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Towards a Cognitive Architecture for Socially Adaptive Human-Robot Interaction

by

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The first law of thermodynamics states that no energy gets created in the Universe, and none is destroyed. Not a bit of you is gone, you are just less orderly. I would like to dedicate this thesis to my dad, for all the energy he gave me.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Ana Tanevska
February 2020

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And I would like to thank ...
Би сакала да се заблагодарам ...

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Abstract

People have a natural predisposition to interact in an adaptive manner with others, by instinctively changing their actions, tones and speech according to the perceived needs of their peers. Moreover, we are not only capable of registering the affective and cognitive state of our partners, but over a prolonged period of interaction we also learn which behaviours are the most appropriate and well-suited for each one of them individually. This universal trait that we share regardless of our different personalities is referred to as social adaptation (adaptability). Humans are always capable of adapting to the others although our personalities may influence the speed and efficacy of the adaptation. This means that in our everyday lives we are accustomed to partake in complex and personalized interactions with our peers.

Carrying this ability to personalize to human-robot interaction (HRI) is highly desirable since it would provide user-personalized interaction, a crucial element in many HRI scenarios - interactions with older adults, assistive or rehabilitative robotics, child-robot interaction (CRI), and many others. For a social robot to be able to recreate this same kind of rich, human-like interaction, it should be aware of our needs and affective states and be capable of continuously adapting its behaviour to them.

Equipping a robot with these functionalities however is not a straightforward task. A robust approach for solving this is implementing a framework for the robot supporting social awareness and adaptation. In other words, the robot needs to be equipped with the basic cognitive functionalities, which would allow the robot to learn how to select the behaviours that would maximize the pleasantness of the interaction for its peers, while being guided by an internal motivation system that would provide autonomy to its decision-making process.

The goal of this research was threefold: attempt to design a cognitive architecture supporting social HRI and implement it on a robotic platform; study how an adaptive framework of this kind would function when tested in HRI studies with users; and

explore how including the element of adaptability and personalization in a cognitive framework would in reality affect the users - would it bring an additional richness to the human-robot interaction as hypothesized, or would it instead only add uncertainty and unpredictability that would not be accepted by the robot‘s human peers?

This thesis covers the work done on developing a cognitive framework for human-robot interaction; analyzes the various challenges of implementing the cognitive functionalities, porting the framework on several robotic platforms and testing potential validation scenarios; and finally presents the user studies performed with the robotic platforms of iCub and MiRo, focused on understanding how a cognitive framework behaves in a free-form HRI context and if humans can be aware and appreciate the adaptivity of the robot.

In summary, this thesis had the task of approaching the complex field of cognitive HRI and attempt to shed some light on how cognition and adaptation develop from both the human and the robot side in an HRI scenario.

Contents

List of Figures

List of Tables

Part I

Introduction

Chapter 1

Human-Robot Interaction

"Human—Robot Interaction (HRI) is a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans. The HRI problem is to understand and shape the interactions between one or more humans and one or more robots." [2]

Human-Robot Interaction (HRI) is a relatively young discipline, but one that has been steadily growing in number of researchers over the past years, both due to the scientific progress and increasing complexity of the new generations of robots, but also due to the increased exposure of people to robots in general in their daily lives.

Robots are nowadays present in people's households in the form of vacuum cleaners, lawn mowers, pill dispensers; they have a very active social presence due to viral videos (like Sophia or Atlas); and they are increasingly being developed and introduced in many real-world application contexts: rehabilitation, assistive therapy, elder-care and other assistive or educational applications. Social robots have a positive impact in interactions with older adults [3][4][5]; they can bring either a physical or mental boost in assistive or rehabilitative robotics [6][7][8], they can significantly improve collaborative learning [9][10] and other aspects of child-robot interaction [11][12], and many others. Additionally, for a social robot to be able to recreate this same kind of rich, human-like interaction, it should be aware of our needs and affective states and be capable of continuously adapting its behavior to them [13][14][15][16][17].

Following this, robotics as a field of study can be divided in subfields depending precisely on the application of the robots, but also depending on the background of the researchers in the field and their interest of study. Here, the distinction can be made between robotic engineers developing advanced robotic systems with the purpose of application in industry; psychologists researching HRI in order to understand some aspects of human-human interaction; AI researchers and cognitive scientists using robots as platforms for developing and testing various frameworks, and so on [18].

Finally, there are also researchers interested in studying precisely HRI, namely how people interact with robots. HRI research can also include in itself some or all of the previous domains - it can make use of a complex AI behaviour embedded in the robotic platform, it can include a psychological or cognitive outllook on the framework and so on [19]. Among the major goals of HRI is the conduction of user studies, looking into the interaction of people and robots, how people perceive different types and behaviours of robots, how they perceive social cues or different robot embodiments, etc.

This aim of this research was to explore precisely the merging of cognitive science with HRI; of designing, engineering and implementing a robotic framework, but then also studying how this framework would perform when the robot would have free-form, adaptive interactions with people. Since the level of adaptability and understanding necessary for an efficient and general HRI can be achieved only through a cognitive agent, the first step was delving a bit deeper into cognition and its various facets when it comes to designing a cognitive framework for artificial beings.

Chapter 2

Cognition

2.1 Cognition in artificial and natural agents

Defining cognition in beings, whether they are natural or artificial, is not a straightforward task. The definition of cognition varies depending on what is the end goal of the cognitive abilities, as well as on how cognition is realized in the physical systems [20].

When a system is said to be *cognitive*, this implies an ability of that system to make inferences about the events in the world around it. These are events which involve the system, the actions performed by the system, and the consequences of those actions. However, for a system to be able to make inferences in the first place, it should be equipped with an ability to remember what happened in the past, so that remembering and knowing about past events will enable that system to predict future ones.

A cognitive system then, or to use the more common phrasing - a cognitive agent - should be capable of *autonomously* predicting the future, by relying on *memories* of the past, *perceptions* of the present, and *anticipation* of both the behaviour of the world around it as well as of its own actions[20]. Considering that predictions of this magnitude are rarely perfectly accurate, the cognitive agent needs to allow for this uncertainty and *learn* by observing what actually happens after an action, and then assimilating that perceptive input into its knowledge about the world, *adapting* on the way its behaviour and manner of doing things.

In this way, the cognitive agent forms a continuous cycle of self-improvement in its ability to anticipate future events. This cycle of anticipation, assimilation and adaptation supports and is supported by the ongoing processes of action and perception, as illustrated in Figure 2.1 [1].

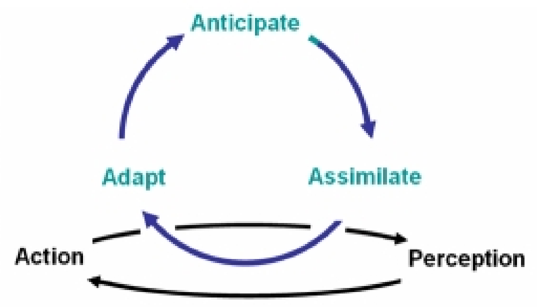


Figure 2.1 The cycle of cognition

Having observed this cycle, cognition can be now be defined as the process by which an autonomous agent perceives its environment, learns from experience, anticipates the outcome of events, acts to pursue goals and adapts to changing circumstances [21].

Expanding on that definition, cognition may also be presented as an umbrella term covering a collection of skills and capabilities possessed by an agent (natural or artificial one):

- Take on goals, formulate predictive strategies to achieve the goals and put those strategies into effect;
- Operate with varying degrees of autonomy;
- Interact (cooperate, collaborate, communicate) with other agents;
- Read the intentions of other agents and anticipate their actions;
- Sense and interpret both expected and unexpected events;
- Anticipate the need for actions and predict the outcome of its own actions and those of others;
- Select a course of action, carry it out and then assess the outcome;
- Adapt to changing circumstances in real time by adjusting current and anticipated actions;
- Learn from experience and adjust the way actions are selected and performed in the future.

[1] http://www.vernon.eu/research.html

2.1.1 Autonomy and Cognition

Autonomy is seen as one of the base requirement for artificial cognitive agents, as it allows the system to be independent without assistance from the human agents around it. The inverse is true for biological cognitive agents, where cognition is seen as an important attribute to the already autonomous biological system. It is however important to note that all cognitive functionalities can also exist in an artificial system without autonomy (for example, like in a cognitive artificial system involving human input), and vice versa an autonomous artificial system can be autonomous without having some or any of the cognitive functionalities [20].

In a cognitive agent there can be said to exist two complementary aspects of autonomy - constructive autonomy (taking care of metabolic processes and rebuilding of the agent's system) and interactive autonomy (making sure the environment conditions are right to facilitate the constructive aspect) [22]. In artificial cognitive agents, interactive autonomy is usually the one that is tackled more explicitly, as the constructive autonomy is something today's artificial agents on general do automatically and implicitly.

To restate it, interactive autonomy can be defined as the processes that govern the agent's interaction with the environment. Placing this into the context of HRI where the artificial cognitive agent is the robot, an autonomous robot is capable of perceiving the state of the environment and deciding which actions to perform in order to either change something about the environment, or keep it as it is. For instance, a social robot interacting with a human that is getting angry would maybe prefer to change its behaviour in order to calm the human, or perhaps - depending on its goals - not.

2.2 Functionalities of cognition

The core of this thesis is focused around developing a cognitive framework for a robot engaging in human-robot interaction. This means that all of the cognitive requirements from Section 2.1 need to be placed in the context where the artificial cognitive agent is the robot that is engaging in a scenario of interaction with people.

Every cognitive interaction can be formulated using four essential characteristics [20]. Cognition focuses on *action*, particularly on prospective *goal-directed* action, giving action and goals as the first two essential characteristics, with the other two being *intention* (which gives the prospective link between goal and action - intention is the plan of action the robot as an agent chooses and commits to in pursuit of a goal), and *perception* - the essential sensory aspect of cognition, which in the context of cognitive interaction is directed perception, focused on the goals and influenced by the expectations. Additionally to these essential functionalities, there are also learning and adaptation which are important for a cognitive agent whose goal is not only to interact, but also learn from that interaction.

For robots engaged in social HRI, the implementation of some (or all) of these cognitive abilities has been demonstrated in the context of autonomous social interaction [23][24], in studies aimed at the employment of joint action [25] as well as in studies where the robot is assisting the humans in achieving their goals [26].

The following subsections give a brief comment on perception, motivation and prospection, and learning and adaptation; they are all addressed in greater length in the chapters of Part 2 in the context of designing a cognitive framework for HRI.

2.2.1 Perception

While also important for agents that do not have a significant interaction with the environment, perception is absolutely crucial for cognitive agents like social robots. Perception is strongly related to social cognition, and to how the cognition in an individual agent relates to the social environment.

Perception is what provides an interface between the absolute external world and the symbolic representation of that world in the robot. The role of perception is to abstract faithful spatio-temporal representations of the external world from sensory data.

This can also be seen as the agent-specific interpretation of the way the environment perturbs the agent, and is at least to some extent dependent on the embodiment of the system - different robots with different sensor sets will have different representations of the environment [27].

2.2.2 Motivation and prospection

When a cognitive agent is imbued with a motivational drive, this signifies the presence of a value system that guides or governs development in that agent [28][29]. The two most important kind of motives that drive actions and development are social motives and exploratory motives [30].

Social motives place the agent in the broader context of other agents providing comfort, security or satisfaction. From these the agent can learn new skills, discover new things about the world, and exchange information through communication. In natural cognitive agents social motives include the need to belong, self-preservation and cognitive consistency with others. Exploratory motives diverge in two different kinds - a drive for discovering the surrounding world (discovery of novelty and regularity in the world), and a drive for finding out the potential of the agent's own action capabilities.

Either or both variants of motives can be included in the motivational drive for a social robot, and this is something that can be either chosen to be as context-independent as possible by having a very general social or exploratory motivational drive [16][11], or the robot instead can be provided with a highly-specific motivational drive dependent on the exact task of the robot in the particular HRI scenario [31][32].

However motivation alone is not sufficient to guide interaction. A cognitive agent's actions are guided by prospection, directed by goals and triggered by affective motives [33]. The importance of affect in the role of prospection stands out most when imagining future events. In the natural cognitive systems like humans, this is done to understand if an event is safe or dangerous - by imagining it happening the person understands how they feel about it. This may function only if the contextual factors are the same in the present and in the future; and if the simulated influence is the same as the eventual perception of the event [34][35][36]

2.2.3 Learning and adaptation

Finally, it is not enough for a cognition-aspiring robot to be perceptive and motivated in its actions, if it never learns how to adjust to the changing circumstances around it. For autonomous robots which function in real-world environments and interact with humans, adaptation to changing or partially-known environments as well as personalization to their human peers are key features for successful integration [37]. This in turn includes the ability to sustain long-term interactions with the humans.

Adaptation is achieved through learning, the process by which the robot progressively obtains new forms of actions and predictive control of these actions. The predictive components are important - to control effectively actions, the cognitive robot needs to be able to anticipate the outcome of the actions as well as anticipate the need for them in the first place [38].

A developmental cognitive robot then needs to be capable of adaptation and self-modification, which is done through parameter adjustment through learning, and through modification of its understanding of the world.

Part II

Designing a Cognitive Architecture

Chapter 3

Overview of the Framework

Chapter 2 elaborated in detail on the most crucial functionalities necessary for a robot with a cognitive framework. To restate them one more time - the necessary functionalities for cognition are: perception, learning from experience, awareness of the action-reaction principle, ability for anticipation and adaptation, and ultimately ability for independent action with the purpose of achieving some goals.

This thesis focused on developing a cognitive architecture for autonomous behavior, supporting all of these functionalities, for generalized applicability on any robotic platform for HRI. The framework over its various developments was tested on both humanoid and non-humanoid robots, most notably on the iCub humanoid robot, but also on the NAO and MiRo robots (more details for each platform are given in Part 3). The architecture relies on the robot evaluating the affective state of its human peers as a factor which determines its own internal emotional condition, and subsequent choice of behavior.

These functionalities were implemented in the cognitive architecture in the following manner:

- *Autonomous perception of environment* – for cognitive robots, perception is the specific way of interpreting the environment as experienced by the robot's sensors. In the robot's architecture, the state of the environment is jointly represented by the stimuli presented to iCub from the users (using the modalities they can to interact with it) and the levels of affect and/or engagement expressed by the users during the interaction (which can be loosely described as their emotions). The robot perceives these emotions by continuously processing the users' facial expressions and classifying them.

- *Ability to learn from experience* – for the robot, learning is the process of acquiring new information about the users as well as learning how the robot's actions affect the users. The robot's learning is reflected in the modifications of the parameters of its architecture as it learns for each person how to best modify its behaviour.

- *Adapting to changing circumstances* – adaptation for a cognitive robot includes adjusting to the environment no longer reacting the same way it did before. Adaptation is triggered when an action does not have the predicted outcome and is carried out by modifying the inner parameters of the robot (as explained above for learning).

- *Acting independently to achieve goals* – an autonomous robot acts in a self-driven manner when it is motivated by some inner goals. In this thesis two different approaches to motivations are explored. One approach is based on pseudo-emotions implemented in the robot. The other is based on a social comfort-like internal variable that varies depending on the robot's interaction with the environment, which is what motivates it to maintain its values in an optimal zone, and this is the approach that was focused most upon in this thesis.

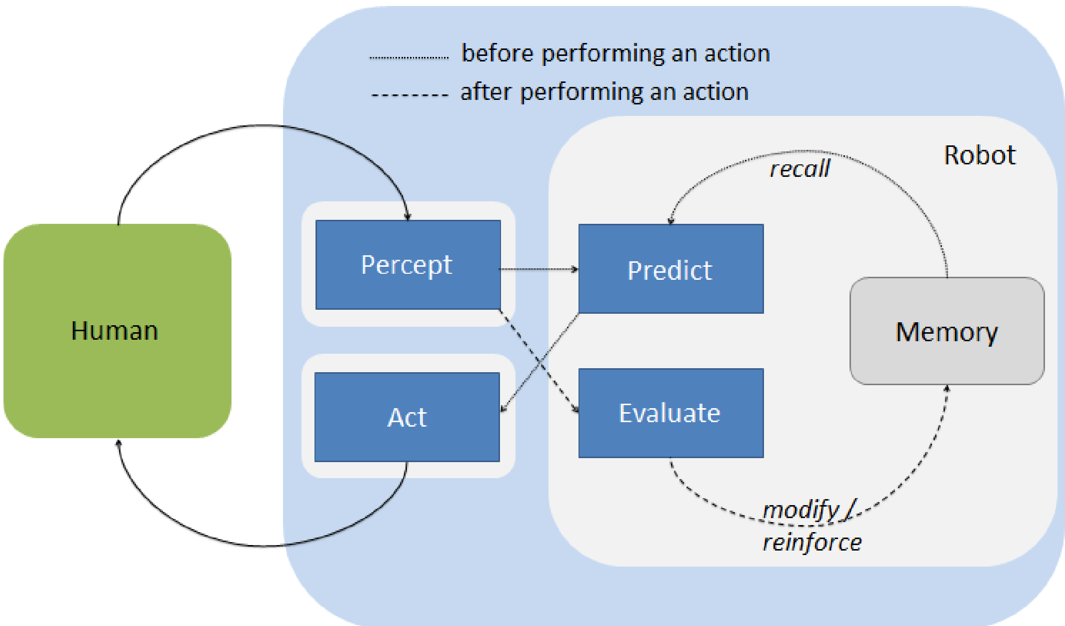


Figure 3.1 An overview of the cognitive framework

Figure 3.1 presents how these functionalities related to each other in the framework. The framework first perceives the state of the human, and then before performing an action it attempts predicting which action would be most beneficial for robot and human (by improving their affective states), after which it performs the most beneficial action. After performing an action, the framework evaluates from perceptual input if the person's reaction was as predicted, and then either modifies the belief values if it was wrong or reinforces them if right.

The cognitive framework is presented in more details in the following chapters: Chapter 4 presenting the perception module and its several functionalities, Chapter 5 presenting the motivation functionality and its background, and Chapter 6 giving the summary of the architecture.

Chapter 4

The Perception Functionality

Subsection 2.2.1 in Chapter 2 highlighted the importance of the perceptual ability for cognitive agents, natural or artificial ones. In particular, the cognitive agents that aspire to be autonomous and adaptive in their behaviour have to possess a perceptive skill allowing them to be aware of the environment and other agents around them.

When discussing a scenario of human-robot interaction, obtaining a full description of the state of the environment (specifically the state of the human counterpart) is very relevant to the robot. Evidently, an ultimate goal for HRI would be to have intelligent robots that would also consider the environment surrounding the human in addition to the human itself. However, for the level of HRI scenarios implemented today, where often the context is limited or well predefined and a priori known by the robot, it is usually more than sufficient to have the robot be able to perceive the state in which is the human. This, in fact, is exactly what was referred to as *directed perception* (or *attention*) in subsection 2.2.1, and it refers to the perception that is directed by the robot's goals and influenced by its prospection and expectations. This kind of directed perception allows for the robot to be aware of how its actions are affecting the person with whom it's interacting, and provides information when selecting its next course of action.

This brings the point of how the robot should evaluate the state of the human. Prior results from recent HRI and human-computer interaction (HCI) studies show that one of the most valid task-independent metric for tracking the state of the person is evaluating the affect and/or engagement experienced during the interaction. This has been shown to give a balanced interaction that keeps the user satisfied [14][10][31][32].

There are several different methods used currently in HRI/HCI studies for evaluating and tracking user affect and engagement. Favoured choices include emotion recognition with audio processing (i.e. from speech and emitted sounds) [39][40][41], body pose estimation and body language tracker (usually done with Kinect sensors) [14][42], detection of micro movements and expressions [43], evaluation by tactile and proximity sensors (so tracking the distance from the robot and the amount of touch) [44], but one of the most often implemented approach with a good trade-off between reliability and complexity of implementation is evaluation from facial expressions [45][46].

Figure 4.1 Some of the most expressive Action Units

Evaluating the user's affective expressions from their facial features is most commonly done by detecting the intensity of the facial Action Units (AUs) as described in the Facial Action Coding System (FACS) [47]. FACS is based on detecting anatomically based facial actions, which are one or few facial muscles that occur individually or in combinations, and can be associated with the expression of certain emotions. As it can be seen in Figure 4.1, some AUs for example are raising or lowering the eyebrows, raising the corners of the mouth, wrinkling the top of the nose, or raising the top of the cheeks.

There are several open-source software packages for tracking AUs, one of the more commonly used being the OpenFace system [48], which reliably detects the appearance and intensity of 18 facial AUs.

4.1 The OpenFace Framework

The OpenFace framework developed by T. Baltrusaitis [48] is an open-source architecture which offers the analysis of images (single image or a series), video or camera feed; and the subsequent extraction of all the relevant information about the face, in particular: the facial landmarks, head orientation, facial expressions, and gaze direction.

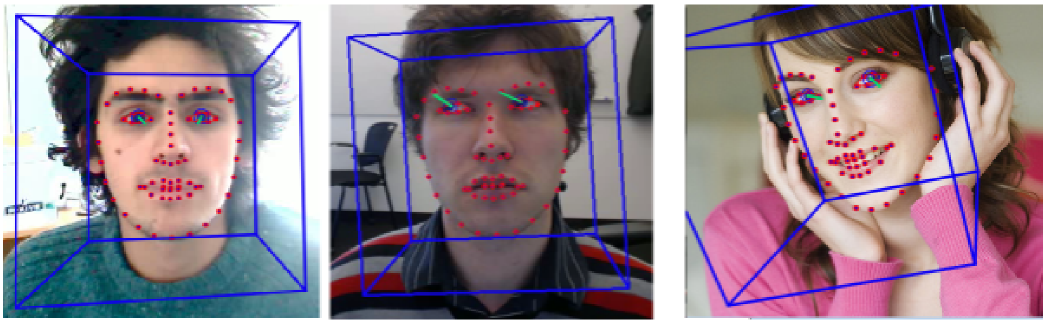


Figure 4.2 The output from OpenFace

The processing done by OpenFace consists of several sub-modules. The first step includes the analysis of the scene from the camera feed and the attempt to detect a face in it, which is done by using the dlib library [49] and its frontal face detector.

Once a human face has been detected, the module proceeds with the step for the facial analysis where the landmarks on the human face (shown in Figure 4.3) are extracted. From the 68 facial landmarks the most important factors for expression analysis can be obtained – the AUs. Their extraction is done using two approaches – extracting the appearance of 19 AUs by using linear-kernel SVM, and extracting the intensity of 18 AUs by using a linear-kernel SVR. Groups of these AUs can be highly exclusive and connected to separate affective states (i.e. anger, happiness, sadness, surprise etc), which simplifies the programming of an affect detection module depending on the intensity value of the AUs at a given frame.

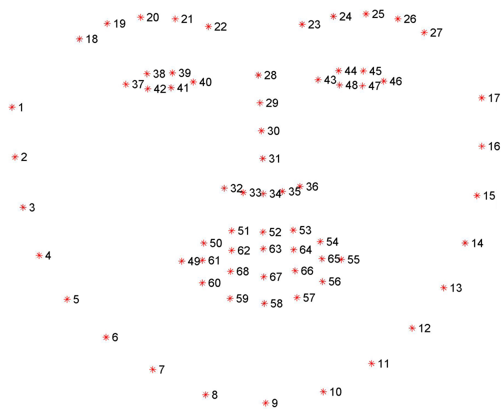


Figure 4.3 The numbered 68 facial landmarks

4.2 The full perception module

The basis of the perception module was the affect detection functionality, which leveraged on a subset of extracted action units from the OpenFace framework. Even though by combining the metrics of appearance and intensity OpenFace allows to obtain the information for a total of 18 action units, after porting the framework on the iCub platform it was observed that the conditions in which the robot would interact with people would not allow for extracting and using all 18 AUs. Constraints for this were the distance between a human participant and the robot (which is considerably larger than the OpenFace-tested distance of a person in front of their webcam), as well as the processing load of running many different modules for iCub (as opposed to only running the OpenFace platform).

The finalized version of the affect detection module for iCub analysed the facial landmarks of the person in front of the robot, and by comparing the values of several groups of action units it estimated the affective state of the person. More precisely, the user's affect was evaluated by the presence and intensity of several highly-salient AUs which are unique for separate emotions.

The positive-associated AUs were smiling (AU12), cheek raising and eye-crinkling (AU6), and the negative-associated AUs were brow lowering (AU4), nose wrinkling (AU9) and raising the upper lip (AU10). Presence of all positive AUs was classified as "smiling" (presence of just a mouth smile but no positive upper AUs signified a fake smile, and was not classified as "smiling"), presence of only the brow lowering but without additional negative AUs was classified as "contemplating" whereas the presence of all negative AUs signified "frowning". If neither of these AUs groups were present in the frame, the user's affect was classified as "neutral".

This was also utilized and implemented in an emotional mimicry demo which additionally used the predefined combinations of the LEDs in the face of the iCub to mimic the facial expression of the person in front of it (see Figure 4.4).

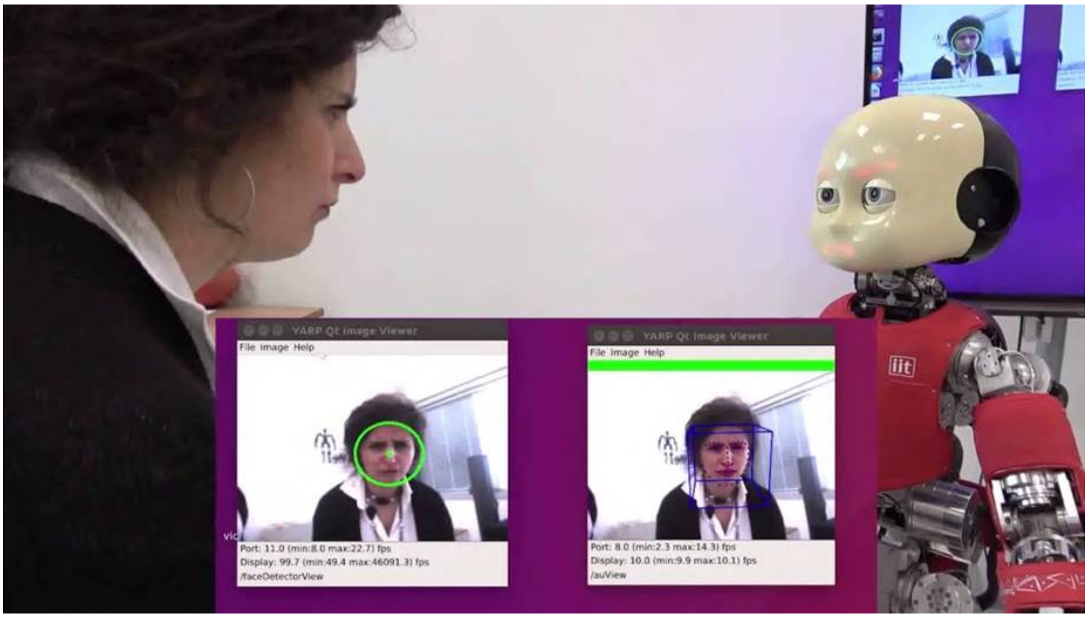
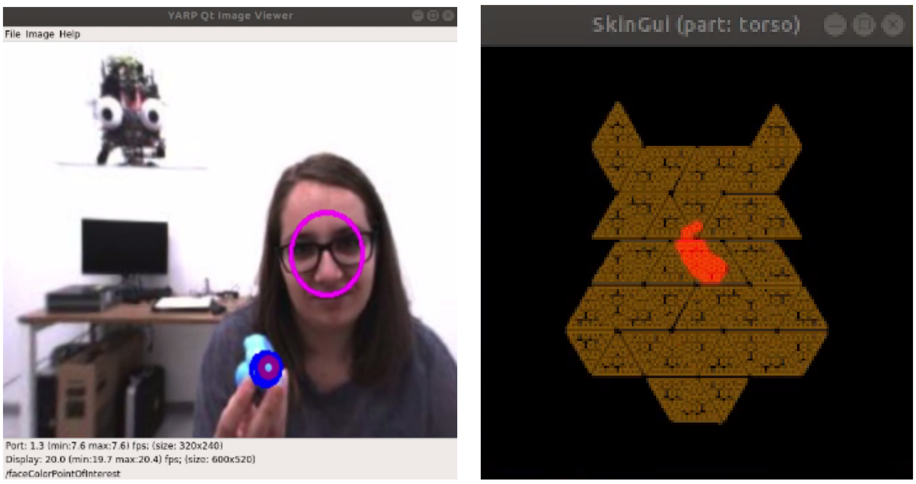


Figure 4.4 The mimicry module, detection of face on left and extracting facial landmarks on right

The affect detection was the core of the perception module, but additional expansions were done to it after deciding on the interactive scenario for the framework (more on this in Part 3, Chapters 7, 8 and 9). The scenario placed the robot and the participant in the role of a toddler and its caretaker (respectively), and this in turn allowed for the addition of tactile interaction, as well as later expanding the visual interaction by having the participant show the robot toys as a way to play with him.



(a) Visual input - face and toys **(b)** Tactile input - touch on torso

Figure 4.5 Images from the perception modules

After the modifications, the visual part of the expanded perception functionality was consisted of two modules - the **affect detection** module and the **color detection** module, which was able to detect and track a set of predefined colors, looking for contours in the image of a certain size (fitting the size of the toys) and color. Figure 4.5.a shows the simultaneous detection and tracking of the face and a toy, whereas Figure 4.5.b shows detected touch on iCub's torso tactile covers. More details on the expansions are given in Chapter 8 and 9.

Chapter 5

Motivation and Adaptation

Social motivation can be implemented in more than one way. As section 2.2 mentioned, social motives place the agent in the broader context of other agents providing comfort or security, from which the agent can discover new things about the world, and exchange information through communication.

Carrying this over to implementing a motivational drive for a social robot gives some liberty in designing the drive. In the scope of this PhD project there were two different approaches used:

- an affect-driven motivation and adaptation that allowed the robot to learn which of its actions (from a predefined finite set of behaviours) were preferred by each user;
- a comfort-based motivation and adaptation that allowed the robot to adapt in free-form human-robot interaction to the modalities of interaction (frequency and duration) particular to each person.

By implementing a (limited) range of emotions as a value system for the robot, it is possible to make them a part of the anticipation and decision phases in the robots schema, supporting learning and adaptation. Some examples of artificial cognitive architectures exploiting emotions as inner motivation are the FAtiMA architecture equipped with modules for appraisal and behaviour [50], the WASABI architecture dealing with implementation of both primary and secondary emotions [51], the CogAff architectural schema (and its upgrade to an actual cognitive architecture - H-CogAff) with reflective, deliberative and reactive processes [52], and the "bidirectional grounding"-based cognitive schema described in [53].

On the other hand, a different way of implementing motivation can be by having a single internal state of the robot guiding the robot's behaviour, still keeping on the track of affective adaptability [54][37], but instead utilizing as motivation the level of comfort of the robot, which could be increasing when the robot is interacting with a person, and decreasing when it is left on its own. This would be a motivation mechanism that would not require a predefined set of behaviours, as it would work independently of the task the robot would need to do.

5.1 Affect-based motivation and adaptation

As mentioned in subsection 2.2.2, affect plays a role in the prospection and motivation system in natural agents. By imagining how an agent feels about the outcome of an action, it can evaluate the desirability of that action and whether to perform it. Then after having performed the action, it observes how it was affected by the action and it remembers, in this way in the next iteration of interaction it will have increased knowledge.

This same principle can be ported to robots as well, implementing in them an affect-driven cognitive framework [24]. This kind of framework leverages on the use of affect in the cognitive reasoning process of the robot, more precisely in the decision-making phase, where the inner motivation and evaluation mechanism is represented by the robot's own affective state.

In this way, the first version of the cognitive architecture developed for iCub was an affect-based one [55]. This framework was originally developed in a previous work on adaptation in CRI in the context of switching between different game-based behaviours [56]. The affective drive meant the robot had its own internal pseudo-emotions which would motivate its anticipation.

The three emotion states chosen for the robot were positive (i.e. happy), neutral and negative (sad). The emotional state was directly affected by the changes in the level of engagement expressed by the users. More specifically, the robot's mood (expressed as a continuous value between -1.0 and 1.0) varied with the changes of the users' engagement level: with an increase in the users' engagement level, the robot's mood also increased, and vice versa.

After having perceived the state of the environment (the engagement of the users), the robot considered all possible actions it could undertake and the effects of those actions, and then would select the one with the highest probability of affecting its emotional state in a positive direction. This prospection happened in every step of the iteration, when the robot had to choose between three possible courses of action – whether to carry on with the same action it was already performing (e.g. telling a story), whether to change the behavior but maintain the same action type (e.g., start telling a different story), or whether to switch to a totally different behavior (e.g. dancing).

Evaluating which action would be the most beneficial for the robot was carried out using Bayesian nets which expressed the interdependence between the robot's actions and the changes in the users' emotions. These nets were the mechanism for both developing the robot's learning and for anticipating and planning the robot's next actions. The learning unfolded by initializing and then modifying the Bayesian nets of probability values which are unique for each user.

Since there is no advice or reinforcement received from an outside teacher, the transition values in the Bayesian nets at the beginning had randomized values. Throughout the process of interaction with the human partners, the robot evaluated which of its probabilistic values are correct and which are not, and modifies its graphs accordingly. If the robot believes that a certain action A will cause the user's engagement level to change from neutral to interested, but in reality the user's mood changes to bored, then the robot would modify the transitional probabilities between those values. Below follows a pseudocode of the iterations in the motivational functionality:

```
initialize(transitionGraphs)
while(interaction):
    evaluate robotMoodForActionA
    evaluate robotMoodForActionB
    if robotMoodForActionA > robotMoodForActionB:
        action:=ActionA
    else:
        action:=ActionB
    perform module(action)
    obtain humanMoodFromEnvironment
    if humanMoodFromGraphs != humanMoodFromEnvironment:
        modify(transitionGraphs) & obtain newRobotMoodAfterAction
```

The self-learning architecture was tested out in a previous CRI scenario with the NAO robot in an educational setting [56]. The architecture was nearly the same in principle as the current one, but NAO did not have a module to autonomously detect the children's engagement. Rather the arousal level was fed directly as input via keyboard during the interaction by an expert human observer.

The interaction modules for the robot were divided in two groups: play-oriented modules modules involving turn-taking games, and learning-oriented modules focused around simple math problems. The idea for having two separate kinds of modules (instead of the robot just deciding which action to perform from one set of modules) was based on the fact that it has been shown that robots which can switch between several types of activity generally prove better in keeping the children's attention than robots that just perform one kind of activity [57].

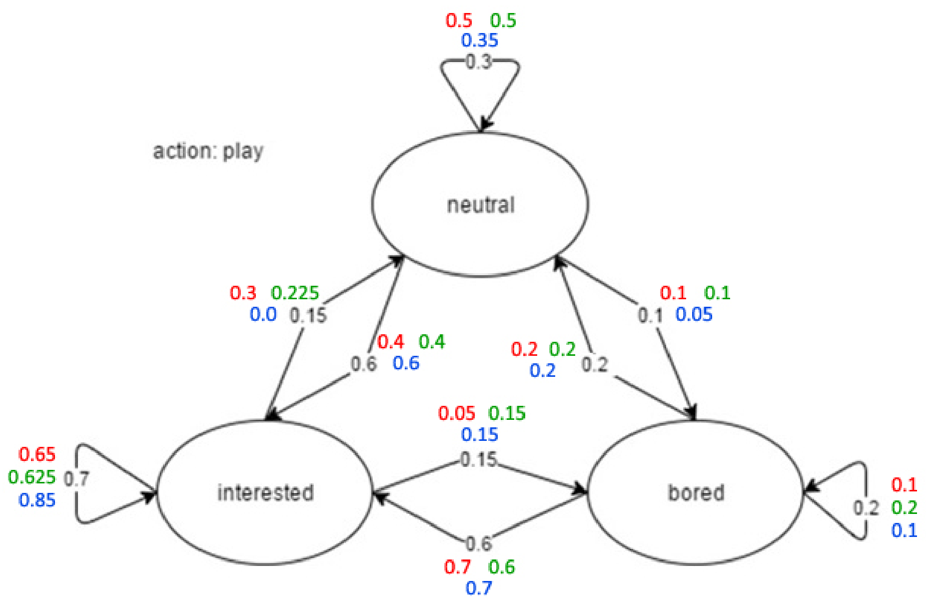


Figure 5.1 A modified transition graph for three participants

Figure 5.1 shows an example of the Bayesian nets used to model the self-learning in the robot and the probabilistic transitions among the three potential states of the people interacting with it. In black are the starting values for the transition probabilities, whereas the colored values correspond to the values modified as a consequence of an action of the robot. Different colors represent different subjects, to show that the same action provoked different responses for each individual involved in the interaction.

However, this approach for implementing motivation was ultimately decided to be slightly too constraining. Affect-based motivation and adaptation requires a more precise level of inference about the state of human, as well as predefining all possible actions the robot would do and how they relate to each other. This in turn signifies that it is limiting and context-dependent, as it defines a fixed set of behaviours and needs more predefinition upfront. Another approach instead was considered, as described in section 5.2.

5.2 Social comfort motivation

The affect-driven adaptation from the previous section functioned on adapting to the preferences of users for particular robot behaviours, with the robot learning how the users' mood would change for each behaviour separately. However, this mode of interaction does not allow for more general learning in terms of when a person would like to interact and for how long, which is also an important metric in free-form HRI.

For example, a person might prefer to engage with the robot on some occasions, whereas at other times the same person might not be available or might prefer not to be bothered by the robot and focus on performing some other task. It is thus important that the robot can adapt to the preferences of the human at different points in time. An intuitive way for the robot to express to the human its desire for interaction is to directly ask and try to engage the person, whereas a natural way for the human to show the robot how they want to interact is by attending or ignoring the robot's request.

The second approach to designing the motivational drive aimed precisely at that, finding a balanced combination of autonomy, proactiveness and user-driven interaction. The motivational drive was inspired by the work of Hiolle and Cañamero [54][37] on affective adaptability and developmental robotics regarding robot-caregiver interactions. Their framework investigated how a "baby" robot that explores and learns objects in a novel environment can adapt its affective regulatory behavior of soliciting help from a human "caregiver" to the preferences shown by the human in terms of varying responsiveness. The varying responsiveness of the caregiver and its effect on the affective regulatory behavior of the robot had in turn an effect on how the robot explores and learns its environment.

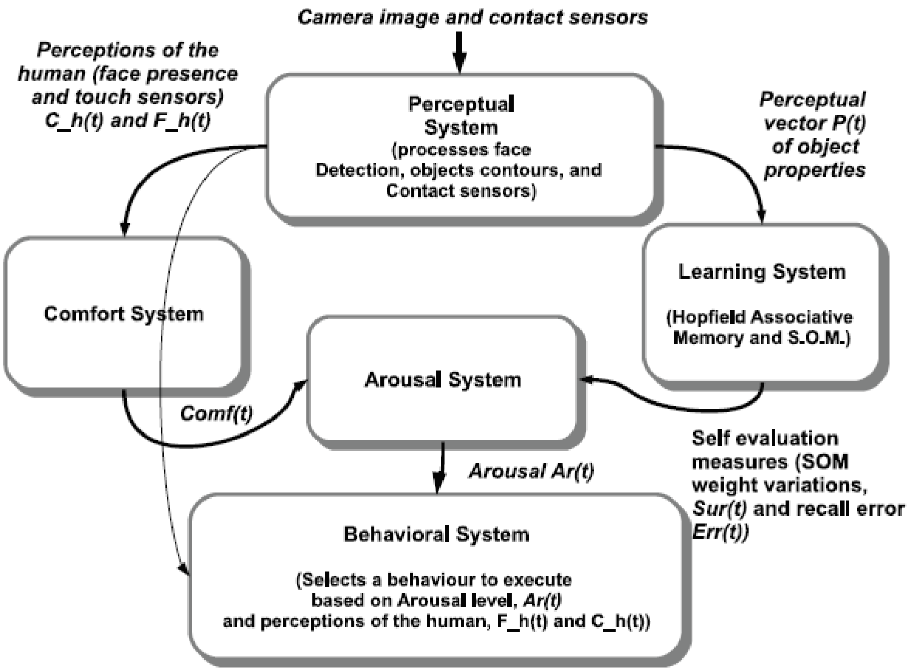


Figure 5.2 The schema for the cognitive framework in [26].

Figure 5.2 illustrates the flow of their framework. It started by calculating a level of arousal of the robot in the Arousal System. The Comfort System uses the tactile and visual perception of the human (C(t) and F(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 them), 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.

The comfort-based platform of Hiolle and Cañamero was implemented and tested on two platforms, the AIBO robot and NAO humanoid robot. Their platform was utilized in the setting of having the robot learn novel elements and its environment, and occasionally get comfort from the human in order to resume learning. However, as the purpose of the envisioned cognitive framework of this thesis was to utilize the motivational drive to guide the interaction itself and learn the social preferences of each person, the framework was modified by changing which variables influence the comfort of the robot, and adding a second threshold for the comfort value.

More specifically, whereas in the original framework the comfort value decreased on encountering novelty in the environment, and was raised by receiving help from the human, in the social version the comfort depended entirely on the stimuli received by the human. The comfort grew when a person would provide visual or tactile stimuli to the robot - being in front of it, smiling at it, showing toys to it or petting it affectionately. On the other hand lack of any stimuli caused the comfort to decay. The modifications of the comfort value took place in the following way:

```
if (V[t] || T[t]):
   C[t] = (V[t]+T[t]+C[t-1]τ)/(τ+0.1)          (1)
else:
   C[t] = β*C[t-1]                             (2)
```

The components in the formulas above are: `C[t]` indicates the current comfort level whereas `C[t-1]` is the previous comfort level; `V[t]` and `T[t]` are the input stimuli from the visual and tactile sensors respectively; and β and τ are the social variables dictating the decay and growth rate of the comfort value.

When there was a human interacting with the robot (the robot was perceiving a face in front of it, or registering touch with its skin), the comfort at time `t` (`C[t]`) was updated using formula (1), which takes into consideration both modalities in which the user could interact with iCub, as well as the previous level of comfort (`C[t-1]`); on the other hand if the robot was not currently engaged in interaction, its comfort was updated as depicted in formula (2), which calculated the decay of the comfort.

The variables τ and β were the growth and decay rates respectively, which were part of the internal variables that the robot could modify in its adaptation process. τ modulated how much `C[t-1]` was taken into consideration: a smaller τ bringing a more rapid growth of the comfort when stimuli were detected, and a larger value a slower, steadier growth. β was indicating how quickly `C[t]` decayed without stimuli; the smaller the value of β, the more drastic the decay of the comfort.

The other modification was the added second threshold. The original framework had only a critical boundary, triggered when the arousal level of the robot got too high, which prompted the robot to call for help upon encountering too many novel items. In the modified motivation drive, the critical threshold was still present, signifying that the robot had gotten too lonely; but there was also a saturation threshold, reached if the person would interact for too long or using all modalities concurrently.

The motivation behind using the thresholds was as discussed above - they provided a way for the robot to a) signal that it would like to interact with the human, particularly if the human had been ignoring the robot for a while; and b) have a way of learning how long a person would like to interact, especially for the people that would normally interact for a long time.

By reaching a critical point and adapting, the robot learns that the person interacts at a lower frequency, so it incorporates this knowledge in its framework, allowing for the robot to remain exploring by itself for longer periods of time before asking for attention. This can be particularly useful in scenarios where the person might have also some other task to take care of, and it would be quite valuable if the robot can learn that the person might need some time without interacting.

On the other hand, by reaching a saturation threshold and adapting, the robot learns that the person likes to interact for longer periods of time. This is overall a good thing in HRI studies, but in some particular cases where maybe the robot also needs to learn some things, disengaging when getting saturated with interaction would give the robot a chance to focus on its own task (parallel to how the critical threshold allows the robot to let the human do the same).

Chapters 7, 8 and 9 from Part 3 delve into more details of how the motivation functionality was implemented for both of the robotic platforms used in the experimental part of this thesis' project.

Chapter 6

Summary

The chapters in Part 2 of the thesis described the process of implementing and validating the cognitive functionalities crucial for the framework. Chapter 4 in particular elaborated over the perception functionality, whereas Chapter 5 covered the development of the motivation functionality.

The cognitive framework was finalized with the implementation of the second version of the motivation functionality and the development of the state machine for organizing the robotic actions. Since this was accomplished during the period of research placement at the EECAiA Lab at the University of Hertfordshire[1], the first validation and testing of the framework was done on the MiRo robot. This was motivated partly in order to stay within the similar context of interaction as in the original study with AIBO [54]; but more importantly this also was seen as an opportunity to truly test the potential for cross-platform usage of the architecture.

The two robots used for the majority of this research - MiRo and iCub - are varying significantly between each other on many aspects - from their configurations and availability of different sensors and actuators, to their forms and sizes - thus necessitating the development of different interaction scenarios.

Upon returning to IIT, the framework was further expanded and ported to iCub, adjusting for the different groups of sensors and actuators as well as the necessary changes to the interaction scenario. While the next chapters go in specifics for how the framework was adapted to each of the platforms and interaction scenarios, here is a summary of the framework's modules:

[1] http://emotion-modeling.info/

- Perception module, processing the input from two sensor groups:
  - tactile stimuli, for MIRO these were the tactile sensors on the head and back, whereas for iCub the skin covers on its hands and torso
  - visual stimuli, for both robotic platforms these were the result of processing the camera feed, for MIRO both cameras were used and the output was only the presence of the person's face (the resolution was too low for accurately extracting the facial expressions), whereas for iCub only one camera was used, but with the full affect detection and color tracking modules
- Adaptation module, which was integrated also with the motivation and memory functionalities in the following manner:
  - memory functionality, only present for the MIRO robot, keeping track of the people's preference for visual over tactile interaction, and adapting to it by interacting at smaller distances with the users who preferred tactile interaction
  - motivation functionality, keeping track of MIRO's/iCub's comfort levels, and adapting to the user's frequency of interacting by modifying the internal variables of the framework beta and tau (see formulas below for more details), and adjusting the values of the critical and saturation points
- Action selection module, implemented in the form of a state machine, which was constantly in communication with the other modules

Part 3 covers the various studies done in the experimental validation of the architecture. Chapter 7 gives an overview of the MiRo platform and the functional testing of the first version of the architecture. Chapter 8 presents the updates to the architecture upon its porting to iCub, as well as the initial validation and pilot studies done with iCub, and finally Chapter 9 presents the full study carried out with iCub, focused on in-depth exploration of the adaptability and personalization of the architecture.

Part III

Experimental Validation

Chapter 7

Functional Testing with MiRo

The first functional testing and validation of the cognitive architecture was performed on the MiRo platform during the period of research placement at the EECAiA Lab. The different physical properties of the platform provided a chance to explore an interaction scenario different from the kinds usually used with humanoid robots, as well as delve into the cross-platform potential of the architecture.

7.1 Materials and Methods

7.1.1 The MiRo platform

MiRo is a fully programmable autonomous robot for researchers, educators, developers and healthcare professionals. MiRo represents a flexible platform suited for developing companion robots, having six senses, eight DoF, a brain-inspired operating system and a simulation software package [58].

Figure 7.1 The MiRo robot

MiRo is based on a differential drive platform with a 3-degrees-of-freedom jointed neck. Weighing in at around 3kg, and sized similarly to a small mammal such as a cat or a rabbit, MiRo can typically run for several hours before needing recharging.

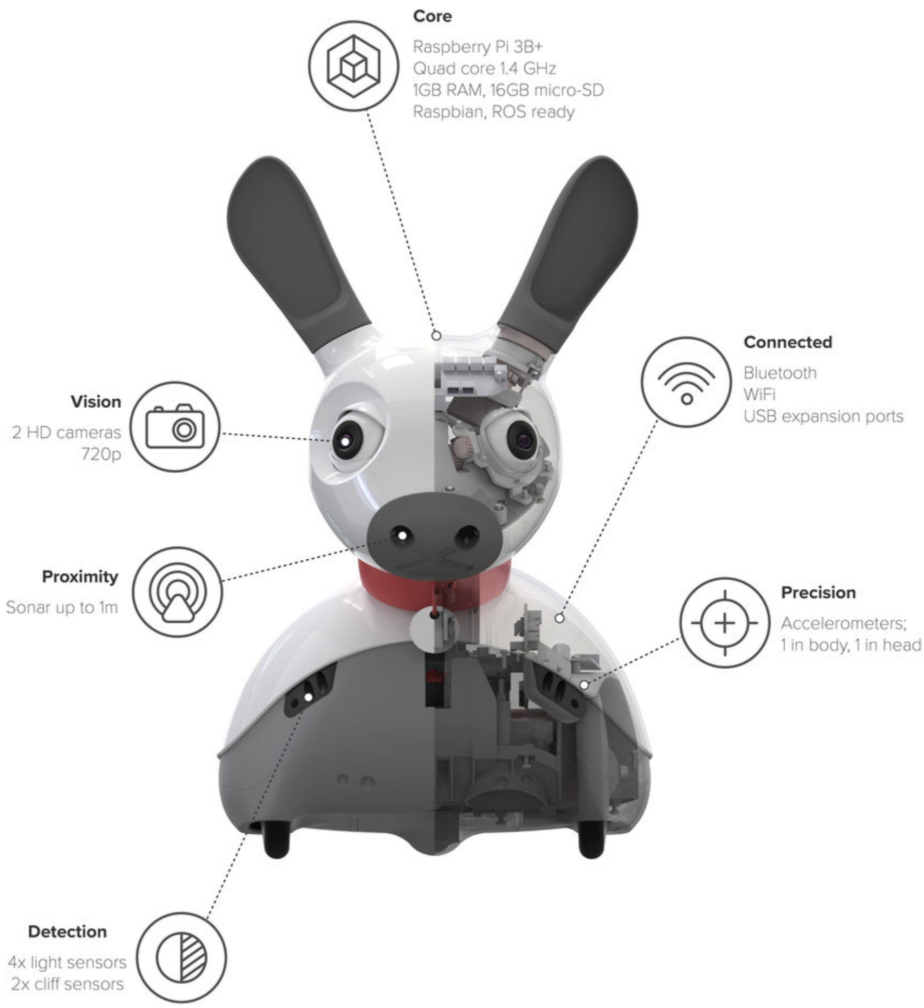


Figure 7.2 Technical specifications of the MiRo platform

Stereo cameras in the eyes and stereo microphones in the ears are assisted by two additional microphones (one inside the head and one in the tail) and by a sonar ranger in the nose. In the body, four light level sensors and two 'cliff sensors' are arranged around the skirt, and many capacitive sensors are distributed across the inside of the body shell and upper head shell to sense direct human contact. Interoceptive sensors include twin accelerometers and battery state sensing.

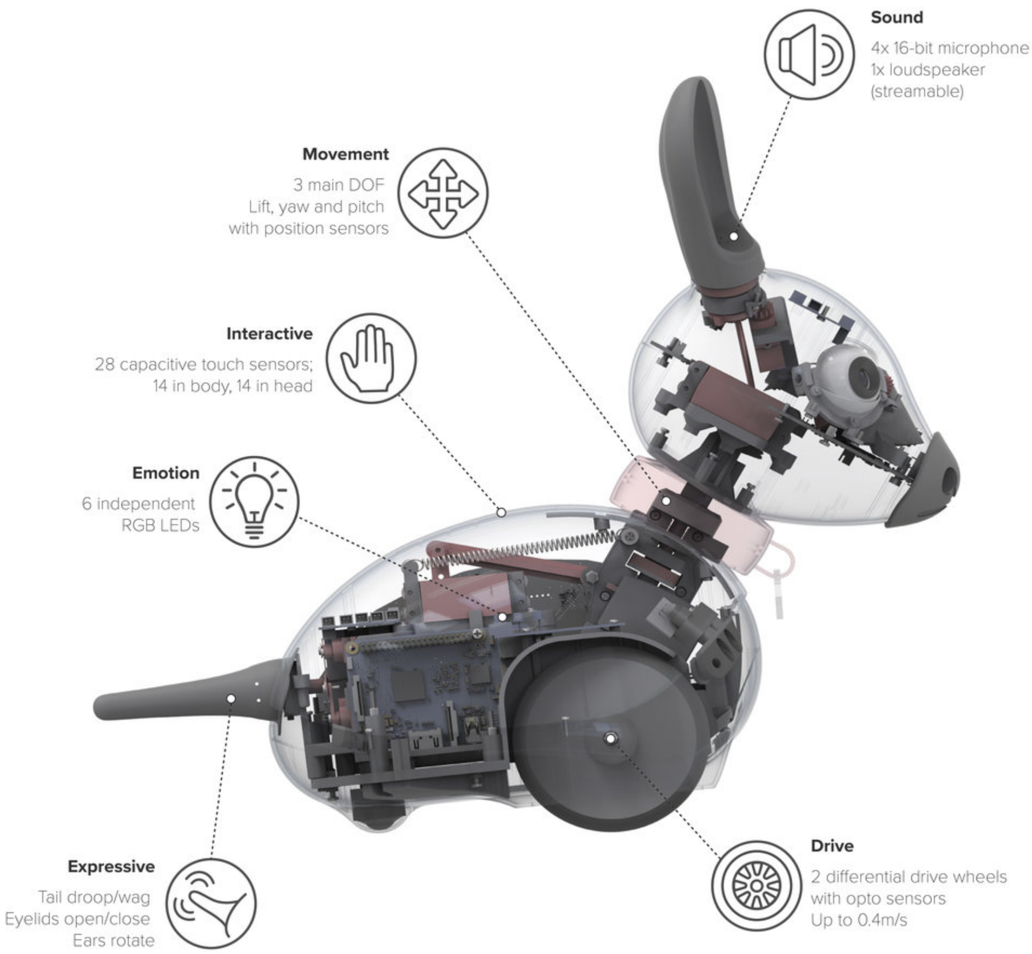


Figure 7.3 Technical specifications of the MiRo platform

Apart from the wheels and the neck, additional servos drive rotation of each ear, tail droop and wag, and closure of each eyelid. The wheel and neck movements are equipped with feedback sensors (potentiometers for neck joint positions and optical shaft encoders for wheel speed). An on-board speaker is also available to generate sound output. MiRo is based around a Raspberry Pi 3B+ running a standard Raspbian distribution.

7.1.2 Experimental Setup

Due to the specifics of the MiRo platform, the designing of an interaction scenario had to take into consideration its size, shape, and sensor and actuator limits. Being a platform in the shape of a small animal, MiRo inspired interaction of a more playful, non-verbal sort. Its very small size meant that people would have to interact with it sitting down; whereas its animal form and limited audio capabilities of just emitting beeps and whistles implied the necessity for a non-verbal communication.

Pairing these constraints with the previous work done by Hiolle and Cañamero with the AIBO robot [54], it was decided on designing a caretaker interaction scenario, where MiRo would wander around the room while the caretaker would be seated nearby. More specifically, MiRo had the task of moving in random directions, exploring the environment around it, while also keeping track of its comfort. The environment space was shared with the human caretaker for MiRo while simultaneously performing a secondary task of reading a paper while MiRo was busy exploring.

Figure 7.4 MiRo exploring while the person is reading the paper

MiRo's comfort was influenced by the interaction with the human in the environment. While MiRo was exploring the environment by moving in random directions and looking around, its comfort levels were modulated by the two internal social variables it had - one regulating the decay of the comfort level when not engaged in interaction (β), and another controlling the growth and possible over-saturation of the comfort level during interaction with the human (τ).

When the comfort level dropped below the critical point, MiRo interrupted its exploration and tried to get the attention of the human by emitting beeping sounds, and looking left and right in an attempt to locate the human. The human could interact with MiRo in more than one modality - its comfort levels were positively affected by receiving tactile and visual stimuli - so depending on the individual preferences of each person interacting with MiRo, they could provide comfort by petting it, looking at it or combining modalities.

7.1.3 Architecture

The cognitive framework was implemented on MiRo following the requirements illustrated in section 2.1, and it consisted of the following modules:

- Perception module, processing the input from two sensor groups:
  - tactile stimuli, coming from the tactile sensors on the head and back of MiRo
  - visual stimuli, the result of processing the feed from the two cameras and only locating the face of the user, as the resolution and framerate of the cameras proved insufficient for tracking also their facial expressions
- Adaptation module, which was integrated also with the motivation and memory functionalities in the following manner:
  - memory functionality, keeping track of the people's preference for visual over tactile interaction (by comparing the total number of received tactile and visual stimuli), and adapting to it by interacting at smaller distances with the users who preferred tactile interaction
  - motivation functionality, keeping track of MiRo's comfort levels, and adapting to the user's frequency of interacting by modifying the β and τ variables, and adjusting the values of the critical and saturation points
- Action selection module, implemented in the form of a state machine, which was constantly in communication with the other modules (shown in Figure 7.5)

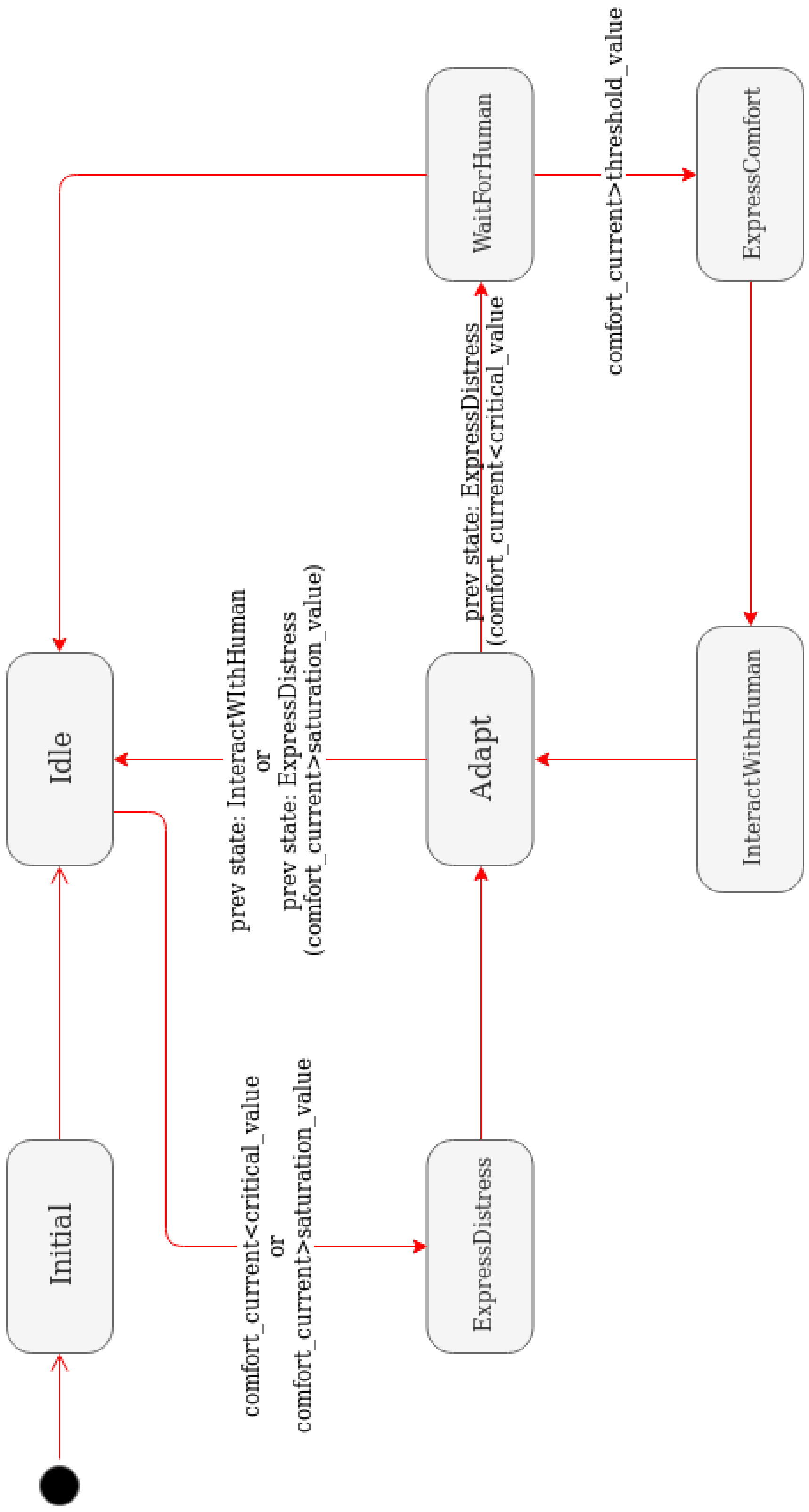


Figure 7.5 The state machine governing the action selection

The comfort level was updated continuously at the beginning of each loop during the interaction, regardless of which state the robot was in. The update happened in the following manner:

```
if (F[t] || T[t]):
   C[t] = (F[t]+T[t]+C[t-1]τ)/(τ+0.1)        (1)
else:
   C[t] = β*C[t-1]                            (2)
```

where *C[t]* indicates the current comfort level whereas *C[t-1]* is the previous comfort level; *F[t]* and *T[t]* are the input stimuli from the visual and tactile sensors respectively. β and τ are the social variables dictating the decay and growth rate of the comfort value.

If there was a human interacting with the robot (MiRo was perceiving a face in front of it, or registering touch with its sensors) the comfort was updated using formula (1) which takes into consideration both modalities in which the user could interact with MiRo, as well as the previous level of comfort; on the other hand if MiRo was not currently engaged in interaction, its comfort was updated as depicted in formula (2), which calculated the decay of the comfort.

The variables τ and β were the growth and decay rates respectively, which were part of the internal variables that MiRo could modify in its adaptation process. τ modulated how much *C[t-1]* was taken into consideration: a smaller τ bringing a more rapid growth of the comfort when stimuli were detected, and a larger value a slower, steadier growth. β was indicating how quickly *C[t]* decayed without stimuli; the smaller the value of β, the more drastic the decay of the comfort. The manner of modifying the τ and β variables was carried over from the related research done in [54][37].

After the comfort values were updated, MiRo continued with the behaviour assigned by the state it was currently in. If in *idle*, MiRo randomly turned and wandered around exploring the environment; *ExpressComfort* and *ExpressDiscomfort* were more affectively expressive states; *waitForHuman* was a relatively static state and *interactWithHuman* varied depending on whether the user had a preference for tactile interaction, so MiRo either just kept at a distance, tracking the person's face, or also approached the person closer so it could be petted.

Finally, if MiRo entered *adapt*, it proceeded with the adaptation process, which could go in two ways:

- If the comfort has dropped to critical levels: increase the decay rate β (so that the comfort lasts for longer), increase the comfort (to allow for the exploration to continue) and lower the critical threshold. This had the effect of MiRo being able to remain exploring for longer periods of time if the person was not particuarly interactive;
- If the comfort reached the saturation level, increase the growth rate τ (so that the comfort grows slower), decrease the comfort (to allow for interaction to continue right away) and raise the saturation threshold, which allowed MiRo to interact for a longer time with a person before getting saturated and disengaging.

7.1.4 Functional testing and validation

For testing the architecture, eight diverse profiles for the participants were designed, with the profiles varying greatly between each other in order to better compare and test all the functionalities of the architecture. MiRo's architecture allowed for adaptation on two dimensions - the frequency of the interaction with the human, which affected the social decay and saturation values; and the preferred modality of interaction of the human, which could be verbal, tactile or a combination, and which affected the distance at which the robot was interacting.

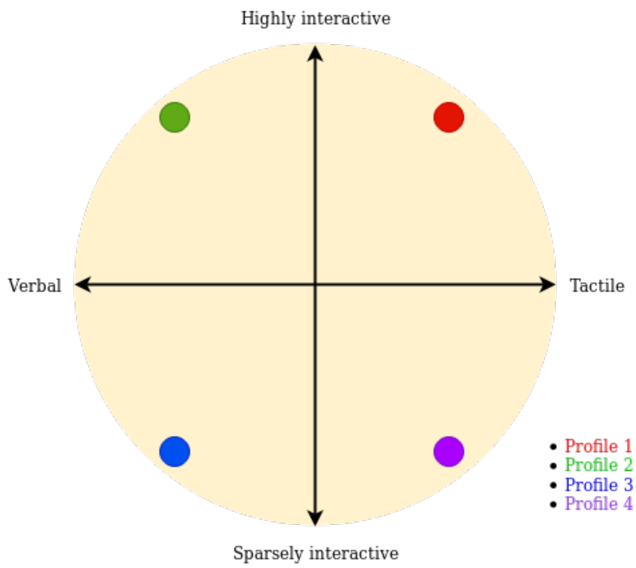


Figure 7.6 The plane of modalities and intensity for the predefined user profiles

With this in mind, four “extreme” user profiles were designed - a highly interactive user with a preference for tactile interaction, a highly interactive user who kept their distance and preferred not to touch the robot, and similarly two profiles of a very sparsely interacting user who either preferred tactile interaction or mostly avoided touching the robot.

After the design of the four base profiles, additional four were also added to serve as a control group of profiles. In the original four profiles, the level of interactivity (highly interactive vs. sparsely interactive) was defined in the way the users were supposed to interact with the robot the instruction for the highly interactive profiles was to try and respond to every distress call from the robot, and also occasionally initiate interaction even if the robot didn’t need to be comforted; on the other hand the sparsely interactive profiles were instructed to only respond to one distress call at maximum, or none at all.

The control group profiles still followed the same distribution on the modality frequency plane, with the one distinction in how the frequency was defined - the highly interactive control profiles needed to initiate interaction every 30 seconds, regardless of the state of MiRo, and the sparsely interactive control profiles needed to do the same every 90 seconds. The total interaction time for all eight profiles was set at 300 seconds.

Figure 7.7 Tactile interaction with MiRo after emitting a sound of distress

7.2 Results

The results from six of the profile runs are shown below in the six figures. Out of the eight user profiles in total, due to technical issues two of them weren't able to be tested - the control condition of visual interaction every 30 seconds, and the control condition of tactile interaction every 90 seconds.

The upper graph in Figures 7.8-7.13 depicts the growth and decay of MiRo's comfort level; the value always started at 20.0 at the beginning of each interaction to allow for some environment exploration, since the initial decay rate was still lower in order to facilitate more interaction attempts. The beginning values of β and τ were the same in every interaction run, with β=0.999 and τ=5.

The lower graph depicts the moments in the interaction when MiRo is perceiving tactile or visual stimuli. The tactile stimuli are shown in yellow, and the visual in green. Due to some technical issues with the tactile sensors and the cameras' framerate, there were moments when a stimulus was not perceived by MiRo (even though given by the user), as well as moments when the length and consistency of the stimuli was not properly perceived as a continuous block, but as lot of brief, unconnected stimuli.

For each of the interaction sessions an explanation is provided below its respective graph.

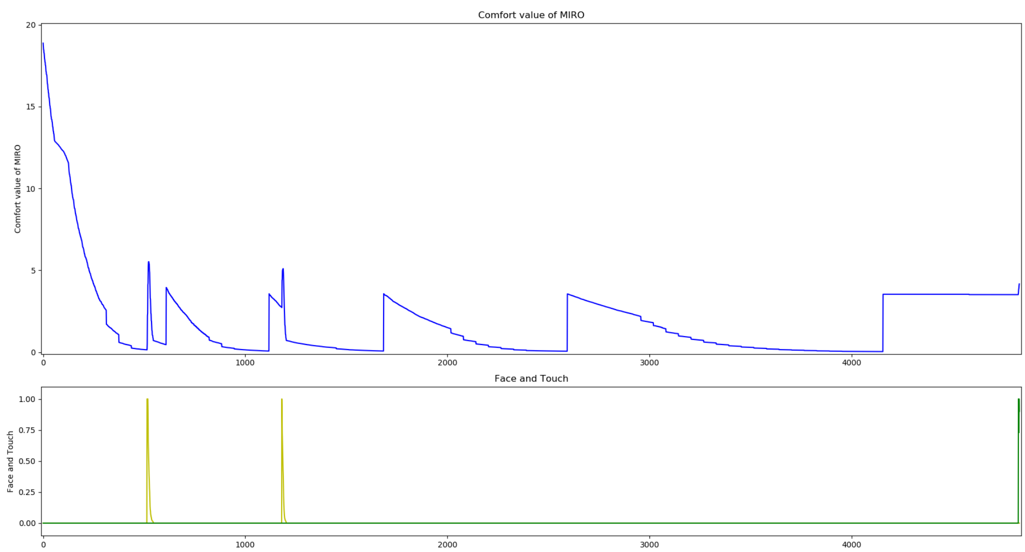


Figure 7.8 Condition 2 – tactile contact every 30 seconds.

Due to the user not knowing the exact locations of the tactile sensors on the back, in Figure 7.8 only two of the tactile stimuli (the ones at the beginning) were actually received by MiRo. There was also an additional visual stimuli at the very end of the interaction. The adaptation of the social decay rate β can be observed in the slopes gradually growing less sharp and eventually β reaches a value of 1, which is why it remains unchanging during the end. Social variable values at the end of the interaction: β=1, τ=5.

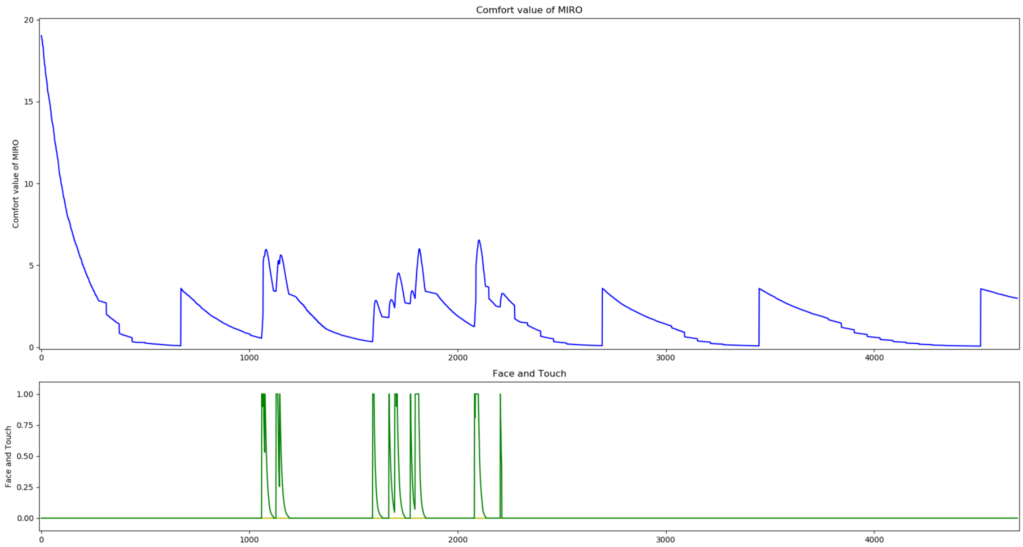


Figure 7.9 Condition 3 – visual contact every 90 seconds.

During this run the user only managed to appear in the field of view of the robot once on purpose, shown in Figure 7.9 as the middle one of the three groups of stimuli in the second graph, while the other two stimuli sets were due to the MiRo randomly exploring the environment close to the user and seeing them, so the facial recognition system activated. During the second half of the interaction when MiRo wasn't receiving any stimuli, the same kind of adaptation as in cond 2 can be seen, with the decay slopes growing softer. Social variable values at the end of the interaction: β=0.9998, τ=5.

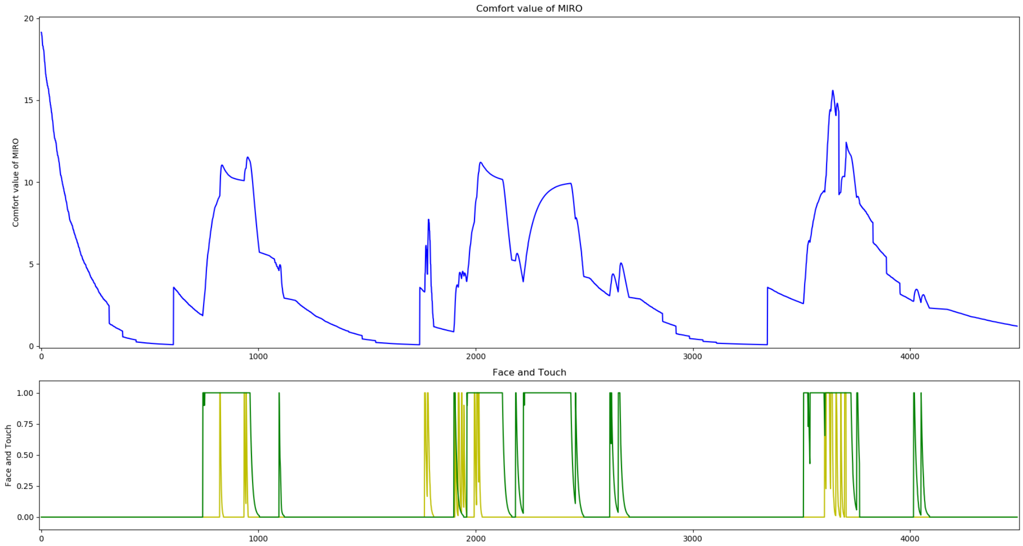


Figure 7.10 Condition 5 – highly interactive, preference for visual interaction.

The user was nearly all of the time in front of the robot, disengaging from the interaction for brief periods to go back to the secondary task, but returning to engage with MiRo for every distress call. There were also occasional tactile stimuli as seen in yellow on Figure 7.10. There were only a few moments when the comfort dropped below the critical point, however there was also afterwards a period of very intense interaction using both modalities (tactile and visual), and MiRo reached a saturation point. Social variable values at the end of the interaction: β=0.9996, τ=7.5.

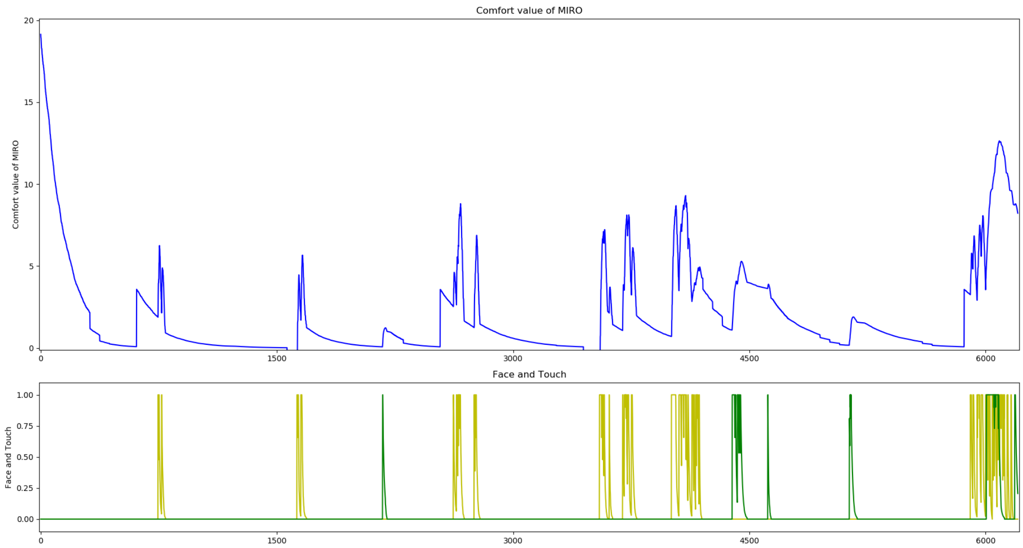


Figure 7.11 Condition 6 – highly interactive, preference for tactile interaction.

Both the peaks of the frequent tactile stimuli and the occasional glimpse of the face of the user can be seen in the graph in Figure 7.11. The run ended with the same adapted values as in condition five, as there was also one point of saturation near the end of the interaction, additionally MiRo had noted the user's preference for tactile interaction, so near the end of the interaction after locating the user it also approached it as an encouragement for more tactile stimuli. Social variable values at the end of the interaction: β=0.9996, τ=7.5.

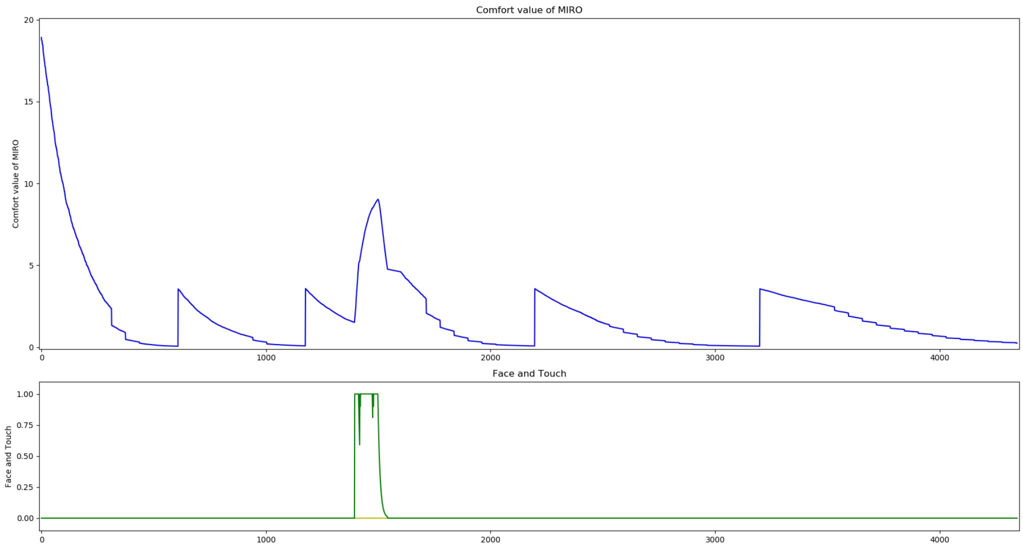


Figure 7.12 Condition 7 – sparsely interactive, preference for visual interaction.

In run illustrated in Figure 7.12 the user only showed up in the field of view of the robot once. The same adaptation as in other sparse interactions (like for example in Figures 7.8 and 7.9) can be seen in terms of the decay slopes. An additional factor that leads to the robot not localizing the user very easily was the fact that MiRo's motion was randomized in the environment, so on some occasions it ended up wandering for a longer period of time in regions of the environment space far from the human. Social variable values at the end of the interaction: β=0.9998, τ=5.

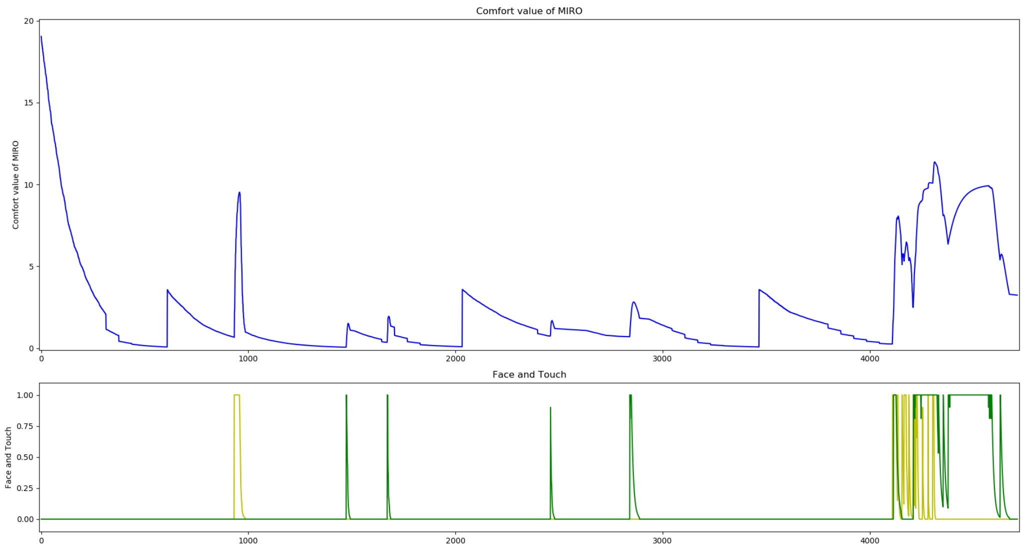


Figure 7.13 Condition 8 – sparsely interactive, preference for tactile interaction.

In this run there were only two tactile interactions initiated by the user, however during the exploration periods the robot caught several glimpses of the user and was comforted by seeing them. The most salient part of the interaction is the time slot towards the end, during which MiRo also approached the user closer as it had noticed the preference for tactile stimuli. Social variable values at the end of the interaction: β=0.9996, τ=5.

Although the research conducted with MiRo was not able to continue to the last stage of implementation and testing with naive human participants, it still provided valuable results. The functional testing of the framework on MiRo validated the cognitive framework and its ability to adapt through diverse profiles, but it also highlighted some issues that could occur when testing a framework in real-life settings with a physical robot - malfunctioning of tactile sensors, issues in visual stimuli due to poor framerate, etc. These problems were taken into consideration when porting the framework back to the original platform for the thesis - the iCub humanoid robot. Chapters 8 and 9 describe the modifications to the framework and the studies done with iCub.

Chapter 8

Porting the framework to iCub

Having conducted the initial research for the motivation and adaptation functionalities with the MiRo robot, the next challenge was porting the completed framework on the iCub [59]. While the MiRo provided some valuable insight into the specifics of testing a cognitive framework on a physical robot, it was still a very particular platform in terms of its shape and capabilities. Even though it showed promising results in terms of the cross-platform potential for the framework, the accuracy of the platform's sensors coupled with its limitations for interaction scenarios encouraged the transfer to a different platform.

8.1 Materials and Methods

8.1.1 The iCub platform

The iCub is an open-systems 53 degree-of-freedom cognitive humanoid robot [60][61]. At 94 cm tall, the iCub is the same size as a three year-old child. To ensure that the iCub's interaction is compatible with humans, the design is aimed at maximizing the number of degrees of freedom of the upper part of the body, i.e. the head, torso, arms, and hands. The lower body, i.e. the legs and feet, has been designed to support crawling and sitting on the ground in a stable position with smooth autonomous transition from crawling to sitting.

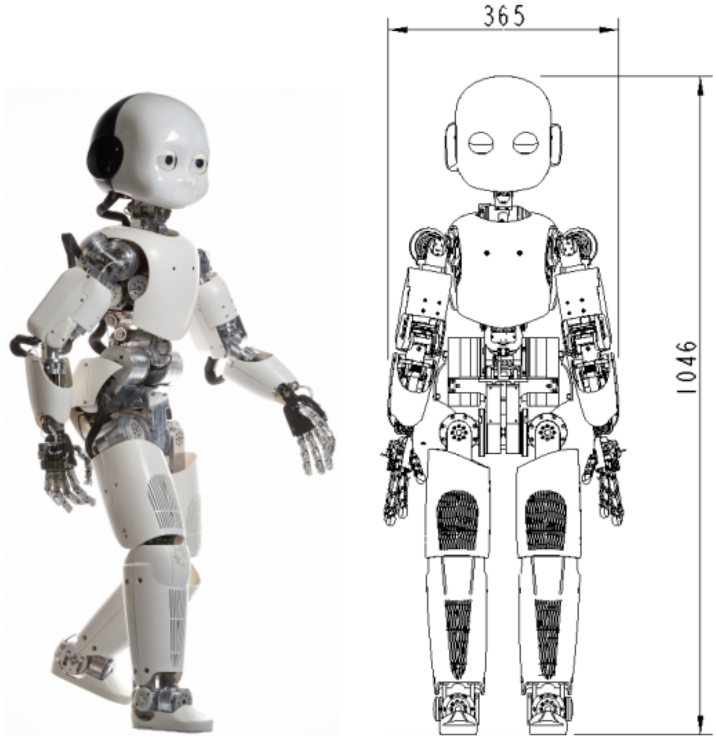


Figure 8.1 The iCub humanoid robot

iCub has been designed to allow manipulation and mobility and has 53 degrees of freedom in total: six in the head (two for azimuth & vergence, one for coupled eye-tilt, and three for the neck) [18], seven degrees of freedom in each of the arms (three in the shoulder, one in the elbow, and three in the wrist), nine degrees of freedom in each of the hands to effect under-actuated control the 17 joints comprising the five fingers), six degrees of freedom in each of the legs (three for the hip joints, one for the knee, and two for the ankle), with the waist also having three degrees of freedom [62].

From the sensory point of view, the iCub is equipped with digital cameras, gyroscopes and accelerometers, microphones, and force/torque sensors. A distributed sensorized skin using capacitive sensor technology is placed on skin patches on the arms and torso [63]. Each joint is instrumented with positional sensors, in most cases using absolute position encoders. A set of DSP-based control cards, designed to fit the iCub, take care of the low-level control loop in real-time. The DSPs talk to each other via CAN bus. Four CAN bus lines connect the various segments of the robot.

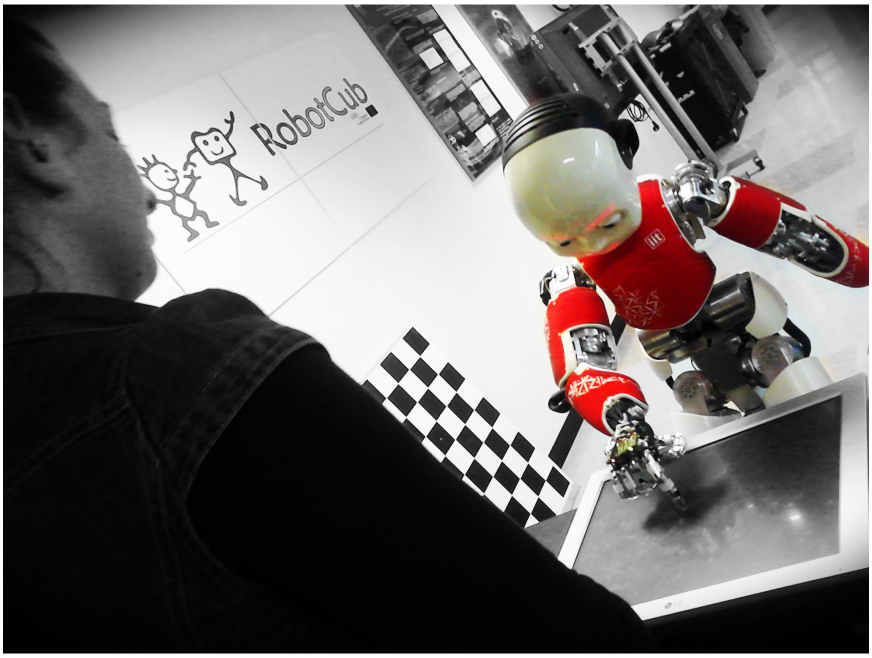


Figure 8.2 iCub interacting with a participant in a study on stimulus estimation [1].

The overall weight of the iCub is 22kg. The umbilical cord contains both an Ethernet cable and power to the robot. At this stage there is no plan for making the iCub fully autonomous in terms of power supply and computation (e.g. by including batteries and/or additional processing power on board).

The mechanics and electronics were optimized for size, starting from an evaluation and estimation of torques in the most demanding situations (e.g. crawling). Motors and gears were appropriately sized according to the requirements of a set of typical tasks. The kinematics was also defined following similar criteria. The controllers were designed to fit the available space.

8.1.2 Experimental Setup

The envisioned role for iCub in the study was one of a toddler exploring and playing with its toys, while the participants were tasked as the iCub's caretaker. Two conditions with different profiles for iCub were considered for the experiment - one where iCub had a fixed, non-adaptive behaviour and no social architecture; and a second adaptive profile where the behaviour of iCub was guided by its social needs.

The interaction between the robot and the caretaker was free-form and left to the person to guide it. iCub was able to receive and process tactile and visual stimuli, which in the adaptive profile of the robot acted as variables that affected its comfort need - lack of stimuli caused the comfort of the robot to decay to a critical level, whereas overwhelming the robot with multimodal (simultaneously visual and tactile) interaction for a long time caused iCub to get oversaturated and disengage from the interaction.The adaptive behaviour was inspired in part by the behaviour of toddlers interacting with their caretakers, where the toddlers tend to seek the attention of their caretakers after being alone for a while, but as soon as their social need has been saturated they lose interest and turn their attention to something else [64].

iCub was positioned in front of a table with toys, and in the time periods when it was not in an engaged state with the caretaker, it "played" with the toys by looking and pointing at them. The participant was offered a chair in front of the table facing iCub, but they also had the freedom to sit or walk anywhere in the room.

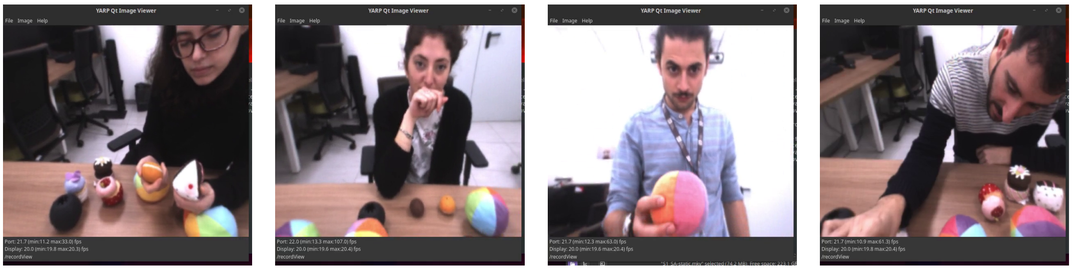


Figure 8.3 Images from iCub’s cameras during the pilot study.

When iCub was in an engaged state and interacting with its caretaker, it maintained mutual gaze and tracked the person’s face, and could occasionally indicate toys to the person by gaze-cueing. In the static profile, iCub transitioned between the disengaged and engaged behaviours on a time basis, whereas in the adaptive profile it had a series of actions designed to either try and attract the attention of its caretaker in order to engage in interaction with them, or to disengage from the interaction if it got oversaturated.

8.1.3 Updated version of the architecture

The framework for the iCub consisted of the following modules and their functionalities:

- Perception module, processing stimuli from two sensor groups:
  - Tactile stimuli - the data processed from the skin patches on the iCub on its arms and torso, carried information about the size of the area that was touched (expressed in number of *taxels* - tactile elements) and the average pressure of the touch.
  - Visual stimuli - the images coming from iCub's eye camera, analyzed for detecting the presence of a face, and for extracting the facial expression of the person.
- Action module, tasked with moving iCub's joint groups.
- Adaptation module, active only in the adaptive profile for the robot and in charge of regulating iCub's social need.
- State machine module, managing the other modules and assigning iCub's current state based on the information it receives from the modules.

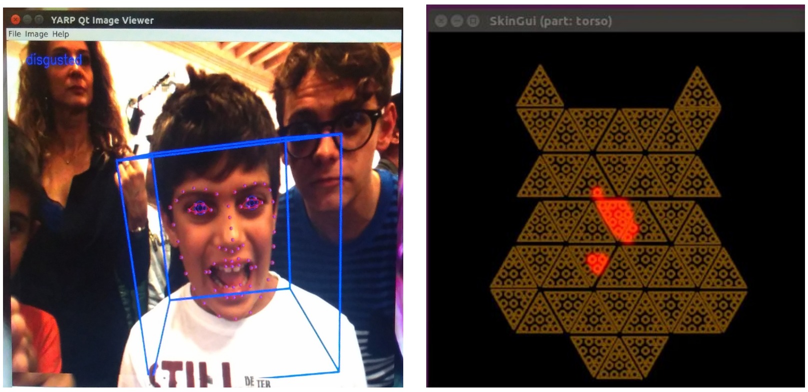


Figure 8.4 The perception module at work

Perception module The perception module was realized using iCub's middleware libraries [61] for processing the data from the skin covers on its torso and arms, and using the open-source library OpenFace [48] for extracting and analyzing the facial features of the caretaker [47]. Figure 8.4 shows the processing of the facial features and the taxels.

The data from the OpenFace library were analyzed for obtaining the most salient action units from the detected facial features - lowering eyebrows, crinkling of nose and cheeks, and smiling/frowning. These action units were weighted accordingly before being sent to the perception module, with the presence of a smiling person being rated as 1.0, a neutral or contemplating face as 0.75, a distant face as 0.5 and a frowning or disgusted face as 0.25. This was done by assuming that in an interaction a smile would bring higher social comfort than a neutral expression, similarly seeing a neutral face would still be more comforting than a distant presence or a displeased person.

For the skin there was some additional processing post-extraction; as during prolonged interaction the tactile sensors tended to overheat and give phantom signals, the data was filtered to register as touch only areas that were larger than 5 taxels and recorded avg. pressure larger than 12.0. This data was processed for the torso and both arms separately, and sent to the perception module.

Action Module The action module communicated with iCub's middleware and performed a finite set of actions by controlling the specific body part in the joint space. These included head and neck motions determined by where iCub wanted to look, and arms and torso motions. If iCub wanted to engage with the caretaker, it would straighten up and look for the person, and then during the interaction engage in gaze-cueing and pointing to objects, whereas when iCub was oversaturated and wanted to disengage, it would pull away from the person and look down to its toys, ignoring other attempts to engage.

State Machine There were different states for the two profiles, as in the non-adaptive profile the transition between states was static and always performed in the same way, whereas in the adaptive profile iCub moved through the states as a result of both the behaviour of the caretaker and its comfort levels.

Figure 7.5 shows the full state machine in the form it was used during the adaptive profile interactions, which was for the most part unmodified from the original one used with MiRo. After the comfort values were updated, iCub continued with the behaviour assigned by the state it was currently in. If in *idle*, iCub randomly turned and played with its toys; *ExpressComfort* and *ExpressDiscomfort* were the emotionally expressive states iCub entered when its comfort would reach the critical or saturation value; *waitForHuman* was a static state of waiting for a fixed amount of time after trying to attract the attention of the caretaker; and *interactWithHuman* was the state in which iCub would interact with their caretaker, following their face and occasionally indicating toys by gaze-cueing. Finally, if iCub was in *adapt*, it proceeded with the adaptation process, which could happen on two dimensions, as described in the next paragraph.

Adaptation and Motivation Module This module maintained iCub's comfort and guided the adaptation process. The motivation in the architecture was represented by iCub's striving to remain in an optimal level of comfort.

The comfort of iCub grew when a person was interacting with it, and the stimuli were weighted accordingly - a multimodal interaction (receiving both visual and tactile stimuli) or a longer, steadier interaction was rated higher and increased the comfort faster. Inversely, lack of any stimuli caused the comfort value to decay. iCub's social architecture was also equipped with a saturation and a critical threshold, which were reached when the interaction was getting too intense or was too sparse/non-existent, respectively.

At the beginning of the interaction with each user, iCub started with its comfort set at 50% of the maximum value it could have. Then the comfort level was updated continuously at the beginning of each cycle of the control loop of the interaction[1]. This happened in the following manner:

```
if (F[t] || T[t]):
   C[t] = (F[t]+T[t]+C[t-1]τ)/(τ+0.1)          (1)
else:
   C[t] = β*C[t-1]                              (2)
```

The components are the same as in Section 7.1.3: *C[t]* indicates the current comfort level whereas *C[t-1]* is the previous comfort level; *F[t]* and *T[t]* are the input stimuli from the visual and tactile sensors respectively. β and τ are the social variables dictating the decay and growth rate of the comfort value.

When there was a human interacting with the robot (iCub was perceiving a face in front of it, or registering touch with its skin), the comfort at time *t* (*C[t]*) was updated using formula (1), which takes into consideration both modalities in which the user

[1] Referring here to the perception-action control loop of iCub's architecture

could interact with iCub, as well as the previous level of comfort (*C[t-1]*); on the other hand if iCub was not currently engaged in interaction, its comfort was updated as depicted in formula (2), which calculated the decay of the comfort.

The variables τ and β were the growth and decay rates respectively, which were part of the internal variables that iCub could modify in its adaptation process. τ modulated how much *C[t-1]* was taken into consideration: a smaller τ bringing a more rapid growth of the comfort when stimuli were detected, and a larger value a slower, steadier growth. β was indicating how quickly *C[t]* decayed without stimuli; the smaller the value of β, the more drastic the decay of the comfort.[2]

iCub's architecture allowed for adaptation on two dimensions - the frequency of interaction initiation and the duration of the interaction. The first one affected the decay rate of the comfort, and the adaptation on the second dimension instead modulated the growth rate of the comfort value. After each instance of iCub adapting on either dimension, it entered a suspension period where it attempted to recover and during which it was not open to interaction with the users. The adaptation process had the following pattern:

- If the comfort reached the saturation limit: increase the value of τ (adapt with a slower comfort growth), and during the period of suspension ignore all stimuli. The resulting lack of sensitivity to stimulation leads to a decrease in the comfort value back to the optimal zone.
- If the comfort dropped to the critical level: increase the value of β (adapt with a slower comfort decay), and during the suspension period simulate stimuli to itself so as to recover back to the optimal comfort level.

Originally the architecture adapted by immediately resetting the comfort level back to the optimal level and continuing with the interaction, which can be seen in Figures 8.5- 8.7. The suspension period was included as a factor only after the validation of the original architecture with subjects, during which it was realized that a continuation of responsiveness of the robot might not have allowed for the participants to infer

[2] The manner of modifying the τ and β variables was carried over from the related research done in [54][37]. After this validation study, it was explored further in a following study [65] how the behaviour of the architecture could be affected by varying the initial values of these rates, using different steps in the adaptation, and starting with different critical and saturation thresholds.

that they were doing something not ideal for the robot. For example - in the case of saturation, after the instantaneous robot withdrawal, it was immediately ready again to respond, which induced participants again to continue to interact in the same manner and trigger again saturation. The effect of different suspension periods is analyzed in greater details in Section 8.3

8.1.4 Validation study with predefined profiles

For testing the architecture, three diverse profiles were designed, varying significantly between each other in order to better compare and test all the functionalities of the architecture. iCub's architecture allowed for adaptation on two dimensions – the frequency of initiated interactions with the person, which affected the comfort decay rate and the critical threshold value; and the duration of the interaction which was related to the comfort growth rate and the saturation threshold value.

With this in mind, three user profiles were designed to be used for the validation – a highly interactive user who constantly tried to attract the interaction of iCub and provided a very salient interaction that oversaturated the robot, a very sparsely interacting user who avoided mutual gaze with the robot and only engaged in tactile interaction once, and an in-between "mixed" profile that had periods of high and low interaction. The length of the interaction was the set at three minutes for each of the three profiles.

The three following figures show the behaviour of the architecture for all three predefined profiles. The moments of received contact by the user are shown on the lower graph, with the visual stimuli depicted in green and the tactile ones in yellow. The upper graph depicts the comfort level of iCub and how it decayed and grew during the interaction.

The moments when the comfort reached over-saturation are shown as green dots on the peaks, and the moments when the iCub was left without stimuli for a while and it reached a critical value are shown as a red dot over the lowest point of the comfort.

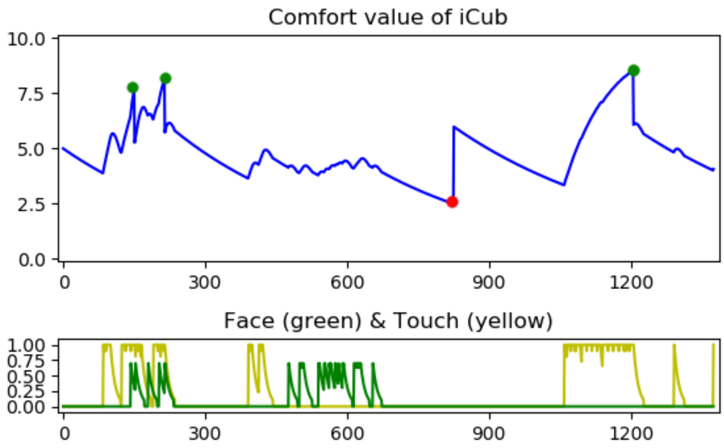


Figure 8.5 Variations of the comfort value - salient interaction

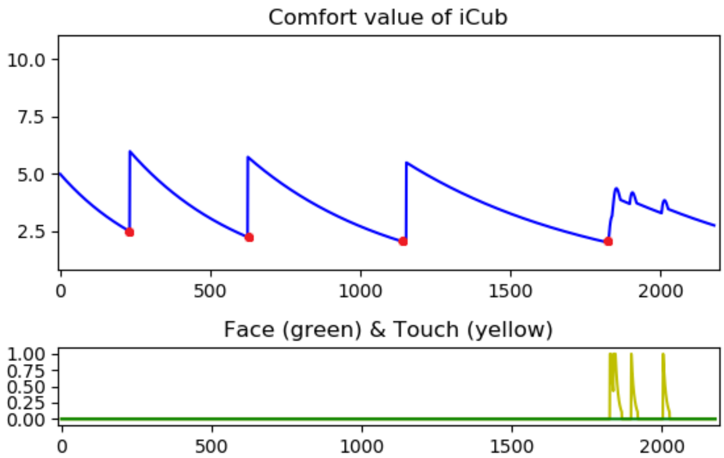


Figure 8.6 Variations of the comfort value - sparse interaction

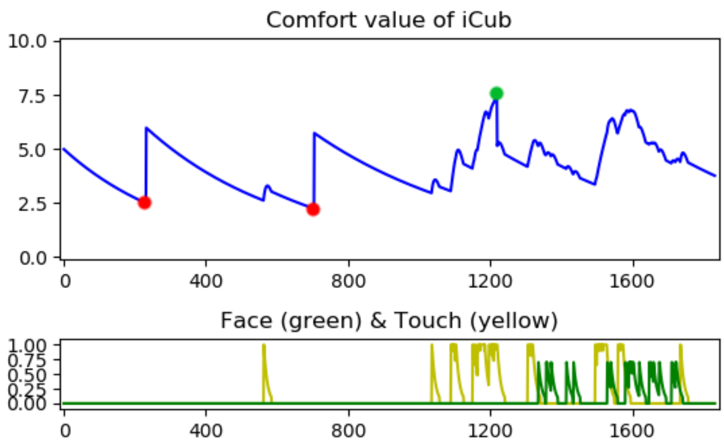


Figure 8.7 Variations of the comfort value - mixed interaction

Table 8.1 shows the number of adaptations for all three sessions, i.e. how many times the architecture's internal values changed for each of the sessions. The architecture manifested the expected adaptation - in the highly interactive salient session there were three adaptations due to oversaturation and one for reaching a critical point (as shown in Figure 8.5), in the sparsely-interactive there were only three adaptations for reaching the critical level of comfort (as shown in Figure 8.6), and finally for the mixed profile there were two critical and one saturation adaptations (as shown in Figure 8.7).

Table 8.1 Number of adaptations for the three profiles

	Beta	Tau	Critical val.	Saturation val.
Sparsely int.	3	0	3	0
Mixed int.	2	1	2	1
Highly int.	1	3	1	3

8.1.5 Validation study with naive users

In addition to using predefined profiles which tested the architecture with the implemented modalities, a second validation study with naive users was also run [66]. The duration of a single session was increased from three to eight minutes, and two different profiles were designed for the robot - one where it maintained the adaptive architecture, and another one where it had a time-dependent static behaviour.

The study was run with 6 participants, 3 female and 3 male, mean age 28 +/- 4.89, half of them interacting first with the static and then the adaptive profile, and the other half vice versa. The participants answered the IOS questionnaire on closeness between them and the robot [67] and the Godspeed questionnaire on animacy and likeability [68], both before and after the sessions, and in addition were asked at the end of the second session to give their own opinion on how the sessions differed and which one they preferred. An overview of the two profiles follows below, and the results from the study are analyzed in Section 8.2.

First condition - static profile

The static profile ran with a modified version of the cognitive architecture described in 8.1.3, with the adaptation module completely removed and iCub switching between between the states of *idle* and *interactWithHuman* on a 40-20 seconds intervals, spending

40 seconds playing by itself and 20 seconds engaging the caretaker. While in *idle* iCub had the same behaviour as in the adaptive profile, but it was not comunicating with the perception module and it could not be engaged by any action of the user. Inversely, when in *interactWithHuman* iCub was perceiving all the stimuli from the caretaker, but they were not being utilised as a means of regulating iCub's internal status. In this case the robot behavious was only reactive, meaning that iCub responded to the tactile signals and tracked the person's face.

Second condition - adaptive profile

The adaptive profile instead was operating with the full architecture as described in 8.1.3. There was the communication between the state machine and the perception and adaptation modules, and the stimuli iCub received from the caretaker were not used solely to guide the action module, but they directly impacted iCub's comfort level and caused the architecture to adapt and personalize iCub's behaviour to each participant.

8.2 Results

From each of the 12 sessions the data from the iCub's tactile sensors and cameras was collected, as well as the adaptive variables from the iCub's framework and the answers from the users' questionnaires. Due to a thermal drift appearing as an issue with the tactile sensors, there was a certain amount of noise in some of the sessions that rendered the data from the architecture not entirely stable, nonetheless even allowing for the noise there was still a significant difference between the two profiles, as well as between the group of participants who interacted first with the static and then with the adaptive profile, and vice versa.

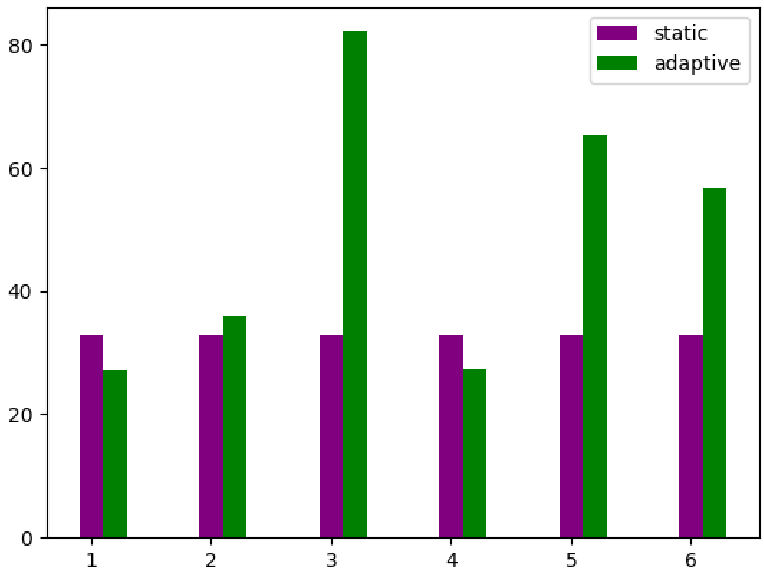


Figure 8.8 Percentage of the session time when the robot is engaged per session for all participants

Figure 8.8 shows a comparison of the part of the session in which iCub was interactive for each participant and in both robot profiles. In the static profile the percentage is the same for all the participants (33%), since the transitioning between states was fixed, however for the adaptive profile there are major differences between the users, which can also be seen by the number of adaptations in Table 8.2.

Table 8.2 Number of adaptations per user in the adaptive profile

S1	S2	S3	S4	S5	S6
4	4	0	5	0	3

One plausible explanation is that this is in major part due to the different interaction profiles of the six participants - some had a very tactile manner of interaction, other tended to just stay at a distance and observe the robot, and some while very interactive, used modalities to which iCub was not sensitive, such as showing iCub the toys and using excessive verbal communication. Another interesting result was the change in the IOS rating results for the people depending on whether they interacted first with the static and then the adaptive profile (SA group) or vice versa (AS group) as shown in Figure 8.9.

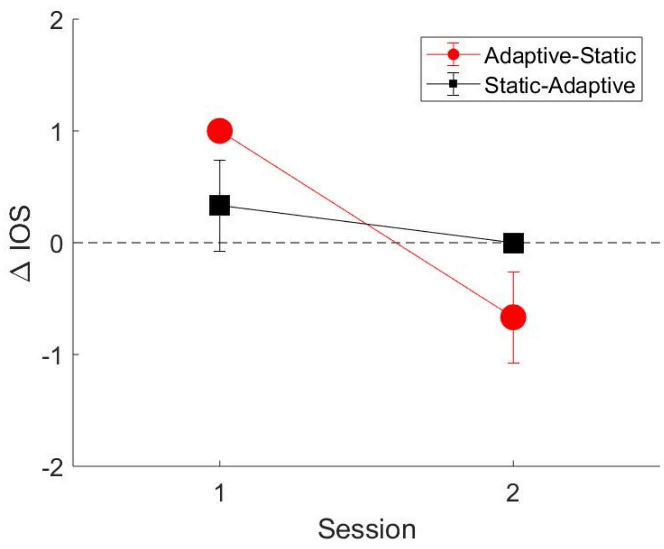


Figure 8.9 Difference in the IOS delta between the two sessions

For the people in the SA group, their rating either stayed the same, or increased after the first interaction and then remained static. On the other hand, for two of the people in the AS group the same pattern was noticed of their IOS rating increasing after the first interaction with iCub, and then decreasing back to the pre-experiment rating after the second (static) session.

This result, while not being a decisive evidence, it is still an interesting indication of how the people that first experienced the static and then the adaptive profile of the robot kept their original (or increased) feeling of closeness, whereas the users that interacted with the static profile after the interactive one felt more distant from iCub at the end of the study. Additionally, 5 out of the 6 participants expressed a strong preference for the adaptive session in the post-study questionnaire, expressing that they preferred that session because they felt iCub was more responsive and interactive with them.

This was also reinforced by the findings from the Godspeed questionnaires, where the users' rating for the Inert/Interactive and Apathetic/Responsive questions had the same change in their pre- and post-interaction ratings as for their IOS ratings. On the other hand, the rating for the Unfriendly/Friendly and I dislike/like iCub questions stayed constant per users through all four questionnaires, regardless of the order of the sessions, suggesting that they formed their impression of the likeability of iCub at the beginning and kept it through both sessions.

8.3 Parameter optimization though simulation study

After testing and validating the functionalities of the architecture as well as trying it out in real-world interaction with participants, the next research question was addressed - how would the architecture adapt to different users when given different initial values of its parameters, i.e. working with different robot profiles [65]? If the considered parameter is the learning rate, would an adaptive robot who is a very fast and eager learner (i.e. takes big steps in the adaptation process) overshoot and miss the chance for personalization? If the considered parameter is the initial threshold value, would a finicky/fussy robot who has very narrow thresholds for interaction (i.e. has a very small difference between its saturation and critical thresholds) be an annoying interaction partner?

In order to test multiple sets of parameters across multiple user profiles, the approach selected was to design five simulated user profiles and running a simulation study (before ultimately proceeding to full user studies), so as to obtain the exact user behaviour across all conditions. This leveraged on the data obtained from the validation study in 8.1.5 to study how different users interacted with the robot [66].

Table 8.3 Features of the five user profiles

	Visual	Tactile	Answer call
Complete (c)	1.0	1.0	always
Frequent (f)	[0.75-1.0],20 sec.	[0.0-1.0],15 sec.	always
Average (a)	[0.5-0.75],60 sec.	[0.0-1.0],10 sec.	always
Sparse (s)	[0.0-0.5],20 sec.	[0.0-1.0],15 sec.	only once
Void (v)	0.0	0.0	never

Table 8.3 showcases the modalities of the profiles. The visual stimuli were designed to be alternated between two values on a fixed time intervals, and the value in seconds shows at which frequency they alternated; the tactile stimuli instead were given depending on the state of the robot, the *average* and *sparse* profiles only provided tactile stimuli as a response to a call for engagement, whereas the *frequent* profile also provided stimuli while the robot was in an interactive state, and the value in seconds shows how long the tactile contact was. The *complete* and *void* profiles had either constant or non-existent input.

8.3.1 Implementing the suspension period

As mentioned in 8.1.3, the current version of the adaptive module leveraged on the functionality of a suspension period in which iCub could "recover" from the failed interaction. Before proceeding with the full simulation study, a preliminary investigation was run across the user profiles to determine the optimal length of the suspension period.

As potential values the durations of 5, 20 and 35 seconds were selected, and the effect the suspension period had on two metrics was tracked - the amount of time (expressed as a percentage from the whole duration of the interaction) in which iCub was in an optimal zone of comfort (i.e. the comfort value was within a maximum of 5% distance of the saturation and critical thresholds), and the number of times it reached a critical or saturation threshold and went into the adaptive module. In the framework the goal was to maximize the former and minimize the latter.

The minimization of the number of adaptation signified a smaller amount of interruptions in the interaction flow by iCub disengaging, whereas maximizing the time iCub was in the optimal zone of comfort ensured an interaction where iCub would be neither too annoying to the person by constantly asking for attention, nor too isolated by not tolerating a sparsely interactive user.

8.3.2 Testing different robot profiles

After running the suspension optimization study, the suspension interval that gave the best results in the adaptation module was implemented and from there it was proceeded to the design the set of robot profiles for the simulation study, i.e. the selection of the sets of parameters to explore. Two dimensions were experimented on - the speed of adaptation, which was the step of modification for the growth and decay rate in the adaptation module; and the width of the band between the two thresholds. In terms of robot personalities, this could be translated to experimenting between a slow and steady vs. a fast and eager learner (depending on the size of the adaptation step for the growth/decay rates); and between a very tolerant vs. a very fussy robot (depending on how wide the threshold band was, i.e. how close the saturation and critical points were to each other).

For both dimensions three values to test were chosen, for a total of nine combinations of profiles. The study explored three speeds of adaptation (slow, medium and fast) and three band widths (measuring in size as 25%, 50% or 75% of the total range of the comfort value of the robot, which could fall between 0.0 and 2.0). The length of the interaction sessions was set to ten minutes.

8.3.3 Simulation Results

As it can be seen in Table 8.4, the most optimal suspension period length was shown to be the one of 20 seconds, which nearly uniformly maximized the comfort of the robot (except for the sparse profile) and had the minimal amount of adaptations across all user profiles.

Table 8.4 Result per different suspension period lengths. Lighter grey highlights the best results per profile, and in darker grey is shown the optimal length.

		Suspend period (sec)		
metric	profile	5	20	35
Comf. %	c	47.54	83.24	71.94
	f	61.12	81.35	74.51
	a	60.13	69.97	59.18
	s	91.56	82.11	73.26
	v	40.55	68.32	65.87
Adapt #	c	8	4	5
	f	6	4	5
	a	7	7	7
	s	1	1	5
	v	8	5	6

Note: Comf % - percentage of total interaction time in which the robot is in the optimal comfort level. *Adapt #* - number of triggered adaptations during the interaction.

The simulation study was run on nine robot profiles and five simulated user profiles, for a total of 45 sessions, which were performed using a 20-second suspension interval, as derived from the previous simulation. The collected data was analyzed for five metrics: the amount of time in which iCub was in an optimal zone of comfort (Comf %), the number of times iCub reached a critical or saturation threshold (Adapt #), and additionally the amounts of time during the interaction that iCub spent in an interactive, idle or suspended state (Idle %, Int % and Sus % respectively).

The results are shown in Table 8.5. Unlike the simulation study for the suspension period, in this study there was not a single dominant "optimal" set of parameters. Depending on the metric, there were different robot profiles which showed the best results.

On general, the slowly-learning robot did not outperform the other personalities in most of the metric categories, except for the % of time spent in an idle state. However, although with this robotic profile of a slowly-learning and highly-tolerant robot there was the least average amount of time spent in the Idle state, this was not due to increased interaction time, but an increased amount of adaptation hits. The robot being slowly learning meant that it hit a threshold limit more often since it adapted only by a small amount each time.

Overall, the best averaged results across profiles were found in the moderate or fast-learning profiles. The moderate learner had the best averaged result for the amount of time the robot was in its optimal comfort zone (81.31% of the interaction, medium step with 50% band width), as well as the second-smallest amount of adaptations, 2.6. The smallest average number of adaptations instead was for the fast-learning robot in the 50% band, 2.4.

The moderate learner also had the two highest % of Interaction times, 55.76% and 55.54% for the 50% and 75% bands respectively. Finally, having a very "fussy" robot with a very narrow threshold band did not produce optimal averaged results even at the fastest learning speed.

All robot profiles were initialized with parameters that made them call out to the user for contact if left alone (or withdraw from interaction if too stimulated) after approximately 30 seconds. After the experiment this changed in various directions as a function of the (simulated) user needs - the *complete* user profile influenced the adaptation exclusively in the saturation attitudes of the robot and slowing down considerably the growth rate, the *void* user profile affected only the decay rate, and the remaining profiles triggered adaptation events depending on their individual frequency and length of interaction.

While at the beginning the *complete* and *void* profiles reached the first adaptation point in all robot profiles after approximately 30 seconds, at the end of the interaction these values had changed to range between 170-260 seconds for the *complete* profiles and 110-140 seconds for the *void* profiles. Apart from being a validation of the adaptation framework, these results also stress the additional benefit of having a two-dimensional adaptation and how it can contribute to the personalization of the robot's behaviour on more than one modality.

Table 8.5 Results for different step sizes for adaptation and different thresholds distance (band width). The best results for each user profile are shown in light grey and the best results over all profiles are highlighted in dark grey

step size		slow			medium			fast		
band width		25%	50%	75%	25%	50%	75%	25%	50%	75%
Comf %	c	72.46	83.25	77.88	73.48	84.64	78.86	70.79	82.13	85.76
	f	71.06	81.96	80.08	71.70	82.34	84.86	69.65	79.81	82.27
	a	22.83	75.49	83.81	16.76	82.57	84.58	20.04	68.37	77.67
	s	28.19	81.83	85.34	39.14	81.44	84.90	51.75	81.14	77.21
	v	57.32	68.34	64.23	15.47	75.56	64.88	66.96	77.99	61.84
avg		50.37	78.17	78.27	43.31	81.31	79.62	55.84	77.89	76.95
Adapt #	c	5	4	4	4	3	3	4	3	2
	f	5	4	3	4	3	2	4	3	2
	a	5	5	7	2	3	6	2	3	6
	s	5	1	3	2	1	3	4	1	4
	v	3	5	8	2	3	7	1	2	7
avg		4.60	3.80	5.00	2.80	2.60	4.20	3.00	2.40	4.20
Idle %	c	3.06	3.18	2.96	3.19	3.29	3.45	3.16	3.33	3.47
	f	3.06	3.10	3.33	3.20	3.17	3.47	2.89	3.62	3.15
	a	33.26	30.82	33.10	61.30	39.60	38.59	45.81	55.99	48.02
	s	11.27	10.14	7.77	18.67	10.04	8.36	20.67	10.14	8.32
	v	44.00	38.20	24.06	21.09	40.63	26.92	41.96	39.49	28.82
avg		18.93	17.09	14.24	21.49	19.35	16.16	22.90	22.51	18.36
Int %	c	55.71	62.07	68.34	61.62	68.45	75.69	62.11	68.69	75.75
	f	55.99	62.69	68.57	61.80	69.17	76.31	62.81	68.43	76.42
	a	63.19	65.66	62.85	36.10	57.56	57.80	51.41	41.46	48.69
	s	48.46	73.45	58.09	47.67	73.61	58.00	40.61	73.60	56.17
	v	9.29	11.39	10.70	3.40	8.90	11.02	7.73	8.86	9.42
avg		46.53	55.05	53.71	42.12	55.54	55.76	44.93	52.21	53.29
Sus %	c	37.95	31.38	25.54	31.81	24.82	17.25	31.39	24.49	17.18
	f	37.66	31.15	24.61	31.62	24.50	16.94	31.24	24.47	17.18
	a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	s	27.97	8.83	23.52	23.33	8.80	23.44	21.56	8.78	22.93
	v	29.03	32.77	43.12	9.82	25.20	42.83	25.09	25.00	42.70
avg		26.52	20.83	23.36	19.32	16.66	20.09	21.86	16.55	20.00

Note: Comf % - percentage of total interaction time in which the robot is in the optimal comfort level. *Adapt #* - number of triggered adaptations during the interaction. *Idle %, Int % and Suspend %* - percentage of total interaction time during which the robot is in one of these three states.

Chapter 9

Caretaker study with iCub

Having established in a previous exploratory study that a game-based interaction scenario would not provide the desired amount of affective expressiveness in participants [69], and having seen the effectiveness of the caretaker scenario in the pilot and validation studies with both MiRo and iCub [66], it was decided to continue in the same direction and expand the existing experimental setup. As before, the interaction scenario placed iCub in the role of a toddler exploring and playing with its toys, while the participants were tasked as the iCub's caretaker.

Having already explored the preference of participants for an adaptive dynamic robotic profile over a static scripted one, the focus was now placed on a different task - evaluating in greater detail the effect of the adaptation modality in two otherwise equally dynamic and responsive behaviour profiles. In that direction, the two different "personalities" of iCub were both equipped with the full cognitive architecture described in the previous sections, with the only difference being that one profile had the adaptation functionality disabled.

9.1 Materials and Methods

9.1.1 Subjects

Twenty-six participants in total took part of the caretaker study. The youngest participant was aged 18 and the eldest 58, with the average age being 32.6 years (SD = 11.98). The gender ratio between the participants was 15:10:1 (M:F:NBGQ[1]).

[1] NBGQ - non-binary/genderqueer

Participants signed an informed consent form approved by the ethical committee of Liguria region (Comitato Etico Regione Liguria-Sezione 1), informing them that their performance could be recorded using cameras and microphones, as well as requesting their consent for the usage of the data for scientific purposes. All but three participants received a compensation of 10 euros and all followed the same experimental procedure.

9.1.2 Experimental setup

In both behaviour profiles iCub's behaviour was guided by its social skills, and in both conditions iCub began the interaction with the optimal values of the growth and decay variables as selected after the simulation study. The only variation in the profiles was that in the *fixed* profile (F) the values remained unchanged throughout the interaction (regardless of how many times the boundaries were hit), whereas in the *adaptive* profile (A) profile instead there was the personalization of the architecture to each participant by modifying the values after each threshold hit.

The interaction between iCub and the participants was again mostly free-form; and while iCub could try during the session to also initiate interaction, or would actively ask for it after hitting a critical or saturation point; for the most part participants had the liberty of guiding the interaction. During the entire interaction iCub could receive and process stimuli from the participants which could be tactile (contact with the skin patches on iCub's arms and torso) and visual (either observing the participant's face at an interacting distance and evaluating the facial expressions, or a new addition to the perception module - detecting toys by recognizing their color and shape).

In the laboratory iCub was positioned in front of a table (as shown in Figure 9.1), holding a box with toys, some of which were out of the box and spread across the table at the beginning of the interaction. The participants were offered a chair in front of the table facing iCub, but they also had the freedom to sit or walk anywhere in the room.

Figure 9.1 The layout of the laboratory setup. Informed consent of participants has been obtained for the use of their photo.

When iCub was in an engaged state and interacting with its caretaker, it maintained mutual gaze and tracked the person's face, or if the person was playing around with some of the toys it would track the toy that was nearest to it. If the person was not showing any toys to iCub, it would occasionally break mutual gaze and try to indicate toys to the person by looking down at a toy and back to the person (gaze-cueing), or by saying the name of the toy. In order to avoid giving participants the impression that iCub could understand them, the verbal utterings (which were the names of the colours iCub could recognize, as well as some encouraging and protesting sounds in order to attract attention or to disengage) were recorded in Macedonian and then processed and low-pass filtered so as to both make them sound more robotic as well as unintelligible to participants.

9.1.3 Secondary task

In addition to the different behaviour profiles, another significant novelty in the full study w.r.t. the previous ones with iCub was the addition of a secondary task for the participants. This was already explored briefly in the validation study with MiRo where the participants had a paper to read while MiRo was wandering in the environment space, but here the implementation of the secondary task was arranged in a different manner.

With the goal of further exploring the potential benefits of having the thresholds in the architecture, the approach devised was to manipulate the behaviour of the participants by introducing a timed secondary task at a certain point in the interaction. While in the pilot study any threshold hits were due to the behaviour of the participants themselves and their way of interacting, there was not a possibility to observe what would the behaviour look like if participants suddenly had a secondary task they needed to fulfill but the robot was still asking for their attention.

For this, a task needed to be considered that would involve a cognitive load on the participants, while at the same time being a task that would neither be too time-consuming (like sudoku), nor too attention-demanding or distracting (like a phone call during which participants would be tasked to write down some information). The solution selected was to present participants with some easier mathematical problems involving the basic arithmetic operations, which meant finding a set of numeric puzzles that would be both simple enough to do in a short time interval, but also appealing and interesting. The final choice for the secondary task was the pollinator puzzle[2].

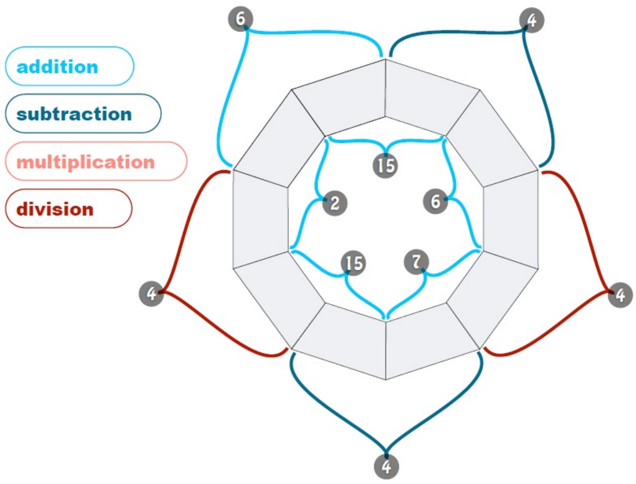


Figure 9.2 Sample pollinator puzzle

The pollinator puzzle is a logic-based, combinatorial number-placement puzzle, where ten empty fields are arranged in a flower-like shape (see Figure 9.2). The digits 0-9 need to be placed in the empty fields, each digit appearing one time only without repetitions, in such a way that each pair of digits gives the specified result for the operation on the petals. Following these rules each puzzle has only one unique possible solution.

[2]https://mathpickle.com/project/pollinator-puzzles/

9.1.4 Updated version of the architecture

The cognitive architecture for iCub was comprised of the same modalities as described in Chapter 8. The only novel addition was the expansion of the perception module - instead of only processing the face and tactile stimuli from the participants, in the latest version it also had a module for color detection that was programmed to track contours of approximately the size of the toys and sporting one of the primary colors (red, blue, or yellow).

9.1.5 Protocol

Participants were evenly distributed in two groups of 13 people, where one group interacted first in the adaptive and then in the fixed dynamic setting, and the other vice versa. According to this division, participant are referred to in the rest of this chapter as belonging to the AF or FA group. A session of interaction in either profile setting lasted 12 minutes, divided in three intervals of 4 minutes, the middle one of which was the interval when participants were asked to work on the secondary task.

Between the two sessions of interaction, as well as at the beginning and end of the interaction participants answered questionnaires (more details on the questionnaires in the following subsection), bringing the total time of commitment for the participants at around 45-50 mins. There were two environments in which the participants were stationed during their visit - the office setting and the laboratory setting.

Upon their arrival to the institute, participants were first brought to the office setting. There they were presented with the consent form and given time to read through it and sign it. Then, while still in the office, participants were informed that during the experiment there would be several moments during which they would be given different forms of questionnaires - related to their personality, relationship to iCub, as well as creativity and problem solving. This was followed by the familiarization phase for the pollinator puzzle. The concept and rules of the puzzle were explained to the participants, and they were presented with the first pollinator puzzle (for obtaining the baseline for their performance). Participants were timed for 4 minutes (the allotted time for the puzzle during the familiarization phase was the same as during the robot interaction). After the time ran out (or if they completed the puzzle in less time - after they were done), participants were taken to the laboratory.

On the way to the laboratory participants were briefed on the experiment. More specifically, they were told that they would have roughly half an hour of free interaction with the robot iCub Reddy, who is equipped with a toddler-like personality.

They were briefed on the modalities they could use to interact with iCub, albeit in an informal way - "iCub can *see* you, it[3] can *feel* you when you pet it, it likes *playing with its toys*, it likes hearing you talk to it even though it does not understand you, it speaks its own language". Participants were purposefully informed that iCub likes hearing them because it was observed in a previous pilot study that people who knew iCub was not capable of speech recognition did not talk at all to the robot during the study.

Additionally participants were reassured that any perceived lack of interest or reciprocity on iCub's part would due to the robot switching its attention to something else (in line with its toddler personality), and not due to them interacting "in a wrong way". This was also deemed necessary to be included in the protocol due to a similar realization from the previous pilot that some people were getting worried when iCub would switch its attention and they thought they "did something wrong".

9.1.6 Data Analysis

The data collected during the study consisted of four main sources - the data collected from the questionnaires filled by the users; the evaluations from the filled pollinator puzzles; the video and audio recordings from the external camera; and the data collected by the robot during the interaction phases from the tactile sensors, internal camera and state machine output.

Questionnaires

Participants responded to questionnaires at three points during the interaction study - the first set of questionnaires was done after they entered the lab with the robot but before beginning with the interaction, the second set was halfway through the interaction (which in reality was the moment after which the robot switched personalities, unbeknownst to the participants), and the last set was at the end of the interaction.[4]

[3] the participants who spoke only Italian were briefed in Italian instead of English. Due to Italian not having a gender-neutral pronoun, iCub was referred to with "him" in Italian (lui)

[4] these 3 points in the interaction are labeled as PRE, BETWEEN and POST in the Results

All three sets of questionnaires collected the IOS rating of closeness between themselves and the robot [67], as well as the Godspeed questionnaires on animacy and likeability [68]. Additionally, in the second and third set of questionnaires there was also a qualitative question asking participants to describe the interaction using three adjectives, as well as a set of questions related to how they perceived the interaction with the robot. Finally, in the third set of questionnaires there were two descriptive questions related to the different sessions, and the TIPI questionnaire [70].

Pollinator puzzle

Participants did in total three rounds of the pollinator puzzle - one as a baseline before starting with the robot, one during the first interaction session, and one during the second interaction session. There were two evaluation metrics for the puzzles - the % of filled fields (out of the 10 empty fields) and the % of accurately filled fields.

A combination metric was then designed in order to obtain a single evaluation value, where if X was the percentage of completeness and Y the percentage of accuracy, the final metric Z was obtained as $Z = 0.4*X + 0.6*Y$. The combination metric was designed with the goal of taking into account as factors both the accuracy and the completeness of the puzzle, but give a higher reward for the accuracy.

Internal data from iCub

The data recorded from the iCub itself comprised of the tactile and visual data, as well as all of the values of the architecture - the fluctuations of the comfort value and the changes to the decay and growth rates. The data from the architecture was annotated for each frame received by the robot with a timestamp and the state (of the state machine) iCub was in.

An important note regarding the frame annotations in the architecture has to be inserted here. During the experiments, due to the specifics of the iCub platform, the framerate was not synchronized with the timestamp. This meant depending on the state of the robot and the actions it was doing, the framerate of the action-perception loop could be 1-2 frames per second (when iCub was performing a movement) or up to 10-12 frames per second (when iCub was just observing the scene and not moving).

9.2 Results

The most general question this thesis sought to answer was whether adaptation is a necessary functionality for human-robot interaction? More precisely, as seen in Chapter 2, adaptation is a very valued and crucial ability for robots engaged in assistive HRI or cooperating with humans in physical HRI, but what about free-form social HRI? If there is not a clear task for the human to perform with the robot, would the adaptive functionality bring anything additional to the interaction?

To address this, three related questions were formulated:

- How much would the adaptive architecture change for each participant during the interaction, and how would people react to such personalization (addressed in subsection 9.2.1)?
- What would be the subjective evaluation of the participants for the interaction, and would it depend on the adaptivity of the robot? (addressed in subsection 9.2.2)?
- Would participants change their way of interaction across modalities or robot adaptivity level? (addressed in subsection 9.2.3)?

The cognitive framework developed for iCub was a continuously-changing one, learning by way of modifying its social variables and adapting to the person's frequency and intensity of interaction. This means that interacting with robot provoked changes in the internal states of iCub and its comfort level. Every time a threshold of the robot was hit, iCub adapted the appropriate comfort variable and its behaviour changed accordingly.

9.2.1 Architecture dynamics

If the critical threshold was hit, signifying lack of stable interaction with the person, iCub modified its decay rate and as a result could remain in an idle state for longer periods of time before it would need again to interact with the person. On the other hand, hitting the saturation threshold meant iCub was engaged with a person who was more intense in the way it behaved and interacted with iCub (using multiple modalities and interacting for a long stable period of time), so iCub modified its growth rate which enabled it to stay interacting for longer time.

Figures 9.3 and 9.4 show the architecture dynamics for two different participants in different sessions of interaction, where the variations in iCub's comfort value are shown on the upper graphs, and the received stimuli from the participant on the lower graph. Critical hits where participants responded the robot's call for engagement are shown in yellow stars, and ignored critical hits are shown in red dots. Figure 9.3 illustrates the behaviour of the architecture for a participant that had its first interaction with the robot in the Fixed session. Here the critical threshold was hit first two times during the participant was performing the secondary task, and the participant ignored the robot's attempts to engage; and additional three times in the last phase of the session after the timer for the secondary task ran out, but in these three instances the participant was no longer distracted and answered iCub's calls.

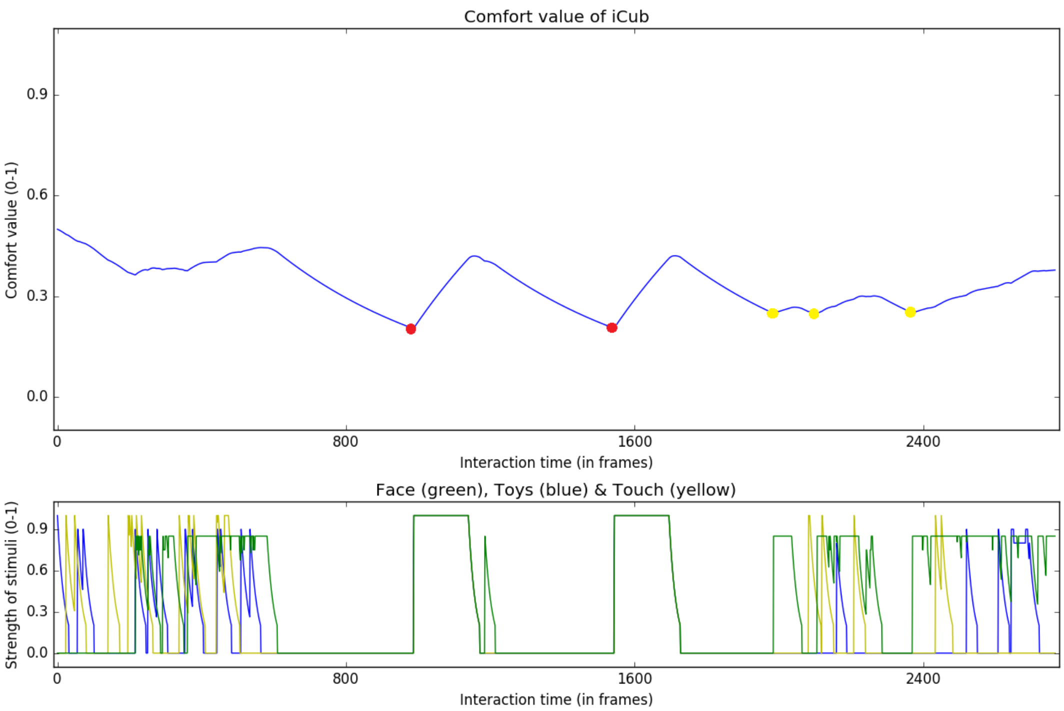


Figure 9.3 FA participant interacting in F session, 5 points of hitting critical threshold.

There are two reasons why the hits of the three responded calls are so close in succession one after the other. The first reason is that iCub was in its Fixed personality, so it did not adapt to the person's lack of interaction during the secondary task. This explains why the first three (out of the five in total) threshold hits happened at an identical regular period. The last two threshold hits instead happen so close to each other since the participant responded unstably to iCub's calls, in a manner of giving brief stimuli and then turning their attention to something else, which did not provide iCub with enough stability to be comforted. Instead in the final instance when the critical threshold is hit the participant's response was a more stable one, interacting on several modalities, so as a result iCub's comfort resumed growing.

Figure 9.4 instead shows the interaction between iCub and another participant interacting with it again for the first time, but in the Adaptive session. This participant was a less interactive one in comparison to the participant in Figure 9.3, but even so the total number of threshold hits was three, out of which only one was not answered.

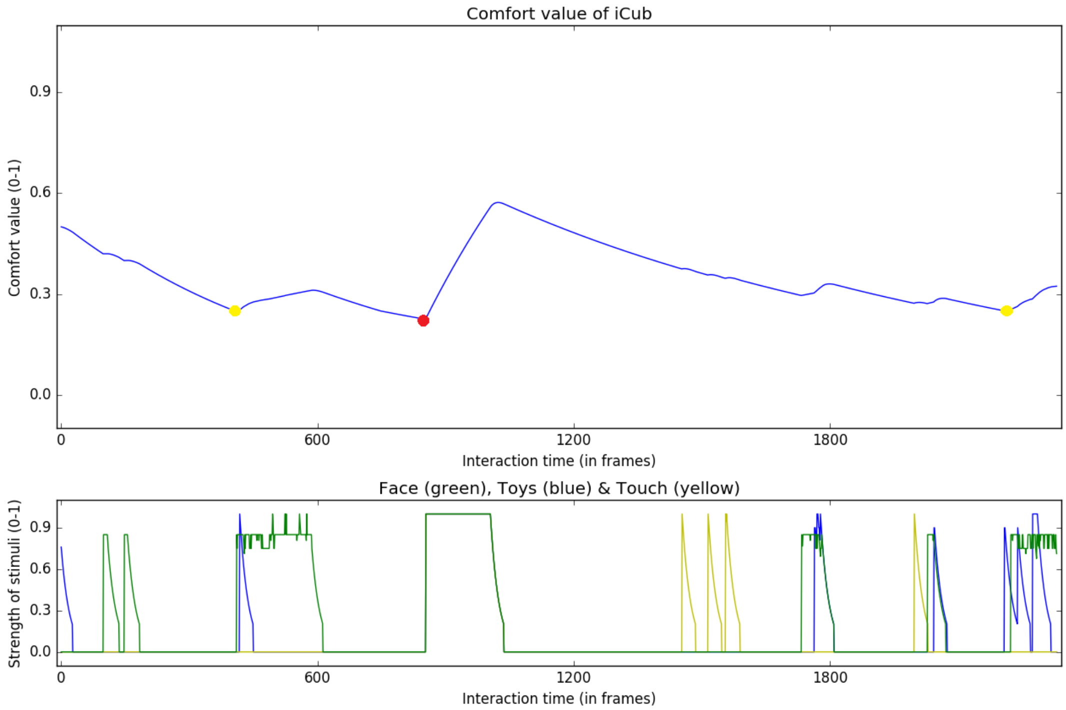


Figure 9.4 AF participant interacting in A session, 3 points of hitting critical threshold.

This demonstrates the effectiveness of the adaptivity of the architecture, which can be observed also in the decay slope during the secondary task. After two adaptations of the architecture the decay slope is a much slower one, allowing for iCub not to hit another critical point until very near the end of the interaction.

Independently of the order of the interaction sessions (AF or FA) or the phase of interaction, overall during the experiment on average people hit a threshold 1.42 times during one session, 1.79 times on average during the first session and 1.04 during the second one.

(a) Participant filling the pollinator puzzle.

(b) Participant interacting with iCub.

Figure 9.5 Participants in interaction with iCub. Informed consent of participants has been obtained for the use of their photo.

The absolute number of threshold hits summed for all participants was 68, out of which only 2 (3%) were saturation hits, and all remaining ones (97%) were critical hits. In these calculations the first two participants were excluded due to technical reasons rendering their number of threshold hits unusable.

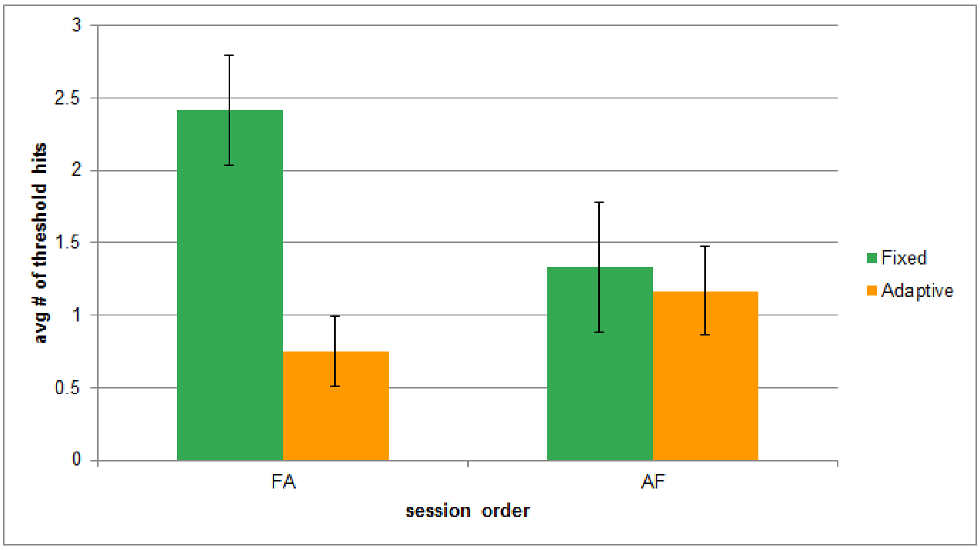


Figure 9.6 Comparison of average amount of threshold hits pers session and order group

Figure 9.6 illustrates the effect of the order of the sessions on people's first interaction with iCub. The main hypothesis for the data of the architecture dynamics was that the participants in the FA group would have noticeably more threshold hits in the Fixed session than in the Adaptive, since that would be both the first session of interaction with the robot, and the session where the architecture does not adapt.

On the other hand, for the participants in the AF group the hypothesis was that the ratio of total threshold hits in the Fixed and Adaptive sessions would be roughly similar, since the participants' first session of interaction with the robot would be the one where iCub is adapting its comfort variables to the participants' interaction profiles.

This was additionally confirmed after running a mixed-model 2-factor ANOVA, with SESSION (levels: adaptive and fixed) and ORDER (levels: AF,FA; signifying the groups of participants) as the within and between factors respectively. A difference has been considered significant for $p < 0.05$. A significant difference was found both over the SESSIONS ($F(1,22) = 7.87$, $p = 0.01$) and for the interaction between the two sessions for the FA group ($F(1,22) = 5.27$, $p = 0.03$), confirmed with a Bonferroni test.

A deeper analysis into the individual modes of behaviour are presented in Figures 9.7 and 9.8. This analysis consisted of measuring the changes in the architecture for each participant, comparing for the two different orders of sessions how many times the thresholds of the architecture were hit, as well as how many times people responded to the calls for interaction in criticial.

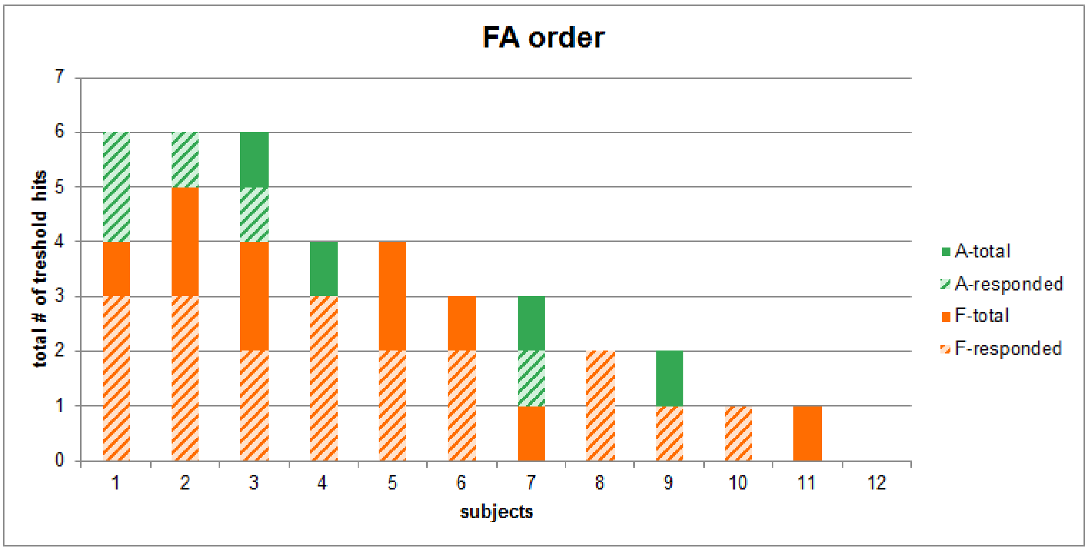


Figure 9.7 Number of occurred and responded threshold hits per session for FA participants

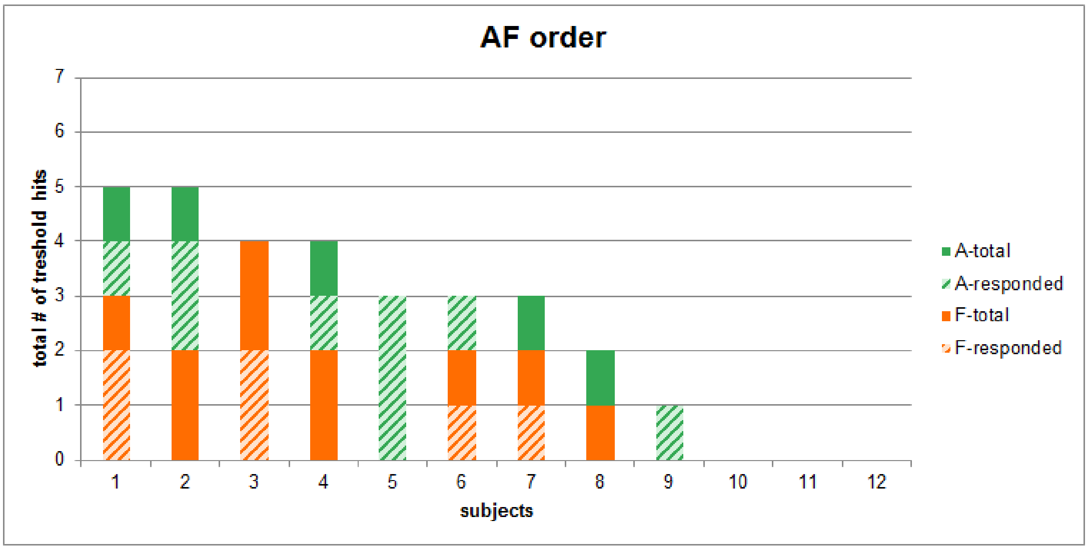


Figure 9.8 Number of occurred and responded threshold hits per session for AF participants

While a large variety in the number of threshold hits (ranging from 0 to 6) can be seen in both conditions and across both session orders, it can be noticed that the majority of people showed a tendency to respond to the robot's calls. There were some participants that never hit a critical or saturation threshold (indicated at the end of both figures), however there were only two participants which did not respond to the robot's calls for engagement, suggesting that in addition to iCub being adaptive in some cases, participants adapted always to the robot.

The analysis of the architecture dynamics highlighted the difference in which session was the starting session for participants as shown in 9.6: FA participants had a more challenging first session since it was both the first session of interaction with the robot, and the session where the architecture did not adapt to their interaction particularities. On the other hand, the AF participants' first session of interaction with the robot was the one where iCub was adapting its comfort variables to their interaction profiles, which contributed to them having less threshold hits in their Fixed session when compared to their FA counterparts.

9.2.2 Subjective evaluation

The subjective evaluation included exploring the explicitly-expressed preference of participants for interacting with iCub in the A or F session, their ability to differentiate between the two different profiles of the robot, evaluating whether their IOS/GS changed as a function of the time spent with the robot or the adaptivity of the robot, as well as whether the rating was dependent on the amount of changes the adaptation went through.

This study explored the comparison between two similarly dynamic and responsive architectures, where the only difference between them was the inclusion of the adaptive component. A part of the subjective evaluation was investigating the effect on the adaptivity level of iCub to the participants‘ self-rated feelings of closeness with the robot (the IOS rating) and the participants‘ evaluation of the robot’s animacy and likeability (the Godspeed ratings). Figures 9.9 and 9.10 show the ratio of the participants’ IOS and Godspeed evaluations before interacting, between the two interaction sessions, and at the end of interaction.

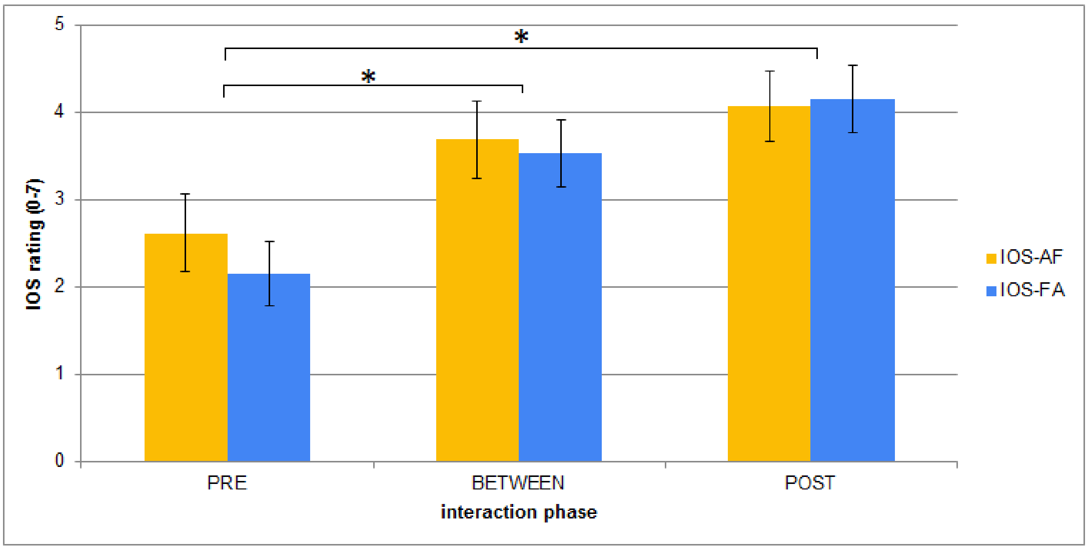


Figure 9.9 IOS ratings distributions across order and phases

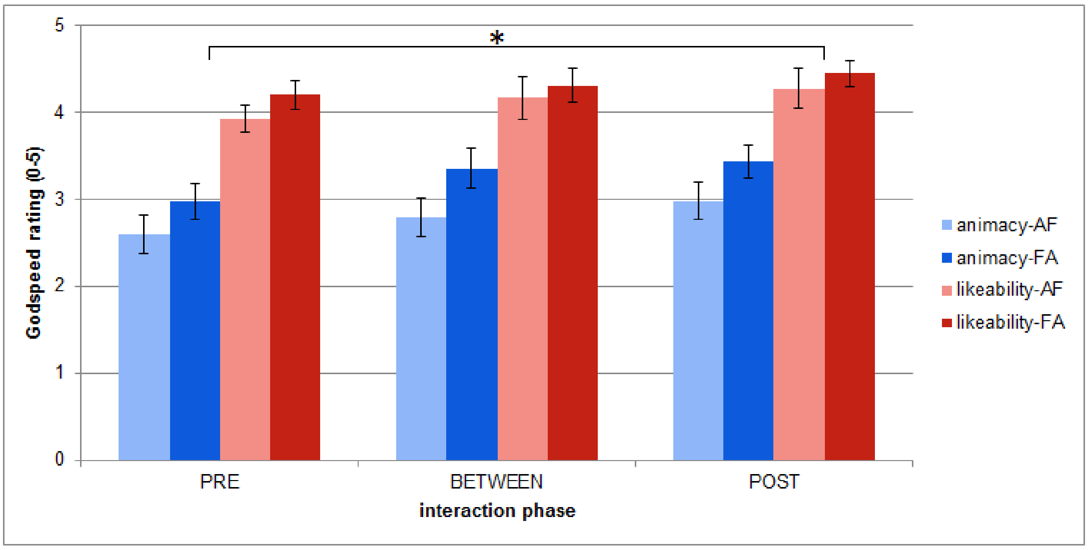


Figure 9.10 Godspeed ratings distributions across order and phases

Statistical analysis was performed on all IOS and Godspeed ratings. To better assess the noted difference between the ratings, a mixed-model 2-factor ANOVA was run, with PHASE (levels: pre, between and post; signifying the rating pre-experiment,between-sessions and post-experiment) and ORDER (levels: AF,FA; signifying the groups of participants) as the within and between factors respectively. The ANOVA results follow below:

- The IOS rating of closeness increased significantly over the PHASE ($F(2,48) = 19.88$, $p < 0.001$), while the factor ORDER ($F(1,24) = 0.128$, $p = 0.723$) was not significant, nor the interaction ($F(2,48) = 0.46$, $p = 0.636$); running a Bonferroni test found significant difference between 1st and 2nd phase and 1st and 3rd phase, but no statistically significant increase between 2nd and 3rd phase;
- The Godspeed rating of Animacy increased significantly over the PHASE ($F(2,48) = 5.65$, $p = 0.006$), while the factor ORDER ($F(1,24) = 0.798$, $p = 0.38$) was not significant, nor the interaction ($F(2,48) = 0.03$, $p = 0.967$); running a Bonferroni test found significant difference only between 1st and 3rd phase;
- The Godspeed rating of Likeability increased significantly over the PHASE ($F(2,48) = 6.28$, $p = 0.003$), while the factor ORDER ($F(1,24) = 2.642$, $p = 0.117$) was not significant, nor the interaction ($F(2,48) = 0.33$, $p = 0.72$); running a Bonferroni test found significant difference only between the 1st and 3rd phase.

From this analysis what was observed was that participants' rating of their perceived closeness with iCub changed significantly as a result of them spending more time in interaction with it, and not as a function of the adaptivity of the robot, which could signify that on their part, participants did not perceive any structural difference between the two sessions. This can depend on the fact that the two sessions were not particularly different to the participants who did not exploit the adaptivity of iCub excessively. Alternately, notwithstanding the differences experienced by the participants, both sessions could have been equally "likable" to them. To further explore this, a correlation was done between their IOS/GS ratings and how much the architecture changed for each participant.

Figures 9.11, 9.12, and 9.13 depict for all participants from both AF and FA groups the relation between the amount of changes the architecture underwent in the adaptive phase, and the difference between the rating in question (Godspeed-Animacy,Godspeed-Likeability or IOS) given at the end of the adaptive and at the end of the fixed phase.

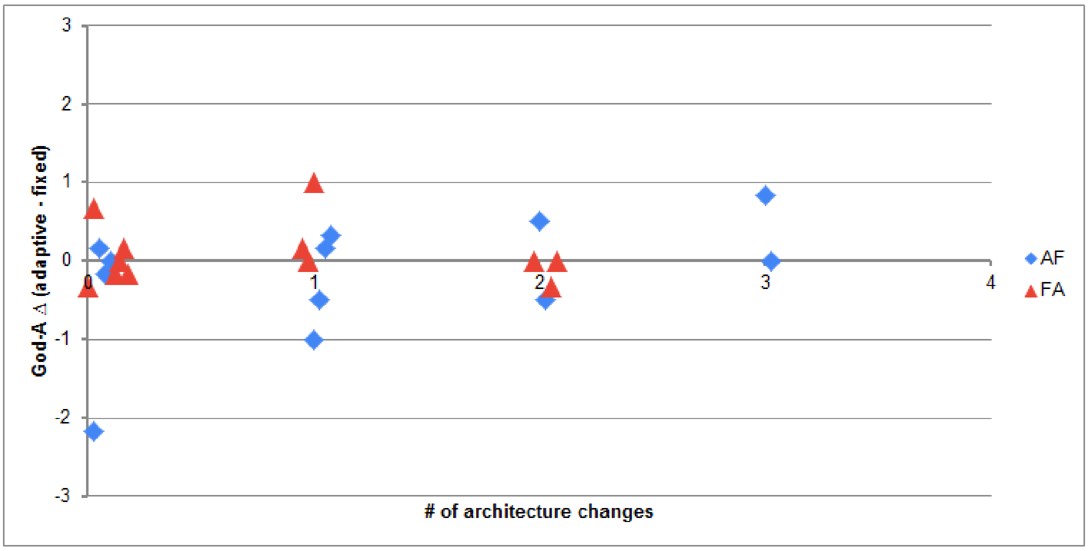


Figure 9.11 Changes in the Godspeed-Animacy rating over changes in architecture

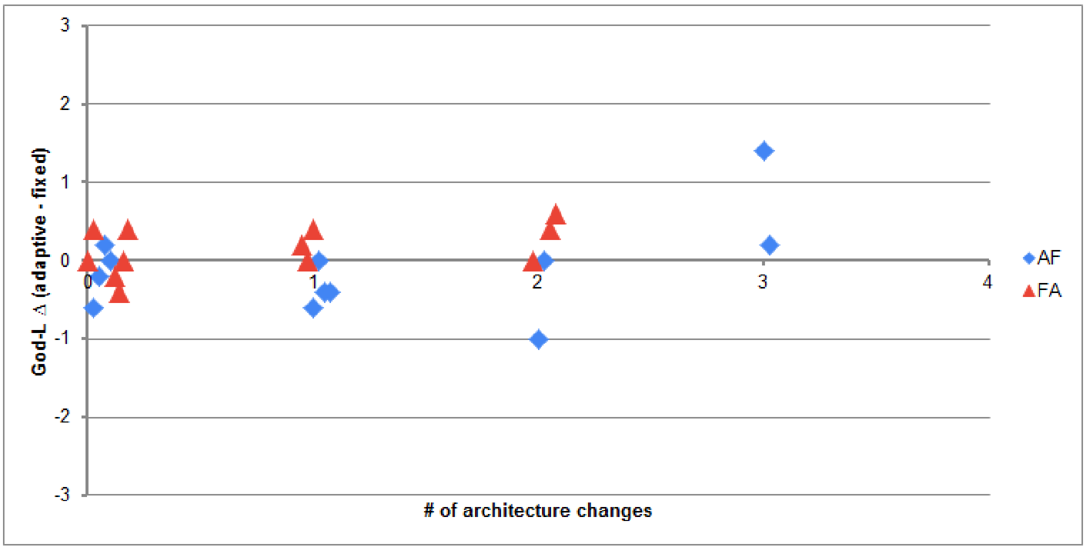


Figure 9.12 Changes in the Godspeed-Likeability rating over changes in architecture

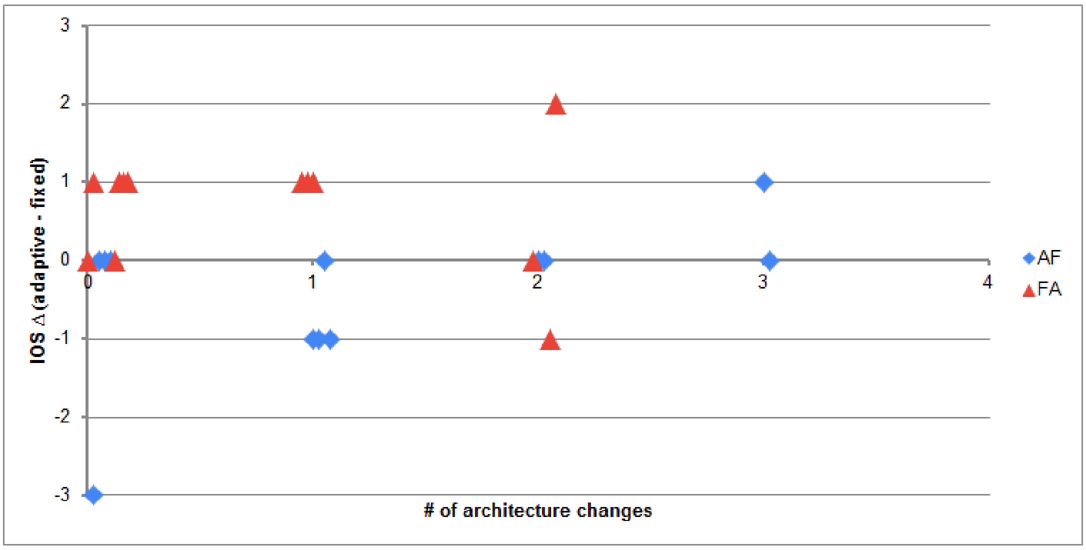


Figure 9.13 Changes in the IOS rating over changes in architecture

The values for delta in the Godspeed answers on general converged towards 0, indicating a tendency for people to be more constant in their Godspeed ratings regardless of how much the architecture changed. Additionally, when the delta values shifted above or below zero there was an overall pattern with the AF ratings having a delta below and the FA ratings above zero, which is consistent with the previous results - a positive delta indicates a higher rating at the end of the Adaptive session when compared to the Fixed, which was true for most of the FA participants, and the inverse was true for the AF participants.

While people seemed more consistent in their Godspeed ratings across all sessions, their IOS ratings tended to be more variable, with bigger differences (usually of 1, but also reaching 2 and 3) between the different sessions. However also here the same conclusion was evident - the rating of IOS closeness increased for most people as a consequence of the prolonged time spent with the robot, and not as a result of the adaptability. It would seem that although there were differences in the two sessions, people did not change their rating.

This was confirmed also by the free questions they had to answer after the second session:

- Which session did you prefer and why?

- What was the difference (if any) you noticed between the two sessions of interaction?

77% of participants answered that they preferred the second session because they felt iCub was more animated or interactive towards them, 19% replied that they enjoyed both sessions equally and only one participant said he did not enjoy any of the two. Additionally, 27 % answered that they did not perceive any difference between the sessions, 46% instead had perceived the robot being more interactive in the second session (however from those 46% half were FA and half AF, signifying random chance), and 23% said they learned how to interact better in the second session.

9.2.3 Behavioural evaluation

After analyzing the subjective evaluation, the final step was processing the behavioural results, which measured how the interaction between iCub and the participants actually unfolded. The behavioural evaluation of the participants analyzed if people actually interacted differently with the robot across different phases and different modalities. This was considered again as a function of the time spent with the robot or the session order. An additional analysis was how the participants' behaviour changed during the dual task.

This section covers the results from the different modalities of interaction - i.e. how people interacted with iCub on the three modalities of visual-face, visual-objects and tactile; the distribution of iCub's states during the interaction and all three phases for each session, and finally how the secondary task impacted the interaction.

Graphs 9.14 and 9.15 provide the analysis of the distribution of the states the robot was in during the interaction. For clarity, the transitional states were not taken into account as they only provided a small fraction of the frame count, instead only the states of idle, interact and suspend were looked into.

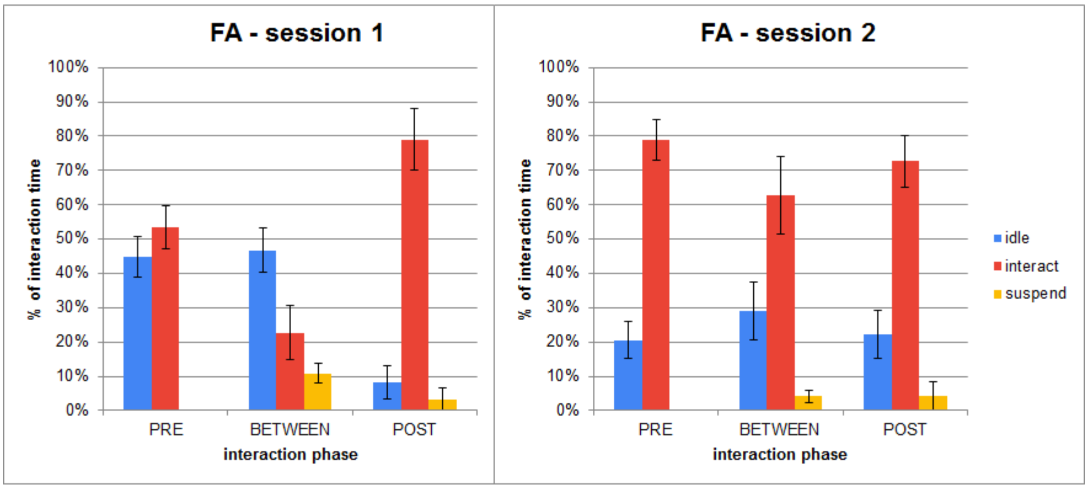


Figure 9.14 Distribution of the states iCub was in across phases for FA participants

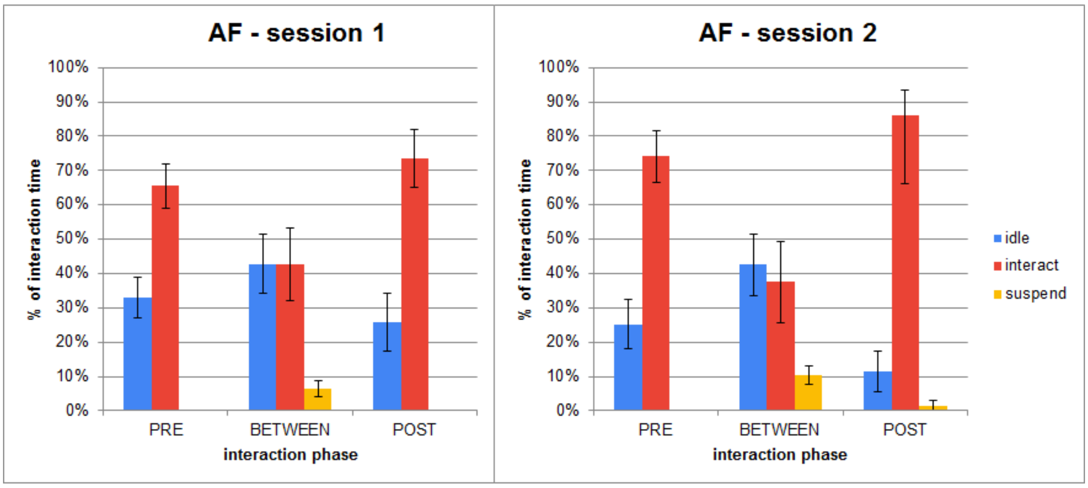


Figure 9.15 Distribution of the states iCub was in across phases for AF participants

From these results several conclusions can be obtained:

- Participants that interacted for the first time with iCub in the Fixed condition spent less time in interaction in the very first phase of the first session when compared to the participants who had their first interaction in the Adaptive session. This effect is not present in the second session as well due to the loss of the novelty effect, since both groups of people had already interacted with the robot;

- In the third phase (the interaction after the secondary task) there seems to be compensation for having previously ignored the robot, in the form of increased interaction. This can be seen especially in the Fixed session (regardless of order group), potentially because the robot asked for more attention without adapting to the users ignoring it;

- The distribution pattern of the states in the last phase of the first session carry over to the first phase of the second session, indicating a training, or learning how to interact. This effect was particularly not obvious and expected for the participants of the AF group, since in their second session of interaction the architecture values of the robot were reset, so the AF participants essentially interacted first with a robot that adapted to them, and then with one that lost its adapted specifics;

- The interactive behavior during the dual task changes significantly for the FA participants between the two sessions. Having ignored the robot during the secondary task in the first session (F) where it did not adapt to them, they seem to overcompensate in the secondary task in the second session (A) and there is a huge jump in interactivity. This may be a combined effect of both overcompensation combined with the added adaptivity of the robot;

- The interactive behavior during the dual task stays nearly identical for the AF participants between the two sessions. Having the robot adaptive in the first session (A) it adjusted to them and it spends significantly more time in interaction than in the first session of FA participants, however due to them not perceiving the robot as particularly annoying or demanding for attention in their first session, there is not the compensation in the second session.

To evaluate the difference between the interaction patterns in the different phases, a 3-factor mixed-model ANOVA was run, with SESSION (levels: adaptive or fixed) and PHASE (levels: 1, 2 and 3; signifying the 1st, 2nd and 3rd phase of an interaction session) as the two within factors, and ORDER (levels: AF, FA) as the between factor. The percentage of time the robot spent in the interaction phase varied significantly both over the SESSION ($F(1,22) = 6.08$, $p = 0.02$) and PHASE ($F(2,44) = 20.14$, $p < 0.001$), while the factor ORDER and the INTERACTION were not significant. The Bonferroni test showed significant differences between the 1st and 2nd, and the 2nd and 3rd phases, but no significant difference between 1st and 3rd phase.

Since there was a noticeable difference in how people behaved with the robot while they were tasked with the pollinator puzzle, the next analysis focused on looking into the score of the pollinator puzzle.

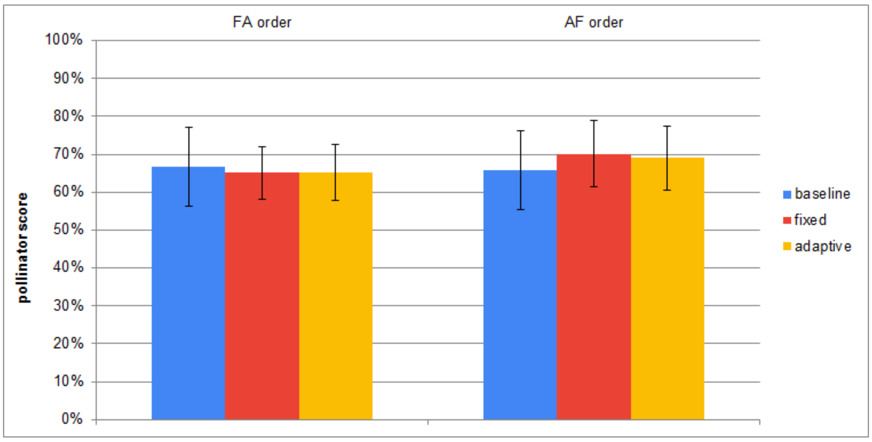


Figure 9.16 Average pollinator scores for the three times participants did the puzzle

From Figure 9.16 showing the averaged pollinator scores for both groups (AF and FA) over the three times they filled the puzzle (baseline, first session, second session) it can be noticed that there is not a significant difference over the average score, signifying that even on the phases when the robot was non adaptive, on average participants could complete the task to some extent.

Figure 9.17 instead correlated the pollinator score with the amount of time spent in interaction during the secondary task. what can be seen here is that the majority of participants in Fixed spend a limited time in interaction during the secondary task, however their score is not related to the interaction - some do well, some less. on the other hands participants in adaptive are spread out more evenly across the scale, with some reaching even 100% interaction, so there seems to be an effect for the robot being adaptive in how the interaction unfolded.

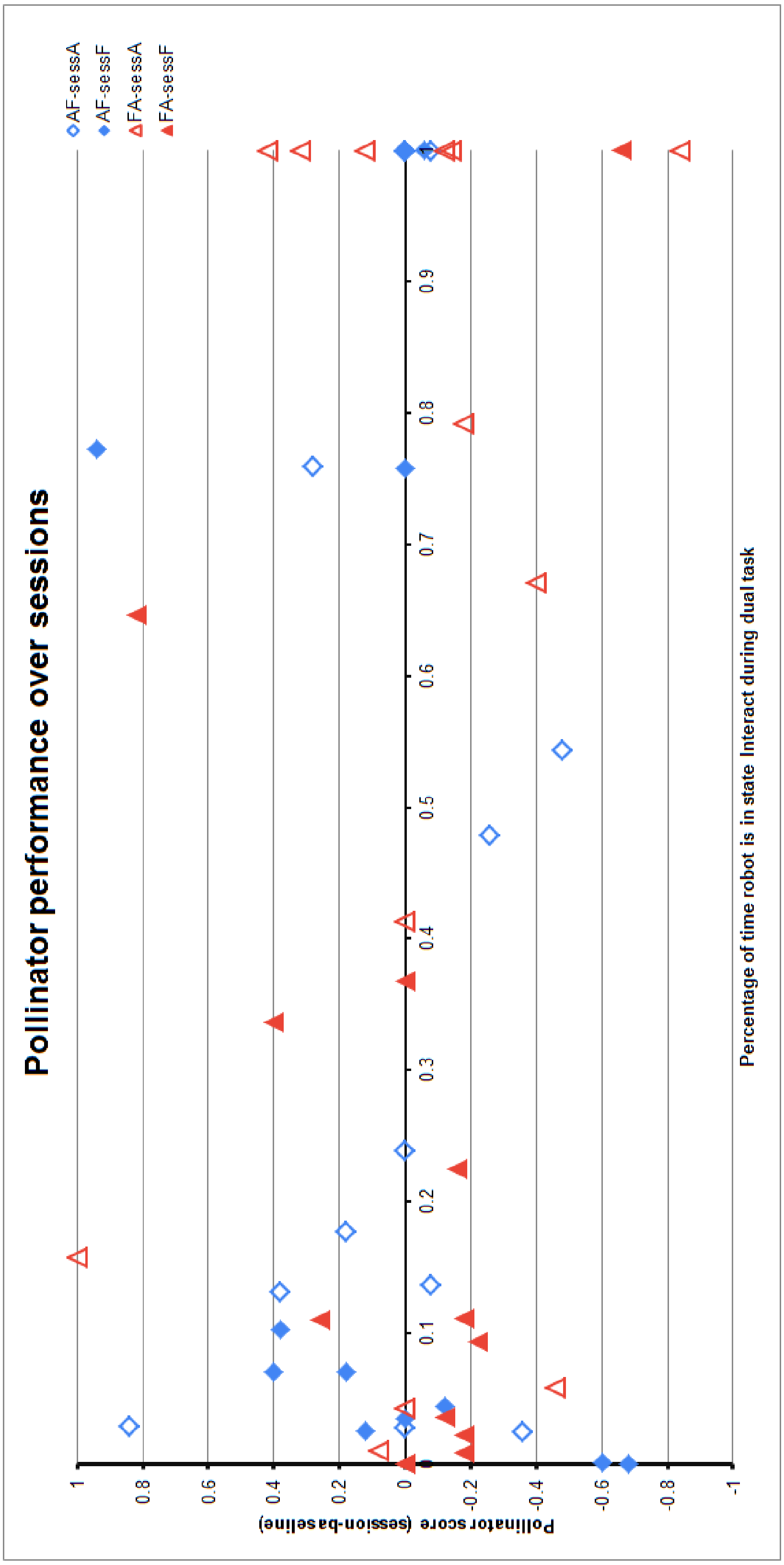


Figure 9.17 Correlation between the pollinator scores over the sessions and the percentage of time iCub was in interactive state

With this analysis it was established that the behaviour of people during the secondary task (interacting with the robot or ignoring it in order to focus on the task) did not strongly impact their pollinator score. In other words, how good people were at the task was something subjective for each person themselves, and did not depend on whether they interacted a lot with the robot or ignored it. The last step of the analysis looked into the modalities participants used when interacting with iCub.

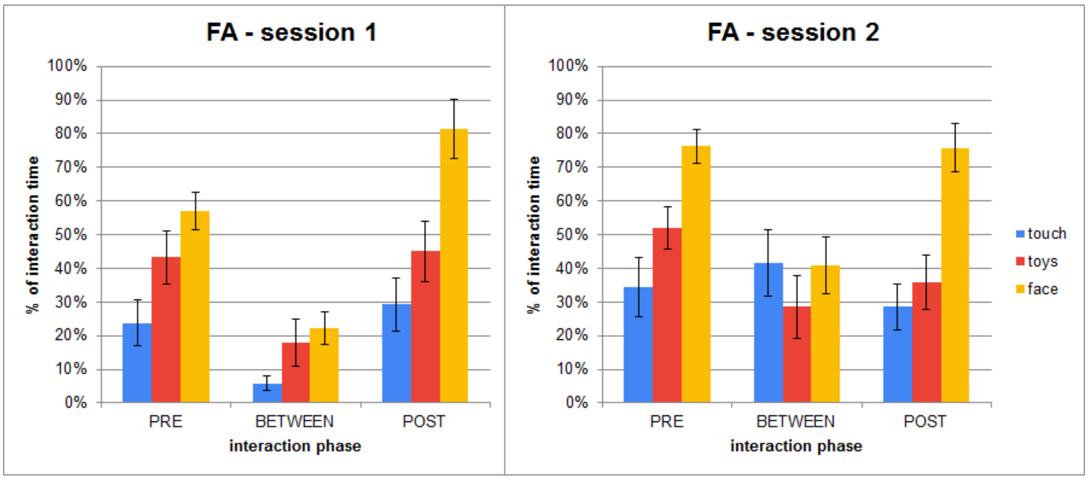


Figure 9.18 Distribution of the perceived stimuli in different modalities during the interaction, shown across phases for FA participants

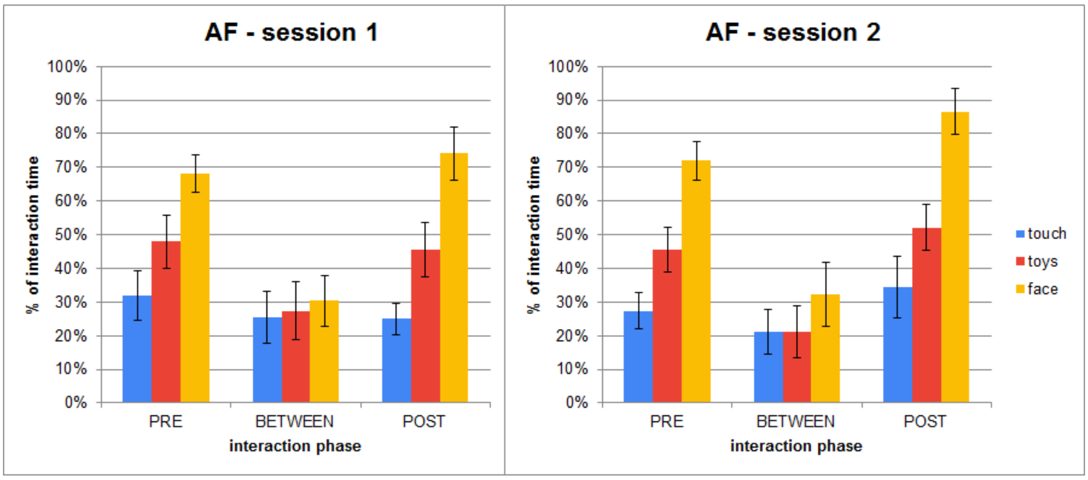


Figure 9.19 Distribution of the perceived stimuli in different modalities during the interaction, shown across phases for AF participants

What can be observed from the modalities graphs shown in Figures 9.19 and 9.18 is that during the secondary task there is understandably the biggest drop in face as input, but compensation with touch, which stays similar and does not have such a significant drop. The patterns in the last phase of session 1 tend to be nearly identical to the first phase of session 2, the reason behind which can be that the mode of interaction carries over between the two sessions. a similar pattern can be also observed in the analysis of the states distribution.

To evaluate the difference between the interaction patterns in the different phases, three 3-factor mixed-model ANOVA were run, with SESSION (levels: adaptive or fixed) and PHASE (levels: 1, 2 and 3; signifying the 1st, 2nd and 3rd phase of an interaction session) as the two within factors, and ORDER (levels: AF, FA) as the between factor. A difference has been considered significant for $p < 0.05$.

- Touch: The percentage of time the robot spent in the interaction phase varied significantly only over the interaction (session*phase*order) ($F(2,44) = 6.22$, $p = 0.004$), while SESSION ($F(1,22) = 1.92$, $p = 0.18$) and PHASE ($F(2,44) = 0.69$, $p = 0.5$), were not significant, neither was ORDER. The Bonferroni test showed significant differences for the FA participants in phase 2 between session 1 and 2 (meaning between the two sessions for the FA group during the secondary task);
- Objects: The percentage of time the robot spent in the interaction phase varied significantly PHASE ($F(2,44) = 24.46$, $p < 0.001$), while both the SESSION ($F(1,22) = 0.08$, $p = 0.78$) and the interaction ($F(2,44) = 0.52$, $p = 0.93$) were not significant, and neither was ORDER. The Bonferroni test for phase showed difference between the 1st and 2nd phase, and the 2nd and 3rd phase;
- Face: The percentage of time the robot spent in the interaction phase varied significantly both over the SESSION ($F(1,22) = 5.3$, $p = 0.03$) and PHASE ($F(2,44) = 46.28$, $p < 0.001$), while the interaction ($F(2,44) = 0.28$, $p = 0.76$) was not significant, and neither was ORDER. The Bonferroni test for phase showed difference between the 1st and 2nd phase, and the 2nd and 3rd phase.

Even though the subjective evaluation of the participants did not express a correlation between the adaptiveness of the robot with its likeability, nor an awareness of the participants for there existing a difference in the profiles at all, there were implicit results pointing to the opposite. The manner of interacting with the robot, both in terms of frequency and of used modalities, changed noticeably, particularly when participants were tasked with the secondary task. More precisely, when the robot was in its adaptive profile, even if the people were given another task to complete, they still managed to interact with the robot in parallel.

Part IV

Discussion

Chapter 10

Discussion

Different individuals have different inclinations to interact with others, which can be seen also in their approach to interaction with robots. At the same time, different tasks might require different level of human intervention (or robot request for help). Creating a unique robot behaviour (or personality) able to fit with task constraints and at the same time with individual desires is an impossible challenge. Endowing the robot with a possibility to adapt to its partners' preferences is therefore important to grant a certain degree of compliance with individual inclinations.

This thesis wanted to tackle this issue by developing a personalized adaptive robot architecture. This architecture enabled the robot to adjust its behaviour to suit different interaction profiles, using its internal motivation which guided the robot to engage and disengage from interaction accordingly, while also taking in account the behaviour of the person interacting with it.

The thesis encompassed several validation studies with different robotic platforms aimed at testing the cognitive architecture both in clearly predefined user profiles, and in-the-wild free-form interaction with naive participants. An additional curiousity that was investigated was how initializing the architecture with different values for its internal variables at the beginning (i.e. endowing the robot with different personalities) would affect the flow of the interaction and the extent of the adaptation.

The findings from the validation studies showed a preference in naive users for an adaptive over static, pre-scripted robot behaviour and in fact they exploited the robot's increased responsiveness. In the simulation study additionally it was observed that there was not one universally optimal set of parameters, i.e. robot profile that exceeded in performance across all evaluation metrics and all user profiles, and that even in case of less-than-optimal selection of initial parameters, the adaptive process was able to progressively tune the interaction to the needs of the individual.

The final study of the thesis turned instead towards investigating and comparing how the internal dynamics of the robot would be perceived by people in a condition when the robot does not personalize its interaction, and in a condition where it is adaptive.

The caretaker study brought to light two different and opposing, but valuable findings. Participants were not consciously, or at least on an affective level, aware of experiencing two different robotic profiles. When asked explicitly for a difference between the two sessions of interactions, the majority of subjects did not report one, or they reported their feeling that the second session had the more interactive robot profile. This however was strongly influenced by nearly all participants having reported they preferred the second session of interaction, signifying that it was not the profile of the robot that influenced their feeling, but rather the gained knowledge on how to better interact with it and the prolonged time spent in interaction. However their manner of interacting with the robot showed noticeable changes depending on the phase and session they were in, as well as depending on the robot behaviour during the secondary task.

This has several implications, especially when designing different HRI scenarios. While this study addressed free-form interaction and how an adaptive robot would personalize to its caretaker; if imagining to port this architecture to an HRI study when the robot would need to learn by processing informations from visual or tactile stimuli, the implications fom this study's findings show that the robot would be still capable to receive and process the necessary information from the person, even if the person would not be highly responsive or present at all times.

Additionally, the element of adaptability and personalization in the cognitive framework was not shown to bring any uncertainty and unpredictability. While on a conscious level they remained unaware, the adaptability of the robot still impacted the efficacy of the subjects' interaction. Moreover, the presence of the critical and saturation thresholds promise an another level of richness that could be added to the interaction.

A robot that has a critical boundary can actively try to initiate interaction with the person, which could be useful not only in scenarios where a person might lose track of the robot or get distracted, but also in scenarios where a person might be very interested to interact with the robot but their shyness would prevent them from attempting to engage the robot first. Complementary to that, a saturation boundary is not only useful for evaluating how much a person is interested in restarting an interrupted interaction, but can be also a crucial element in multi-person HRI scenarios, or if the robot needs to also accomplish some other task in addition to itneracting with the people. The saturation threshold in particular was something that did not get used in its full potential in these studies, which is probably due to the abovementioned effects not carrying over to an 1-on-1 HRI scenario.

The main limitation of the current studies is the generality of the results. Even though the interaction was designed to be as most freeform as possible, it was still a very simplified scenario of interaction. This is in part also due to the limitations of current state-of-the-art: cognitive systems are not yet at the level of replicating human intelligence, and the aspect where this was felt the most was in the absence of a verbal interaction. Even though having a caretaker scenario of HRI might have positively impacted subjects' likeability ratings of the robot, it was still limiting in terms of the richness of interaction desired by implementing an adaptive cognitive architecture.

However, adaptivity is a very important building block of cognitive interaction, and in that way endowing with it even a small robot like MiRo in a simplistic interaction, or a humanoid robot like iCub but in a scenario with behaviour of lower cognitive intelligence is still already a first step towards approaching personalized and cognitive human-robot interaction. The hope and future direction of this research is that by investigating other cognitive functionalities to implement and other scenarios of interaction, the adaptive framework will reach the point of a more individualized, long-term, generalized interaction between humans and robots.

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