approaching the human). For that purpose the responsiveness modulates the rate at which the social motivation increases when the arousal is high, and the intensity of the perceptual incentive factor (α_{social}) when a face is present in the visual field.

The responsiveness therefore modulates the following parameters of the architecture:

- The increase rate of the Social motivation Inc_{social} within the interval $[Inc_{min}\ ;\ Inc_{max}] = [0.2\ ;\ 1]$

- The perceptual incentive coefficient α_{social} for the perception of the human face within the interval $[\alpha_{socialMin}\ ;\ \alpha_{socialMax}] = [1\ ;\ 9]$

The minimum value for the social deficit increment corresponds to a waiting time between a high food deficit and a consequent peak of high social motivation of 50 seconds at a 8 Hz update rate. This value corresponds to the empirical average time based on the experimental setting. After testing the foraging behaviour in the setup, on average, the robot managed to find food in the environment within this time frame.

At every time step, these variables are updated as follows:

$$Inc_{social} = Inc_{min} + Resp(t)(Inc_{max} - Inc_{min}) \tag{8.7}$$

$$\alpha_{social} = \alpha_{socialMin} + Resp(t)(\alpha_{socialMax} - \alpha_{socialMin}) \tag{8.8}$$

Figure 8.5 shows how the two extreme values of the social deficit increment influence the time when the social motivation becomes dominant. Moreover, this figure shows the different rate at which the social deficit decreases when the comfort is provided and when no comfort is provided. The difference in the time of the onset between the low and high increment values for the social deficit is 40 seconds. The high increment leads to a peak after 10 seconds whereas the low value lead to a peak after 50. The offset of the social deficit when comfort is provided lasts 3 seconds, whereas the decay rate of the social deficit ($Decay_{social} = 0.5$) leads to a longer offset of 20 seconds. The responsiveness can be estimated proportionally to the comfort perceived during high social motivation periods and therefore social interactions are requested by the robot. The responsiveness increases when the comfort is provided to account for the presence of the caregiver and the potential of being helped when a high arousal episode and therefore social request should occur. The responsiveness decreases when no comfort is provided and the social deficit is above a threshold set to $\theta_{social} = 95\%$ of the maximum deficit value. This value was chosen so that the responsiveness only decreases when behaviours are performed that target the human.

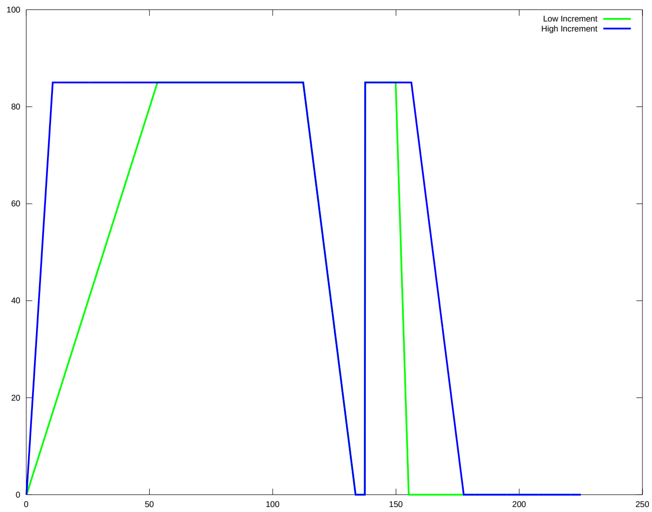


Figure 8.5: Dynamical variation of the social motivation depending on the value of the increment Inc_{social} (x-axis in seconds with an 8Hz update rate). The first phase shows the difference in the rate of the increase of the social motivation assuming the arousal is higher than its threshold. The second phase shows the difference in the rate of decrease of the social motivation when comfort is provided (green labelled - low increment), and when no comfort is provided (blue curve - labelled high increment).

To generalize from the responsiveness modeled in the previous chapter 7, where a decrease in responsiveness coincided with the occurrence of a specific social request behaviour, now the reduction of the responsiveness coincides with the motivation to interact being dominant and with the possible occurrence of all the behaviours that can be triggered by it. The decreases in responsiveness therefore reflect the engagement of a set of behaviours aimed at reducing the distress.

Similarly to chapter 7, the responsiveness $Resp(t)$ can be expressed as a variable which belongs to the interval $[minResp\ ;\ maxResp] = [0.1\ ;\ 1]$. This interval guarantees that the lowest responsiveness is still non-zero in order for the robot to still produce social requests however with a delayed onset due its effect on the activation of the social motivation.

The responsiveness is calculated depending on the levels of comfort and arousal as follows:

$$Resp(t) = Resp(t-1) + \lambda_{Resp}(maxResp - Resp(t-1)) \text{ when } Comf(t) > \theta_c \tag{8.9}$$

Eq. 8.9 ensures that the responsiveness will asymptotically increase to 1 when the caregiver is responsive and therefore provides comfort to the robot.

$$Resp(t) = Resp(t-1) + \lambda_{Resp}(minResp - Resp(t-1)) \text{ when } Comf(t) < \theta_c \text{ and } D_{Social} > \theta_{Social} \tag{8.10}$$

Eq. 8.10 ensures that the responsiveness decreases asymptotically towards 0.1 when the caregiver is not responsive. The coefficient λ_{Resp} is responsible for the speed of adaptation of the responsiveness. It was set to 0.03 in the experiments reported below. This value was chosen based on the duration of the high arousal episodes and on the literature responsiveness (Bornstein and Tamis-Lemonda 1997). This value produces Figure 8.6 and 8.7 show the variation of the responsiveness and the parameters it modulates depending on the comfort provided. We can see that the responsiveness drops from 1 to 0.5 after a period of 20 seconds of lack of attention of the caregiver. However, providing regular and punctual comfort by stroking the head (from time step 50 in Fig. 8.6) for approximately 30 seconds restores the responsiveness to a high level. These values suit the interaction scenario and the setup since they frame a responsive caregiver as responding to the needs of the robot with comfort within a 30 seconds as proposed by (Bornstein and Tamis-Lemonda 1997).

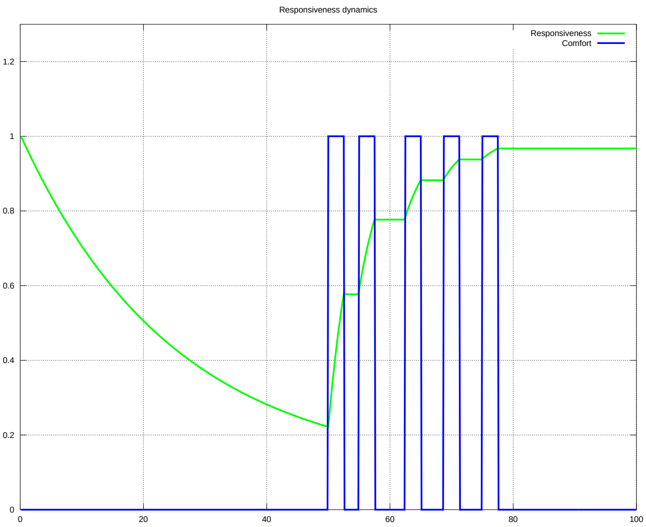


Figure 8.6: Variation of the responsiveness when no comfort is provided, and when comfort is provided (x-axis in seconds with an 8Hz update rate)

8.5 Experimental Evaluation of the Dyadic Regulation of the Social Motivation by the Attachment System

This section presents the results of several runs of the experimental setup during which the behaviour of the experimenter varied in terms of the nature and timing of its responses to the behaviour of the robot. The main goal of the robot is to satisfy its need for food. When the motivation for food is high and the motivation for social interaction is low, the robot searches for food items by exploring the environment with a random walk and scanning the visual field to find food items. When a food item is perceived, the robot approaches it, reaches for it and "eats" it. Alternatively, when the motivation for food is high for a long time the arousal increases and in turn the social motivation increases also depending on its parameters modulated by the responsiveness. The robot then starts looking for the human

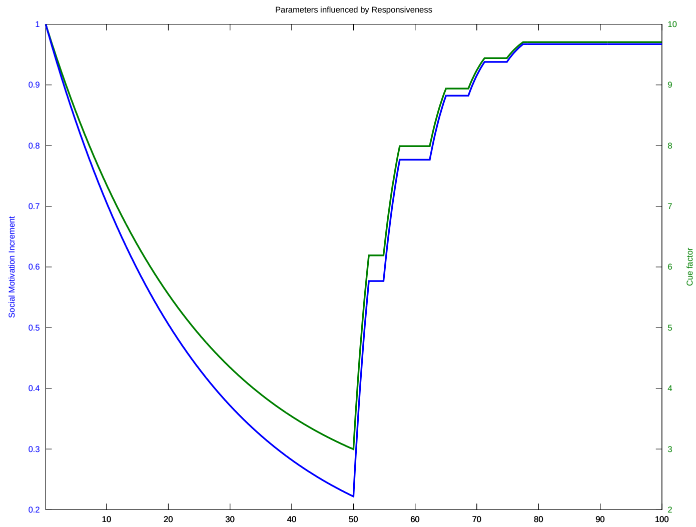


Figure 8.7: Variation of the parameters of the social motivation (the increment Inc_{social} and the perceptual incentive factor α_{social}) with a first low and decreasing responsiveness then increasing with an episode of comfort provided (x-axis in seconds with an 8Hz update rate)

experimenter. One important factor that influences the outcome of these experiments is the behaviour of the experimenter in terms of responsiveness. The human experimenter that behaved as caregiver with a high responsiveness responds to the social requests of the robot as soon as he could. He then comforts the robot and tries to feed it. A caregiver with a low responsiveness does not respond to all the calls of the robot and lets it cope with the situation on its own, and provides only a little comfort to the robot. The evaluation aimed at assessing the impact of the stereotypical behaviour of the human on the behaviour of the robot and its success in satisfying its need for food.

A second factor is the social profile of the robot which depends on its evaluation of the responsiveness and the value of the time parameters of the social deficit and motivation. The evaluation aims at assessing how the social profile of the robot (low or high estimated responsiveness *Resp*) influences the social behaviour of the robot and the resulting satisfaction of its need for food. The main hypotheses are the following:

- A mismatch in the actual responsiveness of the human and the estimated responsiveness of the robot leads to a less successful regulation of the need for food (a higher average deficit for food) and the negative affect of the robot (i.e arousal and social deficit). The "correct" social profile of the robot leads to a better regulation of the needs and affect.

- When the responsiveness of the human varies, the adaptation mechanism helps the robot to improve the outcome of its behaviours (exploratory and regulatory) by changing their dynamics of its behaviour according to the situation. The overall outcome of this adaptation leads to higher satisfaction of the needs of the robot.

8.5.1 Experimental Setting

Arena

During the experiments, the robot was placed in a 3 by 3 metres wooden arena as can be seen in figure 8.8. The arena guaranteed that the robot stays within the setting since the robot uses its sonar sensors to avoid obstacles. To allow the robot to find food items on its own, some plastic food items were taped on the walls of the arena. As can be seen in the picture of the arena, the food items were located in opposite corner of the arena. This leads the robot to travel within the arena to find food and makes the task of feeding itself on its own not too easy. One corner is fitted with two food items and another with only one. Therefore, one region is better for the robot to feed itself than the other.

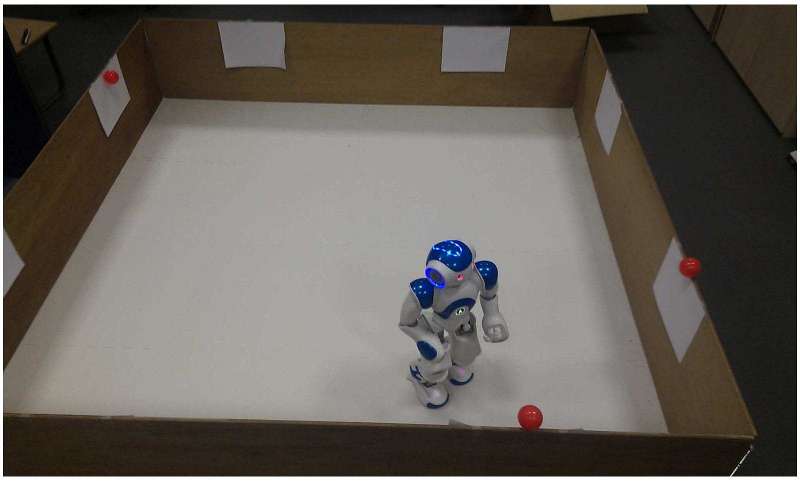


Figure 8.8: Experimental setting for the evaluation of the adapted motivation system for the robot “toddler”

Behaviour of the Experimenter

The human experimenter stands inside the arena with the robot with a food item with him, and could then help the robot to “feed”. Therefore, the success of the robot in satisfying its needs in terms of food depends on its ability to find and reach the items on one hand, and on the responsiveness of the human to help it in doing so. To produce stereotypically different behaviours for the experimenter, two different “styles” were defined to reflect a high or a low responsiveness. In these two interaction profiles, the experimenter responds according to the following guidelines:

High Responsiveness: In this condition, the human experimenter spends most of his time next to the robot, either crouching or kneeling. When the robot starts looking for him, or vocalizing, the experimenter faces the robot so that the robot approaches him, and then comforts the robot by patting it on the head, and then feeds it, or moves the robot closer to and facing a food item. The experimenter also responds to all possible opportunistic bids for attention, which happen when the robot perceives the face of the experimenter and the social motivation increases because of it. This stereotypical behaviour keeps the response time of the human experimenter under 30 seconds (including comfort and resolution of the issue).

Low Responsiveness: In opposition to the previous interaction style, the experimenter is not located in the arena during the experimental run but sits at a nearby desk. The experimenter only comes to help the robot after a long period of calls and search for the caregiver. Whereas a highly responsive human responds to bids for help by comforting and helping the robot within a 30 seconds time frame, the experimenter with a low responsiveness reacts in a time windows of 2 minutes. This response time leads the robot to search for the human for longer, and can result either in finding a food item or not. When the experimenter responds, he behaves as the highly responsive human would, coming into the area, comforting the robot, and responding to its need for food if the robot expresses it by vocalizing or searching for a food item.

The response time windows (30 seconds and 2 minutes) for both conditions of low and high responsiveness were guaranteed using a clock on the monitor of the computer where the processing of the perceptions of the robot was performed. The experimenter could at all time see the time by checking the monitor. This allowed a maximum deviation of 2 seconds from the guideline. In the quantitative evaluation carried out, when the control system of the robot allows it to adapt the responsiveness in real time, the experimenter alternates episodes of high and low responsiveness. Similarly to the setting in chapter 7, the camera image of the robot was streamed to a computer which processes the colour detection for the food item and the face detection algorithm. The robot also streams the data collected concerning its ongoing behaviours, the level of the motivations, and the level of its deficits. The rest of the control system was executed on-board using several scripts in the Urbi language. This allowed to process the perceptions, motivations, and behaviour of the robot at a rate of 8 Hz.

Experimental Conditions

To assess the influence of the responsiveness of the human and the profile of the robot depending on the estimated responsiveness of the robot, experiments were carried out with five different conditions as depicted in Table 8.3. The two stereotypical behaviours (high or low responsiveness) of the human were tested against the profile of the robot in terms of its parameters regulating the social deficit and motivation. The robot had three settings: low responsiveness parameters (RL), high responsiveness (RH), and adaptive responsiveness (RA). In the first two settings the responsiveness (*Resp*) is still continuously updated in the control system but does not modulate the parameters of the social motivation (Inc_{social} and α_{social}). Therefore the “social” profile of the robot is constant in these experiments. The two extremes of the social profile of the robot (RH and RL) were tested against the two stereotypical behaviour of the human (HH and HL).

In the last condition RA, the real time adaptation of the parameters of the social deficit and its motivation to the responsiveness *Resp* was activated. This condition was tested with the experimenter varying its own timing of the responses (HV) during the run and offering periods of high and low responsiveness. Each condition was tested for ten runs of ten minutes.

8.5.2 Data Collected

During the experiments, the following variables of the control system of the robot were logged for later analysis:

- The values of the motivation for food and social interaction

Table 8.3: Experimental Conditions for the Evaluation of the System

Robot	Low Resp	High Resp	Adaptive
Human Low Resp	HL-RL	HL-RH	-
Human High Resp	HH-RL	HH-RH	-
Human Varying Resp	-	-	HV-RA

- The values of the deficits of these two needs (D_{food} and D_{social}) of the robot
- The values of the arousal $Ar(t)$ and comfort $Comf(t)$
- The value of the estimated responsiveness of the robot $Resp(t)$
- The active behaviours executed by the robot

These variables provide a means to quantify the behaviour of the robot depending on the level of the current needs and the history of interaction with the caregiver. They also help quantify the behaviour of the human experimenter. Indeed, in the experiments, the only two factors that are subject to variations are the behaviour of the experimenter and the ability of the robot to find food and satisfy its need. These two factors influence the variables presented above.

The level of the values of the motivations for the need for food and the need for social interaction with the human caregiver show which one is dominant and which strategy the robot is employing, either focusing on looking for food or for the human. Comparing them to the level of the deficits, they also reflect the contribution of the perceptions of the robot. For instance, when the social deficit is lower than the deficit for food, the robot will change its behaviour only when it perceives the perceptual incentive for social interaction, a human face in the visual field. These episodes are opportunistic social requests Soc_{opp}. Therefore, the numbers of opportunistic social requests can be quantified. In addition to these measures, logging the behaviours allows to measure the amount of time the robot spends looking for food or for the human caregiver. This provides the ratio between the two exploration strategies $Exp_{H/F}$, defined as the time spent looking for a human caregiver divided by the time spend looking for food. Finally, the average of the food deficit and social deficits provide an account of the success the robot had had in satisfying its needs. To summarize, the following measures are later used to assess the behaviour and success of the robot depending on the estimated responsiveness and the behaviour of the human. The associated predictions based on the behaviour of the human and the estimated responsiveness used by the robot are also stated for each variable:

- Ar, the average level of arousal: a high responsiveness of the human should provide a lower average level of arousal
- $Comf$, the average of the comfort: higher level of comfort will be correlated with a higher responsiveness of the human
- $Resp$, the average estimated responsiveness: higher estimated responsiveness should correlate with higher responsiveness of the human
- Soc_{opp}, the frequency of opportunistic social requests (high social motivation when $D_{social} < D_{food}$): This frequency should increase with the responsiveness of the human and with the estimated responsiveness of the robot
- $Exp_{H/F}$, the ratio of the time foraging for the human to the time foraging for food: a high responsiveness from the human should lead to a smaller ratio, since the human will help the robot promptly. A high estimated responsiveness should lead to a higher ratio for equal human behaviour, since the robot will look for the human earlier.

- D_{food}, the average of the food deficit: a highly responsive human should lead to a lower food deficit. A lower deficit should be experienced when the estimated responsiveness matches the responsiveness of the human.
- D_{social}, the average of the social deficit: a lower level of social deficit should be experienced with a highly responsive human, and when the estimated responsiveness of the robot matches the responsiveness of the human.

The following sections present a qualitative evaluation of the interactions with a human behaving with a "high responsiveness" when the robot's estimated responsiveness is high, and then with a human behaving with a "low responsiveness" when the robot's estimated responsiveness is low. They illustrate the differences in the behaviour of the robot and the human depending on the conditions, and will help explain the results of the quantitative analysis later presented.

8.5.3 Interaction with a Caregiver with a "High Responsiveness"

In Fig. 8.9, we can see the values of the motivations for food and for social interaction during one run where the robot's estimated responsiveness was high, and therefore the social motivation parameters where $Inc_{social} = Inc_{Max} = 1$ and $\alpha_{social} = \alpha_{socialMax} = 9$. During this run, the experimenter behaved with the high responsiveness profile as well. In this plot, we can observe that due to the high estimated responsiveness, the social motivation grows sharply when food has not been found. However, since the human experimenter responds fast with comfort, the social motivation peaks are narrow and short in time. Moreover, as can be seen around second 150, the effect of the opportunism is sharp as well, since the coefficient α_{social} is high. The levels of arousal, comfort, and responsiveness are represented on figure 8.10. We can observe the timely interventions of

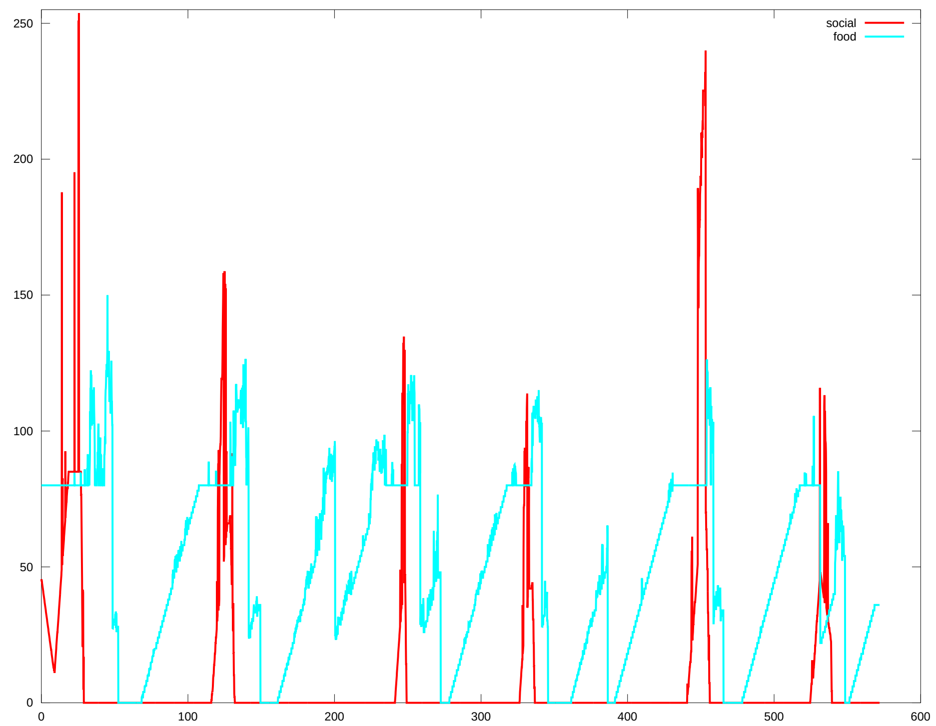


Figure 8.9: Plot of the values of the motivations of the robot while interacting with a caregiver with a “high responsiveness” (social motivation in red and food motivation in blue, the x-axis in seconds)

the human who provides comfort after each arousal peak (which has led to social request by opportunism or after searching).

The level of responsiveness increases every time the robot receives comfort, and therefore reflects the actually responsive behaviour of the human. Starting from a medium level (0.4), the estimation of the responsiveness rises to 0.8 after two interventions as the human comforted the robot before feeding it and then after. Over the whole run, the responsiveness never decreases again since the human is really close to the robot and responds with

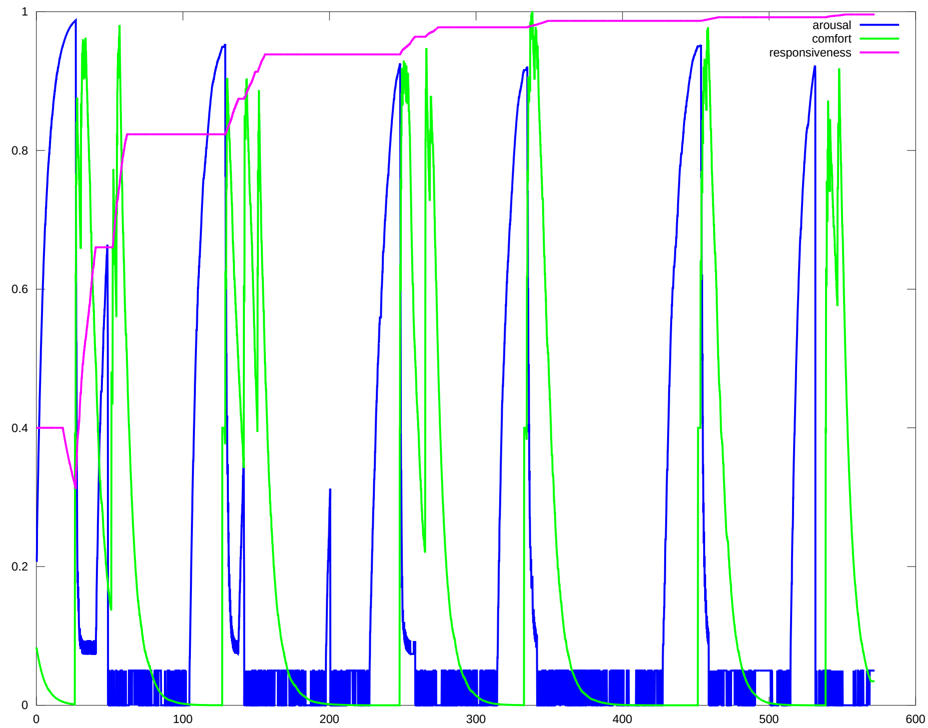


Figure 8.10: Arousal, Comfort and Responsiveness values of the robot while interacting with a caregiver with a "high responsiveness"

comfort to any requests the robot produces. The behaviours performed by the robot are depicted in figure 8.11 (note that the x-axis is measures time steps and not seconds as opposed to the two previous plots).

We can observe on this figure that the robot mainly spends its time searching for food (Search Food Behaviour). When this search does not lead to a decrease in the food deficit, the robot searches for the human. In this case, we can see that these periods are really short, since the human is – by design of his interaction profile– close by, and responds promptly. We can also see the sequence of behaviours when the caregiver intervenes. Just

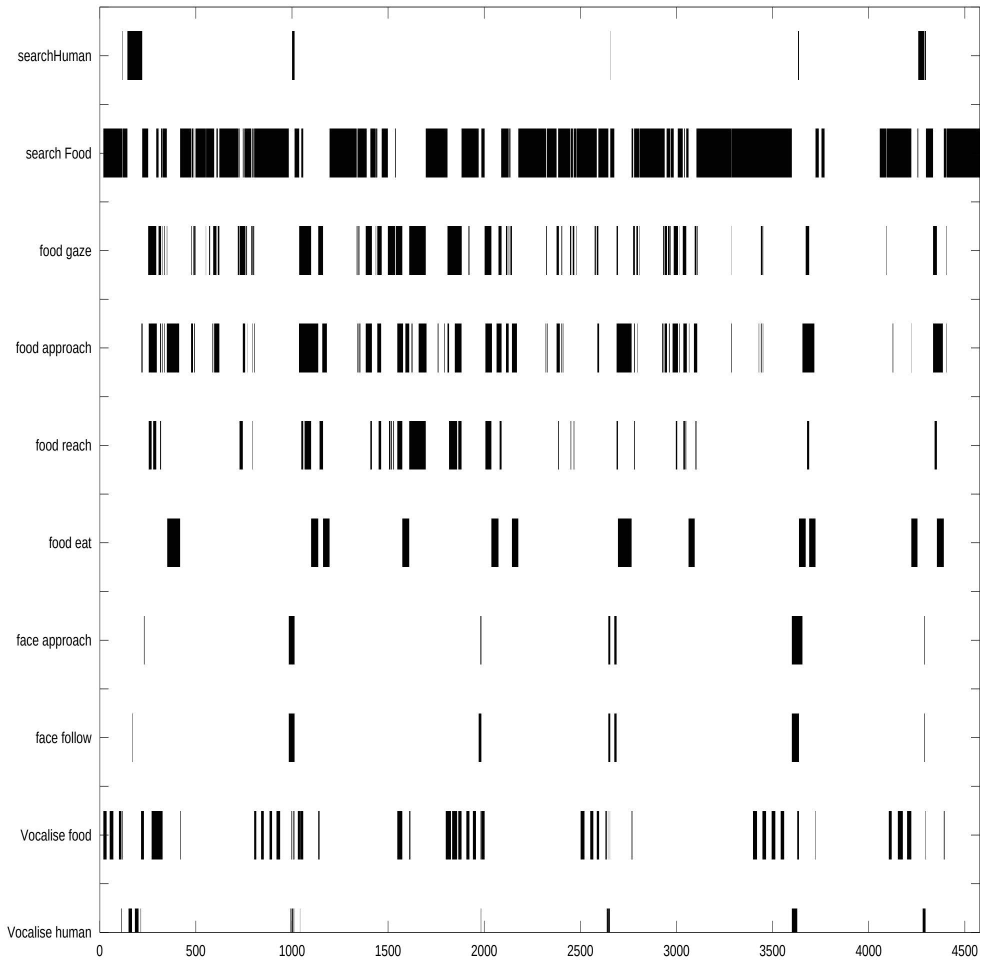


Figure 8.11: Active behaviours of the robot while interacting with a caregiver with a "high responsiveness"

before the time step 1000, the robot briefly searches for the human, then approaches him and follows his face. Then, the robot gazes at a food item presented by the human and reaches and eats it.

8.5.4 Interaction with a Caregiver with a "Low Responsiveness"

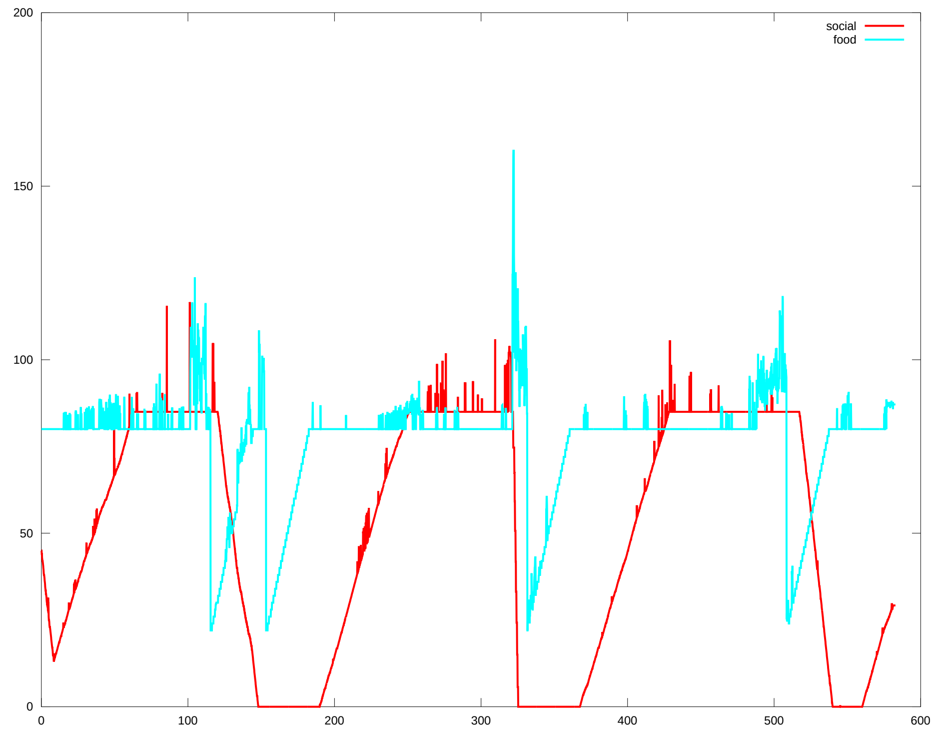


Figure 8.12: Plot of the values of the motivations of the robot while interacting with a caregiver with a "low responsiveness " (social motivation in red and food motivation in blue, the x-axis in seconds)

The following figures show how the motivations, affective variables, and behaviours vary during a run with a caregiver with a "low responsiveness", and with the robot having a profile corresponding to a low expected responsiveness ($\alpha_{social} = \alpha_{socialMin} = 9$ and $Inc_{social} = Inc_{Min} = 0.2$). Figure 8.12 shows the variations of the values of the motivation for food and social interactions. As can be seen, there is a slower onset of the social motivation in comparison to the previous high responsiveness case since the value of Inc_{social}

is lower. The social motivation exceeds the food motivation after 80 seconds instead of 20 in the previous case. In terms of food satisfaction, since the human does not respond at first, it takes the robot 120 seconds to feed itself for the first time. The successful feeding is a result of the opportunistic mechanism, but this time because the robot perceived a food item while looking for the human. Around the $100th$ second, the value of the food motivation becomes higher than the social one because of the perception of a food item. Moreover, before this episode, the robot was actually approaching a food item that was far as can be seen in Fig. 8.14. Before it could reach it, the dominant motivation switched from food to social interaction, interrupting the sequence of behaviour that could have led to successful feeding. The switch in dominant motivation was only possible because the food item was still far away, and therefore the opportunistic contribution of the perception on the motivation was not strong enough. An interesting phenomenon to remark is the longer lasting social motivation after the robot finally fed itself. Since comfort was not provided the social motivation was not satiated and the robot keeps searching for the human instead of resuming its search for food. This phenomenon is a consequence of the separation of arousal and the social motivation and the effect the model produces on behaviour, which will be discussed further. The arousal is alleviated due to the decrease in the food deficit as can be seen in Fig. 8.13. In terms of the behavioural variables collected, this lack of regulation from the human leads to a higher $ExpH/F$ ratio and a higher average of the social deficit D_{social}. Considering the dynamics and frequency of the behaviours produced, figure 8.14 shows how the robot performs almost even foraging periods for the human and for the food. The number of vocalization for the human is also much higher than in the interaction with the human behaving with a “high responsiveness”. Considering the evaluation of the responsiveness of the human, we can see that the first half of the interaction sees the responsiveness $Resp(t)$ drop from 0.4 to 0.1 in the first 100 seconds. However, when the

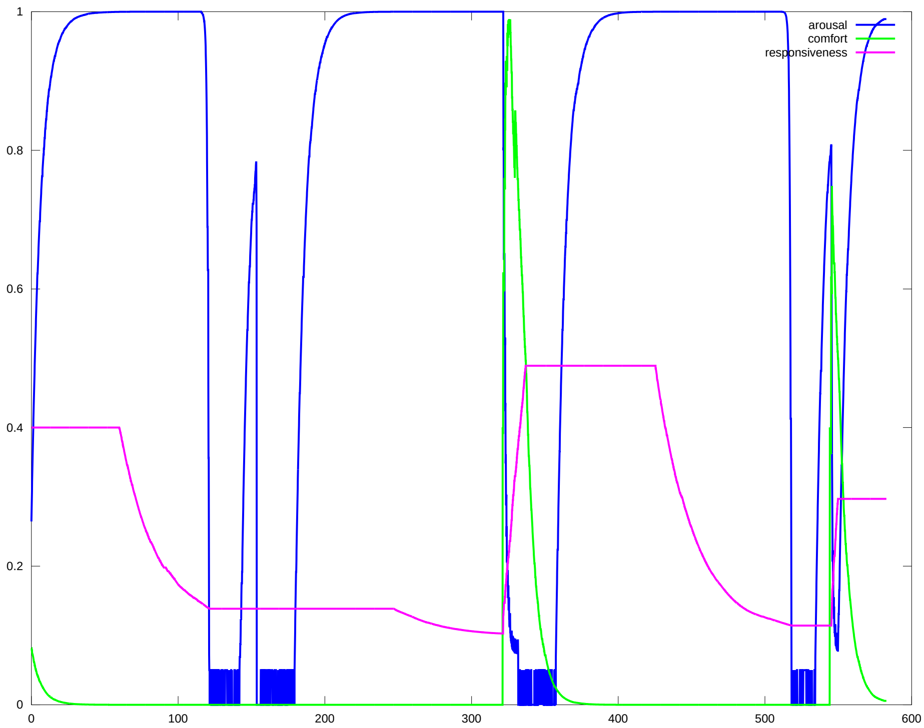


Figure 8.13: Arousal, Comfort and Responsiveness values of the robot while interacting with a caregiver with a “low responsiveness ” (arousal in blue, comfort in green, and responsiveness in pink)

human caregiver finally intervenes around the second 310, one successful intervention with comfort restores the responsiveness to a medium level 0.5. Then, the subsequent absence of the human leads to another drop of responsiveness between seconds 420 and 500.

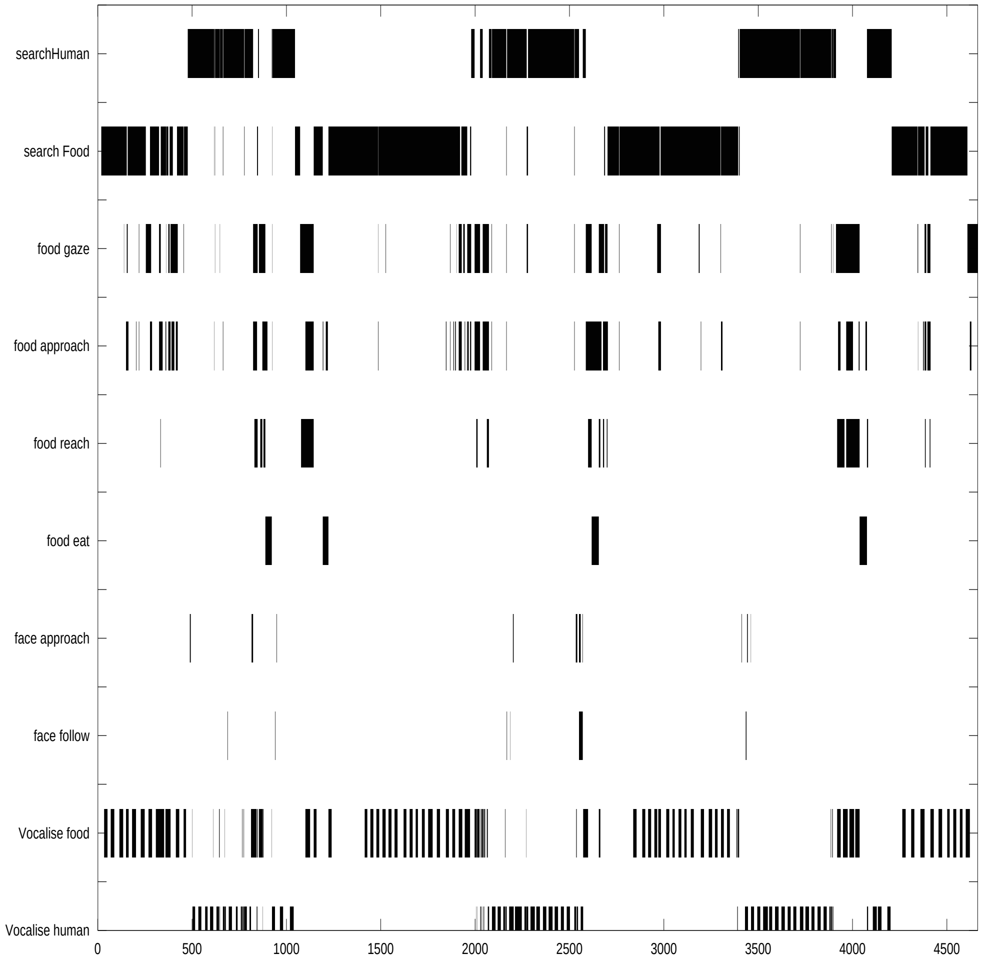


Figure 8.14: Active behaviours of the robot while interacting with a caregiver with a "low responsiveness "

8.5.5 Quantitative Analysis of the Effect of the Responsiveness of the Human Caregiver and the Regulation Parameters of the Robot

The results of the evaluation of the five conditions are presented in Table 8.4. For each condition, the mean and standard deviation is presented for the measures presented above.

Table 8.4: Data collected from the experiments with the five conditions. Means and standard deviations (in parentheses) are presented for each variable

Condition	Resp	Comf	Ar	Soc_{opp}	$Exp_{H/F}$	D_{food}	D_{social}
HL-RL	0.32 (0.12)	0.029 (0.020)	0.62 (0.11)	0.064 (0.036)	0.43 (0.37)	66.0 (5.0)	39.6 (13.8)
HL-RH	0.26 (0.02)	0.020 (0.01)	0.66 (0.35)	0.029 (0.013)	1.5 (0.14)	72.0 (2.51)	58.7 (2.81)
HH-RL	0.75 (0.12)	0.046 (0.0028)	0.37 (0.035)	0.022 (0.021)	0.058 (0.012)	52.8 (4.03)	16.7 (3.81)
HH-RH	0.83 (0.12)	0.085 (0.0092)	0.17 (0.080)	0.048 (0.020)	0.07 (0.037)	42.8 (5.50)	10.1 (5.66)
HV-RA	0.55 (0.22)	0.046 (0.016)	0.55 (0.077)	0.067 (0.04)	0.16 (0.014)	59.5 (6.52)	49.1 (10.6)

Effect of the Stereotypical Responsiveness of the Human

At first, examining the difference in the average of the food deficit D_{food} shows the effect of the high responsiveness of the human. A statistical t-test analysis between the two conditions HL-RH and HH-RH reveals a significant effect of the behaviour of the responsiveness of the human ($p < 0.001$, $t = 4.13$) when the estimated responsiveness of the robot is also high. A higher responsiveness behaviour for the human leads to a lower deficit as hypothesized. A similar effect is observed when the estimated responsiveness of the robot is low (HL-RL and HH-RL provide $p < 0.001$, $t = 8.13$). Therefore, the responsiveness correlates with a lower average of the food deficit. This result is obvious since the human actually helps the robot to feed. As can be seen from the result table, the best condition for a low average food deficit is a highly responsive human and a high estimated responsiveness. Comparing the exploration ratio $Exp_{H/F}$ leads to a significant effects of the behaviour of the human in the case of a high estimated responsiveness (HL-RH against HH-RH gives $p < 0.001$, $t = 41.26$) and a low estimated responsiveness (HL-RL against HH-RL gives $p < 0.001$, $t = 4.26$). A higher responsiveness of the human leads to a lower ratio of social exploration since the human responds promptly.

The effect of the responsiveness of the human also have an effect on the social opportunism Soc_{opp}. Comparing both sets of conditions reveals a significant interaction in the case of a high estimated responsiveness (HL-RH against HH-RH gives $p < 0.01$, $t = -3.46$). However, with a low estimated responsiveness (HL-RL against HH-RL gives $p < 0.001$, $t = 4.19$), but the robot produces more opportunistic behaviours in the case of a low responsiveness caregiver. This can be explained by the fact that, as presented in the qualitative description of the interactions, low responsiveness estimation leads to periods of active social behaviours that happen after food has been eaten. Therefore, the low food motivation and the non-satiated social deficit lead to more opportunism, when both deficits are at similar levels and $D_{social} < D_{food}$. Indeed, if the need for food is just above the need for social interaction, and a face is perceived, an opportunistic behaviour will be performed. However, it has to be noted that the values for Soc_{opp} are relatively low ranging from 0.022 to 0.064, therefore less than 7% of the time of the robot is dedicated to social behaviours of an opportunistic nature. The effect of the behaviour of the human caregiver are all significant, which is a consequence of the stereotypical "styles" described in terms of responsiveness. They do provide some potential extreme boundaries for testing the system. The estimated responsiveness calculated in real time demonstrates that this estimator correlates with the stereotypical behaviour of the human. The other variables collected demonstrate the differences produced by the behaviour of the human in terms of responsiveness. All are consistent with the stereotypical behaviour of the human. A high human responsiveness leads to lower levels of arousal, higher levels of comfort, and lower levels of social and food deficits, than a lower responsiveness.

Effect of the Estimated Responsiveness and the Social Profile of the Robot

As can be seen in the table, for an equal estimated responsiveness of the human, and the associated parameters for the social motivation, a mismatch between the estimated responsiveness and the responsiveness of the human leads to higher food deficits level. A high estimated responsiveness leads to a 72.0 average deficit when the human responsiveness is low which is the worst case scenario. A low estimated responsiveness with a highly responsive human (HH-RL condition) leads to a food deficit average of 52.8. An overestimated responsiveness leads to a higher ratio of exploration for the human $Exp_{H_F} = 1.5$. Again this is due to the robot exploring to find a human earlier, when the food deficit is high, and even after its food deficit was reduced.

Adaptation of the Social Motivation to the Responsiveness

The last experimental condition tested the outcomes of the social deficit and motivation parameters being adapted in real time using the estimated responsiveness $Resp(t)$. We can observe that this strategy leads to a lower average food deficit than the conditions where the responsiveness of the human is low. Interestingly, since during this runs the experimenter alternated episodes of high and low responsiveness, we can see that the average food deficit (59.5) is close to the sum of the averages between the conditions where the constant estimated responsiveness matched the responsiveness of the human (conditions HL-RL and HH-RH), where the average of both conditions gives 54.4. However, the same cannot be said for the exploration ratio which in this condition was 0.16, and would have been averaged to 0.25 with the two matching responsiveness conditions.

8.6 Discussion

8.6.1 Limitations of the model and types of regulatory and foraging behaviours

A first strong assumption of the model and the experimental setting is that a human will eventually help the robot. Indeed, as the robot changes its behavioural strategy through the dominant motivation – from foraging for food to look for the human– if no human would eventually assist the robot will stay "stuck" exploring the environment to look for a human. In this particular set of experiments, the robot can eventually satisfy its primary need for food because the two foraging behaviours can lead to the discovery of both resources, a food item or a human. However, they are both different since they are more suited to find one resource than the other. This limitation will be even more crucial in a setting where the robot uses drastically different set of behaviours to satisfy its primary needs to the one to request and find help from a human. Let us take for instance the experiments in the previous chapter where the robot explores and learn properties of the environment. If the arousal cannot be alleviated with time or by other means (looking away to lower the level of stimulation for instance) than the human caregiver, the robot would keep producing regulatory behaviours endlessly. In adapting the attachment system to other robotic platform with specific autonomous goals this would become a crucial problem. If the regulatory behaviours of the robot do not offer the possibility for the robot to find a solution in order to eventually satisfy its goals, the robot would also be stuck in a pattern of behaviour which does not solve its current problem. There are two avenues to circumvent this issue.

First, the robot can concurrently attempt to solve the current problem or satisfy its needs and produce "non-interfering" regulatory behaviours such as vocalizing for human in the experiments of this chapter. This means that one interactive modality (the voice of the robot here) is used for requesting help from the human while other (locomotion and head panning) are still used to try and carry on the task. This organization requires that the motivation system interacts in a different manner with the behaviours. The two motivations with the highest activation (in this case the motivation for food and the motivation for social interaction) would have to both trigger different concurrent behaviours. Therefore, the winner-take-all principle used to activate one set of behaviours belonging to the dominant motivation is not suited, and the resulting activation of the behaviours should be the product of a specific motivation activation, whether it is dominant or not.

Another solution to this problem is the addition of an extinction mechanism for the social motivation. This mechanism purpose is to inhibit the social motivation after a certain amount of time when it has been unsuccessful in eliciting a response from the human. Again, this mechanism requires some time-based parameters which would depend on the task and the operational setting of the robot, as well as the likelihood of a human providing help.

Another aspect that was noted in the qualitative assessment of the behaviour of the robot is the interruption of ongoing appetitive behaviours. As was noted when the robot with a "low responsiveness" profile interacted with a human with a low responsiveness, when the robot did perceive a food item and started to approach it, if the incentive of the perception of food was not high enough to keep the motivation for food dominant, then the robot tries to look for the human instead. These interruptions do not help the robot in the overall goal of satisfying the need for food. In case the human actually responds promptly to the request of the robot then this strategy is suitable, however, with a low estimated responsiveness, and a human with a behaviour corresponding with a low responsiveness, this proves not to be a good strategy. One possibility to avoid this situation would be to for the estimated responsiveness $Resp(t)$ to also increase the perceptual incentive values of the other motivations (α_{food} in this case). This modification would help maintain the food motivation as dominant due to the perception of the stimuli which would reduce the current need to be satiated.

Another solution to this issue is to alter the evaluation of the level of arousal. In addition to being alleviated by the reduction of the needs, the arousal can be reduced by the perception of a stimuli that predicts a decrease in the current high deficit. This solution is slightly more complex than the previous one. In the case reported in this chapter, only the perception of a food item (P_{food}) can play this role, and the level of arousal could be evaluated using the formula in the following equation 8.11.

$$Ar(t) = Ar(t-1) - \alpha_{ar}\ P_{food}(t) \text{ if } D_{food} < D_{social} \tag{8.11}$$

8.6.2 Responsiveness adaptation and behavioural outcomes

The experiments reported in this chapter focus on the notion of responsiveness to first qualify the behaviour of the human caregiver, and to adjust the parameters of the social deficit and motivation. When the responsiveness used by the robot corresponds to the responsiveness exhibited by the human caregiver, the behaviours of the robot appear more coherent. A low estimated responsiveness results in later and fewer social requests whereas a high estimated responsiveness leads to earlier requests which are quickly satisfied by the human. However, as we have seen in the qualitative and quantitative evaluation of the interactions, a human with a "low responsiveness" profile leads the robot to keep producing regulatory behaviours after its current need for food was satiated, leading to an even higher exploration for human against food ratio $Exp_{H/F}$. This effect of the model has a potentially positive aspect. During these periods, from a subjective robot-centred point of view, the robot has fulfilled its need for food and its remaining need for social interaction is neither satiated nor yet extinguished with time. These periods can be seen as the robot testing the responsiveness of the human in a now safer state (again in terms of vital needs such as food). This could prove useful in order to re-evaluate the behaviour of the human. If the human now responds to these regulatory bids and provides comfort, the real-time estimation is updated, and during the next "dangerous" or critical situation (if the robot does not find food in this case), the robot will try and use the human support accordingly. Another way to interpret these periods of requests of social interactions after the relief of the arousal and of the need for food, is to suggest that the robot is communicating past distress of discomfort to the human after an episode of unsuccessful dyadic regulation. They provide the opportunity for the human to comfort the robot and again help it estimate the responsiveness of its caregiver. This persisting effect only occurs due to the separation of affect and the drive of the social behaviours.

One main problem of this property of the model might manifest itself if the interventions of the human only coincide with these periods. If the human caregiver comforts the robot, this will increase the estimated responsiveness used to drive the social motivation and the social behaviours. Next time the food deficit becomes critical, the social motivation will rise quickly, driven by the high value of the responsiveness, which corresponds to the scenario with a constant high estimated responsiveness and low responsiveness caregiver (HL-RH). This type of interaction has similar properties to disorganised attachment patterns. As Ainsworth discovered (Ainsworth et al. 1978), disorganized attachment patterns are marked by longer lasting periods of expressed distress even when the object of distress is no longer perceived or even present. However, in this typology, the comfort provided by the mother does not alleviate the discomfort of the infant as well as in organised patterns of attachment. The model proposed here does not show this property since the effect of the comfort of the human is not affected by the estimated responsiveness. In the best case scenario presented, when both the estimated responsiveness and the actual responsiveness are high (HH-RH), the interaction is similar to what is predicted by Ainsworth's typology of organised attachment. The requests are answered promptly and adequately, leading to longer period of exploration and independent behaviours.

8.7 Summary

In this chapter, the dyadic regulation system was applied to a robot endowed with a motivation control system. The affect – the arousal– of the robot was modeled after the satisfaction of the needs of the robot. This work exemplifies one way to generalize the dyadic regulation involved in affective bonds and the attachment system in a more complex architecture with several competing goals and the motivations and behaviours to satisfy them. If the robot needs to try and fulfil its goals independently and only interact with humans when needed then a social motivation only modeled after the need for regulation of negative affect can be sufficient. In this case, the robot only triggers regulatory behaviours, such as looking for the human, approaching him when a face is perceived, and vocalizing for help, when its current goals are not satisfied.

In comparison with other human-robot interaction system based on motivation and drives, here the social interaction solely stems from the need of the robot to be helped achieving one goal and satisfying one need, whereas other research projects model the social motivation after a social drive depending on the amount of interaction the robot previously had (Velásquez 1998, Breazeal and Scassellati 1999). These previous implementations and experiments had goals to trigger social interactions with human beings to give opportunities for the robot to learn or to assess the expressive behaviour of the robot in face-to-face interactions. This chapter takes a more functional approach of early social interactions. The motivation for social interactions is used to regulate the affect of the robot and its needs, as well as to evaluate the responsiveness of the human in order to adapt the dynamics of the regulatory behaviours of the robot.

To summarise, the following conclusions can be drawn:

1. The two step modelisation of the attachment system where the social drive reflects a high arousal leads to a different behavioural organisation than the arousal system used in the previous chapters. When the social need is not responded to after the disappearance of the stressor (the stressor here being the lack of food and regulation of the associated need), the resulting social drive leads the robot to query the responsiveness of the human. This new model of the attachment system dissociates affect and motivation and offers a more varied range of behavioural outcomes than the arousal drive. It might be better suited to investigate human-robot attachment-like interactions with real users, especially when trying to reproduce patterns of behaviours related to AInsworth typology (Ainsworth et al. 1978).

2. An adequate estimation of the responsiveness of the human leads to a more coherent behaviour and a better regulation of the needs of the robot. However, obviously a high responsiveness of the human is preferable in all cases.

3. The adaptation to the responsiveness of the human allows the robot to regulate its ratio of foraging behaviour depending on the current behaviour of the human. The results demonstrate that this adaptation produces almost an average of the outcomes of the two conditions where the estimation of the responsiveness corresponded to the actual stereotyped responsiveness of the human.

Chapter 9

Conclusions and Perspectives

In this chapter, I summarise the work and experimental results described in previous chapters, and highlight how and to which extent they address the research questions proposed in the introduction. Following this, I draw some perspectives from the research presented, showing how furthering the work stemming from this approach could benefit the field of autonomous and developmental robotics.

9.1 Summary

The research undertaken in this work was focused on adapting the paradigms from Attachment Theory and especially the role of the attachment figure as a Secure Base, to the autonomous development of robots. The psychological findings emphasise the central role of the mother, or primary caregiver, in shaping the development of young infants. Specifically, the Secure Base is hypothesised to be used by infants in order to relieve their distress in unusual or unfamiliar episodes. This distress is conveyed by emotional displays, and other regulatory behaviours such as proximity seeking and gazing. The responsivity and sensitivity of the caregiver to these regulatory behaviours are hypothesised to be important factors for the socio-cognitive development of infants. Following these key points, the research carried out aimed at adapting these concepts for a developing robot, and assessing their impact on the learning outcomes and behavioural dynamics of the robot.

First, in chapters 2 and 3, I presented the key features of attachment theory and how they can be operationalized using existing notions and architectures from the literature on natural and artificial affective interactions. This review highlighted the necessary components of an attachment system for the dyadic regulation of affect. These components include an evaluation of the affect, which was centred around the construct of arousal. This construct is flexible enough so that it can include useful notions such as novelty, surprise, incongruity, or even frustration. The arousal can then be used to "drive" the behaviour of the robot from exploratory behaviours to increase the arousal to regulatory behaviours aimed at attracting the help of a human to reduce the arousal. This human can then relieve the high arousal of the robot through *Comfort* , as is done in secure relationships between a mother and an infant (Sroufe 1995). This work highlighted the cyclic nature of the arousal drive which seeks stimulation when low and comfort when at a high and sustained level. This notion of drive is similar to some other artificial affective interaction systems which seek to maintain a drive within some predefined boundaries (Velásquez and Maes 1997, Breazeal and Scassellati 1999, Breazeal 2003).

Chapter 4 presented the design steps to model and produce a robotic architecture with an attachment system. The dynamics of the arousal was designed as an average of the *Stimulation* received. This level of arousal can then be alleviated by a comfort variable, which depends on the external interventions of a human caregiver through distal or proximal interactions. The model designed was compared to a similar one developed in the same period (Stevens and Zhang 2009). As this model was designed to simulate the emergence of attachment patterns in infants some main conceptual differences are highlighted. Their model allows for a stabilization of the arousal level even when comfort is provided, which is not suitable to drive the behaviour of a robot between exploration and regulatory periods. This chapter then introduces two neural networks used throughout the dissertation. These algorithms are used for the robot to learn features of the environment and to compute measures of novelty and learning performance. These measures serve as input to stimulate the arousal. The chapter ends by proposing a robot architecture which contains the properties highlighted in the literature on attachment and uses the arousal regulation model proposed. This architecture drives a robot to explore and learn until too much novelty or complexity is met. When this occurs regulatory behaviours are performed to attract a human caregiver and get comforted. This architecture proposes a minimal operationalization of the tenets of attachment to assist and influence the development of a robot.

The architecture proposed was used in a set of experiments in Chap. 5. In these experiments, a SONY AIBO robot was exploring an environment and trying to learn features from low-level perceptions. The aim was to study how the interplay between exploration, novelty and distress, and the comfort provided by a human partner could influence the learning outcome of the robot and its behaviour. The architecture was evaluated depending on the "responsiveness" of a human caregiver, which role was played by the experimenter. The results demonstrate how different levels of responsiveness lead to different duration in exploration behaviour and regulatory behaviour production. This is a result of the design of the arousal drive based on the stimulation and the comfort. However, when looking at the performance of the learning system and exploration metrics (number of unique patterns explored and closest representation of one patter in the SOM), we saw that a highly responsive caregiver leads to a more varied exploration but a more shallow learning of the perceived patterns when compared to a "medium" responsiveness caregiver. A low responsiveness caregiver leads to discovering less patterns and learning them less deeply then a medium responsiveness caregiver due to the excessive time spent looking for a caregiver for help. This suggests that depending on the task and the perceptions to learn, some caregiving styles in terms of responsiveness or more suited than others. Additionally, this architecture shows how a human can implicitly bias what and how a robot explores and learns the environment, and could provide a minimal system for implicit personalisation of the development of a robot.

To assess the attachment system model with adult subjects and its potential in real world interactions, the setup was tested at the London Science Museum (Chap. 6). This experiment with a small sample of naive (non-expert users) adult subjects showed that the architecture and the regulatory behaviours of the robot trigger clear and varied caregiving behaviours from human adults, therefore supporting the validity of the approach and its implementation. To achieve this, the architecture was modified in order for the robot to exhibit two opposite stereotypical behavioural profiles, one *needy*, and one *independent*. The "needy" profile was designed to respond faster and request human attention more often than the "independent" one. The experiment was designed to assess which profile the subjects would prefer to interact with, and whether or not they would recognise the profiles for what they were designed. During a special event at the London Science Museum as part of the FEELIX GROWING project, 21 adult subjects interacted with the two profiles of the robot. All subjects reported having enjoyed the interactions. Direct observations already showed clear differences in their behaviour with the two robot profiles. Since the "needy" profile was more reactive and demanding, the subject reported enjoying this profile the most. With the "independent" profile, subjects were less confident as to how or when they should interact with the robot. The results of the questionnaires showed that the subjects did recognise each profile distinctly. Moreover, after coding the videos of the interactions, a trend was noticed regarding the number of positive and affective gestures displayed. More were observed when subjects interacted with the "needy" robot. These results demonstrate that the architecture and its dynamics were suited to trigger and maintain caregiving behaviours from human adults. They behaved in accordance to the robot profiles, and were responsive to the regulatory behaviours displayed by the robot. The work presented in this chapter provides a set of initial tools that could be valuable to evaluate future human-robot caregiving interactions with the questionnaire designed and the behaviours coded in the video.

Chapter 7 evaluates the influence of the regulatory profiles designed on the behaviour of the robot depending on the complexity and variability of the environment. In this set of experiments, an Aldebaran NAO robot was used as part of the ALIZ-E project. The robot was learning features of objects laid on a table, allowing for an easier manipulation of the complexity of the task, by changing the objects or modifying the amount of them. The results showed that the attachment system reacts to general change as well as punctual outliers as the regulatory behaviours and their frequency performed by the robot were correlated with such changes. Moreover, with an equally responsive simulated caregiver, the "independent" profile would explore the environment faster than the "needy" in a complex environment, while both have similar pace in a simple one. This evaluation demonstrates how the profiles react differently to these situations under equal responsiveness. The "needy" robot profile also spends longer periods of time trying to learn the features of the environment when the arousal is at a medium level. To cater for a varying caregiving responsiveness, a mechanism to adapt the profile of the robot in real-time has been developed and tested in this setting. The results show that using the correlation between the occurrence of regulatory behaviours, and the comfort provided can help the robot evaluate the responsiveness of the human caregiver and adapt its profile between the "needy" and "independent" extremes.

In a final experiment in chapter 8, the attachment system was adapted to and integrated in a a motivation-based action selection system. The control system used an existing architecture developed for diabetic children interacting with the NAO robot, and adapted the "social" motivation to reflect the lack of regulation of the arousal. In this architecture, the arousal increases when the needs of the robot are not satisfied and the robot requires the help of the human. This demonstrates how to adapt the attachment system to other architectures or robot experiments. As in the previous chapters, two extreme sets of parameters were designed for the robot to exhibit regulatory behaviours more or less frequently. The analysis of the performance of the adapted architecture was performed by varying the responsiveness of the human against the two sets of "social" profiles of the robot. The human was required to help the robot when its need for food was not satisfied. The profile of the robot influenced the onset of the social motivation and the behaviours it triggers. The adaptation to the responsiveness of the human was integrated in this architecture as well. The results demonstrate that when the robot's social profile is constant and corresponds to the one of the human in terms of responsiveness a more coherent behaviour emerges and the robot's needs are better satisfied. When the social profile of the robot and the responsiveness of the human do not match, the organisation of the behaviour of the robot leads to poorer outcomes. Moreover, this discrepancy between the two social profiles of the human and the robot leads to behaviours which can be interpreted as similar to disorganised attachment patterns in infants (Ainsworth et al. 1978). Finally, when the robot adapts its profile in real time to the one of the human, an averaging of the outcome is observed, which is beneficial to the robot.

9.1.1 Summary of the Contributions to Knowledge

This dissertation brings forth the following contributions:

1. A review of the literature on the psychology of mother-infant attachment and the existing artificial affective systems leads to the selection of requirements to design a minimal model of human-robot dyadic regulation. This model aims at operationalizing the principles of attachment for the robot to use the human as an external resource for affect regulation.

2. A dyadic regulation architecture based on the construct of arousal was developed, implemented and tested on two robotic platforms to evaluate the benefits and limitations of the attachment system for a robot learning features of a new environment. Key features of the architecture have been identified to lead to different outcomes and behavioural profiles. This is the first operationalisation of an attachment system for a developing robot. The evaluation of the architecture provides evidence for the differential effect of the behaviour of the caregiver on the development of the robot as predicted by attachment theory. Although the robot is executing simple tasks, this evidence can be used as ground to further the research in more complex architectures or learning tasks.

3. A set of experimental setups have been designed offering simple test beds for the extension of the attachment model, and its comparison to other systems which may aim to use the human as a resource for developing robots

4. I proposed a mechanism to adapt the regulation profile of the robot based on the responsiveness of the human, a measure used in attachment interaction in psychology. This mechanisms was illustrated in two experiments where the human responsiveness

varied and provoked an *affective adaptation* of the robot. To the best of my knowledge, this is the first time that such a measure is used to adapt the social behaviour of a robot in real-time. I also provide evidence of the benefits of this mechanism depending on the task of the robot (food foraging or learning perceptions of a new environment)

5. The attachment system was integrated in motivation-based action selection architecture, thus providing evidence of its transferability by selecting its core features. This provides a road map to integrate the attachment system to other architecturess or control systems that wish to use this minimal approach to human-robot social interactions.

6. Finally, a set of tools has been developed for human-robot interaction experiments with naive users. Although they were tested on a relatively small sample, the questionnaire and the behavioural grid can be of use for researchers assessing the perception of their robot control system in terms of attachment interaction.

9.2 Perspectives

The research presented in this dissertation offers some perspectives worth investigating. The dynamics of the arousal system to modulate the explorative behaviour of the robot can benefit from a more adaptive approach. In the current implementation of the model, its dynamics was suited to the environment, its noise, and its available features. The arousal increased proportionally to the novelty perceived and therefore the variability of the perceived environment. As the parameters were chosen a posteriori, one would expect an autonomous robot to be able to sample the environment and then adapt to it. By definition, one cannot completely predict and know the amount of noise or variability of a new environment. Therefore, for long term viability and a greater robustness of the system, studying how the arousal can be modulated as a product of the available novelty and noise would be beneficial for the system and the development of the robot. This would lead to a subjective and local arousal level, which in turn would lead the robot to explore depending on the current range of noise and variability, ultimately getting closer to an exploration algorithm such as that proposed by Oudeyer et al. (2007).

Finally, from a long-term interaction perspective, it would be interesting to assess whether the affective bond, which is encoded in the robot is actually reciprocal. One question not addressed in this dissertation is whether a robot displaying regulatory behaviour aimed at triggering helpful interventions, as infants do, would lead to a bonding effect from the human. In mother-infant dyads, the bond is believed to stem from a biological imperative from the infant and the mother. However, it can be expected that with time and repeated successful interactions a similar affective bond might develop, as is the case with peers. Assessing whether this is the case or not is not trivial, and might lead to ethical dilemmas. First, a method for assessing peer bonding and its strength is not readily available. Relying on questionnaires might not be accurate enough due to their subjective nature and ceiling effects. Other experimental manipulation such as bargaining for the withdrawal of the robot (offering money or compensation to get the robot back from the subject), would be considered unethical. Another solution would be to use wearable physiological sensors, to measure if the body responds differently when interacting with the robot with which the hypothetical bond exists, and another robot with similar capabilities.

Appendix A

Publications and Dissemination

Several contributions developed in this thesis have been published in, or submitted to relevant conferences and journals. The work has been promoted and disseminated in TV documentaries, news reports, and conferences.

A.1 Publications

A.1.1 Journal Articles

- (Hiolle et al. 2014a) Hiolle, A., Lewis, M. 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*, 8, Frontiers Media SA. Journal article summarising the work carried out in chapters 7 and 8.

- (Hiolle, Cañamero, Davila-Ross and Bard 2012) Hiolle, A., Cañamero, L., Davila-Ross, M. and Bard, K.: 2012, Eliciting caregiving behavior in dyadic human-robot attachment-like interactions, *ACM Transactions on Interactive Intelligent Systems (TiiS)* **2**(1), 3. Journal article summarising the findings from Chapter 5 and 6.

A.1.2 Conference Publications

- (Hiolle, Lewis and Cañamero 2014b) Hiolle, A., Lewis, M. and Cañamero, L.: 2014, A Robot that Uses Arousal to Detect Learning Challenges and Seek Help, *ALIFE 14: The Fourteenth Conference on the Synthesis and Simulation of Living Systems*. First publication of the results presented in chapter 7.

- (Lewis, Hiolle and Cañamero 2014) Lewis, M., Hiolle, A., and Cañamero, L.: 2014, Pleasure, Persistence and Opportunism in Action Selection, *ALIFE 14: The Fourteenth Conference on the Synthesis and Simulation of Living Systems*. Summary of part of the original model of motivation-based action selection system used in chapter 8.

- (Damiano, Hiolle and Cañamero 2011) Damiano, L., Hiolle, A. and Cañamero, L.: 2011, Grounding synthetic knowledge: An epistemological framework and criteria of relevance for the scientific exploration of life, affect and social cognition, *Advances in Artificial Life, ECAL 2011*. Article presenting a novel view on relevant criteria for the synthetic approach to robotics and artificial life systems. This article illustrates its novel stance using the work on the artificial attachment system reported in chapters 4, 5, and 6.

- (Hiolle, Bard and Cañamero 2009) Hiolle, A., Bard, K. and Cañamero, L.: 2009, Assessing human reactions to different robot attachment profiles, *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, IEEE, pp. 251–256. Article presenting the first results of the study reported in chapter 6.

- Hiolle, A. and Cañamero, L.: 2009, Learning Affective Landmarks. *In Proceedings of the Ninth International Conference on Epigenetic Robotics: Modelling Cognitive*

Development in Robotic Systems. Lund University Cognitive Studies, 146. Lund: LUCS. Poster presenting a small associative model of arousal variations and visual landmarks.

- (Hiolle and Cañamero 2008a) Hiolle, A. and Cañamero, L.: 2008, Conscientious caretaking for autonomous robots an arousal-based model of exploratory behavior. *Proceedings of the Eighth International Conference on Epigenetic Robotics: Modelling Cognitive Development in Robotic Systems. Lund University Cognitive Studies, 139.* Paper presenting an extended version of the arousal model from chapters 4 and 5.

- (Hiolle and Cañamero 2008b) Hiolle, A. and Cañamero, L.: 2008, Why should you care? an arousal-based model of exploratory behavior for autonomous robots, *Artificial Life XI: Proceedings of the Eleventh International Conference on the Simulation and Synthesis of Living Systems* pp. 242–248. Paper presenting the arousal model from chapters 4 and 5.

A.2 Dissemination

- ICT Event: “I”s to the Future: Invention – Innovation – Impact, Lyon 2008. Presentation and demonstration of the progress made within the FEELIX-GROWING project. Demonstration of the work reported in Chapters 4 and 5.

- STRI Showcase, University of Hertfordshire, March 2008. Presentation and demonstration of the work reported in chapters 4 and 5.

- Plus Math magazine: "Baby robots feel the love" (http://plus.maths.org/content/making-robots-feel). News article on the work reported in Chapter 5.

- Interview broadcast in EuroNews' science program FUTURIS, July 2008, (http://www.euronews.com/2008/07/02/robots-learn-to-express-emotions/)

- "Research Connection" EU event, presentation of the FEELIX-Growing project at "ICT that think and learn, just like us"' press briefing given with Prof. Kim Bard, May 2009, Prague, Czech Republic.

- EUCOGNITION I Network, fourth Six-Monthly Meeting, Venice, Italy, 10 & 11 January 2008, Oral presentation given within the PhD student presentation competition.

Appendix B

London Science Museum Experiment

B.1 Data from the questionnaires

Table B.1: Sample demographics and information from subjects. In order, the fields are: id of the participant, self-rated experience with children (low to high on a five points scale), age range (18-20, 21-30, 31-40, 41-50, 51-60, and over 60), age group (age> 30), parenthood, and gender

ID	Exp. Child	age	age group(1 is > 30 y.o.)	parenthood	gender(M/F)
1	1	4	1	0	F
2	5	5	1	1	F
3	5	3	1	1	F
4	3	1	0	0	F
5	5	2	0	0	F
6	4	2	0	0	F
7	5	2	0	0	M
8	1	2	0	0	M
9	1	3	1	0	F
10	5	3	1	1	F
11	5	4	1	1	F
12	5	3	1	1	F
13	5	4	1	1	M
14	4	6	1	1	F
15	2	2	0	0	F
16	4	2	0	0	F
17	1	2	1	0	F
18	1	2	0	0	M
19	3	3	1	0	F
20	1	2	0	0	M
21	3	3	1	0	F

B.2 Ethics approval

Table B.2: Questionnaire results for the "needy" robot

ID	enjoyment	reactivity	predictability	will to assist	ease to interact	autonomy
1	5	3	2	4	3	2
2	4	5	4	4	4	3
3	4	2	2	3	2	2
4	4	5	3	4	5	1
5	5	3	3	4	4	2
6	3	4	2	4	4	2
7	5	4	3	2	4	4
8	5	4	3	5	4	2
9	2	5	3	1	1	5
10	5	4	2	4	5	4
11	4	3	4	4	5	3
12	4	2	2	3	2	3
13	4	2	2	4	3	3
14	3	3	2	5	3	2
15	2	3	3	2	2	2
16	2	2	3	2	2	4
17	4	4	3	4	4	2
18	5	3	4	4	5	2
19	4	4	4	3	3	4
20	4	3	5	5	5	1
21	3	4	2	4	3	3

B.3 Consent Form

Table B.3: Questionnaire results for the "independent" robot

ID	enjoyment	reactivity	predictability	will to assist	ease to interact	autonomy
1	4	2	2	4	2	4
2	3	4	2	3	2	2
3	4	3	3	3	3	1
4	5	4	3	4	3	3
5	2	1	1	1	1	5
6	2	4	2	4	3	4
7	2	1	2	1	1	5
8	4	1	4	3	2	5
9	1	2	2	4	1	2
10	2	2	2	2	1	5
11	2	2	1	5	2	1
12	4	3	2	3	2	4
13	3	3	2	3	2	3
14	2	2	2	3	1	3
15	2	2	2	2	2	3
16	1	1	5	1	1	5
17	3	2	2	4	3	3
18	2	1	5	5	2	5
19	3	2	1	2	2	4
20	3	1	5	2	5	4
21	3	2	2	4	3	4

B.4 Questionnaire used

UNIVERSITY OF HERTFORDSHIRE
FACULTY OF ENGINEERING AND INFORMATION SCIENCES

M E M O R A N D U M

TO **Antoine Hiolle**

STUDENT No: N/A

C/C **N/A**

FROM **Professor Alan Davies, Chair - Faculty Ethics Committee**

DATE **5 February 2009**

Your project entitled

Study of interaction styles with infant-like robot

has been granted ethics approval and has been assigned the Protocol Number: **0809/107**

This approval is valid

from 5 February 2009

until 28 February 2009

If it is possible that the project may continue after the end of this period you will need to resubmit an application in time to allow the case to be considered.

CONSENT FORM – Information

Title of study: Study of interaction styles with an infant-like emotional robot

Chief investigator: Lola Cañamero
Other principal investigators: Antoine Hiolle, John Murray (possibly assisted by Sven Magg and Nicolas Oros)

Description of Experiment:

This study has been organised by scientists from the University of Hertfordshire.

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's 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 some level of stress. When the robot feels a bit too overwhelmed by this novelty, it will express this by barking and looking around for a human, trying to attract the attention and support of its human caregiver. The caregiver can relieve the robots' distress 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.

What is today's experiment about? This study is designed to explore which styles of interaction with a robot different people prefer depending on the behavior and "personality" of the robot. The feedback gained from this study will contribute to our longer-term goal of designing pet and household robots that learn to interact appropriately with their human owners.

What will happen in the experiment? Adult visitors, possibly accompanied by children observing the interaction, will be invited to play the role of caregivers of the baby Aibo robot. They will be free to choose whether or not, when and how (from a set of simple actions explained to them such as those described above, i.e. showing toys, patting the robot on top of head or back, etc) to attend the requests for attention that the robot expresses by barking or looking around for a human. Participants in the experiment will be given a chance to interact consecutively with 2 Aibos with slightly different behaviors. To be able to analyze the interaction styles in more detail for research purposes, we would like to film the interactions for which participants voluntarily gave their consent. Participants will also be invited to fill in a questionnaire regarding their impressions about the interaction with the robot.

Who can take part in this experiment?
We are looking for women and men aged 18 or over to take part in this research.

The experiment lasts approximately **between 4 and 10** minutes. **You can stop the experiment at any time if you wish, without having to give a reason.**

In order to maintain confidentiality, you will be assigned a numerical code. The data collected will be analysed and used to draw conclusions from the study. Data collected by the University of Hertfordshire, from the visitors to the Science Museum, will be processed only for the purposes of this study in accordance with the Data Protection Act (1998). Your data will not be stored or processed by the Science Museum.

CONSENT FORM

1. I have freely volunteered to participate in this experiment

2. I have been informed in advance as to what my task(s) would be and what procedures would be followed.

3. I am aware that I will be filmed during this experiment.

4. I am aware that data collected will be anonymous, kept in accordance with the data protection act, and will only be analysed by the research team as part of their studies.

5. I have been given the opportunity to ask questions, and have had my questions answered to my satisfaction.

6. I am aware that I have the right to withdraw consent and discontinue participation at any time, without prejudice.

7. My signature below may be taken as affirmation of all of the above, prior to participation.

Name...Date of birth ....
Signature ....
Participant ID (to be completed by investigator)..

Withdrawal of consent

If you wish to withdraw from the study once you have completed the experiment and left the Science Museum please complete this form and return it to the main investigator (Dr Lola Cañamero at L.Canamero@herts.ac.uk).

Title of project:

I WISH TO WITHDRAW FROM THIS STUDY

Signed ....Date...
Participant ID...

Number:

Briefing before the interaction:

An Aibo robot will be placed on a child's play mat, and will try and discover this new environment. As novel features are met, the situation for the robot will get increasingly stressful, it will express this through communicative behaviours which you can hear and see. and You can calm the robot with looking and touching. You can also stimulate the robot by showing it toys and other objects or carry it to a spot you have chosen.

Questionnaire

1. Do you have much experience playing with (or taking care of) young children?

Not At All					**A Lot**
	1	**2**	**3**	**4**	**5**

2. How enjoyable did you find this experiment?

Not Enjoyable					**Really Enjoyable**
	1	**2**	**3**	**4**	**5**

Why?

This research is being carried under protocol 0809/107

3. How would you rate the reactivity of the robot. In terms of how responsive was it was following your interventions or new stimuli encounters?

Not Reactive	1	2	3	4	5	Extremely reactive

4. Was the robot behaving as you were exepecting, i.e., was its behaviour predictable?

Not Predictable	1	2	3	4	5	Very Predictable

5. Were you more inclined to assist the robot, or leave it on its own?

Very Low	1	2	3	4	5	Very High

6. How would you rate your ease interacting with the robot?

Very Hard	1	2	3	4	5	Very Easy

7. How would you rate how autonomous the robot was?

Very Needy	1	2	3	4	5	Very Independe nt

This research is being carried under protocol 0809/107

8. To conduct some statistical research we would appreciate if you could indicate your age and gender and if you have children.

□ - 20 or less
□ - 21-30
□ - 31- 40
□ - 41- 50
□ - 51-60
□ - 60 or more

□ -Male
□ –Female

Children:
□ Yes
□ No

Thank you very much for your time and your help!

This research is being carried under protocol 0809/107

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