Universidade Estadual de Campinas
Instituto de Computação

Letícia Mara Berto

Exploring Cognitive Functions in Robotics

Explorando Funções Cognitivas em Robótica

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Supervisor/Orientadora: Profa. Dra. Esther Luna Colombini

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Resumo

O avanço da inteligência artificial trouxe muitos benefícios à robótica. Hoje, é possível desenvolver robôs que não apenas executam o que foram pré-programados para fazer, mas que aprendem de acordo com a interação com o ambiente e outros agentes. Para isso, os robôs devem ter funções cognitivas, como memória, tomada de decisão, aprendizado, atenção, planejamento e outras suportadas em sua estrutura. Até o momento, não existem maneiras padrões na literatura de avaliar arquiteturas cognitivas. Nesse contexto, neste trabalho, estudamos funções cognitivas com o objetivo de identificar quais componentes são necessários para validar um projeto que implementa uma arquitetura cognitiva. Estudamos o desenvolvimento de crianças de 0 a 2 anos e a teoria construtivista de Piaget acerca da construção do conhecimento e desenvolvimento da inteligência. A partir dos estudos realizados, conseguimos classificar os estudos da area de Developmental Robotics nos estágios definidos por Piaget. Com isso, construimos um conjunto de experimentos incrementais levando em consideração o desenvolvimento motor e intelectual das crianças no período de 0 a 2 anos, bem como uma metodologia para o design desses experimentos. Para o desenvolvimento desta pesquisa, o CONAIM (Conscious Attention-based Integrated Model), um modelo formal para consciência de máquina com base em um esquema atencional para a cognição de agentes semelhantes aos humanos e o CST (Cognitive Systems Toolkit), um kit de ferramentas geral para a construção de arquiteturas cognitivas, foram usados. Demos inicio a implementação dos experimentos propostos a partir da melhoria do módulo atencional bottom-up baseado em saliencia (fator que guia o aprendizado da criança em suas fases iniciais) do CONAIM modelado no CST, e utilizando a metodologia proposta fizemos a implementação de um agente atencional inteligente aprendendo sob o espaço atencional usando Aprendizado por Reforço. Os testes foram realizados em simulação e conseguimos controlar com sucesso o robô Pioneer P3-DX, aprendendo com seu espaço atencional.

Abstract

The advancement of artificial intelligence has brought many benefits to robotics. Today, it is possible to develop robots that not only perform what they were pre-programmed to do but also learn according to the interaction with the environment and other agents. For this, robots should have cognitive functions, such as memory, decision making, learning, attention, planning, and others supported in their structure. To date, there are no standard ways in the literature to evaluate cognitive architectures. In this context, in this work, we studied cognitive functions aiming to identify which components are necessary to validate a project that implements a cognitive architecture. We studied the development of children aged 0 to 2 years and Piaget's constructivist theory about the construction of knowledge and intelligence development. Based on the studies carried out, we were able to classify the studies in the Developmental Robotics area in the stages defined by Piaget. With that, we built a set of incremental experiments taking into account the motor and intellectual development of children from 0 to 2 years. We also described a methodology for the design of these experiments. For the development of this research, the CONAIM (Conscious Attention-based Integrated Model), a formal model for machine consciousness based on an attentional schema for human-like agent cognition and the CST (Cognitive Systems Toolkit), a general toolkit for the construction of cognitive architectures were used. We started the implementation of the proposed experiments by improving the bottom-up attentional module, an essential drive to child's learning in early stages, of CONAIM modeled on CST. Then, by using the proposed methodology, we implemented an intelligent, attentive agent learning over the attentional space using Reinforcement Learning. The tests were performed in simulation, and we were able to successfully control the Pioneer P3-DX robot, learning from its attentional space.

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Chapter 1

Introduction

With the advancements of artificial intelligence and robotics, there is an interest in increasingly introducing robots into daily activities that involve interaction with other agents (robots or humans). This insertion is known as service robotics and, according to the International Organization for Standardization [32], represents robots that perform useful tasks for humans or equipment, excluding industrial automation applications. This definition implies autonomous robots operating in more complex scenarios (partially unknown, unpredictable, and unstructured), which makes preprogramming impossible and requires robots to have a superior capability of performing tasks.

Through this challenge, questions such as how to incorporate new knowledge and skills through interaction with the world have emerged, resulting in the research area of Cognitive Robotics, which is intrinsically related to other fields of science such as psychology, philosophy, and neuroscience. Cognitive Robotics are intrinsically related to Cognitive Architectures, that represent comprehensive computer models providing theoretical frameworks to work with cognitive processes in the search for complex behavior.

Inspired by the way humans construct knowledge through interaction with the world, scientists seek to reproduce the same with artificial creatures. However, although there is progress in the area, we are still far from having the same behavior as humans. Indeed, cognitive skills development requires the coordination of a complex set of mechanisms that depend on each other. That is, to develop more complex skills, it is necessary to have developed some basic skills. The process of developing these skills is incremental and evolutionary, and as presented by Piaget, a child's way of thinking is different from that of an adult. But then, what are the basic skills needed, how to develop them, how do they relate, and how do they serve as a basis for boosting and developing higher cognitive skills?

As Turing [86] once said, "Instead of trying to produce a program to simulate the adult mind, why not rather try to produce one which simulates children? If this was then subjected to an appropriate course of education, one would obtain the adult brain." and to investigate what these skills are, the area of Developmental Robotics (DevRobotics) has emerged. The goal of DevRobotics is to enable robots to develop in the same way as humans, inspired by the cognitive development of children. For this purpose, incremental and multimodal experiments are carried out, based on child development, sometimes based on the stages of development defined by Piaget. These experiments, usually, are performed over cognitive architectures. However, although a multitude of cognitive architectures exists, it lacks clear experimentation and evaluation processes to fulfill the goal of DevRobotics.

1.1 Objective

In this work, we aimed at investigating which modules in a cognitive architecture are necessary to control a robot that interacts with its environment while performing a set of sensorimotor experiments. The experiments have increasing difficulty levels while the robot learns new knowledge in procedural memory (how to behave to solve a task) over the attentional space.

More specifically, to achieve this goal, we aimed:

- Built a corpus of experiments inspired by developmental robotics and Piaget's equivalent to the sensorimotor stage
- Defined the set of sensors and actuators required to perform such experiments in a physical (real or simulated) robot
- Built the test scenarios to perform such experiments
- Defined the minimal body of knowledge and behaviors that can support learning through interaction
- Specified the operating components in a cognitive architecture necessary for implementing this knowledge and behavior base
- Specified the metrics that will be used to evaluate the experiments
- Implemented and tested the proposed framework in the reported scenarios

Based on these objectives, we formulated two hypotheses to confirm if we succeeded with our objectives:

- H_1: It is possible to propose equivalents to Piagetian experiments to assess the level of development of robots in DevRobotics
- H_2: A robot could learn how to make decisions from attentional maps and not through sensory maps directly.

By the end of this work, we aim at contributing to the area by having a protocol to investigate how learning procedures evolve in a robot that interacts with its environment through sensorimotor experiments with increasing difficulty levels. We also will contribute with a set of cognitive modules implemented for a specific cognitive architecture/framework.

1.2 Contributions

As the main contributions of this work, we emphasize:

- The design and implementation of the bottom-up pathway of CONAIM in CST;
- The design and implementation of a learner attentional agent in CST;
- The evaluation of the possibility of learning over the attention space;
- The definition of cognitive experiments, inspired by Piaget's theory, that could be used to assess the agent's learning in DevRobotics.

1.3 Text Organization

We organized the remaining of this text as follows:

- Chapter 2 introduces the area of Developmental Robotics (DevRobotics), and its main research focuses along with Piaget's Theory of how learning develops, that was used as pillars of our research;
- Chapter 3 addresses cognitive functions and memories present in humans that can be modeled in robots, defines the concept of cognitive architecture, presents the attentional model that supports our proposal and the toolkit used as the basis for our work;
- Chapter 4 presents the related works and a summary containing the main characteristics associated with DevRobotics in each of them;
- Chapter 5 presents the sensorimotor experiments inspired by Piaget proposed in this thesis and a methodology to design these experiments;
- Chapter 6 shows the experiments made to validate the attentional module developed associating CONAIM + CST;
- Chapter 7 presents the extension of the architecture that allows learning over the attentional space instead of the feature space;
- Chapter 8 assess the final considerations and presents the possibilities of extensions in future work;
- Appendix A shows the experiments conducted to tune the parameters of the low-level controllers used in the robots.

Chapter 2

Developmental Robotics

Developmental robotics (also known as epigenetic robotics or DevRobotics) is an interdisciplinary field to robotics including psychology, neuroscience and computer science [89] [49]. Inspired by the developmental principles and mechanisms observed in children's development [17], the projects in the field typically focus on having robots develop the same skills as human infants.

Developmental robotics (DevRobotics) is interested in the development of an individual machine's capabilities (single robot) through experience over time. The most notable characteristics researched are:

- The robot deals with signals that come directly from its sensors
- The robot learns what to do in new situations by trial-and-error
- The robot learns from its own mistakes
- There is an interaction between robots and other agents (other robots or humans)
- The robot acquires new skills based on the skills it already has

In DevRobotics, the human engineer creates a developmental architecture that can autonomously learn [11], not merely solving a specific task, which allows the robot to construct its representation of its body and environment [55]. According to [55], the absence of pre-defined tasks, and no external goals makes the developmental approach differ from previous AI approaches. They further claim that the robot is self-motivated to choose its actions.

According to [3], the developmental process consists of two phases: the individual development at an early stage and the social development through interaction between individuals later on. Whereas the former relates mainly to internal mechanisms, the latter refers to behavior observation.

As in humans, learning is expected to be cumulative [12] and of progressively increasing complexity [17]. It is also the result of self-exploration of the world in combination with social interaction [49].

Non-social interaction is characterized by a strong coupling between sensory and motor processes over the surrounding environment. It does not involve interaction with other agents [50]. Learning to grasp [42], perceptual categorization [10] and visually-guided manipulation [44] are some examples. On the other hand, socially oriented interactions relate to robots that learn skills via interaction with other robots or humans [50]. Imitation [74][73] [39] [6] and attention sharing [63] [35] are examples of the later.

Typical tasks of DevRobotics usually involve challenges related to:

- **Reinforcement Learning**: It is inspired by Skinner [78], who proposed the operant conditioning, in which the behavior is followed by a consequence and the nature of the consequence changes the organism's tendency to repeat the behavior in the future. So, Reinforcement Learning is learning through trial and error by interacting with a dynamic environment that provides rewards or punishment to each interaction. The tasks to be achieved are not specified, and the agent's job is to find a policy that maps states to actions to maximize some measure of reinforcement [46]. Usually, the environment is non-deterministic.

- **Imitation:** Learning by observing the behavior of other agents acting in the environment. This approach needs a teacher to demonstrate the actions, which allows teaching the new behaviors to the robot by showing instead of telling. According to [74], true imitation is present only if (1) the imitated behavior is new for the imitator, (2) the same task strategy as that of the demonstrator is employed, and (3) the same task goal is accomplished. A prerequisite for imitation is the connection between the sensory and motor systems [74]. Finally, imitation requires perceptual and cognitive abilities, but understanding many of these abilities is still an open problem in psychology, robotics, and artificial intelligence [6].

- **Affordance:** The term was introduced by the American psychologist Gibson [33], who defined the affordances of the environment as what it offers the animal, what it provides or furnishes, either for good or ill. It refers to all action possibilities on a certain object, concerning the actor's capabilities, which promotes learning through interaction with the world. Therefore, the affordance concept is a kind of perception based on actions [58].

2.1 Piaget's Theory

For Piaget [67], knowledge does not depend solely on social relations or hereditary genetic baggage. It also results from interactions of the subject with objects that will enable the construction of knowledge and development of intelligence structures. In his view, children are the active builders of knowledge themselves, continually creating and testing their theories about the world.

The Piagetian theory has two main concepts:

- *Assimilation*: Attempt of the subject to solve a given situation, using an already formed mental structure, that is, by assimilating the new situation into an already-ready system. It refers to the process of using schemes to understand experiences.

Piaget defined it as "integration with previous structures, which can remain invariant or are more or less modified by this integration, but without discontinuity with the previous state, that is, without being destroyed."

Example: the moment a child builds the knowledge of "climbing stairs", this knowledge will be used in all cases that involve climbing stairs.

- *Accommodation*: The subject's attempt to solve a given situation by modifying the old structures and building new ways of acting to dominate a new scenario, i.e., it is a complementary process of assimilation which involves changing the scheme as a result of new information acquired through assimilation. Through accommodation, we perfect our skills and reorganize our ways of thinking.

  Example: The child already knows how to climb stairs, but never climbed an escalator (an object similar to the first, but with new elements that the child does not know). In this situation, she will try (by assimilation) to act as before, to solve a novel situation based on the old structures, but she will not succeed. Then, she will build new ways of acting, hence modifying her old structures to master and accommodate new ones.

Assimilation and accommodation are inseparable, complementary, and co-occur in any act (physical or mental) of knowledge. Wadsworth [90] says that accommodation explains the development (a qualitative change), and assimilation explains growth (a quantitative change).

- *Primary circular reaction*: Simple repetitive actions of the baby, discovered randomly, in sub-stage 2 of the sensorimotor stage, organized around the baby's own body.

- *Secondary circular reaction*: Repetitive actions in sub-stage 3 of the sensorimotor stage, oriented around external objects.

- *Tertiary circular reaction*: Deliberate experimentation with variations of previous actions that occur in sub-stage 5 of the sensorimotor stage.

Figure 2.1 shows an example of circular reactions.

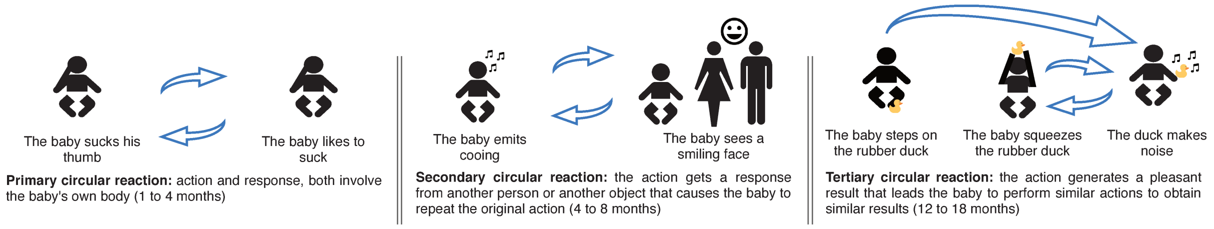


Figure 2.1: Example of circular reactions. Adapted from [65].

Some observations regarding the circular reactions:

- The circular reaction implies the discovery and conservation of novelty, and in this, it differs from pure reflection.
- The only difference between secondary and primary reactions is that in the secondary, the interest is centered on the external result and no longer on the activity.
- The difference between tertiary and secondary reactions is that in the secondary, the child repeats the movements that led to an interesting result, while in the tertiary, the child repeats these movements, not literally, but grading them and varying them from to discover the fluctuations of the result itself.

To examine the process of thought development, Piaget observed his children and other children, concluding that the child's way of thinking is qualitatively different from the idea of adults. Thus, to understand the logic of the adult, Piaget studied infantile thought development and reached periods that he called stages of cognitive development. These stages are described below and briefly illustrated in Figure 2.2.

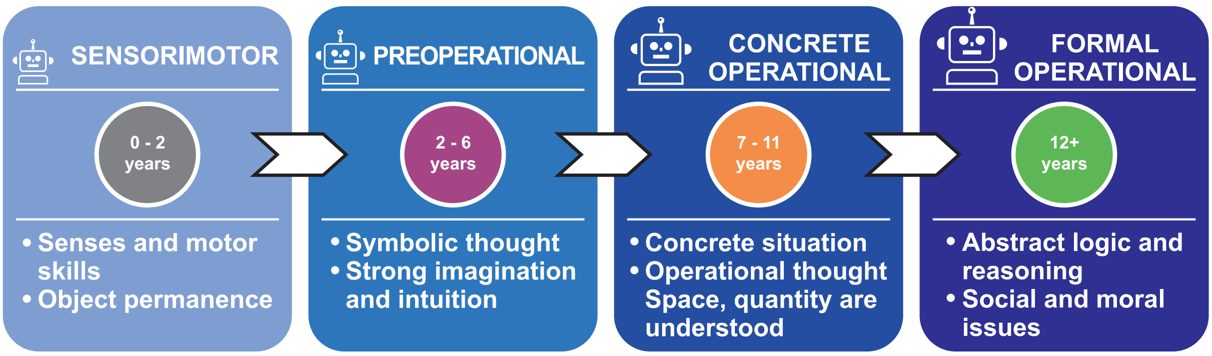


Figure 2.2: Piaget's four stages.

2.1.1 Sensorimotor Stage (0 - 2 years)

Babies are born with reflexive, innate, and automatic actions and are, at first, passive subjects who construct simple schemes that work in isolation circularly and repetitively (catch, look, beat, suck). During this period, one develops voluntary and conscious behaviors, and chain actions towards an inevitable end become an active subject (domain and variation of operations). Schemes become complicated with invention and creation of actions (pick up, listen, look/listen, pick up, look/lift, walk, pick up, suck).

Piaget affirms that these behaviors are intelligent acts and that it is in the sensorimotor period that the birth of the child's intelligence occurs. Thus, the process of a child's adaptation at the sensorimotor stage is marked by assimilation, which occurs in three ways:

- *Functional assimilation*: Repetition of the scheme. Example: If children see an object falling and bouncing like a ball, they will want to repeat this entire process.

- *Generalized assimilation*: Use of the scheme in different situations. Example: if we hide an object somewhere and remove it from this place, a child will look for where the object was placed first.

- *Cognitive assimilation*: Recognition of schemes. Example: a child will not look for the object where it was first placed, but rather for the last place where it was placed.

According to Piaget, the sensorimotor stage is composed of six substrates that encompass how children coordinate and organize information about their environment to progress with learning.

- *1st Substage (birth to 1 month)*: Formation of the first schemes through the exercise of reflexes. By exercising their innate reflexes, the baby constructs a control over them. Therefore, all stimuli are incorporated (assimilated) into reflex and modified schemes (accommodation) as a result of their repetitive (circular) use and interaction with the environment. Limited imitation, inability to integrate information from different senses.

- *2nd Substage (1 to 4 months)*: At this moment, there is a change of reflexive behaviors in the function of the experience (circular repetition), and the genetic adaptation happens to an acquired adaptation. Results obtained by chance are conserved by repetition, and the first habits are formed: the child repeats an action that has worked (primary circular reaction).

  Another relevant aspect is that the movement of objects begins to be followed by the eyes (coordination of the vision), and the head moves towards the sounds (coordination of vision-hearing). Although advances have taken place, there is still no intentionality - the act of initiating behavior towards a particular end—the beginning of the coordination of schemes of the different senses.

- *3rd Substage (4 to 8 months)*: The infant has secondary circular reaction or reproductive assimilation - the child repeats interesting results obtained by chance with intention. There is coordination between vision - apprehension. Imitation can occur, but only from schemes that already exist in the baby's repertoire. About the concept of an object, the child does not have the notion of a permanent object, which depicts a phase of transition from pre-intelligent (random) acts to intelligent acts (intention).

- *4th Substage (8 to 12 months)*: The formation of sensorimotor intelligence occurs. Some behaviors constitute actual acts of intelligence, that is, the application of means already known to solve new situations. The child is already able to vary, coordinate, generalize different actions, or the mechanisms to reach an end. There are intentionality and desire. However, it does not create a new means to an end. Imitation of new behaviors occurs.

  The child constructs the notion of a permanent object, seeks the object taken from his/her visual field, and sees the moment when it is hidden. However, if hidden a second time in another place (under your sight), he/she will look in the first place again, repeating what went right.

- *5th Substage (12 to 18 months)*: The baby presents a tertiary circular reaction, that is, repeats an action to know and explore the properties of the object. They thus begin to experiment with new behaviors to see what happens. Through trial and error, they experiment with behaviors until they find the best way to achieve a goal.

  Concerning the notion of object, they take into account the successive displacements of the object, search for it at the point where it was last seen, but know of its existence. If they do not find it, they will look for it in other places.

- *6th Substage (18 to 24 months)*: This is a moment of transition, marked by the end of the sensory-motor stage and the beginning of the preoperational stage. At this point, actions will also be represented as imaginative events. Thus, developing the representational capacity, that is, the ability to mentally represent objects and actions through symbols (words and images). By doing so, it leaves attempts by trial and error to anticipate events by combining mental actions rather than physical actions. This moment is marked by the passage from explicit action to mental representation, with the appearance, for example, of language. Besides, deferred imitation is made possible because it requires the ability to represent the event to be imitated internally.

Figure 2.3 illustrates a summary of these substages.

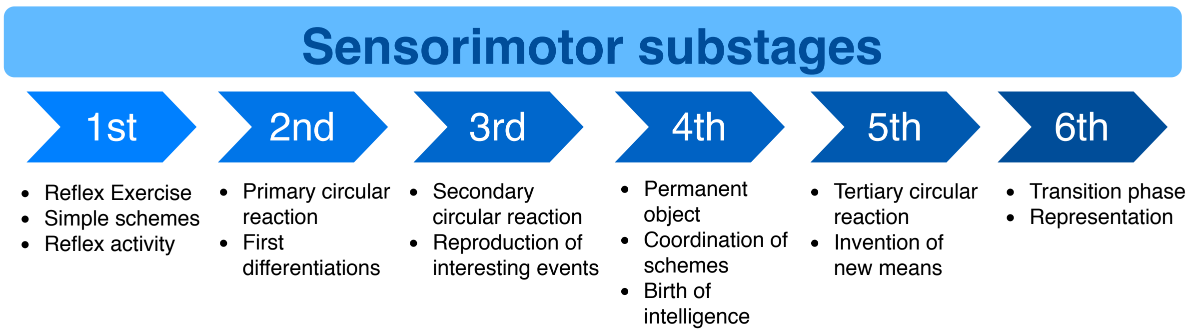


Figure 2.3: Sensorimotor substages.

2.1.2 Preoperational Stage (2 - 6 years)

In the preoperational stage, children evolve from a sensory-motor functioning, expressed through actions, into a conceptual and representational mode. Thus, this period marks the passage of sensory-motor intelligence or practice for representative intelligence, and the child becomes apt to represent objects and events. From the age of two, the child has a function of thought, a symbolic or semiotic function, which enables the representation of an absent object, which they express in several ways.

Thus, there are several types of representation that have development relevance in this period. In order of appearance, they are imitation, symbolic play, drawing, mental image, language, or verbal evocation.

- *Deferred imitation*: the child's ability to mentally represent (remember) a behavior imitated in the absence of the model. Children imitate objects and events, away from the situation or the imitation object, after their occurrence.

- *Symbolic play*: children construct symbols that represent anything that they desire, meaning they can go to the real world through symbols, gestures, and simulation games. Although it has an imitative character, it is also a form of self-expression, since it does not address the other, only the self. Symbolic play is a make-believe game in which the child attributes meaning to things and plays with them in a magical and imaginary context.

- *Drawing or graphic image*: The first forms of the drawing are not imitative of the real but an exercise game in which the child has fun scrawling the wall, floor, or paper in large and repetitive movements.

  Around two years old, they begin to give a meaning to scribbles, recognize shapes in her scribbles, tries to repeat a model from memory. There is a commitment to represent things through drawing realistically. Therefore, the intention to serve reality through graphics, imitation, and mental image (memory) arises.

- *Mental Image*: These are internal representations (symbols) of preceding perceptual objects or experiences, through mental images (interiorized imitation).

- *Language spoken*: Around two years, the child begins to use the words to represent objects. This form of symbolic representation allows cognitive development in children because it will enable: exchange with people and, therefore, the socialization; internalization of the world and the appearance of thought; internalization of actions that, from perception and motion, become representative (conceptual).

  Also, in conversations between children, Piaget observed two forms of language in the preoperational stage: egocentric speech and socialized speech.

2.1.3 Concrete operational (7 - 11 years)

The main characteristic of this stage is that the thinking stops being pre-logical and becomes operative. That is, children have the cognitive ability to logically coordinate different points of view, expressing more elaborate cognitive actions. However, although they have the possibility of a higher expression of thought, to be able to use it reasonably, it is necessary to handle and observe concrete objects. This is because dealing with purely abstract and hypothetical ideas will acquire the next stage of formal operations. The operative child can consider different references simultaneously, identify the reversibility of internal/mental action, conserve quantities, classify, and sequential.

A significant mark of this period is that the child is freed from intellectual and social egocentrism, capable of new coordinations since the foundations of logical intelligence are founded, that is, the coordination of points of view among themselves (from different people as well as from one person). From the social and affective point of view, this will imply the beginning of the morality of cooperation and autonomy. Morality moves toward autonomy.

2.1.4 Formal operational (12+ years)

At this stage, the subject can form abstract conceptual schemes (love, justice) and perform mental operations according to a more sophisticated formal logic in terms of content and flexibility of reasoning.

From this stage, they are able to discuss moral values with parents, build their values, acquire autonomy, raise hypotheses, and express propositions. Then, they test them, reflect on their thoughts, and seek logical justifications for their judgments, leading to the construction of autonomy and identity.

In this way, occurs the transition from inductive logic to deductive logic. The subject has the cognitive ability to think from a general principle, arriving at the anticipation of an experience (walking from the general to the particular).

One can then synthesize the three essential acquisitions of this fourth and last Piagetian stage, abstract operations: formal thought, the achievement of personality, and insertion in adult society.

2.2 Sensorimotor stage specifics

Due to the incremental nature of our experiments, we focused on the **sensorimotor stage**.

Regarding the senses in this stage, we have the following initial sensory capabilities:

- **Sight**: the newborn's eyes focus better at a distance of 30cm. Newborns blink in the presence of bright light. Its peripheral field of view is very narrow; it is already well developed in the 3rd month.

  At birth, visual acuity is approximately 20/400 and reaches the 20/20 level around eight months. "20/20" means that you can see and identify something 20 feet (609 centimeters) away from that an average person is also able to see at 20 feet—the higher the second number, the worse the person's visual acuity.

  The *Binocular vision*: the use of both eyes to focus, making it possible to perceive depth and distance - usually does not develop before the 4th or 5th month.

- **Intermodal perception**: formation of a single perception of a stimulus based on information from two or more senses. For example, the processes of recognizing only by touch a toy that you have already seen but never touched. It is possible already in the first month and becomes common at six months. With four months, children can relate sound rhythms to movements.

- **Hearing**: 3-day-old babies can distinguish new speech sounds from those they have heard before. At one month of age, the baby can distinguish sounds as similar to *ba* and *pa*.
- **Touch**: It is the first sense to develop, and in the first few months, it is the most mature sensory system.
- **Smell and taste**: They start to develop in the womb. The preference for pleasant odors seems to be learned in the womb and during the first days after birth. Newborns prefer sweet flavors to sour or bitter.

Besides that, one of the most important things in this stage is related to motor development. In this period, babies learn how to move the parts of their bodies and integrate these parts to achieve goals. In the following, we briefly describe three skills developed by babies.

- **Head control**: At birth, they can turn their heads from side to side while lying on their backs. While lying face down, they can lift their heads high enough to turn them over, raising your head higher and higher in the first 2 or 3 months. Around four months, they can keep their head erect when held or supported in a sitting position.
- **Hand control**: At around 3.5 months they can grasp a moderately sized object, but have difficulties with small objects. Then they start taking objects with one hand and transferring them to the other and then holding (but not picking up) small objects. Between 7 and 11 months, they pick up small objects using the pincer grasp. Around 15 months, they know how to build a tower with two cubes. Between 5 and 7 months, develop tactile perception (ability to acquire information by handling objects).
- **Locomotion**: After three months, the baby starts to roll deliberately. They can sit without support at around six months and assume a sitting position without assistance at around 8.5 months. Between 6 and 10 months, babies start moving on their own by dragging themselves or crawling. Babies can stand by holding someone's hand or leaning on furniture shortly after seven months and can drop the support and stand by themselves around 11 months. A few weeks after the 1st year, they can walk reasonably well.

Table 2.1 shows the milestones of the child's motor development up to 2 years of age, while Table 2.2 presents milestones of motor development using the Denver scale [28] for the same period. The data presented in these tables are one of the bases used to design the experiments described in Chapter 5.

2.3 Psychosocial Development - Emotions

Emotional development is an ordered process from which complex emotions unfold from simpler ones. The baby shows signs of contentment, interest, and distress right after

Age (months)	General motor skills	Fine motor skills
1	Gait reflex; slightly raise your head	Hold object placed in hand
2 to 3	Lift your head to a 90-degree angle when lying face down	Start hitting objects in sight
4 to 6	Turn the body; sit with support; move on hands and knees (dragging yourself); keep your head upright while sitting	Reach and grasp objects
4 to 6	Turn the body; sit with support; move on hands and knees (dragging yourself); keep your head upright while sitting	Reach and grasp objects
7 to 9	Sit without support; crawl	Transfer objects from one hand to another
10 to 12	Stand up and walk on the furniture; then walk alone; crouch and leans; play clap games	Show signs of preference in the use of hands; hold a spoon with palm, but don't have good aim when bringing food to mouth
13 to 18	Walk back and sideways. run (14 to 20 months); rolls the ball back to adult; clap hands	Stack two blocks; put objects in a smaller container and dump them
19 to 24	Up and downstairs, two feet per step; jump off the ground with both feet	Use a spoon to feed; stacks 4 to 10 blocks

Table 2.1: Milestones of motor development in the first two years. Extracted from [14].

Skills	50%	90%
To roll	3.2 months	5.4 months
Get a rattle	3.3 months	3.9 months
Sit without support	5.9 months	6.8 months
Stand upright leaning on something	7.2 months	8.5 months
Pick up with thumb and forefinger	8.2 months	10.2 months
Stand upright alone firmly	11.5 months	13.7 months
Walk well	12.3 months	14.9 months
Assemble a tower with 2 cubes	14.8 months	20.6 months
Climbing stairs	16.6 months	21.6 months
Jump in the same place	23.8 months	2.4 years

Table 2.2: Approximate age at which 50% and 90% of children can perform each skill, according to Denver Training Manual II. Extracted from [65].

birth. These are diffuse, reflexive responses, mostly physiological, to sensory stimulation or internal processes. In the first six months, these initial emotional states differ in genuine emotions: happiness, surprise, sadness, disgust, anger, and fear. The emergence of these basic emotions is related to neurological maturation.

Emotions can be:

- **Primary or basic emotions**: Emotions such as happiness, surprise, sadness, aversion, anger, fear. It appears during the first six months.
- **Self-conscious emotions**: Emotions such as embarrassment, empathy, and jeal-

ousy, which depend on self-awareness (Perception that the own existence and functioning are separate from those of other people and things), which seems to emerge between 15 and 24 months.

- **Self-evaluating emotions**: Emotions such as pride, shame, and guilt, which depend on both self-awareness and knowledge of socially accepted patterns of behavior. It appears around the age of 3 years.

There are several theories of emotion, but in this dissertation, we present only 3 of them. They are:

- **William James**: William James proposed that an individual, after perceiving a stimulus that in some way affects him, undergoes disturbing physiological changes, such as palpitations, shortness of breath, anguish, etc. And it is precisely the recognition of these symptoms (by the brain) that generates the emotion.

- **Cannon - Bard**: When an individual faces an event that affects him, the nervous impulse reaches the thalamus, and there, the message is divided. Part of it goes to the cerebral cortex, where it gives rise to subjective experiences of fear, anger, sadness, happiness, etc. The other is directed to the hypothalamus, which determines peripheral neurovegetative changes (symptoms).

- **Schachter and Singer**: Conscious experience for the definition of an emotion. "Cognitive label," which would be produced through the information that the subject acquires from his social environment to "label" his emotional reactions.

An illustrated example of these theories can be seen in Figure 2.4.

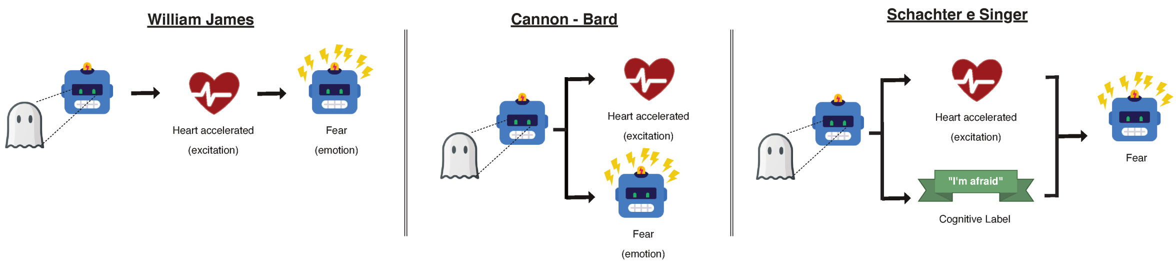


Figure 2.4: Theories of emotion example.

2.4 Motivational/Emotional System

Humans have many needs, which are from physiological needs, like get food/water, avoid danger, and get sleep, to self-actualization, like personal acceptance and overcoming challenges.

Maslow's Hierarchy of Needs [54] (Figure 2.5) illustrates these needs for humans. It shows that some requirements may take priority over others, and the highest priority needs will be met first. But that raises some questions: the hierarchy of needs may be unique to each creature (free will)? How to prioritize, ponder, and suppress some needs? Can (and how) the hierarchy of needs change during the creature's existence? Can new needs be created and inserted into the hierarchy? These points still need to be explored.

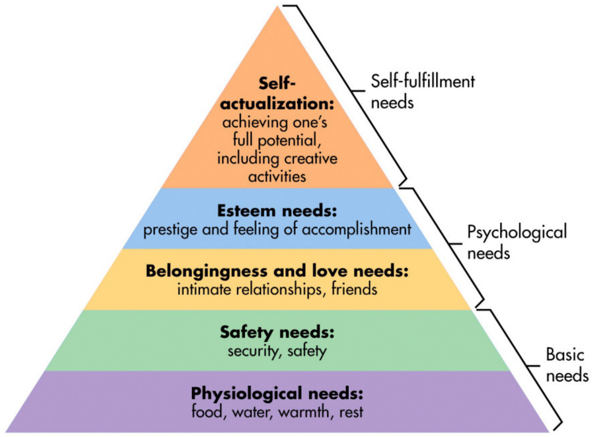


Figure 2.5: Maslow's Hierarchy of Needs. Extracted from [54].

Emotions and motivation are connected, but this connection is still not well defined in the literature.

We will consider that emotion arises to express the motivational state, so it is possible to have motivated behavior without having emotion. The states would be "rewards" (or reinforcements) used in the learning of actions to cause the reduction of drives of the motivational system, and we propose that there should be different types of rewards associated with the different needs of the creature.

2.5 Summary

In this chapter, we presented the reference background that supports the DevRobotics area as well as the Piagetian theory that is usually associated with the experiments carried out in DevRobotics. This formalization, along with the literature review conducted in the area, will work as the basis for our contribution regarding the formalization of experiments that could assess the development level of agents built in DevRobotics.

Chapter 3

Cognition and Cognitive Architecture

Cognition is our ability to assimilate and process the information we receive from different sources, converting it into knowledge [19]. It includes different cognitive processes that are part of our intellectual development and experiences. Different cognitive functions play a role in these processes. Each of these cognitive functions works together to integrate new knowledge and create an interpretation of the world around us. The more relevant cognitive functions are described next.

- *Reasoning:* Ability to organize and structure data to build a logical chain. Formulate ideas, deduce something from one or more premises.
- *Planning:* Ability to analyze information, evaluate all possible actions, and choose the one that best meets the objective. It represents an internal simulation of the agent with the environment through its actions and its consequences [12].
- *Emotion:* Some investigators define emotions as states elicited by reinforcement [83] while others consider that emotions are involved in the conscious (or unconscious) evaluation of events [4]. According to [25, 26], there are six universal emotions: anger, fear, happiness, aversion, sadness, and surprise, and he focuses on these basic emotions, but there are more deep definitions that extend this set to comprise moral ones [59] like pride. Social effects and past experiences can generate it. The same stimulus can generate different emotions in different agents [84]. This is because it depends on their knowledge.
- *Learning:* The learning processes require short-term and long-term memories [11]. It is the process of understanding the data received and stored in long-term memory. Learning occurs by taking small steps and building on what is already known [12]. It is one of the most important capabilities of cognition. There are different kinds of learning: Reinforcement learning, imitation, attentional learning, etc. Interactivity is an important element in the learning process.
- *Motivation:* Degree of interest in performing a certain action supported by emotion. It is a condition that energizes behavior and guides it. There are two types of motivation: extrinsic motivation, which seeks external rewards and avoids punishment

and intrinsic motivation, which is the desire to be efficient and to perform a behavior by yourself (like curiosity) [58].

- *Volition:* Ability to use motivation and decision making to perform a particular action to fulfill your goals. It is the process of transforming the agent's intention into a goal [76]. It concerns the translation of existing goals into action and, specifically, the regulation of these processes [77]. It turns motivation into action.

- *Attention:* Capacity of filtering information received according to parameters of interest and objectives, reducing the agent state space [76][21]. Attention is an essential function to promote learning. From it, information that has higher values of attention passes to higher layers of the architecture, allowing learning. The higher the attentional level dedicated to a feature, the more likely it is to learn it.

- *Perception:* Capacity of processing sensory data. Through perception, the objects of the world gain representation to be stored in memory. It refers to the recognition and interpretation of sensory stimuli. It is a process whereby an agent is informed about the state of its environment [10].

- *Sensing:* Ability to receive information from the environment through sensors [66]. Sensing is fundamental so that the agent can know where it is since it is responsible for receiving the data from the environment, allowing, later, the fulfillment of other cognitive functions.

- *Language:* Ability to communicate. Ability to express yourself to other individuals and to understand them.

- *Behavior*: There are many processes involved in behavior execution. Some of them are:

  - *Decision-making:* To select a single behavior from the available ones. It consists of sets of attentional, emotional, evaluation, and proprioceptive states, a list of goals, set of tasks, working memory, set of motivations, planning function, and body schema [76].
  - *Action selection:* To select the steps (intermediate actions) that must be taken to complete the execution of the chosen action.
  - *Execution of Tasks:* To perform the chosen action.

- *Prediction:* Ability to predict future actions from similar events that occurred previously. It is the ability to foresee consequences of actions [12].

3.1 Memory

Memory is essential for the development of cognitive functions and consequently, cognition, and it is usually divided into short-term memory and long-term memory.

Short-term memory is limited in size. It stores data from the real-time interaction of the agent with its environment for a short period. In most cases can be considered as:

- *Sensory:* It is a short-term memory that allows retaining impressions of sensory information after the original stimulus has ceased. It buffers the stimuli received. This memory usually contains uninterpreted data used in the first steps of perception [66].
- *Working:* It is a short-term memory with limited capacity [66]. It is a mental representation of current situations, which stores information for reasoning in progress. It receives information from the map of projections and sensory memory. It feeds long-term memories and several modules of the cognitive system (for example, planning).
- *Motor:* It is equivalent to sensory memory, but for the system's actuators [66]. It knows how to manipulate the actuators. It is connected directly to procedural memory.

Long-term memories are higher-level memories. They store the knowledge acquired by the agent during its lifetime, information obtained after the analysis of the real data stored in short term memories. In most cases, they can be classified as:

- *Perceptual:* Contains categories of things and the ability to interpret incoming stimuli by recognizing individuals, by categorizing them, and by noting relationships between such individuals and categories [13].
- *Episodic:* Refers to specific events (what, when, and where) localized in time and space, allowing the association to particular details [69]. It is a constructive process, which each time an event is assimilated, it reconstructs past episodes. However, they are reconstructed a little differently each time [89]. It is a memory of the self. It stores, for instance, the first time you traveled by plane, your first day at a new job, etc.
- *Semantic:* Stores general and abstract facts, common sense knowledge, not contextualized in time and space. It deals with facts and their meaning [69], and it is intrinsically related to perceptual memory. Authors claim that episodic memory highly influences the semantic one once the experience acquired over situations enhance the semantic knowledge.
- *Procedural:* It is a long-term memory responsible for knowing how to do things, also known as motor and behavioral skills [29][69], such as walking, talking, and riding a bike. It is the long-term memory that stores information on how to perform certain procedures.

3.2 Cognitive Architectures and frameworks

Ron Sun [81] defines cognitive architectures as "the overall, essential structure and process of a broadly-scoped domain-generic computational cognitive model, used for broad, multiple-level, multiple-domain analysis of cognition and behavior." Usually, a cognitive architecture comprises a composition of modules responsible for the implementation of different cognitive capabilities, allowing the study of the interaction between them. The architecture defines what the system should have, but does not determine how it should be done. A hallmark of cognitive science is developing a theory of cognition powerful enough to encompass all human mental abilities [47].

There are several cognitive architectures described in the literature with distinct models of functionally. Some of the best known architectures are: SOAR [48], ACT-R [1], Clarion [80], LIDA [30] and OpenCog [34]. In particular, our research group has proposed in the last years the CST [66] and CONAIM [76, 21], which will be used as the focus of our work and are presented next.

3.2.1 CONAIM

The Conscious Attention-Based Integrated Model (CONAIM) [21, 76] is a formal model based on an attentional schema to machine consciousness. The model provides an agent based on consciousness that performs computations over attention-directed schemes, significantly reducing the space of the model's input dimensions. It has both a top-down and a bottom-up attentional pathway, such that the first refers to decision-making processes and goals, and the second comes from the stimuli that the environment promotes in the system. In this work, we will cover only the bottom-up component. Figure 3.1 depicts the model architecture, composed of two main systems:

- **An attentional system** (illustrated in Figure 3.2) in that follows the selection for perception components of the model proposed in [21]. This architecture incorporates several aspects of other related projects and is capable of handling multiple sensory systems, multiple extracting characteristics processes, decision making, and learning support. It comprises sensory memory, feature maps, weights associated with feature maps, combined feature maps, saliency map, and attentional map. The model formalization is described ahead, and the attentional course's dynamics are detailed in [21].

- A **cognitive system** that comprises decision-making, short-term memory (working memory), Long-term memory (Episodic memory, Semantic memory, Procedural memory), and evaluation components (goals, evaluator, evaluation state, task, volition, individuality component). The Working Memory receives information from the Attentional System (Salience Map and Sensory Memory) and provides information for the blocks: motivation, emotions, decision making, performance, and other cognitive processes. Semantic, Episodic, and Procedural Memories exchange information with Working Memory in a bidirectional flow. The cognitive cycle and model operation are described in [76].

To complete the model, a set of **processes** with various purposes, running in the background, is defined. The system operates under the central paradigm that any function or process of the cognitive system can request information from any other module and/or

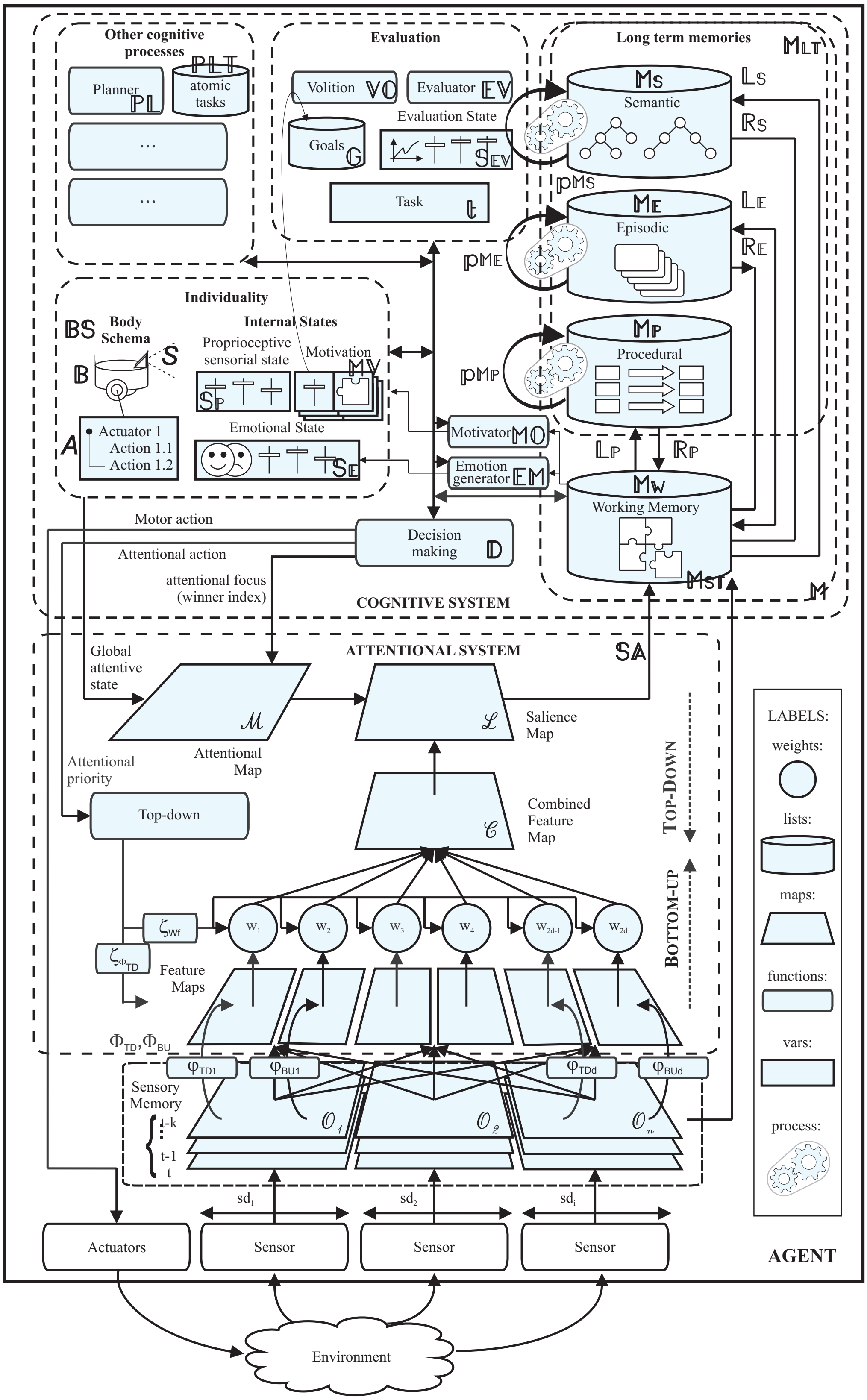


Figure 3.1: CONAIM architecture, comprised of an attentional system and a cognitive system.

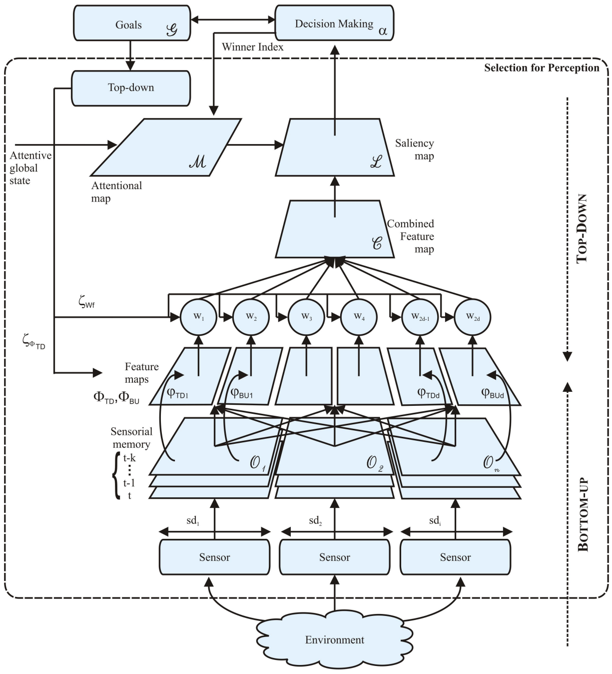


Figure 3.2: CONAIM attentional system.

change the agent's internal states. Therefore, the flow of information through the Decision-Making module is not mandatory.

The model has a formal description of its variables and functions defined in [21], and the cognitive cycle and model operation is described in [76]. We described here in more detail the **Bottom-up** path of attention in the model, which will be the focus of our work.

Bottom-up

Data from various sensors are expected to be captured at each attentional cycle and stored in sensory memory. This data is combined to produce the feature maps. These maps are then combined to produce a single combined feature map, which has all features of the same dimension on that map and is made using the weighted value. This single map will contribute to generating the saliency map (the result of multiplying the attentional map with the combined feature map).

From the bottom-up perspective, the feature map serves as an indication of what should be perceived in the environment, as it provides information that represents the state salience to which attention should be directed. The Winner Takes All (WTA) approach is used to choose a region for which directs attention, and the winner is added to a list of winners, and their attentional cycle begins. Over some time, the attentional map will highlight the corresponding region and then enter an inhibitory period. This process is called Inhibition Of Return (IOR) and is a mechanism that makes it difficult for a certain period to keep an agent's attention on the same location.

Model Formalization

According to [21] the model is described by:

- A set of ns sensors $\{s_1, s_2, ..., s_{ns}\} \in \mathcal{S}$;
- A set of ns sensor dimensions $\{sd_1, sd_2, ..., sd_{ns}\} \in \mathcal{S}d$, with each $sd_i \in \mathcal{S}d$ associated to sensor $s_i \in \mathcal{S}$;
- A set of observations of sensors, denoted by $\{\mathcal{O}_1, \mathcal{O}_2, ..., \mathcal{O}_i\} \in \mathcal{O}$, where $\mathcal{O}_{i_{j_k}}$ denotes the observation of $j-th$ dimension of the $i-th$ sensor in time k, with $j \in \{1, \ldots, sd_i\}$, $k \in [t-k, t]$ and t is time of current observation;
- A number of feature dimensions $d \in \mathbb{N}^*$ in which bottom-up features can emerge or top-down features can actuate;
- A set of d *bottom-up feature dimension functions* $\{\phi_{BU_1}, \phi_{BU_2}, ..., \phi_{BU_d}\} \in \Phi_{BU}$;
- A set of d *top-down feature dimension functions* $\{\phi_{TD_1}, \phi_{TD_2}, ..., \phi_{TD_d}\} \in \Phi_{TD}$;
- A set of $2d$ n-dimensional *Feature Maps* $\mathcal{F} \in \Re^n$, with elements denoted by $\{\mathcal{F}_1, \mathcal{F}_2, ..., \mathcal{F}_{2d}\}$, with each feature map $\mathcal{F}_i$ represented by $\{f_{i_1}, f_{i_2}, ..., f_{i_n}\}$;
- A $2d$-dimensional *Features Weight Vector* $\mathcal{W}_f \in \Re^d$, with elements denoted by $\{wf_1, wf_2, ..., wf_{2d}\}$;
- An n-dimensional *Combined Feature Map* $\mathcal{C} \in \Re^n$, with elements denoted by $\{c_1, c_2, ..., c_n\}$;
- An n-dimensional *Saliency Map* $\mathcal{L} \in \Re^n$, with elements denoted by $\{l_1, l_2, ..., l_n\}$;
- An n-dimensional *Attentional Map* $\mathcal{M} \in \Re^n$, with elements denoted by $\{m_1, m_2, ..., m_n\}$, all initialized with ones;
- A set of *winners* $\mathcal{B}$, with elements denoted by $\{b_1, b_2, ..., b_z\}$. Each element $b_i \in \mathcal{B}$ is a 3-tuple $\{\xi, t, (0,1)\}$ where the elements are: an index ξ that refers to a winner $l_i \in \mathcal{L}$, a firing time t and a binary element $\in \{0,1\}$ that indicates if the firing was caused by an exogenous or endogenous process;
- A set of goals $\{g_1, g_2, ..., g_t\} \in \mathcal{G}$;
- A *decision making function* α that maps the current saliency map ($\mathcal{L}$) and the current goal g_t into a winner index;
- A *top-down weights mapping function* ζ_{W_f}
- A *top-down feature dimension mapping function* $\zeta_{\Phi_{TD}}$

3.2.2 CST

The Cognitive Systems Toolkit (CST) [66] is a general toolkit for the construction of cognitive architectures, which allows the use and integration of various technologies. The cognitive functions are classes, which can be combined in different ways.

The CST architecture is **codelet** oriented since all main cognitive functions are codelets or groups of codelets interacting together. Codelets are small pieces of code that run in parallel, each one responsible for a well-defined task. They are running constantly and cyclically, with a specific time interval. Codelets have two main inputs and two outputs that are specified by default. One input is the local (LI) and the other global (GI). One output is the default (O) and the other an activation level (A). They are similar to the special-purpose processes described in Baar's Global Workspace Theory [5]. Below are the specifics of each input and output.

- **LI**: Receives information about selected Memory Objects. It is a standard and favorite source of information.
- **GI**: Used to get information from the Global Workspace.
- **O**: Used to change or create new information in the Raw Memory.
- **A**: Indicates the relevance of the information provided at the output, and is used by the Global Workspace mechanism to select information to be destined to the global workspace.

Memory Objects (MO's) are objects used by codelets to store and access data. The MO holds its Information (I), a timestamp (T), which is a marker indicating MO last update, and an evaluation (E), which has many different uses. The Information (I) is the main property, while others can be ignored depending on the application.

A container, called **Coderack**, stores the codelets, whereas the Raw Memory container stores the MO's set, composing the CST core (Figure 3.3) and modeling the **Mind**. Codelets interact with each other through Memory Objects, which can generate coalitions (for example, one MO is output from one codelet, but input from another).

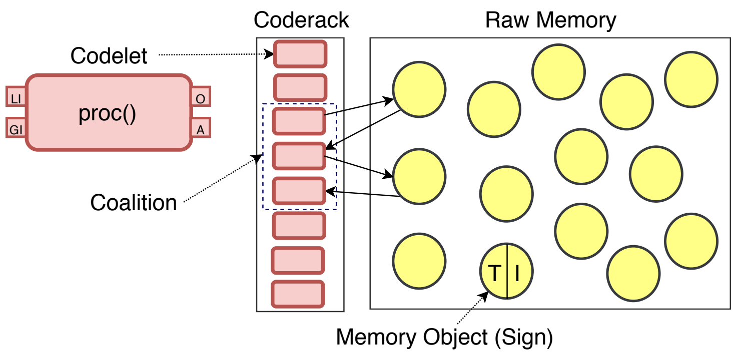


Figure 3.3: The CST Core. Extracted from [66].

Some cognitive functions require more priority than others, and specific processes must be performed before others (e.g., sensory process before perceptual ones). With this, CST provides real thread codelets and pseudo-thread codelets.

As in CST, many different codelets can write in the same MO at the same time. It is necessary to have a Subsumption Architecture [16] to determines which information should be used at each moment.

The original subsumption architecture was a control architecture developed by Rodney Brooks [16] that gave rise to the field of *Behavior-Based Robotics* [2]. While the traditional Artificial Intelligence fields proposed a pipeline approach for processing information, subsumption brought the option of parallel data processing.

In standard Subsumption Architectures, modules are grouped into competency layers, being the lower layers associated with survival, while higher oriented to the agent's objectives. Modules in a layer can inhibit or override output behaviors of other layers. But a downside to this classical subsumption method is that once a layer is set to a higher priority level, it will always prioritize setting up its behavior. Even though this is desirable in some situations, it is always possible to envision situations in which this priority should be reversed, at least on special occasions. To deal with this kind of situation, we have a Dynamic Subsumption scheme [64, 43, 41], in which there is no fixed dominant input in a suppression node. Still, this dominance can be changed dynamically in time, according to specific situations.

In a Dynamical Subsumption, each control message (x_i) comes with an evaluation tag (e_i), which is generated by its behavior. Instead of using fixed priorities to choose an output value, the dynamic model chooses the x_i with the greatest e_i. Figure 3.4 illustrates the Standard and Dynamic Subsumption schemes.

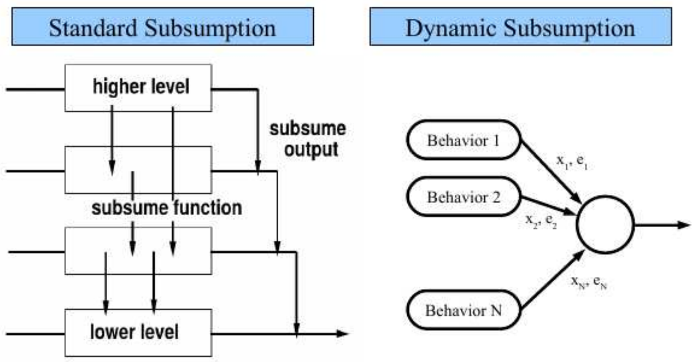


Figure 3.4: The Standard (fixed priority levels) and Dynamical (updatable priority levels) Subsumption Schemes. Extracted from [38].

CST implements the Dynamical Subsumption. It provides the **Memory Container**, which is a boosted Memory Object where multiple codelets might write simultaneously, and the Memory Container will hold separate objects for input a standard mechanism for output. The Selection Codelet, which is implicitly embedded into a Memory Container, selects the Memory Object, which holds the maximum eval (E) field, which can be set by the codelet, which generated the Memory Object [38]. The mechanism of the Memory Container is illustrated in Figure 3.5.

Finally, CST is a tool that allows the creation of multi-agent systems is running entirely asynchronously and in parallel. Also, the standard modules in a cognitive system are already implemented as codelets in the CST architecture, as can be seen in Figure

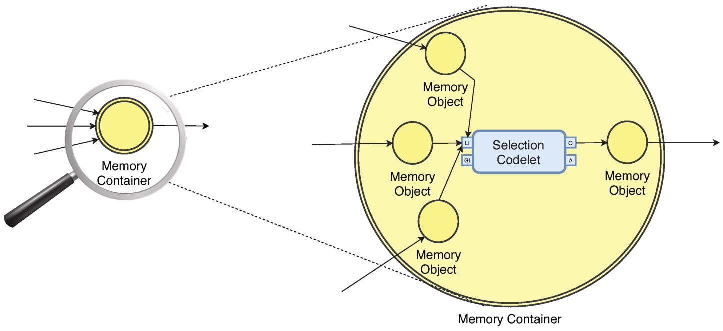


Figure 3.5: The CST Memory Container. Adapted from [38].

3.6.

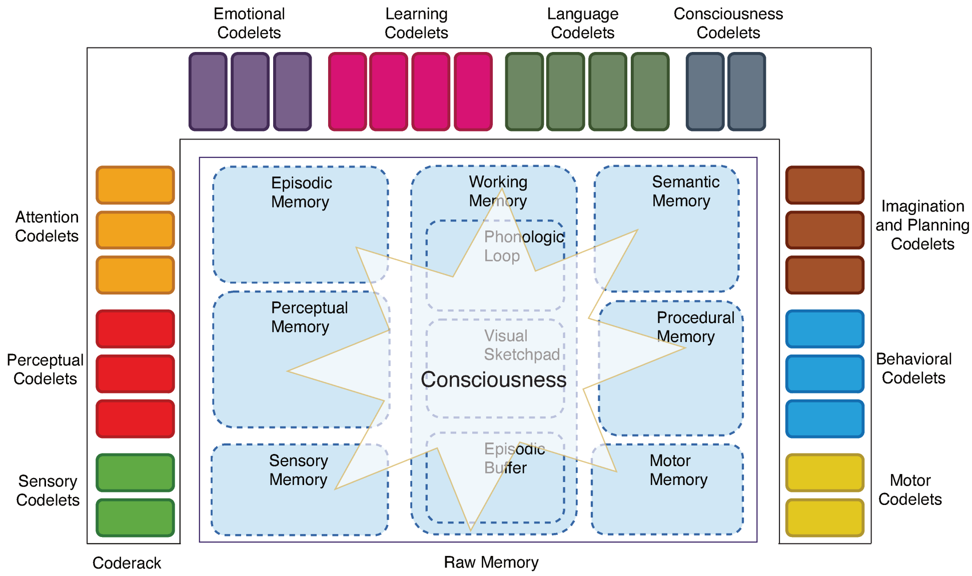


Figure 3.6: The CST architecture. Extracted from [66].

This describes the main CST classes, which can be seen in UML in Figure 3.7.

3.2.3 Cognits

Aiming at approximating Piaget's theory to the cognitive models and frameworks of our interest, we will use the concept of **Cognits** [31], which constitute the basic unit of memory or knowledge and represents a neural network that implements a cognitive function. In our terminology, a Cognit is represented as a **codelet**.

When fitting the **Cognits** in the sensorimotor stage, applying the assimilation, accommodation, and circular reactions concepts, we achieved the following characterization:

- **1st Substage:** Create Cognits (formation of the first schemes through the exercise of reflexes).

- **2nd Substage:** Create and change Cognits based on function but not on intention (change of reflexive behaviors in the function of the experience (circular repetition)).

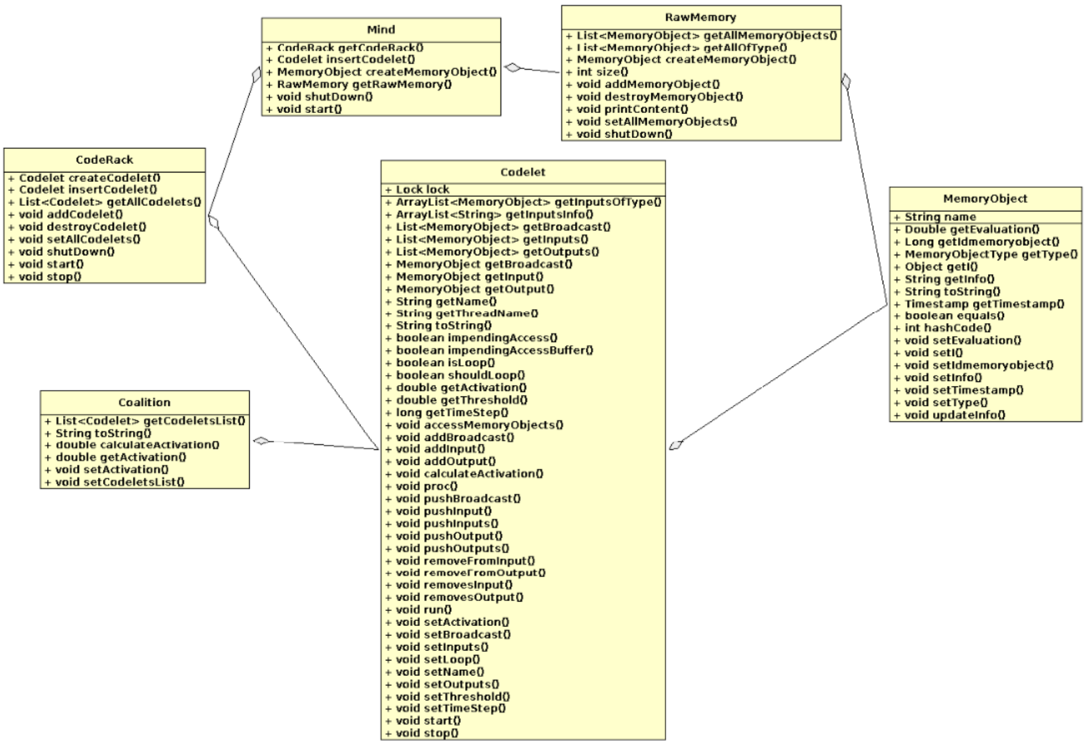


Figure 3.7: UML scheme from CST's main classes

- **3rd Substage**: Create/change/use and coordinate Cognits to form plans and meet objectives (intention) (secondary circular reaction - the child repeats interesting results obtained by chance with intention).
- **4th Substage**: Reuse plans and generalize them. Learn the concept of permanent objects (application of means already known to solve new situations. The child is already able to vary, coordinate, generalize different actions, or the mechanisms to reach an end.).
- **5th Substage**: Systematic exploration of the affordances of objects (tertiary circular reaction, that is, repeats an action to know and explore the properties of the object).
- **6th Substage:** Perform imagination and mental simulation (develop the representational capacity and anticipate events by combining mental actions rather than physical actions).

3.3 Summary

In this chapter, we presented the CONAIM cognitive architecture and the CST toolkit that will be used as reference models for this work. The bottom-up pathway of CONAIM is described in more detail, as it will support the extraction of information passed to other levels of decisions in the system.

Chapter 4

Related Work

The development of artificial agents with autonomous and adaptive behavior [8], roles of embodiment [8][10] and developmental learning are objectives of the research in cognitive robotics and DevRobotics. As biological agents provide the best examples of such behavior in the real world, they are the sources of concepts and design principles for artificial agents [8][11][12]. One such principle is that biological cognition can be described as fundamentally related to the manipulation and utilization of memory, perception, thinking, and action [88].

Based on that, we prepared a literature review studying works that use Piaget's theory as a basis, cumulative learning and progressively increasing complexity, self-exploration of the world, social interaction, and cognitive architectures. In this chapter, we present these studies according to the classification we produced according to the Piagetian stages.

The end of each subsection contains a table that presents a summary of the works reported. In this summary, we describe the DevRobotics aspect treated in each work, the robot architecture used (sensors and actuators), the cognitive functions that were, directly or indirectly, presented, and the cognitive architecture where they are implemented.

4.1 Sensorimotor stage - 1st substage

The work performed by [8], uses the Memory-Based Cognitive Framework (MBCF) and its associated computational architecture EMA (Embodied MBCF Agent) to evaluate the performance of the agent, whose objective was to explore the environment, as much as possible, within 500 time-steps. Experiments were performed with the benchmark random walker and three types of EMA configurations, which in computational aspects are identical but undergoing changes in morphological (sensory and motor) aspects. The results obtained by the EMA were higher than those of the random walker regarding area covered, but for distance traveled were more equivocal (due to the small size of the motor space used). The work demonstrates the dependence of the development of behavior on physical embodiment and that sensory-motor capabilities can form the basis for higher-order cognitive functions.

The ability to represent and perceiving the body of the self is one of the most interesting issues in cognitive robotics since it is essential to enable the development of higher cognitive abilities. Given the importance of learning this representation, [93] studied the body scheme acquisition by cross model map learning among tactile, visual, and proprioceptive (joints) spaces. In their experiments, they use the upper body of a robot that touches itself. The cross-modal map is learned by Hebbian rule, which activates the similarity units simultaneously in the experience.

A humanoid robot called iCub [57][56] was designed to test the embodied cognition hypothesis: that human-like manipulation plays a vital role in the development of human cognition. It has perceptual and motor systems of a small child that enables the interaction with the world in the same way a child does. Using the iCub simulator, the research made by [27] explores Reinforcement Learning (RL) while studying the autonomous development of robot controllers to perform complex actions in complex scenarios through learning. To test the methods from its own proprioceptive experience and guided with internal perception-based reward signals and external ones, the complicated tasks for the iCub utilized are: hit the ball and throw a cube in the target. The results demonstrate an RL algorithm's ability to act and learn in complex, highly stochastic environments to control a significant number of Degrees of Freedom (DoF), without any previous knowledge. The authors conclude that perception-based reward signals that utilize embodiment features can perform better than external ones.

Table 4.1 presents the summary of the works in this stage.

Work	**DevRobotics Aspect**	**Cognitive functions**	**Sensorial modality/ physical architecture**	**Goal**	**Cognitive Architecture**
[8]	Learn by interaction	Sensorial Memory/Motor Memory	ultrasonic sensors with multiple arrangements wheeled robot	To explore the interplay between development and embodiment.	Memory-Based Cognitive Framework - MBCF
[93]	Learning by interaction	Sensorial Memory /Perceptual Memory /Associative Memory	The upper body of a robot with a pair of stereo cameras, touch sensors on its body surfaces including the end-effectors of its arms	Learn to represent own body scheme by touching itself	Defined by the authors (similarity units)
[27]	Learn by interaction (Reinforcement Learning)	Sensorial and Motor Memory/Reward Module	A child-like humanoid (iCub) robot 1,05m tall, with 53 degrees of freedom distributed in the head, arms, hands, and legs are used. A camera is positioned in the robot.	The robot must learn a policy for controlling four Degrees of Freedom (DoF) of the robot's right arm to hit a ball positioned in a specific and permanent place on a table, with the minimum number of joint movements. It also should learn how to throw the cube in the target	YARP (Yet Another Robotics Protocol)

Table 4.1: Comparison among works related to Sensorimotor stage - 1st substage in DevRobotics in the literature.

4.2 Sensorimotor stage - 2nd substage

The study performed by [71] used the iCub simulator to test if the interaction with the world along with experience limited by constraints imposed by the physical characteristics of the arm (two and then four degrees of freedom), can help the learning process if this is segmented. The authors cite the property of overcompleteness existing in limbs of natural systems (such as humans), which turns the problem of controlling a limb more complex in computational terms. However, it also can represent an advantage in terms of finding solutions that allow executing more than one action at the same time (like reaching a target at the same time that an obstacle is avoided).

In [75], the problem involving grasp stability was studied. Using a humanoid robot ARMAR-IIIb and Support Vector Machine (SVM) to classify the grasp as either stable or unstable, the robot learned to grasp stability from labeled data. Also, the authors extended the SVM based grasp stability classifier with the use of filters to classify the whole grasp sequence instead of just the end of the grasp sequence, which allows faster decisions for stable grasps.

Ogino et al. [53] propose a model for a robot to acquire new communication based on the reward prediction. The system keeps the sensor data in short term memory and puts into the long term memory when the value of the internal state corresponding to the emotion is increased. Once the memory is formulated, the sensor data is compared with it, and the robot expects the regular response of the caregiver. With this model, the robot acquires early communication. The experiments were realized with and without memory.

Table 4.2 presents the summary of the works in this stage.

Work	**DevRobotics Aspect**	**Cognitive functions**	**Sensorial modality/ physical architecture**	**Goal**	**Cognitive Architecture**
[71]	Learning by interaction	None explicit in the architecture	Simulated iCub with camera and head (tilt and pan joints positions)	Reach a red ball by progressively unlocking DOFs	not defined
[75]	learning by interaction	None explicit in the architecture	Joint encoders and pressure sensors in ARMAR-IIIb's right hand	Learn coupling between auditory perception and motor production to imitate speech sounds	not defined
[53]	Attention and Learning by interaction (human and reward)	Long and Short term Memories/ Reward prediction module/ Internal state/ Emotion	Computer simulation (robot modeled as the computer graphics using OpenGL) with camera and microphone	Acquire the early communication	defined by the authors

Table 4.2: Comparison among works related to Sensorimotor stage - 2nd substage in DevRobotics in the literature.

4.3 Sensorimotor stage - 3rd substage

In [60], several experiments were conducted to illustrate the capability of the system using Bayesian networks integrated within a general developmental architecture to discover affordances associated with manipulation actions (grasp, tap, and touch), applied to objects with different properties (color, size, shape). Also, the robot recognizes actions performed by a human, and play simple interaction games (the robot observes a human performing an action on an object. Then, it is presented another object and the robot has to perform a compatible action). The approach was able to deal with uncertainty, redundancy, and irrelevant information since it detects the features that matter for each affordance and allows social interaction by learning from others.

The study reported in [92] developed a computational model that learns a coupling between motor parameters and their sensory consequences in vocal production during a babbling phase. They conducted experiments to explore how the sensorimotor coupling alters perception and production during a babbling period and how the presence of sounds that are not produced by the model itself shapes its perceptual and model properties. The study was based on the evidence that the coupling between auditory perception and motor production forms the basis for the imitation of speech sounds in infants.

Involving the speech aspect, [85] using the iCub simulator showed that it could acquire behavioral, cognitive, and linguistic skills through individual and social learning. They realized experiments involving reaching (with neural network configured as a feed-forward controller), grasping (with a neural controller configured as a Jordan neural network). They focused on object manipulation capabilities, where refined motor control is integrated with speech understanding (with the Sphinx-3 system, which is a hidden Markov model-based speech recognition system). The output of speech was: idle, reach, grasp, and drop. As a result, the robot could learn to handle and manipulate objects autonomously, to understand basic instructions, and to adapt its abilities to changes in internal and environmental conditions.

Table 4.3 presents the summary of the works in this stage.

Work	**DevRobotics Aspect**	**Cognitive functions**	**Sensorial modality/ physical architecture**	**Goal**	**Cognitive Architecture**
[60]	Affordance, Learning by interaction (environment) and Imitation	Sensorial Memory/Motor Memory/Perceptual Memory/Behavior Selection/Action Selection/ Long-term memory (no distinction of models)/ Planning/ Visual recognition	The humanoid robot Baltazar with camera	Learn affordance by interaction with the world and human actions imitation	developmental architecture
[92]	Learning by interaction and Imitation	None explicit in the architecture	Hearing sensor	Learn coupling between auditory perception and motor production to imitate speech sounds	Defined by the authors (neural receptive fields, Hebbian connections)
[85]	learning by interaction (environment and human)	Long and Short term Memories/ Sensorial Memory /Procedural Memory /Perceptual Memory/ Motor Memory /Action selection	Simulated iCub with vision, touch, audition, and proprioceptive sensorial	Learn to handle and manipulate objects, and to understand basic instructions	defined by the authors using YARP support
[53]	Attention and Learning by interaction (human and reward)	Long and Short term Memories/ Reward prediction module/ Internal state/ Emotion	Computer simulation (robot modeled as the computer graphics using OpenGL) with camera and microphone	Acquire the early communication	defined by the authors

Table 4.3: Comparison among works related to Sensorimotor stage - 3rd substage in DevRobotics in the literature.

4.4 Sensorimotor stage - 4th substage

In the studies [11] and [12], the authors described an approach using a cognitive architecture called Multilevel Darwinist Brain (MDB). It permits an automatic acquisition of knowledge (models) in a real robot through the interaction with its environment so that it can autonomously adapt its behavior to achieve its design objectives. The structure of MDB has two different time scales: reactive, which is devoted to the execution of the actions in the environment, and deliberative, which deals with learning of the models and behaviors. The most relevant information in MDB is the action-perception pair because all the learning processes (short and long-term memory are required) depend on it. Also, in these papers, the authors study the relationship between short-term memory and long-term memory. The main difference between the MDB to other cognitive architectures for real robots is that MDB agents acquire knowledge through evolutionary techniques.

Hart and Grupen [42] utilized an approach that is consistent with Piaget's processes of assimilation and accommodation [67], governed by the robot's intrinsic drive for affordance discovery. They propose a framework in which the robot is intrinsically motivated to control interactions with the environment, providing a mechanism to guide both autonomous skill development and the acquisition of knowledge about the world. They examined three phases of learning in which the proposed intrinsic reward function can build knowledge: skill acquisition, skill generalization, and world modeling. They demonstrated how a fixed intrinsic reward function could guide a robot to acquire generalizable control programs (called schema) that it can then use to model the conditions in which these schemas apply intelligently.

Macura et al. [51] used the iCub simulator to train a robot to use objects using different manipulation modalities (e.g., precision grip (for small objects) vs. power grip (for big objects)), and to be able to replicate psychological experiments where the objects can be categorized using different grips (e.g., precision grip for artifacts (big and small cubes) and power grip for natural objects (big and small balls)). The results showed that the reaction times for larger objects were faster than for smaller objects. This indicates that the robot was able to generalize a grasping sequence for each task and object, hence learning to appropriately grasp and categorize objects based on their shapes and sizes. Table 4.4 presents the summary of the works in this stage.

4.5 Sensorimotor stage - 5th substage

By focusing on the first twelve months of a human infant, the study described in [44] reproduced on humanoid or anthropomorphic robot systems the following behavioral competencies: active vision, visual attention, hand-eye coordination, and simple object manipulation (reaching and grasping). The experiments validated the approach towards the integration of reaching, grasping, and active vision, demonstrating how the object features determine visual search, besides how visual and non-visual object features define the system's attention concerning fixation patterns. They also noted that gaze space mapping could only be learned after the eye-saccade mapping is correctly learned, like in infants, who first establish eye-saccades and much later start to master hand-eye coordination.

Work	DevRobotics Aspect	Cognitive functions	Sensorial modality/ physical architecture	Goal	Cognitive Architecture
[11]	Learn by interaction (environment)	Sensorial Memory/Motor Memory/Perceptual Memory/Behavior Selection/Action Selection/Satisfaction Model/ Long-term memory (no distinction of models)	AIBO robot. In this example, we are using the camera data, and the head angle as sensorial information and a predefined gait for the actions the robot can execute, in this case, just moving.	Learn the basic behavior of catching its pink ball	Multilevel Darwinist brain (MDB)
[42]	Affordance and Learning by interaction (environment)	Perceptual Entities/Motor Variables/Intrinsic reward function/ Declarative and Procedural memories	Dexter robot have a two degree of freedom pan/tilt head equipped with two Sony color cameras and two 7-DOF whole-arm manipulators. Each WAM is equipped with a 3-finger Barrett Hand with an F/T load cell on each fingertip. Each hand has four degrees of freedom(one for each finger and one for the spread angle between two of these fingers).	To perform skill acquisition, skill generalization, and world modeling	not defined
[51]	Affordance and Learning by interaction	Sensorial Memory/Motor Memory/Perceptual Memory /Visual Memory /Procedural Memory /Action Selection /Long-term memory (no distinction of models)	Simulated iCub with camera and proprioceptive (arm, hand)	To learn different manipulation modalities and categorise objects	Combination of the epigenetic robotics methodologies with the embodied connectionist
[12]	Learn by demonstration	Sensorial Memory/Motor Memory/Perceptual Memory/Behavior Selection/Action Selection/Satisfaction Model/ Long-term memory (no distinction of models)	Pioneer 2 wheeled robot (has a sonar sensor array around its body and a laptop placed on its top platform. The laptop provides two more sensors, a microphone and the numerical keyboard) and Sony's AIBO (digital camera, the microphones and the speaker)	To build an autonomous robot with real time learning capabilities and the capability for continuously adapting to changing circumstances in its world, both internal and external, with minimal intervention of the designer	Multilevel Darwinist brain (MDB)
	Learn by interaction (environment)		Hermes II hexapod robot has six legs with two degrees of freedom (swing and lift), six infrared sensors, each one placed on top of each leg, two whiskers, inclinometers and six force sensors.		
[27]	Learn by interaction (Reinforcement Learning)	Sensorial and Motor Memory/Reward Module	A child-like humanoid (iCub) robot 1,05m tall, with 53 degrees of freedom distributed in the head, arms, hands, and legs are used. A camera is positioned in the robot.	The robot must learn a policy for controlling four DoF of the robot's right arm to hit a ball positioned in a permanent place on a table, with the minimum number of joint movements. It also should learn how to throw the cube in the target	YARP (Yet Another Robotics Protocol)

Table 4.4: Comparison among works related to Sensorimotor stage - 4th substage in DevRobotics in the literature.

In [72], the authors demonstrated that a robot could first acquire knowledge by sensing and self-exploring its surrounding environment by interacting with available objects and building up an affordance representation (associates verbal descriptions to the physical interactions) of the interactions and their outcomes. After, the robot is capable of generalizing its acquired knowledge when it observes (gesture recognition) another agent (human person) performing the same motor actions (grasp, tap, and touch the objects on a table) previously executed during training.

Mar et al. [52], aiming at allowing a robot to autonomously discover the set of distinct affordances that a group of tools provides, condcuted a study using iCub and its simulator. The study takes into account both how tools are grasped, and how actions are performed, enabling the robot to predict which will be the affordance of a grasped tool based on the tool's functional features. They used seven different tools for the experiments on the simulator and 4 for those on the real robot, and each tool has the end-effector oriented in three different ways: to the front, to the right and the left.

Table 4.5 presents the summary of the works in this stage.

4.6 Sensorimotor stage - 6th substage

In [45], the authors proposed a dynamic deep neural network model called Visuo-Motor Deep Dynamic Neural Network (VMDNN) that consists of three types of subnetworks (one for processing dynamic visual images, one for controlling the robot's action and attention and another to dynamically integrates them). In this study, the robot was trained to recognize human gestures and to grasp the target object (tall object and a long object placed with five different orientations at ten positions symmetrically distributed on the XY-plane of the task space) indicated by the gestures. This task thus required a set of cognitive skills such as visual perception, intention reading, working memory, action preparation, execution, and attention. In the learning stage, the robot learned a task in the supervised end-to-end manner, while in the testing stage, it was examined the model's learning and generalization capabilities. Furthermore, the robot was examined under a visual occlusion experimental paradigm to verify whether the proposed model was equipped with a sort of memory capability for maintaining task-related information.

Using the upper body of a small-sized humanoid robot, [62] addresses how the body schema changes as a result of tool use-dependent experience. The model implemented enables a robot to reach and touch a target with a tool as the tool is the robot's hand. Knowledge about the tool is a priori unavailable, and the robot autonomously incorporates the tool and learns to use it. As a result of this study, the robot was able to judge whether the target is reachable by the hand or by the stick.

Infants are suggested to acquire joint attention by 18 months of age, which means that they develop their perceptual, motor, and memory functions as they learn to achieve joint attention [63]. In this study, the authors propose a developmental learning model by which a robot develops its visual function as it learns to gain joint attention based on an adaptive evaluation by a human caregiver. The task changes in difficulty, from easy to difficult, by reducing the tolerance against the robot's output error according to

Work	DevRobotics Aspect	Cognitive functions	Sensorial modality/ physical architecture	Goal	Cognitive Architecture
[44]	Attention	Spatial memory/ Visual memory/ Action Selection/ Feature Space / Sensorial and Motor Memory	Active vision, visual attention, hand-eye coordination, and simple object manipulation (reaching and grasping)	To learn hand-eye coordination and the cognitive competence of multimodal visual attention	Defined by the authors
[72]	Learning by interaction (environment and humans), Language and Affordances	Sensorial Memory/Motor Memory/Perceptual Memory /Visual Memory /Procedural Memory / Episodic Memory /Action Selection /Long-term memory (no distinction of models)	iCub with camera and depth sensor	Combine knowledge acquired from interacting with elements of the environment with the observation of another agent's actions	Bayesian Network and Hidden Markov Models
[52]	Affordance	None explicit in the architecture	iCub with force-torque, joint angle, and inertial sensors, binocular vision	Select, given a tool, the best action to achieve a desired effect	YARP, SVM, Kmeans
[12]	Learn by demonstration	Sensorial Memory/Motor Memory/Perceptual Memory/Behavior Selection/Action Selection/Satisfaction Model/ Long-term memory (no distinction of models)	Pioneer 2 wheeled robot (has a sonar sensor array around its body and a laptop placed on its top platform. The laptop provides two more sensors, a microphone and the numerical keyboard) and Sony's AIBO (digital camera, the microphones and the speaker)	To build an autonomous robot with real time learning capabilities and the capability for continuously adapting to changing circumstances in its world, both internal and external, with minimal intervention of the designer	Multilevel Darwinist brain (MDB)
	Learn by interaction (environment)		Hermes II hexapod robot has six legs with two degrees of freedom (swing and lift), six infrared sensors, each one placed on top of each leg, two whiskers, inclinometers and six force sensors.		

Table 4.5: Comparison among works related to Sensorimotor stage - 5th substage in DevRobotics in the literature.

improvements in the robot's performance. This adaptive evaluation accelerated the speed of learning, and, as in infants, the experiments showed that visual development helped the robot to learn to establish joint attention first horizontally and then vertically.

Table 4.6 presents the summary of the works in this stage.

4.7 Preoperational stage

In [10], the agent's behavior is controlled by a continuous-time recurrent neural network (CTRNN). Its task is to catch circular objects while avoiding diamond-shaped ones. The analysis of the work indicates that only when there are embodiment and situatedness within the environment in which the CTRNN evolved, the distinction about the difference

Work	DevRobotics Aspect	Cognitive functions	Sensorial modality/ physical architecture	Goal	Cognitive Architecture
[62]	Learning by interaction (inverse kinematics)	Sensorial Memory/Motor Memory/Perceptual Memory/ Planning/ Associative Memory	The upper body of a small-sized humanoid robot with one camera (color CCD) and two touch sensors (located in its hand)	Learn to reach the target using the hand or a tool as an extension arm	not defined
[63]	Attention and Learning by interaction (human)	Sensorial Memory /Perceptual Memory/ Motor Memory / Attention /Action perception	Physical robot with camera	Learn joint attention	not defined

Table 4.6: Comparison among works related to Sensorimotor stage - 6th substage in DevRobotics in the literature.

between circles and diamonds arises. It occurs through the interaction of the subsystems (environment, body, and nervous system). As a result of the study, the authors show that sensory inputs can influence the agent's behavior. Still, they do not place it in a state that corresponds solely to a given stimulus, since dynamic agents follow a path specified by their current state and by their dynamics. As the behavioral consequences of a given sensory input may differ significantly depending on the agent's internal state when it occurs, continuous neural activity sets a context for perceptual processing.

Vernon et al. [89] identified ten desiderata to endow a cognitive architecture with a capacity for development that is driven by both exploratory and social motives, as espoused by Piaget. The desiderata are value systems and motivations, physical embodiment, sensorimotor contingencies, perception, attention, perspective action, declarative and procedural memory, multiple modes of learning, internal simulation, and constitutive autonomy.

Table 4.7 presents the summary of the works in this stage.

Work	DevRobotics Aspect	Cognitive functions	Sensorial modality/ physical architecture	Goal	Cognitive Architecture
[61]	Learning by interaction (environment and humans), Language and Affordances	Sensorial Memory/Motor Memory/Perceptual Memory/Episodic Memory/ Goals/ Planning/Perception/Action Selection/ Behaviors/Needs	iCub with a camera, speakers and body DOFs	To solve the Symbol Grounding Problem, i.e., how a cognitive agent forms an internal and unified representation of an external world referent from the continuous flow of low-level sensorimotor data generated by its interaction with the environment.	DAC-h3
[87]	learning by interaction (environment and humans) and Language	Not explicit in the architecture	iCub with a camera, speakers and body DOFs	To assess the robot capacity to choose the single novel object using a novel label and to evaluate the implications of having more competitor objects in retaining labels.	Epigenetic Robotics Architecture (ERA)

Table 4.7: Comparison among works related to Preoperational stage in DevRobotics in the literature.

4.8 Summary

From the works presented in this chapter, it is possible to notice that, although there are plenty of Cognitive Architectures in the literature and that DevRobotics is a rising topic inspired by Piaget's theory, there is no universal protocol to either conduct or to evaluate the acquisition of cognitive abilities by robots. It is in this context that we conducted this research.

Chapter 5

Proposed Sensorimotor Experiments

As presented in Chapters 2 and 4, experiments in cognitive architectures in the field of DevRobotics are heavily based on child development. Still, one of the common points in these experiments is the lack of standardization of the evaluation. So, this work aimed to contribute to the development of a set of experiments, defining them clearly and identifying evaluation criteria that can be used in equivalents to the robotics scenario, according to the Piaget stages.

After careful review of the literature [14, 65, 40, 17], inspired by the activities proposed in [36] to evaluate the cognitive development of children based on Piagetian experiences and the experiments realized by Piaget with babies described in [67] and considering scenarios that we could mimic with robots [27, 44, 42, 12, 11, 8, 45, 51, 72, 71, 52, 60, 62, 92, 75, 53, 85, 63, 17], we organized the experiments according to following abilities:

- **Track objects:** experiments related to the ability of learning how to track objects in a scene (Table 5.1). As the goal is for the robot to learn to track objects, it must have visual information. Considering the development of the child's visual acuity, activities in this category involve objects positioned at different distances from the robot but which are visible according to the visual acuity presented by the baby at the specified age (Sensorimotor substage). Along the substages, the distances become longer, and the visual acuity improves. Besides, we also use the development of the child's ability to turn his head to follow objects that are entering and leaving the field of view by varying the speed at which these objects move (consequently, increasing the level of difficulty). Finally, we created initial experiments involving the learning of depth and distance, that will be dominated only from the 4th or 5th substage, which correspond to the period in which the child develops binocular vision.

- **Search for touch and sound source:** experiments related to the ability to search for multimodal event sources in a scene (Table 5.2). Given that touch and hearing are developed rapidly during the first months of the child, we do not use the progressive improvement of the sensors for these experiments. Through the experiments proposed in this category, the robot learns its body scheme incrementally, starting from reflex movements to circular reactions when touched on different parts of its body. The robot learns to incrementally coordinate vision and hearing through sounds emitted from different places in the environment.

- **Handle objects (Affordance):** experiments related to the ability of learning how to handle objects and to identify affordances (Tables 5.3 and 5.4). In this category, the robot learns incrementally how to manipulate objects. The experiments start with the robot learning to hold an object placed in your hand through the reflex movement of closing the hand when touched and will evolve throughout the stages. Following the child's motor development, the objects must initially be of moderate size and light, considering that the child does not yet have the movement to close his hands well developed and does not have the strength to hold heavy objects. These factors are developed over the experiments by modifying the sizes of the objects involved. There is also the first stage of coordination of vision and other parts of the body, which then develops the coordination of vision and hand to bring objects within the visual field. Initially, the objects are placed close to the robot, because the objective is that it learns first to pick up the objects. Still, then the objects are placed with greater distances to promote the learning of the use of auxiliary tools to reach the desired object and later develop the coordination of vision, locomotion, and catching schemes to reach this object. Also, the ability to pick up occluded objects, combine objects with building new ones, correctly fitting them, and changing hands during object manipulation is also developed.

- **Inter-modal perception:** experiments related to learning inter-modal perception (Table 5.5). Intermodal perception corresponds to the formation of a single perception of a stimulus based on information from two or more senses. Although it is possible in the first month, it becomes common only in the 6th month. In our experiments, we developed activities considering the skills developed during the third sub-stage (4 to 8 months), as it is the moment when the skill is most common. The activities aim to develop intermodal perception involving sensory information of vision-touch and vision-hearing (relate sound rhythms to movements).

- **Concept of Object Permanence:** experiments related to the process of learning the concept of object permanence (Table 5.6). Given that the Concept of Object Permanence starts developing in the third substage, our experiments also begin in that period. As described in Chapter 2, in the 3rd substage, the child does not yet have the concept of the object's permanence, so when the object is not within its visual field, it ceases to exist for the child. From the 4th substage, we start the displacement and occlusion of objects within the agent's visual field. Concerning occlusion, the child can find the object, which demonstrates that the concept of permanent object is beginning to be established, but not 100% given that at this stage, the child is not yet able to follow the displacements of that object, which is achieved in 5th substage. Finally, in the 6th substage, the child can search for objects that have been moved out of his field of vision, which demonstrates that the concept of a permanent object has been completely acquired. In this category, it is essential to note that the size and position of the object must be possible to be manipulated and seen by the child considering its motor development and vision. Otherwise, if the child does not see the object, he/she will not be able to store it in his memory and, consequently, develop the concept of Object Permanence. These details are listed in the *Comments* column.

- **Perceptual constancy:** experiments related to the ability of learning perceptual constancy of form and greatness (Tables 5.7 and 5.8). Perceptual constancy is the tendency to perceive objects as unchanged, despite sensory differences and must be acquired by the child to make sense of the physical world around him. Once we have formed a stable perception of the object, we will recognize it from almost any angle. Constants develop from the first five weeks and are fully developed at approximately four years of age. In our experiments, we elaborate activities from the 3rd substage, as it is the period in which the child begins to develop the concept of object permanence that we have seen to be essential for the development of perceptual constancy. There are several classifications of constancy, but in this work, we created experiments involving only the constancy of form and greatness.

  Constancy of greatness is responsible for recognizing that an object remains the same or has the same dimension despite the retinal image becoming larger as the object is closer. When you watch a person walk away, the projection of the person on your retina decreases, although it did not decrease in size, we know that it moved away.

  Constancy of form is responsible for recognizing the shape of known objects (regardless of variations in their orientation, position, size, colors, texture) despite the constantly changing shape of the retinal image. Example: when we open the door at 45° and later at 90°, we know that it remains rectangular even when viewed from different angles.

We encompass all experiments in the sensorimotor stage, but not all of them make sense for each sub-stage. Hence, they are described incrementally whenever suitable for a sub-stage or a sequence of sub-stages. In the beforementioned experiments, we define which sensors we require for each test and what we expect as an outcome. We also considered the Bayley Child Development Scales [9]: the best known and most widely used child intelligence test that mainly evaluate sensory and motor skills.

The *Sub-stage* column contains the sensorimotor substage that comprises the activity described in the *Activity* column. In the *Expected result* column we show the expected result of each activity taking into account the development of sensory capabilities, psychosocial development, the increase in complexity incrementally, the Circular Reactions and skills developed in the specific Sensorimotor substage that comprises this activity, as seen in detail in the Chapter 2. The *Comments* column contains specific details for each activity described considering the development of sensory capabilities, motor development, and skills developed by babies referring to the corresponding substage. Finally, in *Sensors* column are the sensors that capture the data needed to carry out the activity. It is important to note that it is not necessary to use the described sensor specifically, being able to be exchanged for some other sensor that allows the extraction of equivalent data.

Due to the complexity of the experiments already defined and the fact that they related to the early stages of child development, at this point, we decided not to consider language formation.

Following this structure, André Barros de Medeiros (student of scientific initiation supervised by Profa. Dra. Paula Dornhofer Paro Costa) designed the experiments involving expression of emotion. Those experiments are organized according to:

- **Indirect Learning**: Learning through the actions and expressions of others (Table 5.9).

- **Inherent and Non-Inherent Fears and their Modification throughout Time**: Modification of knowledge through emotional interaction (Table 5.10).

- **Object Modification as to Avoid Pain/Fear**: using new information to avoid/prevent unwanted emotions (Table 5.11).

5.1 Methodology to conduct the experiments

To carry out these proposed experiments, we created a methodology (Figure 5.1) composed of 6 steps:

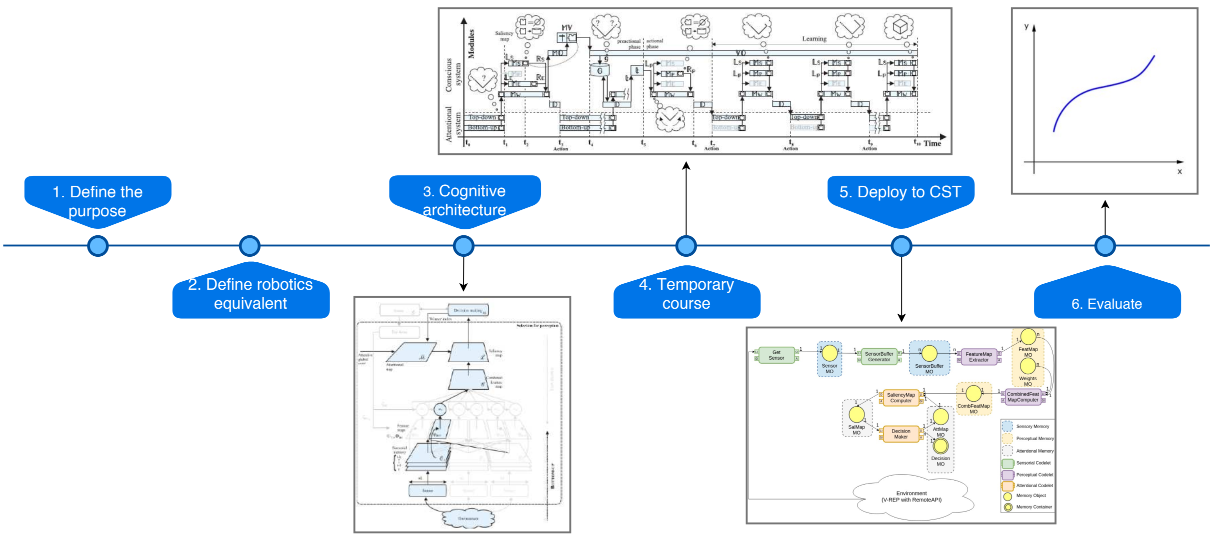


Figure 5.1: Sequence of activities necessary for the development of each experiment

1. *Define the purpose of the experiment*: Define what we want to analyze and evaluate in each experiment, i.e., its basic proposition, the classification of the experiment, and the correspondent activity on the proposed sensorimotor experiments described above.

2. *Define robotics equivalent*: Identity in which sensors and actuators are needed according to the sensors indicated on the activity description of the table chosen above.

3. *Cognitive architecture*: Identity which sub-set of modules of CONAIM are involved in each experiment. Particularly, Piaget's theory of cognitive development and related literature must be guides for the selection of modules and the specifications of these modules.

   Example: Figure 5.2 shows the components of CONAIM that are active during the experiment conducted in [21] to explore learning semantic information in CONAIM.

4. *Define the temporary course*: To determine the temporal course of interactions among the modules. An example is shown in Figure 5.3. It depicts the equivalent temporal attentional and conscious courses to the experiment presented in Figure 5.2.

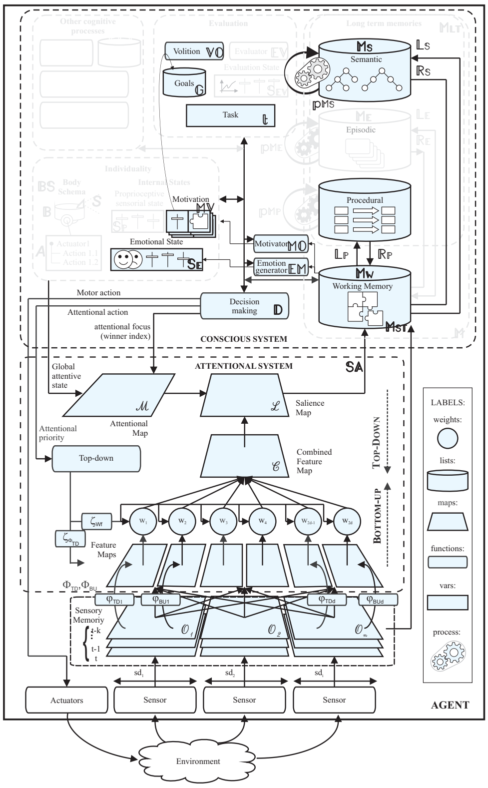


Figure 5.2: Model elements active while learning semantic information in CONAIM.

5. *Deploy to CST*: It consists of developing the code (codelets and Memory Objects (MO's)) referring to the CONAIM modules in the CST.

   Example: Figure 5.4 illustrates the CONAIM bottom-up attentional module implemented in the CST. It shows the MO's and codelets required for the system to receive the sensor data, construct the feature maps, the combined feature map, and the salience map. Finally (through the Winner Takes All approach) choose the region to which to direct attention.

6. *Evaluate*: This step is divided in 3 sub-tasks:

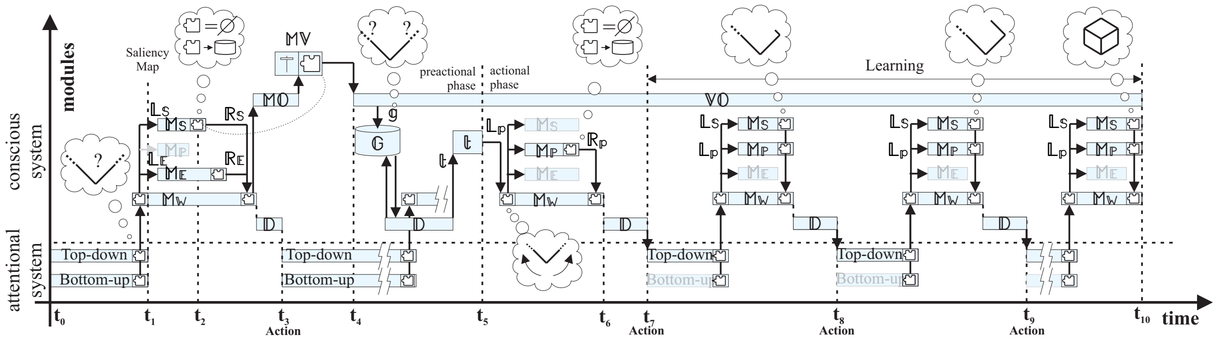


Figure 5.3: CONAIM system dynamics for the experiment of learning semantic information while interacting with the environment.

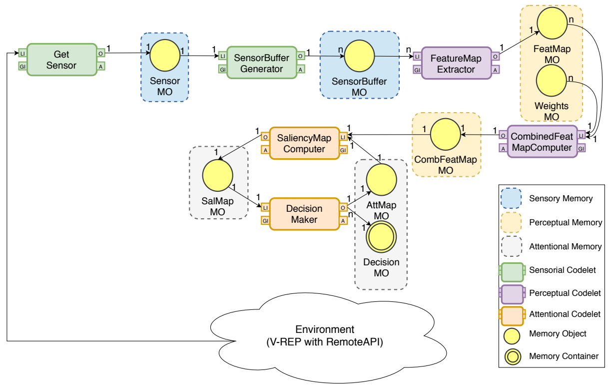


Figure 5.4: The bottom-up attentional elements of CONAIM implementation over the CST architecture.

- *Define evaluation criteria*: Identify the metrics that will evaluate each experiment, i.e., the scenario overcoming criteria using the column 'Expected result' on the table of abilities chosen previously.
- *Implement the experiments*: It consists of carrying out the tests of the implementation in a simulated or real environment.
- *Perform the tests and evaluate results*: Refers to performing the tests that will allow us to analyze what was proposed and to evaluate the results according to the criteria defined.

5.2 Summary

In this chapter, we presented the proposed sensorimotor experiments classified according to the development of abilities, as well as a methodology for the design of each experiment.

After studying human development, we observed that salience seems to be very important at the beginning of the learning process, guiding children's early stages. With that in mind, we aimed to evaluate through experiments if a robot could be guided only by the salience and how this process would adjust its behavior. Therefore, a computational framework that supports the attentional model is needed, so we created the CONAIM model (which adopts saliency-based attention) in the CST framework.

Track objects				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
1	Position robot in front of an object at 25 cm	Staring at the object	Object within the visual field, in a fixed position, and of primary color. Visual acuity: 20/400. Small FOV.	Vision
1	Position robot in front of an object at 25 cm	Track object with the look	Object within the visual field, moving slowly and primary color. Visual acuity: 20/400. Small FOV.	Vision
1	Position robot in front of an object at 25 cm	Do not follow the object with the look	Object within the visual field, moving quickly and of primary color. Visual acuity: 20/400. Small FOV.	Vision
2	Position robot in front of an object at 80 cm	Track object with the look	Object within the visual field, moving at medium speed and primary color. Visual acuity: 20/100. Increase FOV.	Vision
2	Position robot next to an object at 60 cm	Does not look at the object	Object outside the visual field, in a fixed position and of primary color. Visual acuity: 20/100. Increase FOV.	Vision
2	Position robot next to an object at 60 cm	Accompany object while looking within visual field	Object entering the visual field, moving in medium speed and primary color. Visual acuity: 20/100. Increase FOV.	Vision
2	Position robot next to an object at 60 cm	Accompany object while looking within visual field	Object exiting the visual field, moving at medium speed and primary color. Visual acuity: 20/100. Increase FOV.	Vision
3	Position robot in front of an object at 1.5m	Track object with the look	Object within the visual field, moving at medium speed and primary color. Visual acuity: 20/20. Increase FOV.	Vision
3	Position robot in front of an object at 1.5m	Accompany object with the look (turns the head to continue accompanying the object)	Object coming out of the visual field, moving at medium speed and primary color. Visual acuity: 20/20. Increase FOV.	Vision
3	Position the robot in front of two equal objects, but with different distances	Note that the object that looks smaller is further away than the one that looks larger	The objects must be in fixed positions, one closer to the robot and the other another more distant. Must be equal in size.	Vision
3	Position the robot in front of two objects, one copper part of another	Observe that the object that is partially occluded is further than what is possible to see completely	The objects must be in fixed positions, being one in front of the other.	Vision
3	Position the robot in front of an object initially stopped at 1.5m	Note that the object is heading towards it and when it is close enough to the robot to try to defend itself or catch the object	The object must move towards the robot	Vision

Table 5.1: Experiments related to the ability to learn how to track objects in a scene

Search for touch and sound source				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
1	An external source touches the robot	Random moves	Touch the robot on several parts of the body and on both sides	Tact (pressure sensors)
1	An external source emits a beep near the robot	Do not identify the sound source	The sound source shall be emitted from different places	Hearing (microphone)
2	An external source touches the robot	The robot must learn to perform the action with the associated function of "look at the source" of the touch, but without intention	Touch the robot on several parts of the body and on both sides	Tact (pressure sensors)
2	An external source emits a beep near the robot	The robot must learn to perform the action with the associated function of "looking at the source" of the sound, but without intention. First there is the accommodation of the head towards the sound and then the coordination between sight and the ear	The sound source shall be emitted from different places	Hearing (microphone)
3	An external source touches the robot	The robot organizes the cognits to fulfill the goal of looking at the touch source	Touch the robot on several parts of the body and on both sides	Tact (pressure sensors)
3	An external source emits a beep near the robot	The robot organizes the cognits to fulfill the goal of looking at the sound source	The sound source shall be emitted from different places	Hearing (microphone)

Table 5.2: Experiments related to the ability of searching for multimodal event sources in a scene

Handle objects				
Sub-stage	Activity	Expected result	Comments	Sensors
1	An external source inserts an object (or a slight pressure) into the robot's palm	Close the hand	-	Tact (pressure sensors)
2	An external source inserts an object into the robot's hand	Grab and hold the object in hand without seeing it.	Gripping. Moderately sized object	Tact (pressure sensors)
2	An external source inserts an object into the robot's hand	Has difficulty grasping small objects	Gripping. Small size object	Tact (pressure sensors)
2	Position robot close to objects	Shaking any body, shaking fingers, hands or arms	Tactile and kinesthetic reactions	Tact (pressure sensors)
2	Observe the own actuators	Coordination between vision and the same general movements (look at hands and fingers)	-	Vision
3	An external source inserts an object into the robot's hand	Grab to look	Moderately sized object	Tact (pressure sensors) and vision
3	Position robot in front of an object at 30 cm	Catch the perceived objects (reach and catch)	Object of moderate size, within the visual field, and in a fixed position. The object and the hand must be perceived simultaneously	Vision
3	Position robot in front of an object at 70 cm	Grab the objects you see. Can rotate to explore object properties	Object of moderate size, within the visual field and in a fixed position. Coordination between vision and grasping	Vision
3	An external source inserts an object into the robot's hand	Hold (but do not catch)	Small size object	Tact (pressure sensors)
3	An external source offers a stick to the robot, with enough distance that it can pick up	Make most of the adjustment of hand to object after contact	Use as object a stick, within the visual field	Vision
3	Evaluate the ability to transfer objects between hands	Transfer objects from one hand to the other	Use an object of moderate size, which can be held with only one hand	Tact (pressure sensors) and vision
3	Position the robot in front of an object at 50 cm	Push the object, hit the object.	Use objects of any size that move easily to the touch (like a ball). Here the robot moves the object, but still does not understand the dynamics	Vision
3	Position the robot in front of two objects at 70 cm	Catch the new object (you can transfer the object you are holding to the other hand if the occupied object is closer to the new object)	Objects of moderate size, within the visual field. One of the objects may already be in the robot's hand, or he can pick both of them from the beginning	Vision

Table 5.3: Experiments related to the ability of learning how to handle objects - part 1

Handle objects				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
4	Position robot in front of an object at 30 cm	Catch object using tip prehension	Object of small size, within the visual field and in fixed position	Vision
4	Position robot in front of an object at 80 cm and then hide it under a cloth	Use grasp to remove the cloth and then pick up the object	Object of any size, within the visual field and in a fixed position; a cloth that can cover it completely	Vision
4	Position robot in front of the desired object at 1.5m and an auxiliary object next to the robot (∼10cm)	Use auxiliary object to achieve the desired object	Desired object: moderate size; auxiliary object: the size must be close to the distance between the robot and the desired object. Both objects must be within the visual field, in a fixed position and have different colors	Vision
4	Position robot in front of the object at 3 m	Walk to the object to get it (Scheme Coordination)	Object of any size, within the visual field, and in fixed position	Vision
4	An external source offers a stick to the robot, with enough distance that it can pick up	Rotate the hand to make adjustments before picking up the object	Use as object a stick, within the visual field	Vision
4	Position the robot in front of three objects at 70 cm	Pick up the new object using the storage strategy in which the robot empties one hand by placing the object on its side or on the lap to be able to pick up another object	Objects of moderate size, within the visual field. Two of the objects may already be in the robot's hand, or he can pick up the three from the beginning	Vision
5	Assess ability to identify affordance of stack	Assemble a tower with 2 cubes	Use 2 cubes of moderate size as objects, within the visual field, and in fixed position	Vision
5	Position robot in front of an empty container at 50 cm and with objects to the side.	Place objects in a large container and clear them	Small to moderate-sized objects and large and unopened container	Vision
6	Position robot close to objects	Stack the objects	Use 4-10 moderately sized cubes as objects	Vision
6	Position the robot facing objects	Fit the object correctly	Provide a box-fit with several shapes to fit	Vision
6	An external source offers a book in the horizontal position for the robot	Flip the object upright so it can pass through the grid	Use a lightweight book. A grid must separate the robot and the external source. The book must be smaller than the distance between the bars of the grid, so it is possible to pass it between them	Vision

Table 5.4: Experiments related to the ability of learning how to handle objects - part 2

Inter-modal perception				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
3	An external source places an object in the robot's hand	Recognition by touching only the object	Use an object that the robot has seen but never touched.	Tact (pressure sensors)
3	An external source displays two movies simultaneously for the robot. A speaker positioned between the movies performs a rhythmic sound that matches the rhythm of one of the videos	Prefers to watch the movie whose rhythm matches the sound	Uses two similar movies but at different speeds. In an experiment conducted by Elizabeth Spelke (1979) [79], she exhibited a movie showing a toy kangaroo jumping up and down and another showing a donkey jumping up and down, with one of the animals jumping faster. The rhythmic sound should match only one of the videos	Hearing (microphone) and vision
3	Show two movies side by side, each showing a train riding on rails. Through a loudspeaker, play engine sounds of various types	Look longer for the train's movie whose movement matched the pattern of engine sounds. This demonstrates that there is some understanding of the link between the sound pattern and the kinetic pattern	Originally performed by Jeffery Pickens (1994) [68]. For the sounds of the engine, he used a sound that was getting louder (appearing to be approaching) or lower and lower (appearing to be distancing itself)	Hearing (microphone) and vision

Table 5.5: Experiments related to the ability of learning inter-modal perception

Concept of Object Permanence				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
3	1st: Position the robot in front of an object and let manipulate it for a while. 2nd: An external source covers the object with a handkerchief	Withdraw the hand as if it had disappeared	Medium-sized object and handkerchief that can cover it in full	Vision
4	1st: Position the robot in front of an object and let manipulate it for a while. 2nd: An external source covers the object with a handkerchief	Raise the handkerchief in search of the object	Object of any size and handkerchief that manages to cover it completely	Vision
4	An external source picks up the object and, inside the robot's visual field, places it under the tissue A on its right, and then moves it to the tissue B on its left	Find the object in A, ignoring the offsets	Object of any size and wipes that can cover it in full	Vision
5	An external source picks up the object and, inside the robot's visual field, places it under the tissue A on its right, and then, it moves it to the tissue B on its left	Searches for the object in the function of its displacements. Looking at the last place you saw him hidden, however, you will not search in a place where you did not see him hidden	Object of any size and wipes that can cover it in full	Vision
6	An external source picks up the object and, out of the robot's visual field, places it under the handkerchief and then adds a pillow over the handkerchief	Lift the cushion, lift the handkerchief and find the object. The permanence of the object is fully conquered; he seeks an object even if he has not seen it hidden. Can master various combinations	Object of any size, handkerchief that can cover it completely and cushion that covers the scarf	Vision

Table 5.6: Experiments related to the process of learning the concept of object permanence

Perceptual constancy - Constancy of form				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
3	An external source delivers one object at a time to the robot	Do not position the received object in the appropriate model among those that are positioned in front of it	Position 4 objects with different shapes (triangle, circle, square and rectangle) in front of the robot, in a fixed position. These objects will be used as templates. The external source has more objects equal to the models, but also varying the color. Then, deliver these objects to the robot by changing the angle on objects that allow	Vision
4	An external source delivers one object at a time to the robot	Position the received object in the appropriate model from the ones that are positioned in front of it	Position 4 objects with different shapes (triangle, circle, square and rectangle) in front of the robot, in a fixed position. These objects will be used as templates. The external source has more objects equal to the models, but also varying the color. Then, deliver these objects to the robot by changing the angle on objects that allow	Vision

Table 5.7: Experiments related to the ability of learning perceptual constancy - Constancy of form

Perceptual constancy - Constancy of greatness				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
4	1st: An external source several times, places a familiar object for the robot inside the larger box so that he gets used to choosing the larger of the two boxes when looking for the object. 2nd: Replace the larger box with one that is smaller than the small one. 3rd: Place the object under the larger box between the two and check which of the two the robot chooses	It is confusing and often errs when choosing	The boxes should be similar, but of different sizes. Staying at each stage of the experiment for a period that is sufficient for the robot to adapt and observe the changes	Vision
5	1st: An external source several times, places a familiar object for the robot inside the larger box so that he gets used to choosing the larger of the two boxes when looking for the object. 2nd: Replace the larger box with one that is smaller than the small one. 3rd: Place the object under the larger box between the two and check which of the two the robot chooses	Trained to choose the largest of two boxes, the robot continues to choose correctly, even if the larger box is moved away and this corresponds, then, to a smaller retinal image	The boxes should be similar, but of different sizes. Staying at each stage of the experiment for a period of time that is sufficient for the robot to adapt and observe the changes	Vision

Table 5.8: Experiments related to the ability of learning perceptual constancy - Constancy of greatness

Indirect Learning				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
2	Place two Robots together	Each one begins exploring the environment independently	Objects placed within reach, that either o nothing, cause a good reaction or cause a bad reaction.	Vision
2	Objects in environment affect the robots emotional state	Robot expresses the altered emotional state	Use LED or something of the sort to express the current emotional state	Vision
2	Emotional state expressed by the robot	Robot learns about the object the other was interacting with through the emotion that was expressed	This is possible since both robots are the same (analogy to being of the same "species"). So it is safe for one robot to assume that what affects the other will affect him in the same way (also possible because we are considering the primitive emotions: joy and fear/anger)	Vision

Table 5.9: Experiments related to the ability of indirect learning

Inherent and Non-Inherent Fears and their Modification throughout Time				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
2	Place two Robots together	Each one begins exploring the environment independently	Each robot has inherent fears (for example to a color or shape)	Vision
2	Objects in environment affect the robots emotional state and (or) inner state	Robot expresses the altered emotional state	Depending on the effect the object has, it can positively or negatively reinforce the inherent fear. Also, depending on the object, it can introduce (a) new fear(s)	Vision and Battery life
2	Emotional state expressed by the robot	Robot learns about the object the other was interacting with through the emotion that was expressed	This can cause positive or negative fear reinforcement (indirectly). Observations in the last line of Table 5.9 column *Comments* remain of importance	Vision
3	Continue exploring	Robots are less or more inclined to interact with different types of objects	This is due to the reinforcement (direct or indirect) which previously occured	Vision and Battery life

Table 5.10: Experiments related to the ability of inherent and non-inherent fears and their modification throughout time

Object Modification as to Avoid Pain/Fear				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
2	Place two Robots together	Each one begins exploring the environment independently	Each robot has inherent fears (for example to a color or shape)	Vision
2	Objects in environment affect the robots emotional state and (or) inner state	Robot expresses the altered emotional state	Depending on the effect the object has, it can positively or negatively reinforce the inherent fear. Also, depending on the object, it can introduce (a) new fear(s)	Vision and Battery life
2	Emotional state expressed by the robot	Robot learns about the object the other was interacting with through the emotion that was expressed	This can cause positive or negative fear reinforcement (indirectly). Observations in the last line of Table 5.9 column *Comments* remain of importance	Vision
3	Continue exploring	Robots are less or more inclined to interact with different types of objects	This is due to the reinforcement (direct or indirect) which previously occurred	Vision and Battery life
4	Continue exploring	Robots learn what characteristic identifies an object with negative effects	Maybe all objects of a certain color or a certain shape are "bad"	Vision and Battery life
5	Eliminating the Threat	The Robots at least avoid the "bad" objects, but if possible, eliminate the threat by either changing them as to not cause harm or eliminating them entirely		Vision

Table 5.11: Experiments related to the ability of object modification as to avoid pain/fear

Chapter 6

Attentional framework experiments

Although there are many modules of cognition implemented in CST [70][18][37], the attentional pathway that was considered an essential element for cognition, and that has been proposed by a recent work of our group [23, 22], needed some adjusts to fit this work (such as normalization of sensor readings and their combination for specific feature maps) purposes. Also, it required improvements related to the time interval used to calculate the inhibitory and excitatory periods, which was done throughout this work. In this chapter, we show the implementation, deployment, and validation of the attentional system of CONAIM in CST, modeling the components and the cycle of one architecture to another. The validation environment, the sensors we used, the features we chose, CST modeling, and results are detailed next.

6.1 CONAIM+CST Attentional System

In this work, we enhanced an initial implementation of the CONAIM attentional system in CST. Figure 6.1 presents the general diagram with components of the bottom-up attentional elements of CONAIM implementation over the CST architecture. Note that this diagram minimizes the multiplicity of relationships by assigning cardinalities of 1 or n to them.

In CONAIM, the attentional cycle starts when the sensors of the agent receive information from the environment. The sensor data is captured by the *Get Sensor* codelets and stored in the respective MO'S at each cycle, and a limited quantity of them is stored in Buffers forming the Sensory Memory [66]. The next step is the construction of *Feature Maps* through *Feature Map Extractors* (responsible for the process of object identification through features as shape, motion, color, etc [20]) that composes the Perceptual Codelets. Continuing the flow in CONAIM+CST, the next step is to compose the Combined Feature Map. This map is calculated by a weighted sum of the values in each Feature Map, considering the weights presented in WeigthMO. This Combined Map is multiplied (point to point multiplication) with the *Attentional Map* (which is initialized with unitary values, simulating an environment without winners) to compute the Saliency Map. Then, the DecisionMaking codelet updates: a) the Attentional Map values and define the winner of that timestamp using the Winner Takes All (WTA) approach (this procedure may be

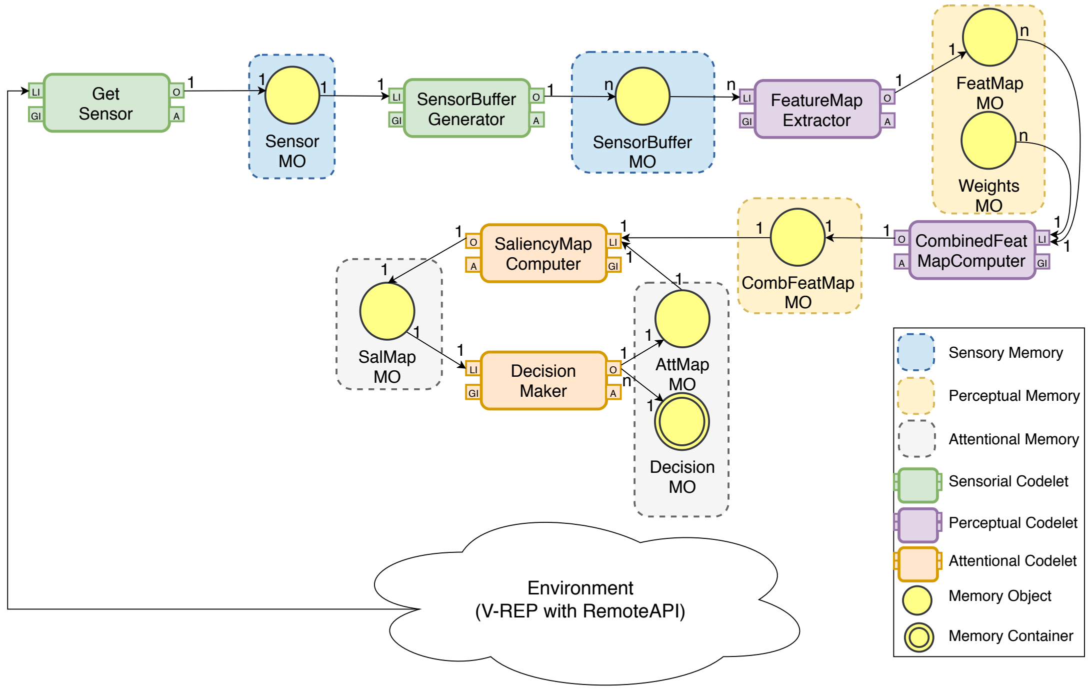


Figure 6.1: The bottom-up attentional elements of CONAIM implementation over the CST architecture.

extended by the user); b) the Saliency Map and c) the inhibitory and excitatory cycles of the Bottom-up model. This process comprises the Attentional codelets implemented.

It is important to remark that this diagram refers to the general representation in CST to any bottom-up pathway based on CONAIM and implemented in CST. In the next section, we will present an implementation of these new framework elements for the sake of our application.

6.1.1 Deploy to CST

After the modeling presented in the last section, three new classes were built and implemented within the new CST sensory package. These were SensorBuffer Codelet, FeatureMap Codelet, and CombinedFeatureMap Codelet. The UML diagram of these 3 classes can be seen in Figure 6.2.

When detailing the structure of these classes, it should be noted that they all inherit from *Codelet*, so they must all implement their abstract methods, the most important of which is *proc()*, which is Codelet's logical process. However, FeatureMap and CombinedFeatMap Codelets are also abstract. This is because semantically, it is much more robust to let each application choose and build its features on FeatureMap. Same for CombinedFeatMap, where there may be different types of data for which it is not possible to construct a generic concrete method.

For the SensorBuffer, on the other hand, a generic method for *deep copies* of the MOs related to the sensor data was implemented. These copies are made through existing serializer objects within the Java language. As the MemoryObject class already implements this interface, it is enough that the information stored inside an instantiated MO also

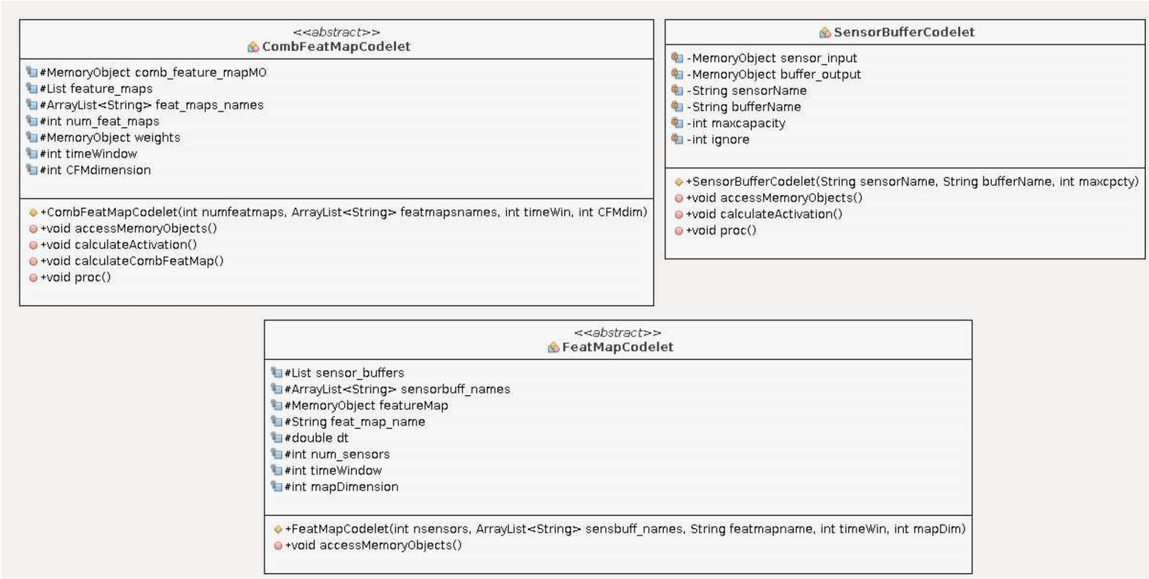


Figure 6.2: Diagram classes of Sensorial package

implements it.

From this, we implemented the attentional process (Figure 6.3) itself: Attentional Map generation, bottom-up Inhibition of Return (IOR) calculation, Salience Map calculation, and the election of winners, closing the cycle that influences the Attentional Map.

Functions that implement IOR are always based on negative exponentials as a function of time to generate a decay of attention. They are regulated by constant parameters, influencing the excitatory or inhibitory course of the agent's attention. More details on the modeling of IOR in CONAIM can be found in [21].

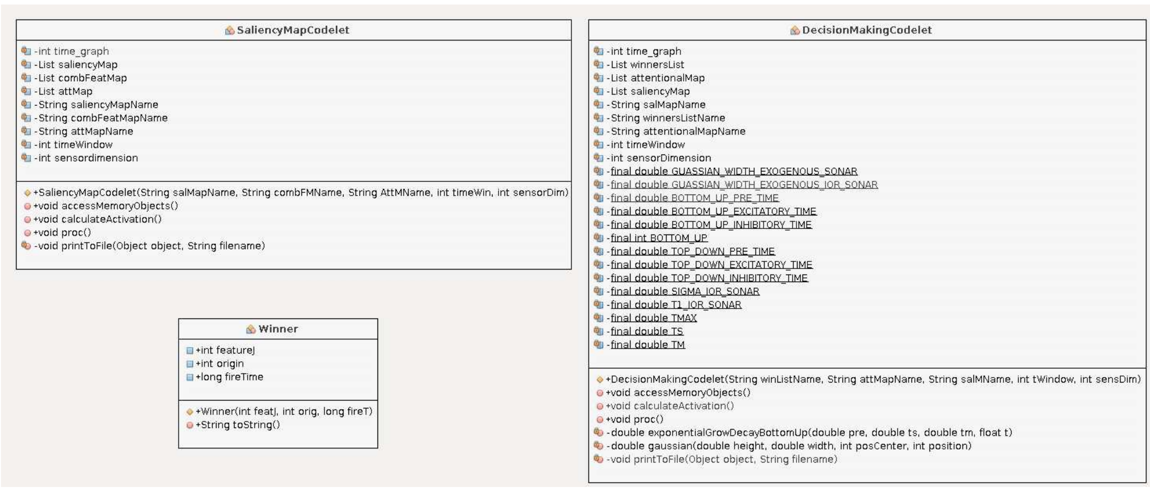


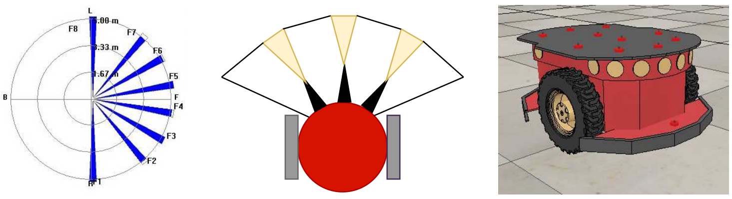
Figure 6.3: Diagram classes of Attentional package

6.2 Validation Scenario

The experiments were performed in a simulated environment. The chosen simulator is V-REP (Virtual Robot Experimentation Platform) [24]. This simulator is exceptionally accessible and user-friendly with an intuitive scene editor, flexible remote API, and multiple alternatives for the physical back-end. Mainly, V-REP's dynamics module currently supports Vortex Dynamics, a physics engine that produces high fidelity physics simulations. Pioneer P3-DX robot was used as our reference robot architecture. More details about the robot configuration are presented next.

6.2.1 Sonars

The original Pioneer P3-DX model in V-REP has sixteen proximity sensors (8 of them in the front 180^o, and the other 8 in the rear 180^o). These sensors rely on ultrasonic propagation to produce data. By emitting and receiving pulses, the sonar is capable of calculating a distance to an obstacle based on the pulse's echo.



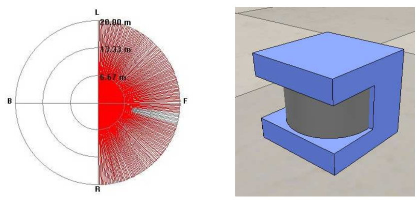
(a) (b) (c)

Figure 6.4: (a) Sonar readings (Extracted from [21]); (b) Example of sonar sensors overlap (yellow) and blindspots (black); (c) V-REP modeled Pioneer P3-DX.

As it can be seen in Figure 6.4 the Pioneer's sonars positioning produces no overlapped data. Since the sensor's capturing spectrum is broad and cone-shaped, there will be noise in the acquired data. Another concern is the blind-spots in which no information is captured, thus, making it a risky situation for the robot's safety.

6.2.2 Laser

Since using sonars can generate an extensive amount of noise in the point-clouds acquired, the 2D laser scanner was an option used to cope with this situation. Therefore, this piece of hardware can be described as a non-collision high-resolution sensor. Although also basing its information on obstacle distance, it is possible to see in Figure 6.5 that the positioning of the laser rays emitted do not overlap each other, but cover well the surroundings of the robot. Is is also a sensor with a larger scanner range than sonars.



(a) (b)

Figure 6.5: (a) 2D laser scanner emission (Extracted from [21]); (b) V-REP modeled 2D laser scanner.

6.3 Data Observation

To conduct the experiments proposed in this work, we used a combination of sonars and laser sensors. Although both measure distance, we positioned them at different heights in the robot, thus capturing distinct data and having different ranges (sonar ranges up to 1m and laser ranges up to 10m). This allows us to simulate inter-modal perception (a combination of data from different sources). Pioneer P3-DX is already equipped with 16 sonars, but we used only the eight-front sonar readings ($sonar_n$ with $n \in [1, 8]$). The 2D Laser Scanner sensor was positioned in the top-center of the robot body, which was able to obtain 180 readings ($range_n$ with $n \in [1, 180]$) each cycle, referring to the data from the front of the robot. Figure 6.6 illustrates the final disposition of the sensors and their measurements and ranges in the robot.

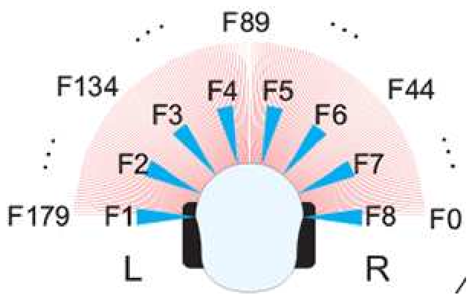


Figure 6.6: Disposition and labels for the eight sonar measurements (F1-F8) and 180 range scanner measurements (F0 - F179). Extracted from [76]

The observation spaces represent the data collected from the sensor and they are defined as:

- O_1 represents the observation space for sonar readings, defined by: $o_{1_{n_t}} = sonar_{n_t}$ with $n \in [1, 8]$
- O_2 represents the observation space for range scanner readings, defined by: $o_{2_{n_t}} = range_{n_t}$ with $n \in [1, 180]$

Where t represents the current time.

6.4 Feature Extraction

For the following experiments, two feature maps that aim at detecting saliences in their specific domain were constructed from data from multiple observation spaces: direction and distance. The first feature map, $\mathcal{F}_1$, represents saliences over the relative direction from objects in the scene to the attentive robot (the robot running the CST+CONAIM system). The second feature map, $\mathcal{F}_2$, is concerned with saliences in the static displacement of objects relative to the attentive robot.

- $\mathcal{F}_1$: Direction

Considering the Attentive Robot as a reference and 3 possible directions: 1) approximation to the robot; 2) remoteness from it and 3) no change of direction. Because the direction feature map employs sonar and range scanner readings to compute the corresponding feature map, we will need to combine them to form the final direction feature map. First, we compute for all sonars:

$$tf^1_{1_{n_t}} = \begin{cases} 1 & if \ \frac{\Delta s^1_n}{\Delta t} > 0 \\ -1 & if \ \frac{\Delta s^1_n}{\Delta t} < 0 \\ 0 & otherwise. \end{cases} \tag{6.1}$$

where $\Delta s^1_n = o_{1_{n_t}} - o_{1_{n_{t-1}}}$ is the sonar reading between time t and $t-1$ (Δt), with $n \in [1, 8]$. Then, to measure the level of discrepancy, each $tf^1_{1_{n_t}}$ is used to compute:

$$z_{O_{1_{n_t}}} = \frac{count(tf^1_{1_{n_t}})}{8} \tag{6.2}$$

where $count(tf^1_{1_{n_t}})$ is a function that determines the number of occurrences of the value -1, 1 or 0 for all $tf^1_{1_{n_t}}$. Then, we perform the same calculation to compute $tf^2_{1_{n_t}}$ for the range scanner readings. However, now $n \in [1, 180]$, $\Delta s^2_n = o_{2_{n_t}} - o_{2_{n_{t-1}}}$ and $z_{O_{2_{n_t}}}$ is given by:

$$z_{O_{2_{n_t}}} = \frac{count(tf^2_{1_{n_t}})}{180} \tag{6.3}$$

Finally, we compute each $f_{1_{n_t}} \in \mathcal{F}_1$, with $n \in [1, 8]$ by:

$$f_{1_{n_t}} = max(z_{O_{1_{n_t}}}, z^{max}_{O_{2_{n_t}}}) \tag{6.4}$$

where $z^{max}_{O_{2_{n_t}}}$ is the maximum value for $z_{O_{2_{i_t}}}$ with i varying in the intervals $[1, 22]$, $[23, 44]$,..., $[155, 180]$ for $n \in [1, 8]$, respectively, This reduces the dimension of the final feature map to 8.

- $\mathcal{F}_2$: Distance

  This feature is responsible for extracting information concerning the disposal of elements around the attentive agent. We compute it using the range scanner readings according to:

$$f_{2_{n_t}} = |o_{2_{n_t}} - \frac{\sum_{k=1}^{180} o_{2_{k_t}}}{180}|/mr \tag{6.5}$$

  where $n \in [1, 180]$, and mr is the saturation value of the range scanner, 10m in this case.

6.5 Modeling at CST

To implement the attentional model proposed with the Sensor, Observation Spaces, and Feature Maps described in CST, we extended the framework presented in Figure 6.1 with the attentional module structured as shown in Figure 6.7.

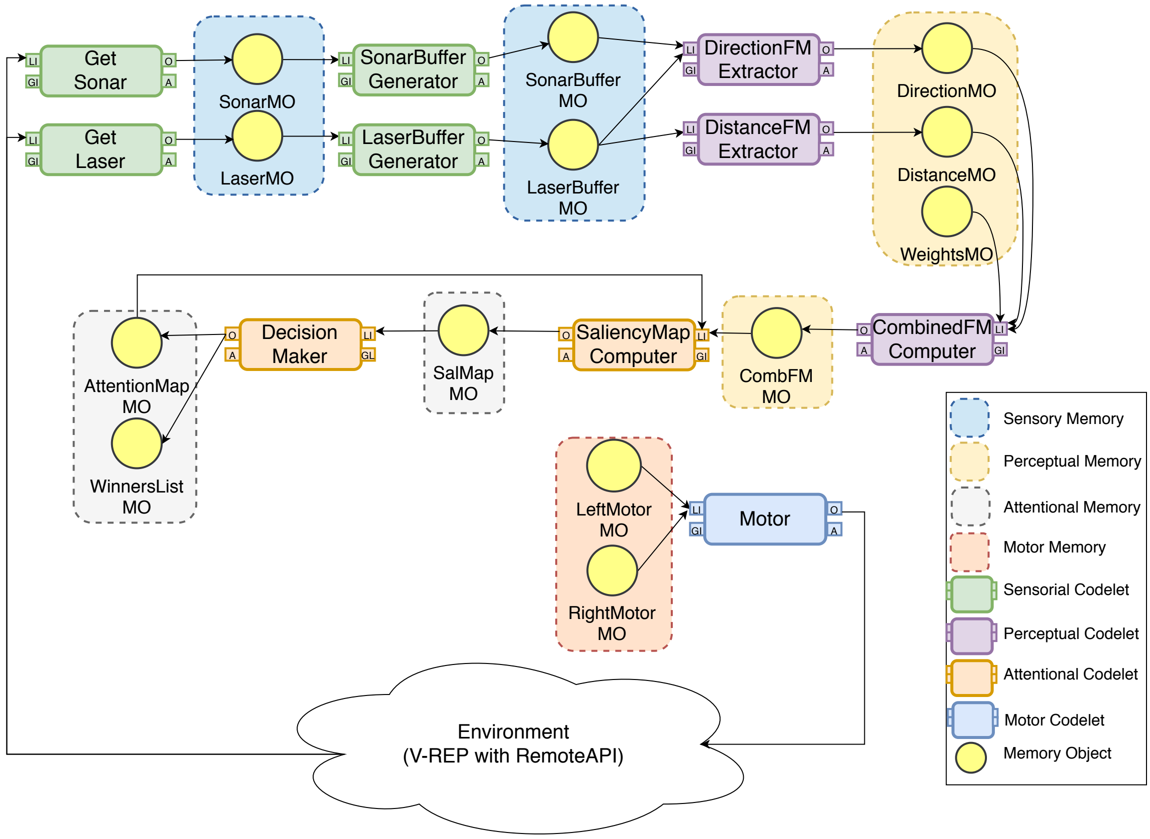


Figure 6.7: Validation Attentional Module CONAIM implementation over the CST architecture.

The most primitive codelets are represented by *Motor* Codelet, *Get Sonar* Codelet, and *Get Laser* Codelet. These components are directly connected with the V-REP simulator remote API and communicate directly with the Pioneer robot. Therefore, the raw distance data is passed directly to the *Sonar Buffer Generator* and *Laser Buffer Generator* Codelets that output Memory Objects that will be used to compute the robot's distance and direction values by the *Direction FM Generator* and *Distance FM Generator* Codelet. The Distance (Equation 6.5) is a direct calculation of the values computed by the laser (measurements are only normalized before the computation of distance), while the direction (Equations 6.1 - 6.4) is obtained by a combination of laser and sonar values (both normalized before the computation of direction), and its final dimension is equal to the sonar dimension: eight, relating to the front sonars.

The UML diagram of the classes implemented for this application can be seen in Figure 6.8. The two key components of the application are the AgentMind classes and OutsideCommunication, which were adapted from the material available at [38]. AgentMind is inherited from Mind class, which aggregates Raw Memory and Coderack to form the cognitive system. Thus AgentMind will be the creator of all MOs and Codelets of the application. In turn, OutsideCommunication deals with the robot's external communication, i.e., its sensors and actuators. This class is designed to have specific implementations, depending on the simulation program used or if it is communicating with a real robot.

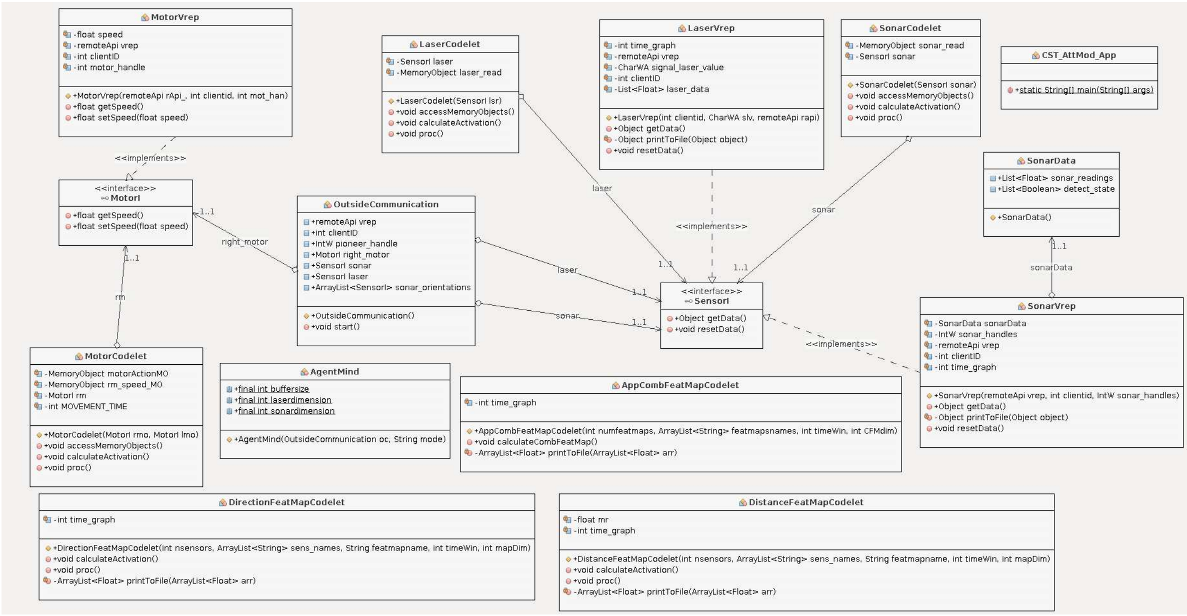


Figure 6.8: Validation application class diagram

In this sense, minimal Sensor and Motor interfaces have been created, thinking of Pioneer P3DX robots, which have two motors, one for each wheel. These interfaces define methods such as *getData()* to get sensor data and *setSpeed()* to change motor speed.

6.6 Attentional Modules Validation Experiment

As a first validation of the deployment of CONAIM in CST, we proposed to experiment with one immobile attentive Pioneer robot (equipped with laser and sonar sensors) standing in an environment and running the CST+CONAIM system. Along with this robot, there are static obstacles in the scene (walls and colored objects) and a moving robot (equipped only with sonars) running the Braitenberg algorithm [15], as shown in Figure 6.9. This experiment aimed to test the functioning of the framework attentional modules, and verify if they were working as proposed.

The most basic Sensor codelets (Sonar and Laser) must collect environmental information, which is stored in limited quantity in the Sensory Memory (Buffer codelets) and then used to construct the Feature Map (Distance, Direction and Combined Feature). The codelet that assembles the Salience Map must be correctly multiplying the Combined Feature Map with the Attentional Map (which is initialized with unit values, simulating an environment without winners).

Finally, the Decision-Making codelet must correctly assemble the next Attentional Map and define the winner of that timestamp, based on the Salience Map and the inhibitory and excitatory cycles of the Bottom-Up model.

The Motor codelet receives the speeds of the left and right wheels through the *LeftMotorMO* and *RightMotorMO*, respectively. As in this experiment, the attentive robot remains immobile throughout the simulation, the values contained in these Memory Objects are defined directly in the AgentMind (speed of both wheels equal to 0) instead of being output from a codelet responsible for calculating speeds.

Figure 6.10(b)-(i) shows the results obtained by running the bottom-up attentional cycle of CONAIM in CST for the attentive robot (immobile), whereas Figure 6.10(a) presents the trajectory executed by the Braitenberg robot. In our simulation, we use 1m as the maximum distance value for sonar and 10m for laser. As we can see in this figure, as the Braitenberg robot approaches the attentive robot from the left side, it is captured by central and left sonars. The laser sensor of the attentive robot does not capture the robot using Braitenberg because the sensor is positioned on top of the attentive robot; that is, it is higher than the Braitenberg robot.

Furthermore, as the distance between the attentive robot and the other objects (walls and colored objects) in the scene is less than 3m but higher than 1m, they are captured by the laser but not by sonars. This information is used to create the Feature maps that will detect salience in the environment. In this experiment, most salience was created by the movement of the Braitenberg robot.

As the decision-making approach implemented was a Winners-take-All (WTA), the winning features are in the region of the central sensors and to the right of the attentive robot, as the region of the focus and attention is also in this location. The graphs in Figure 6.10 illustrate the values obtained in only part of the simulation (time interval = first 30 iterations). As the non-attentive robot movement was done using the Braitenberg algorithm to avoid a collision, and the attentive robot remains immobile throughout the simulation, there was no collision between the robots.

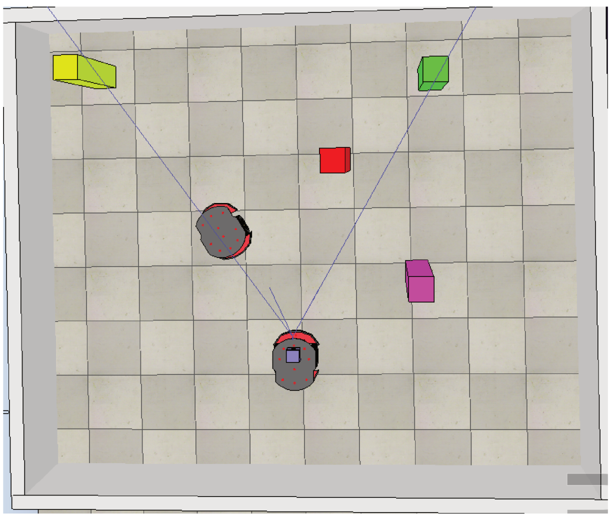
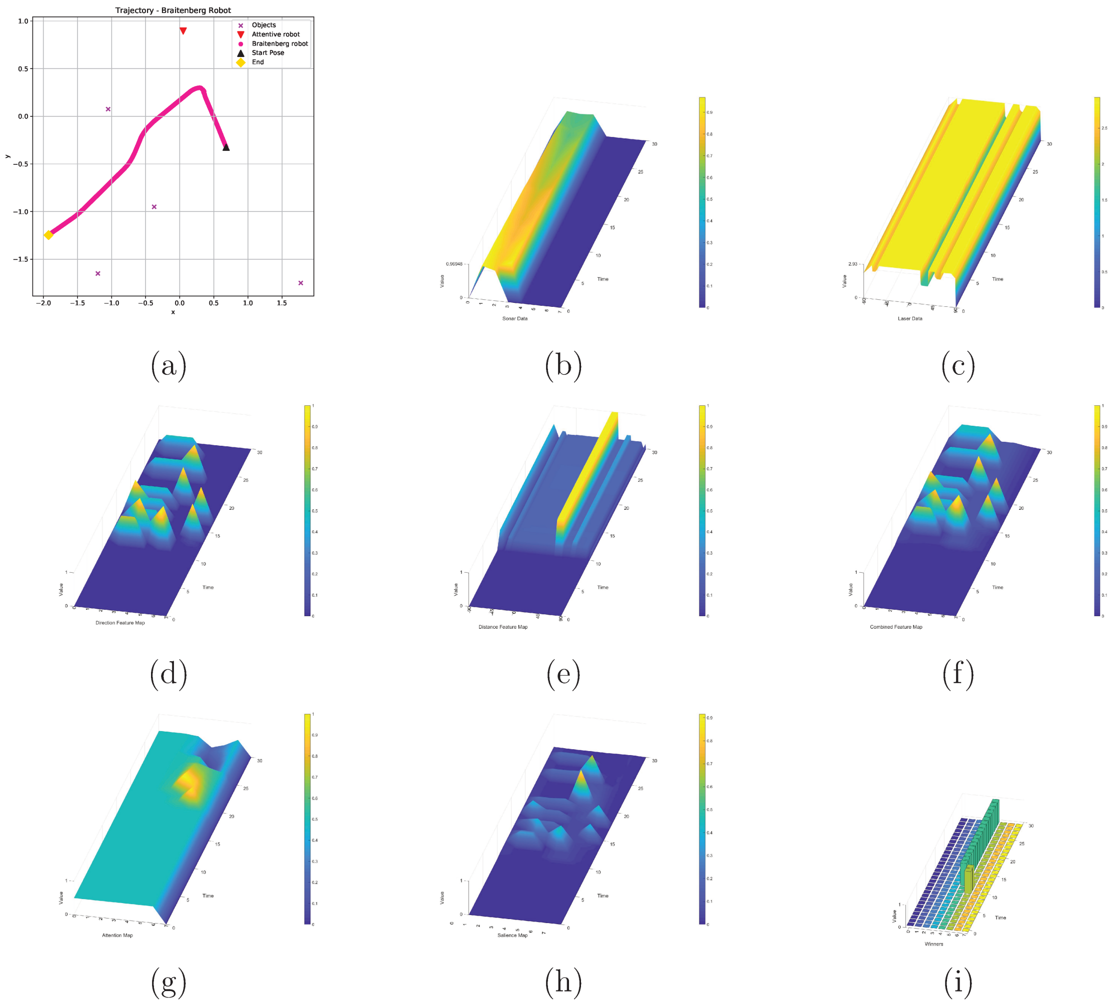


Figure 6.9: Scene used in attentional modules basic validation experiment. The robot equipped with laser is the attentive agent, while the other is the robot using the Braitenberg algorithm to avoid obstacles.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 6.10: Dynamics of bottom-up attentional cycle. (a) Refers to the Braitenberg robot, (b-i) Refers to attentive robot. (a) Trajectory of the Braitenberg robot, (b) Sonar readings, (c) Laser readings, (d) Direction Feature Map, (e) Distance Feature Map, (f) Combined Feature Map, (g) Attentional Map, (h) Salience Map, (i) Index of the winner of the attentional focus.

Chapter 7

Attentional learner agent

In this Chapter, we aim to extend the framework proposed in Chapter 6 to allow an agent, running the bottom-up course of attention, to learn how to improve its behavior. This new set of experiments will assess the importance of attention in the learning process by evaluating the possibility of learning over the attentional space. For this purpose, we modeled the essential cognitive functions necessary to learn and used bottom-up attention as input to a reinforcement learning (RL) algorithm. More details will be presented next. For all experiments, we will use the same robot, sensors, observation spaces, and feature maps described in the last chapter.

To design this experiment, we used the methodology presented in Section 5.1.

7.1 Purpose of the experiment

In this experiment, the goal of the robot is to learn to detect and react to saliences in the environment, which corresponds to the objectives of the activities of second sub-stage for the ability *Search for touch and sound source* using the classification of our proposed sensorimotor experiments (Chapter 5) and it is highlighted in the Table 7.1.

7.2 Robotics equivalent experiment

As the Pioneer robot has no microphone and tact sensors, we employed other sensors to obtain data simulating the multimodal experience. The sensors used and their arrangement was the same as in the previous Chapter (sonars and laser) with the addition of the Ground Truth sensor to capture the real position of the attentive robot in the environment.

The actuators also remain the same (left and right wheels). However, in this experiment, the wheels speeds are not fixed as in the previous Chapter.

7.3 Cognitive architecture modeling

In this step, we identified which sub-set of modules of CONAIM are involved (Figure 7.1). We used two sensors (laser and sonar) to capture the data from the environment, and

Search for touch and sound source				
Sub-stage	**Activity**	**Expected result**	**Comments**	**Sensors**
1	An external source touches the robot	Random moves	Touch the robot on several parts of the body and on both sides	Tact (pressure sensors)
1	An external source emits a beep near the robot	Do not identify the sound source	The sound source shall be emitted from different places	Hearing (microphone)
2	An external source touches the robot	The robot must learn to perform the action with the associated function of "look at the source" of the touch, but without intention	Touch the robot on several parts of the body and on both sides	Tact (pressure sensors)
2	An external source emits a beep near the robot	The robot must learn to perform the action with the associated function of "looking at the source" of the sound, but without intention. First there is the accommodation of the head towards the sound and then the coordination between sight and the ear	The sound source shall be emitted from different places	Hearing (microphone)
3	An external source touches the robot	The robot organizes the cognits to fulfill the goal of looking at the touch source	Touch the robot on several parts of the body and on both sides	Tact (pressure sensors)
3	An external source emits a beep near the robot	The robot organizes the cognits to fulfill the goal of looking at the sound source	The sound source shall be emitted from different places	Hearing (microphone)

Table 7.1: Sensorimotor experiment ability chosen.

their values compose the Sensory Memory. As described in section 3.2.1, in this work we covered only the bottom-up component of attention. CONAIM's bottom-up attentional cycle is composed of the Feature Maps and the weights associated with each (all have the same importance here), Combined Feature Map, Salience Map, and Attentional Map. So, we used these modules. For decisions, it is necessary to use the Decision-Making module. Concerning the memories, we used the Working Memory and Procedural Memory. Finally, the actuators module must perform the robot's actions in the environment.

7.4 Temporary course and Deploy to CST

For the learning experiment, a codelet called *Learner* Codelet has been implemented to use the class QLearning [91, 7, 82] (that implements the Q-Learning algorithm in CST) and gather the memory components necessary to make the attentive agent learn. Figure 7.2 shows the final scheme of codelets and memory objects (the temporary course starts with the sensorial codelets and follows the order of the arrows).

This diagram differs from the one in the last Chapter (Figure 6.7) in two points: (1) the addition of Ground Truth sensorial codelet and its respective Memory Object,

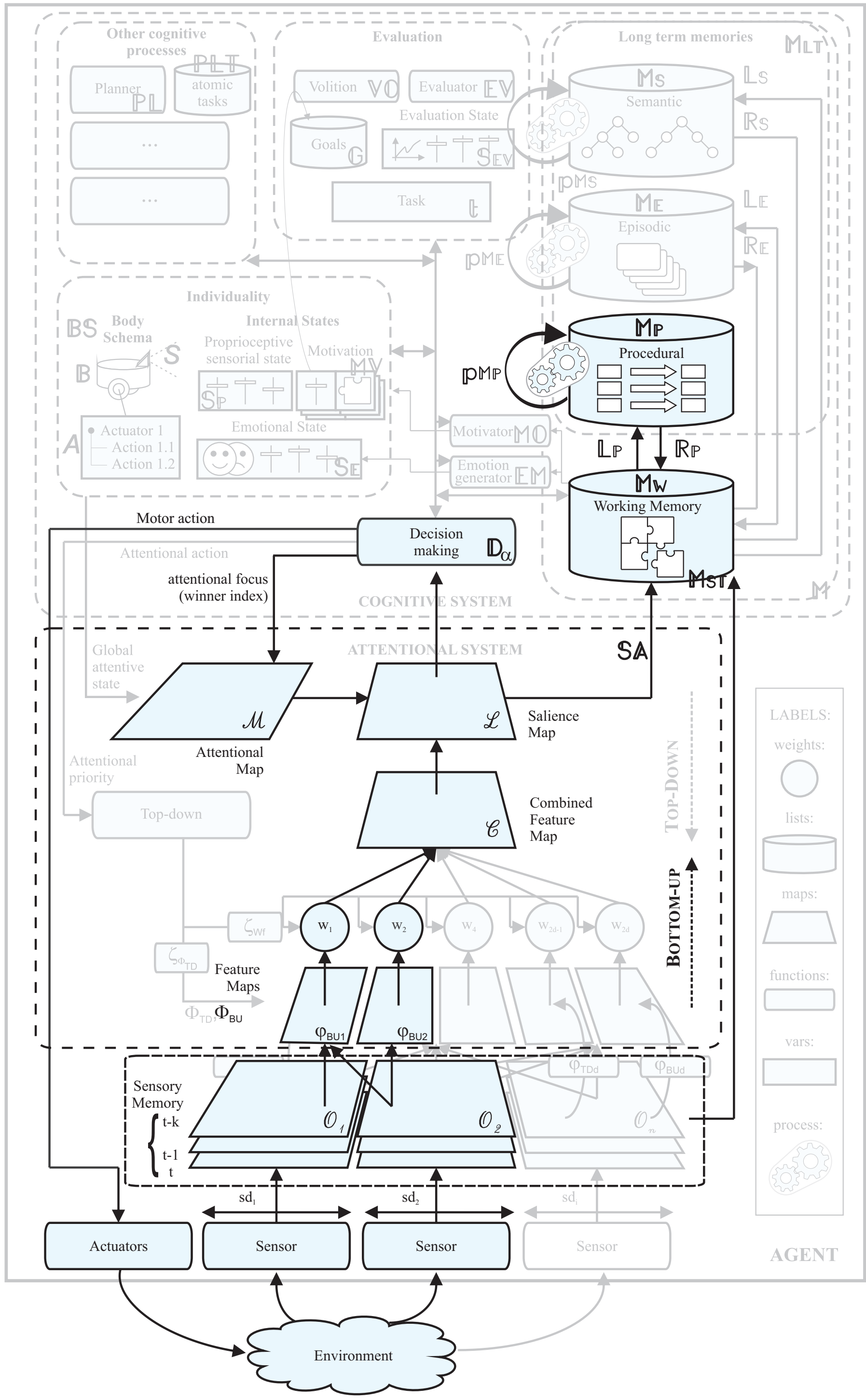


Figure 7.1: Modules of CONAIM involved in the experiment.

(2) the addition of the Learner and Behavioral codelets with their respective Memory Objects, and the change of input to the Motor Codelet (left and right wheels speed) to WheelsContainer.

With the information of the Winner (output of Decision Maker codelet) and the salience levels, we can use it to feed the Learner Codelet that implements an intelligent algorithm to learn what action the agent must take at each time step. Finally, this action is passed to the Behavioral Codelets, which fulfills each of their behavior. It sends the action instructions to the Memory Container (Subsumption Architecture [16]), which decides which action must be performed by the Motor Codelet and save the values in the Motor Memory [66].

In this learning agent, Q-Learning requires the specification of the associated MDP (Markov Decision Process) in terms of actions, states, and rewards. The list of actions is directly related to the task the agent must learn to perform, and it will differ among our experiments.

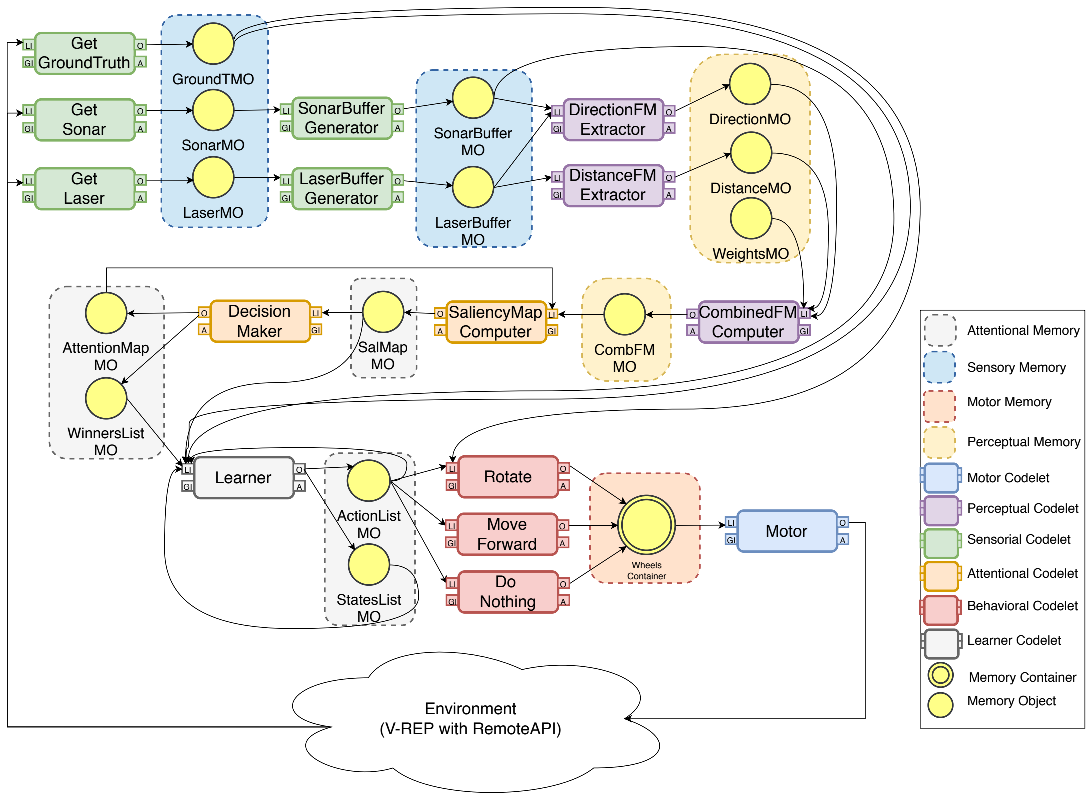


Figure 7.2: CONAIM deployed in CST with Learning

All these actions are translated into the robot's behavior, so the action learned in each cognitive cycle is saved in ActionListMO. The behavioral codelets implement the wheel's speed calculation specifically for their behavior regardless of the action that came from the learner. However, in every cognitive cycle, each behavioral codelet verifies if the action received corresponds to its specific behavior. If positive, it sets the parameter *eval* (E) of its corresponding Memory Object in WheelsContainer to 1 (maximum); otherwise to 0 (minimum). As the WheelsContainer (a Memory Container) has an internal selection structure that selects the information (I) of MO with the highest value in each cognitive cycle, only the speeds corresponding to the action determined by the learner will proceed further in the cognitive cycle as an input to the Motor codelet. Finally, through the Motor codelet, the agent updates and moves around the environment, restarting the cycle. Figure 7.3 illustrates this process.

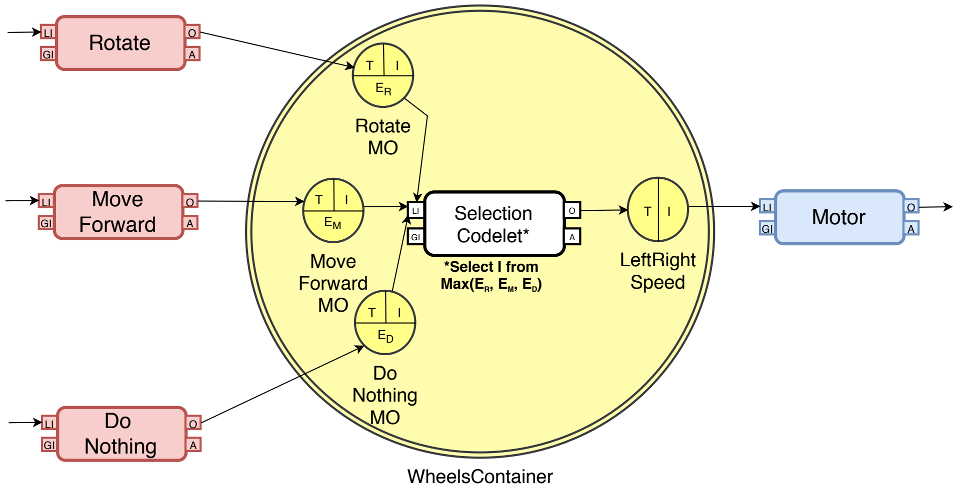


Figure 7.3: Detailed dynamic subsumption architecture to this experiment.

When an action selected by the algorithm is to **Move Forward**, the same speed (greater than 0) is passed to the left and right wheels. When the action is **Do nothing**, a velocity equal to zero is passed to these wheels.

To decide which side the agent should **Rotate** when the corresponding action is selected, it is necessary to have access to Pioneer's current orientation and the sonar angular position referring to the feature V_t (index of the winner feature of the attentional focus in instant t selected by the Decision Maker codelet). $V_t \in$ **[0, 7] (dimension of Salience Map)**. To acquire the agent's orientation via V-REP, a new codelet was created. The GroundThruth, which could capture these values in the simulator and stores in the memory object GroundTMO. Once these values are obtained, the target angle is calculated as pioneerOrientation + SonarAngles(V_t), and a **P Controller** that controls the angular velocity is executed (until the learner sends a new action). The Controller has Kp = 8 (Kp is the Proportional gain), and the error to the desired angle allowed is 0.0349066 rad. The experiments executed to define the controller variables are shown in appendix A. Figure 7.4 shows how the target angle is computed.

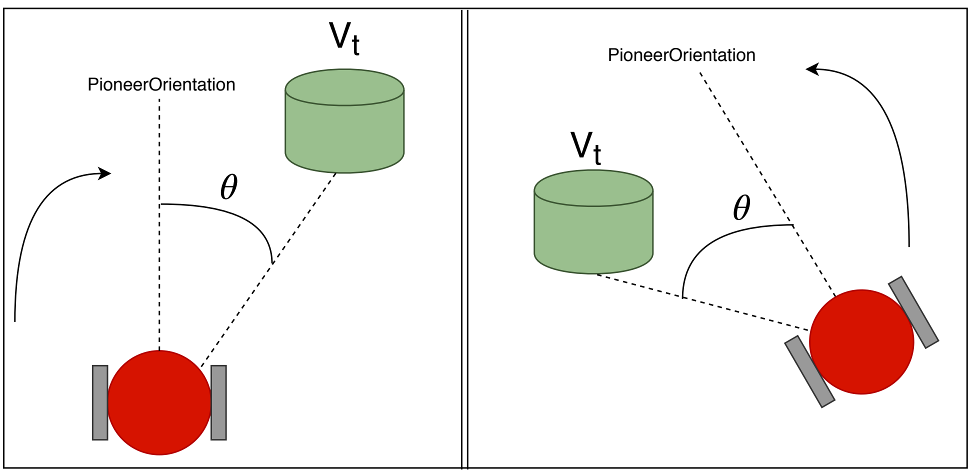


Figure 7.4: Scheme illustrating robot rotation decision logic

The states (E) designed for our experiments are directly linked to the Salience Map

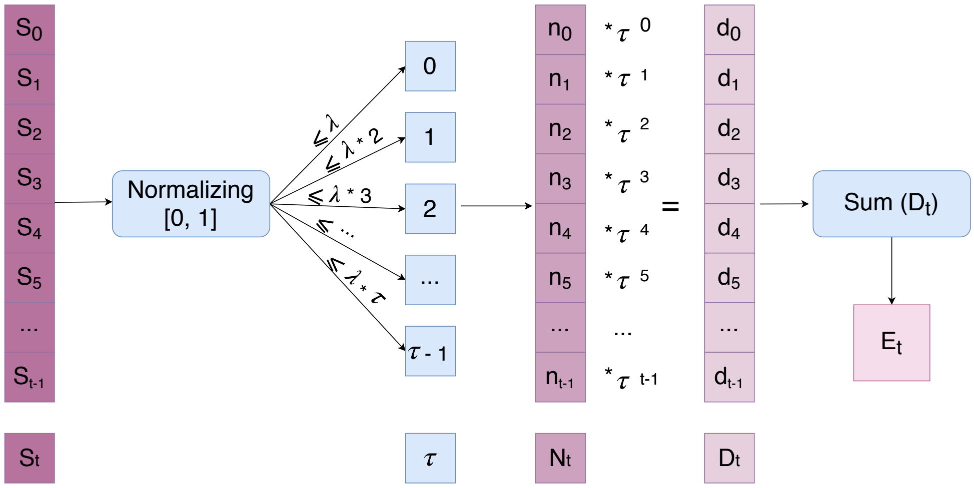


Figure 7.5: Scheme illustrating single-state Salience Map discretization process.

(S). If the map has t possible dimensions ($t = 8$ in this case, the same dimension as the Salience Map), it is necessary to map these values to one that represents the current state: $S_t \Longrightarrow E_t$.

As indicated in Figure 7.5, to perform the mapping procedure, we first normalize each of the S_t values between 0 and 1, according to:

$$n_i = \frac{s_i - min(S_t)}{max(S_t) - min(S_t)} \tag{7.1}$$

Each element n_i is discretized into one of τ possible values, that are defined according their values inside the range $\lambda * \tau_i | 1 \leq i \leq \tau$, giving rise to the intermediate map N_t. Each value of this map is multiplied by its respective τ^t, and when added they return the state E_t. It is important to note that S_t, N_t e E_t have the same dimension t. In our experiments we chose $\tau = 5$ and $\lambda = 0.2$. This allows us to work with a fixed uniform discretirzation over the continuous input received from the Salience Map.

Therefore, given a Salience Map, we can infer its state. The states, for $\tau = 5$, range from 0 to $5^8 - 1$, which is one of the dimensions of the QLearnig algorithm table. The other dimension is the same as Actions.

To perform the learning, that is, to update the table in each iteration, the algorithm still needs the reward function, and it will vary among our experiments.

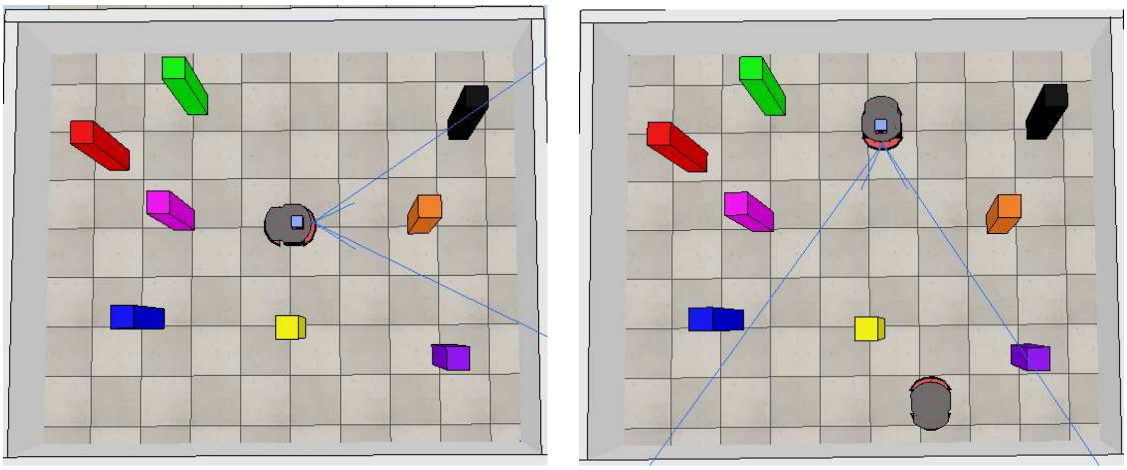
At the beginning of each Learner Codelet iteration, the state and action of the previous instant e_{t-1} and a_{t-1} were first acquired. With these variables, and calculating the reward r_t that the current instant provides, the learning table is updated at position e_{t-1} and a_{t-1} with the value computed considering r_t. After the update, the next action is selected, and e_t is the new state.

7.5 Evaluation

Each experiment executed and presented in the following section had a specific objective: either to explore more regions of the environment without crashing, to approach or to keep away from the salience detected in the environment during the simulation. They employed different rewards, state and action spaces, but they also shared a common structure. An RL process can be divided into two parts: learning and testing. To the agent learn, it is necessary to make a series of simulation rounds by randomly drawing the agent's starting position and setting a stop condition to reset the round and start a new simulation while updating table Q. We employed 1,000 episodes with a maximum of 700 actions each. We defined a simulation round to start again when the robot collided with any object or when it completed 700 actions. The analysis of whether the agent struck any object is made using a threshold value over its sensor readings.

In addition, some QLearning parameters were common among learning experiments. These parameters and their values are: $\epsilon = 0.95$, $\alpha = 0.5$ and $\gamma = 0.9$. ϵ refers to the probability that the algorithm will choose a random action over the best one. It decays linearly with the episodes to zero. The α value refers to the *learning rate* and γ to the temporal discount factor.

Figure 7.6 illustrates the scenes used in the experiments described next.



(a) (b)

Figure 7.6: Scenes used in the experiments. (a) EXP01, EXP02 and EXP03, (b) EXP04, EXP05 and EXP06.

Each experiment involving the attentional agent (EXP02, EXP03, EXP05, and EXP06) had three modes of execution, differing in the data used to calculate the states. They are:

1. **Mode Salience**: uses the Salience Map to compute the states.

2. **Mode Sonar**: the states are calculated using the sonar readings.

3. **Mode Salience + Sonar**: the states are calculated using the Salience Map and the Sonar readings. Here $t = 9$, $\tau = 5$ so the states range from 0 to $5^9 - 1$. All the calculations illustrated in Figure 7.5 remain the same, except the process between S_{t_8} and N_{t_8}, which corresponds to the sonar. In this part, we used only the combination of 4 frontal sonars, discretized in 2 possible values (1 if sonar reading is ≤ 0.5, 0 otherwise).

The sensors employed in the experiments are the Sonar and Laser sensors deployed in the Pioneer P3-DX robot (as depicted in Figure 6.6). In total, the data from 8 frontal sonars and 180 readings of the laser, also covering the frontal 180°, were captured. While the sonar scanning range varied from [0-1]m, the laser was in the [0-10]m interval.

All the experiments described next follow the purpose presented in Section 7.1, but we separate them into two experimental sets modifying the dynamics of the salience source between them. While in the experiments EXP01, EXP02 and EXP03 (first experimental set) the salience source is static (only fixed objects in the environment), in EXP04, EXP05 and EXP06 (second experimental set) the salience source can be static (fixed objects in the environment) or dynamic (presence of a second robot in the environment using the Braitenberg algorithm to move). In the latter case, we have a more complex environment, as it involves the attentive robot operating in a scenario with both static and dynamic elements.

Each experiment described next used a set of actions and their respective rewards according to their objective. However, the fundament for the reward functions was the same: the robot should not stay immobile in the environment for a long time. Therefore the associated values for this action are null (minimum). Furthermore, we do not want the robot to turn for a long time, so the cost associated with this action is intermediate. Finally, as the objective of the experiments is for the robot to explore more regions of the environment without crashing, the action of moving forward is the one that promotes the most significant movement of the robot in the environment considering the space traveled, so this action is associated with a higher score.

7.5.1 EXP01: Non-attentive agent

The goal of this experiment was to make the robot learn to explore the environment to the fullest (explore more regions of the environment without crashing) using the set of actions listed in Equation 7.2 but without any influence of an attentional system. The states were computed using the sonar readings. The reward function was defined according to Equation 7.3.

$$\begin{aligned} A =& \{a_1, a_2, a_3, a_4\} \\ & a_1 \rightarrow \text{Move forward} \\ & a_2 \rightarrow \text{Turn Left} \\ & a_3 \rightarrow \text{Turn Right} \\ & a_4 \rightarrow \text{Do nothing} \end{aligned} \tag{7.2}$$

$$\begin{aligned} r_t = \{&1,\ \text{Move forward} \\ &0.5,\ \text{Turn Left, Turn Right,} \\ &0,\ \text{Do nothing}\} \end{aligned} \tag{7.3}$$

Figure 7.7 shows the average and standard deviation of rewards and actions during the learning phase for this experiment.

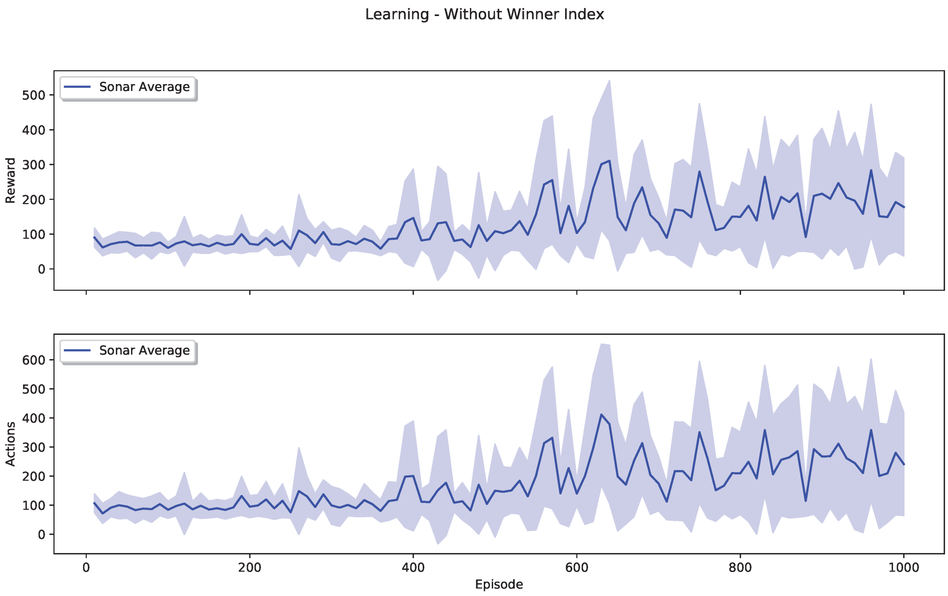


Figure 7.7: EXP01: Turn without the Winner Index using. Average and standard deviation using 10 episodes window.

7.5.2 EXP02: Turn Towards the Winner

In this experiment, we aim at learning to go to the winner feature found by the attentional module, using the set of actions listed in Equation 7.4, where V_t is the index of the winning feature in instant t, where index $\in [0, 7]$.

$$
\begin{aligned}
A =& \{a_1, a_2, a_3\} \\
& a_1 \rightarrow \text{Move forward towards } V_t \\
& a_2 \rightarrow \text{Rotate towards } V_t \\
& a_3 \rightarrow \text{Do nothing}
\end{aligned}
\tag{7.4}
$$

The reward function was defined according to Equation 7.5.

$$
\begin{aligned}
r_t = \{&1, \text{Move forward towards } V_t, \\
&0.5,\ \text{Rotate towards } V_t, \\
&0,\ \text{Do nothing}\}
\end{aligned}
\tag{7.5}
$$

Figure 7.8 shows the average and standard deviation of rewards and actions during the learning phase for the three modes of defining the state space described earlier.

To validate the agent learned policy, we loaded the learned policy and ran it on the same scene used during learning. However, we started the robot in three different positions and orientations, this time in testing mode, only choosing the next action based on the

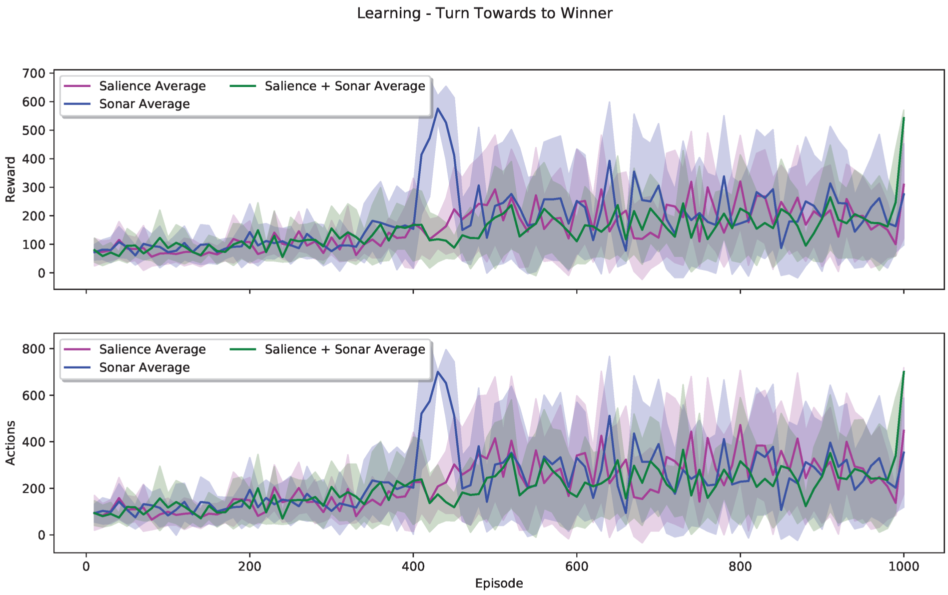


Figure 7.8: EXP02: Average and standard deviation using 10 episodes window to action **Turn** = Turn Towards the Winner. Shadows show the standard deviation

best values in table Q, without any updating. Figure 7.9 shows sample trajectories of this experiment.

7.5.3 EXP03: Turn Away from Winner

For this experiment, some changes were made in small parameters aiming to improve the policy learned in 7.5.2.

First, the set of actions has been modified to serve the goal. Instead of the action **Rotate towards** V_t, mentioned in the previous section, we changed it to *Rotate in the opposite direction of* V_t. Thus, the information of which is the Winner of the attentional focus in each instant helps the agent avoid going to the salience, as it can turn in the opposite direction.

The reward function stayed the same (but now the value presented to *Rotate towards* V_t is the value of *Rotate in opposite direction to* V_t).

Figure 7.10 shows the average and standard deviation of rewards and actions during the learning phase. The trajectories performed by the robot are illustrated in Figure 7.11.

7.5.4 EXP04: Non-attentive agent + Braitenberg robot

In the following experiments, the attentive robot's initial positions were the same as those used in the previous experiments (EXP01, EXP02, and EXP03).

As in this experimental setting, we have the presence of two robots moving in the environment. For each mode of calculation of the states, we plot the trajectories of the two robots for each initial position in separate graphs for better visualization. However, we maintained the color relationship between the two sets of experiments (ex: start pose shown in the blue trajectory in image 7.9(d) is the same point shown in the first graphic

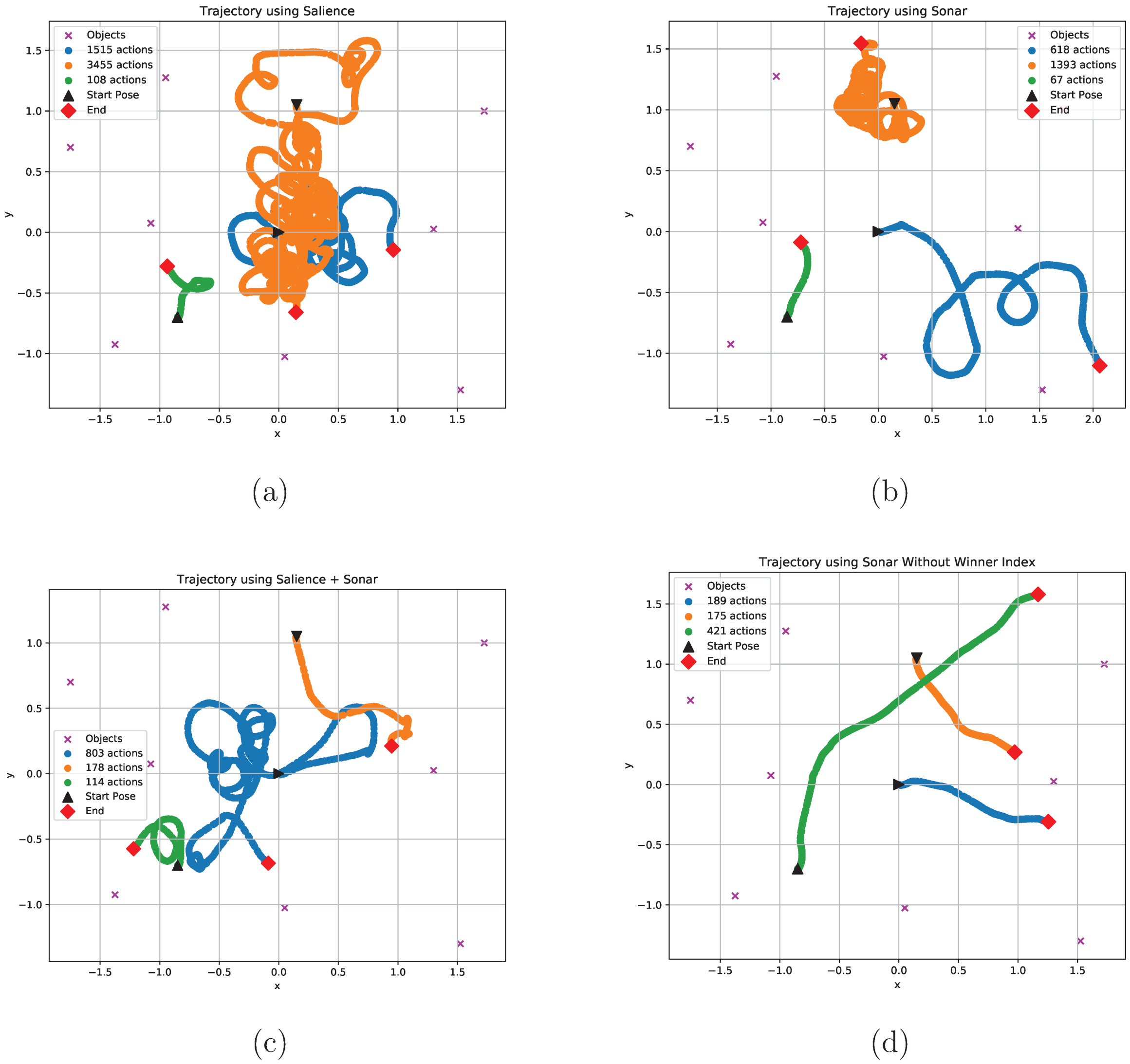


Figure 7.9: EXP02: Trajectory with action **Turn** = Turn Towards the Winner (a-c) and Without Winner Index (d). The states are calculated from (a) Salience, (b, d) Sonar, (c) Salience + Sonar. (d) corresponds to EXP01 - the non-attentive agent

in the image 7.14(d); start pose illustrated in the orange trajectory in image 7.9(d) is the same point illustrated in the second graphic in the image 7.14(d) and so on).

For all the following experiments, the initial positions of the trajectory to be performed by the robot using Braitenberg were the same in all states' calculation modes.

In this experiment, we used the same set of actions and rewards of EXP01 (7.5.1) but now we have a moving robot as a distractor in the environment.

Figure 7.12 shows the average and standard deviation of rewards and actions during the learning phase for this experiment.

7.5.5 EXP05: Turn Towards the Winner + Braitenberg robot

In this experiment, we used the same set of actions and rewards of EXP02 (7.5.2) but now we have a moving robot as a distractor in the environment.

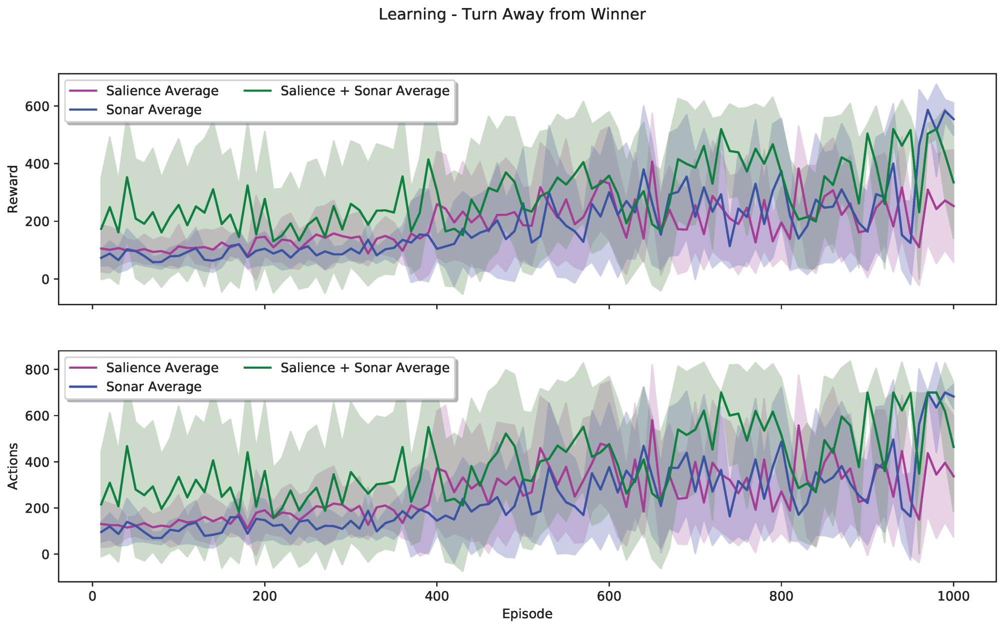


Figure 7.10: EXP03: Average and standard deviation using 10 episodes window. The action **Turn** used is (a) Turn Away from Winner.

Figure 7.13 shows the average and standard deviation of rewards and actions during the learning phase for the three modes of defining the state space described earlier.

Figure 7.14 shows sample trajectories of this experiment.

7.5.6 EXP06: Turn Away from Winner + Braitenberg robot

In this experiment, we used the same set of actions and rewards of EXP03 (7.5.3) but now we have a moving robot as a distractor in the environment.

Figure 7.15 shows the average and standard deviation of rewards and actions during the learning phase. The trajectories performed by the robot are illustrated in Figure 7.16.

7.6 Discussion

The rewards presented in Figures 7.7, 7.8 and 7.10 (EXP01, EXP02 and EXP03, respectively) show that all the experiments have achieved similar behavior considering the results obtained from the different modes to calculate the states. When analyzing the average reward and standard deviation from action *Turn towards the winner*, the values among the different configurations are close, except near to episodes 500 and 1000. In this period, the rewards obtained from the **mode Sonar** and **sonar + salience**, respectively, were close to the maximum possible. However, when analyzing the action *Turn Away from winner*, the experiment composed by Salience + Sonar had greater rewards than the other configurations. Despite that, these values went down near the 1000th episode and

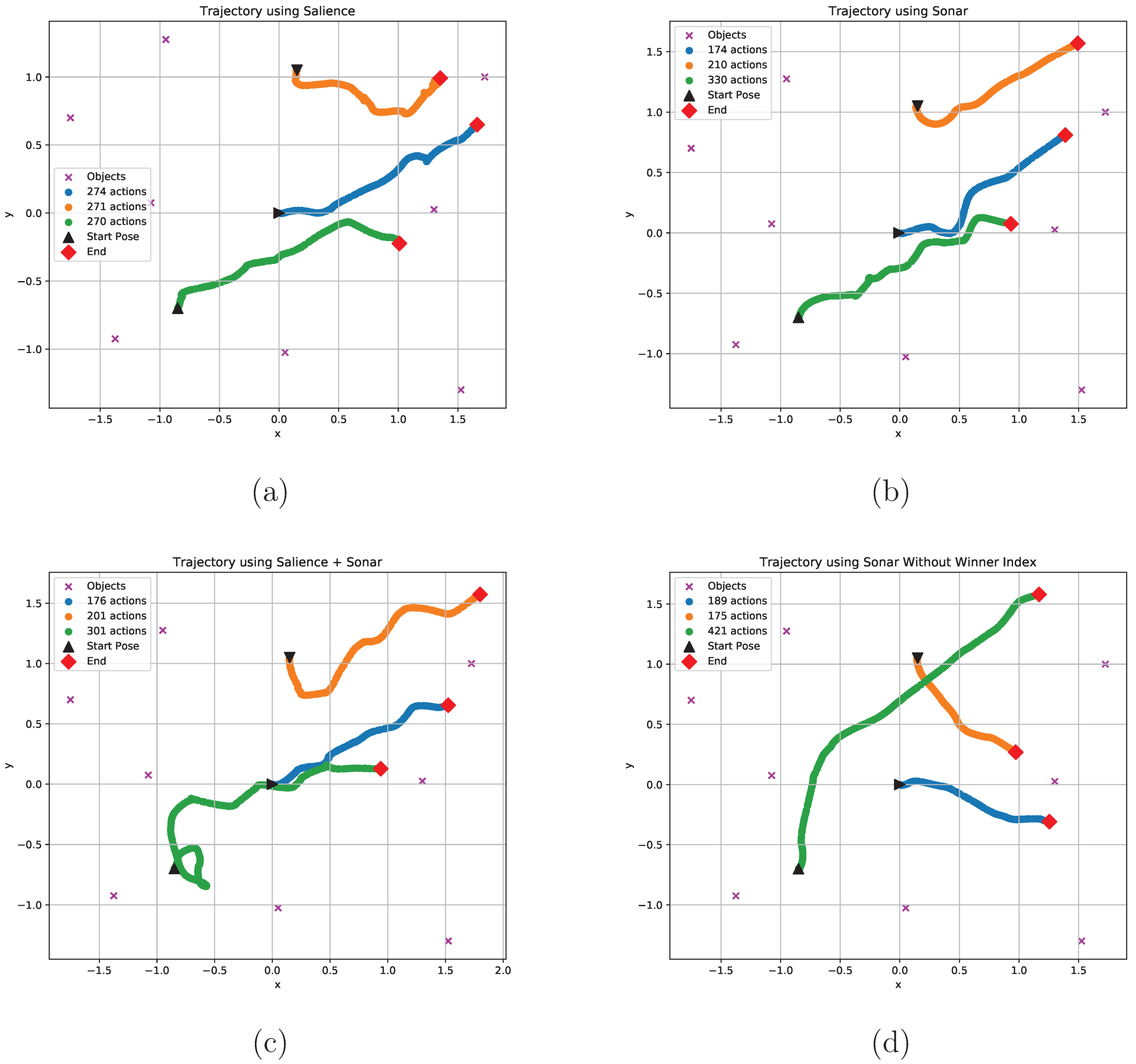


Figure 7.11: EXP03: Trajectory with action a_2 = Turn Away from Winner (a-c) and Without Winner Index (d). The states are calculated from (a) Salience, (b, d) Sonar, (c) Salience + Sonar. (d) corresponds to EXP01 - the non-attentive agent

did not stabilize.

In the EXP04, the rewards presented in Figure 7.12 were greater than 500 after the 600th episode, not reaching the maximum reward possible (700). In this image, we can also see that the number of actions increased during the training, getting very close to the maximum quantity (700). This experiment got better results than EXP01 (same configuration of states, rewards and actions calculation, except that the EXP04 has the addition of one Pioneer P3-DX Robot using the Braitenberg algorithm moving in the environment).

In the EXP05, the learning behavior for all state calculation modes are similar, with the **Salience** mode showing better rewards and number of actions in almost all episodes. The learning stabilized only for Salience, obtaining values of rewards and actions equal (or very close) to the maximum allowed (700). This experiment got better results than

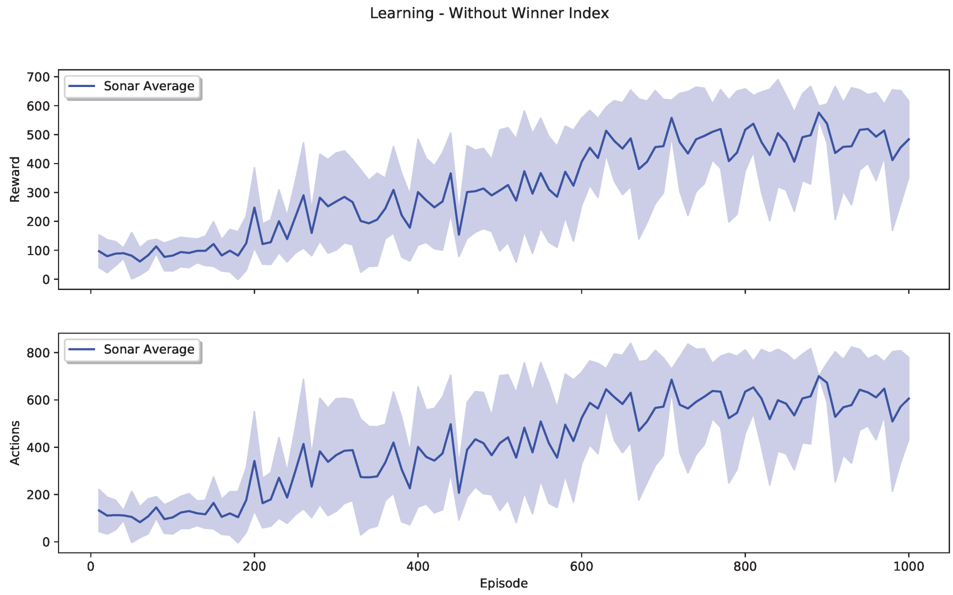
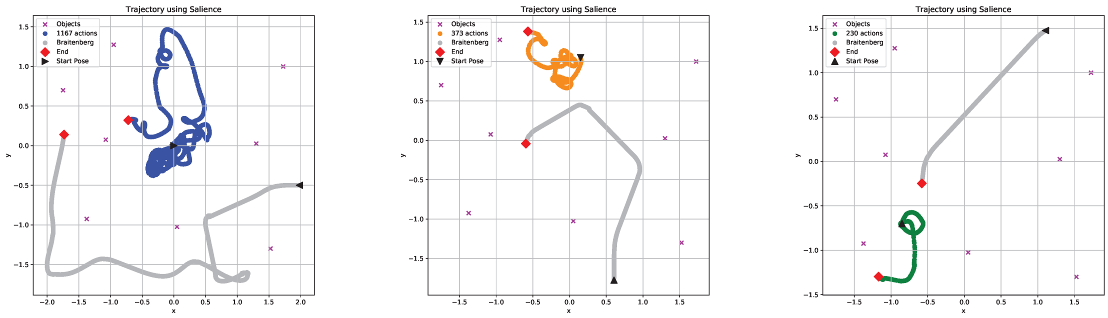


Figure 7.12: EXP04: Turn without the Winner Index using. Average and standard deviation using 10 episodes window.

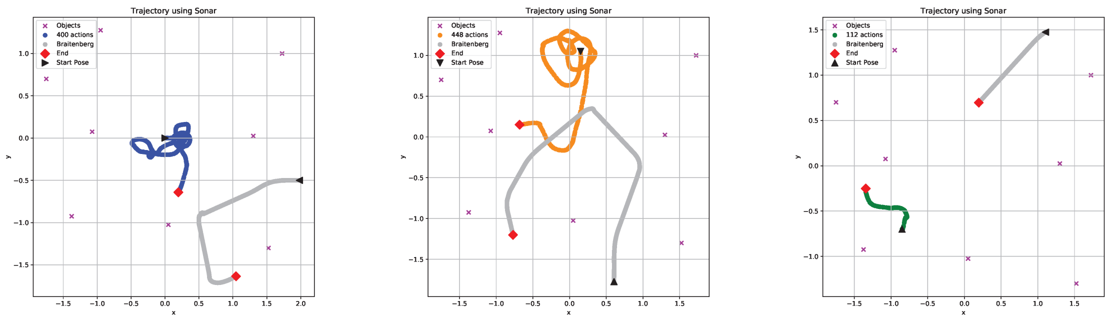
Figure 7.13: EXP05: Average and standard deviation using 10 episodes window to action **Turn** = Turn Towards the Winner. Shadows show the standard deviation

EXP02 (same configuration of states, rewards and actions calculation, except that the EXP05 has the addition of one Pioneer P3-DX Robot using the Braitenberg algorithm moving in the environment).

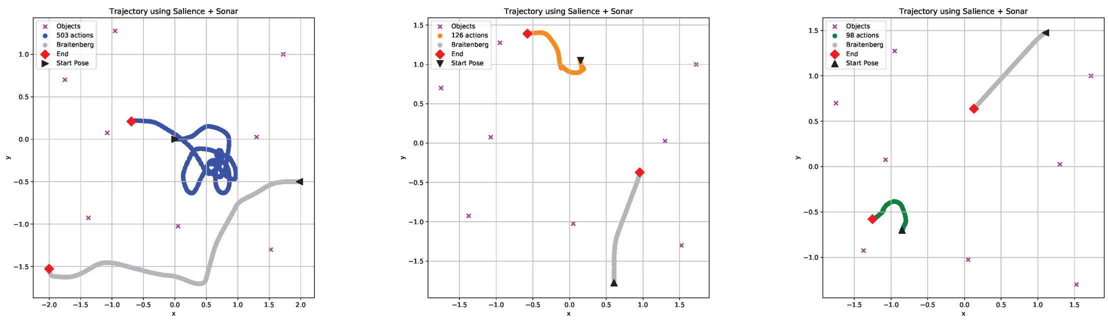
In the EXP06, the calculation of the states using sonar showed very low values and stabilized rewards. This mode was worse in this experiment compared to the equivalent experiment (EXP03). The Salience showed better results than the comparable experiment (EXP03), unlike the Salience + Sonar.



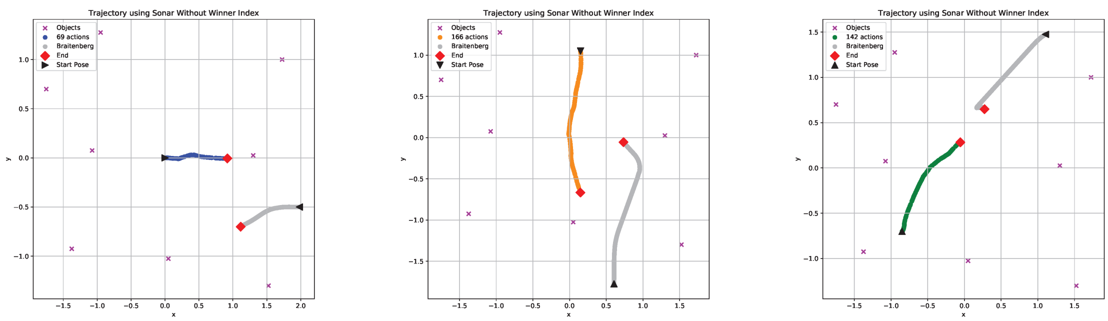
(a)



(b)



(c)



(d)

Figure 7.14: EXP05: Trajectory with action **Turn** = Turn Towards the Winner (a-c) and Without Winner Index (d). The states are calculated from (a) Salience, (b, d) Sonar, (c) Salience + Sonar. (d) corresponds to EXP04 - the non-attentive agent

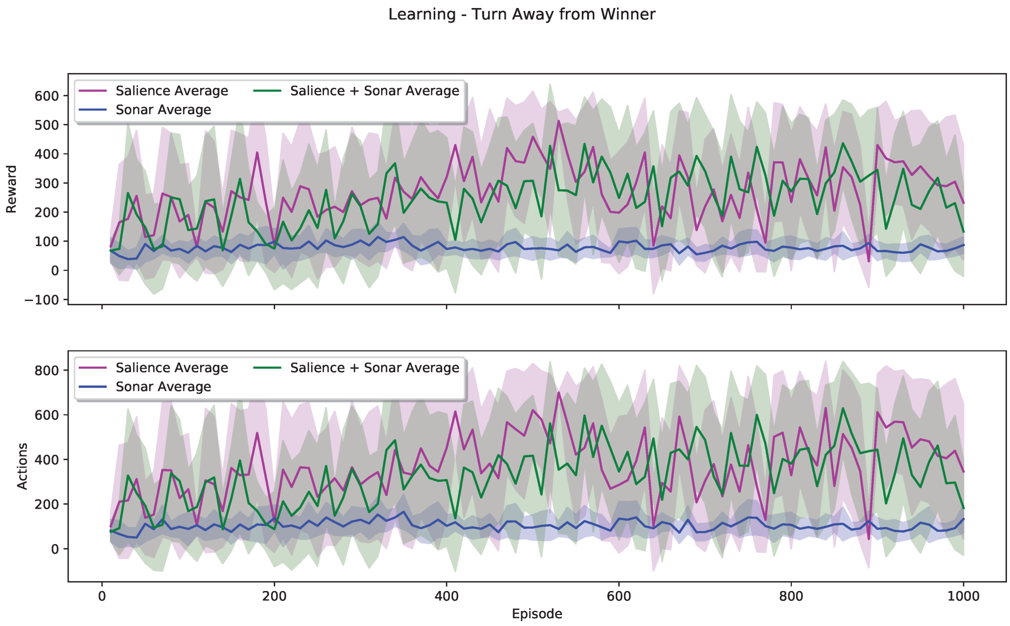
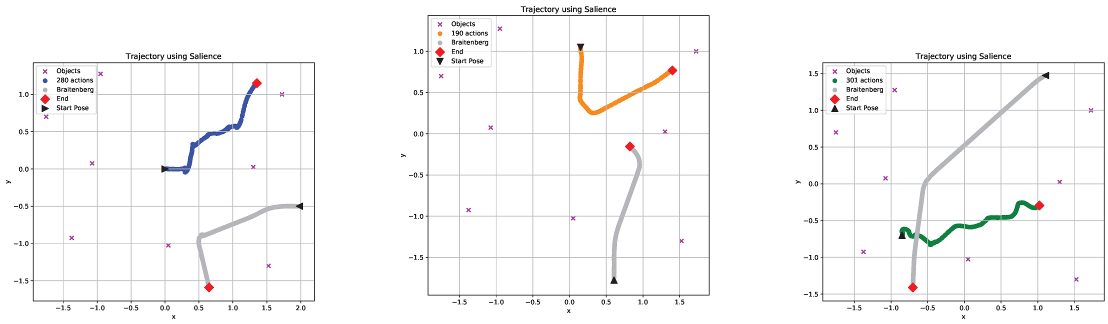


Figure 7.15: EXP06: Average and standard deviation using 10 episodes window. The action **Turn** used is (a) Turn Away from Winner.

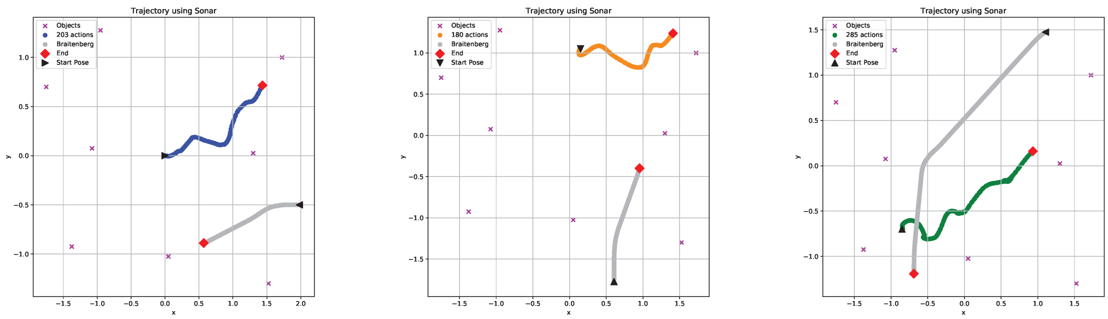
The number of actions executed while learning the policy demonstrates that the action *Turn away from winner* enables the robot to operate more in the environment since it turns in the opposite direction of the obstacle avoiding a collision. But, sometimes, when the robot is running away from the winner, it collides with another obstacle.

Through Figures 7.9 and 7.11 is possible to note that the behavior of all the configurations is similar in all experiments (with the same Actions set) considering the trajectories performed by the robot. By observing the action *Turn away from winner* in Figure 7.11a-c (EXP03) one can see that the trajectories using Salience and Sonar are almost the same, except by the number of actions that is, on average, greater for the Salience mode (271 against 238 - Sonar, 226 - Salience + Sonar, 261 - sonar without attention). By observing this same action in Figure 7.16a-c (EXP06), the trajectory for the first position was almost the same for all state modes, differing only in the number of actions (280 - Salience, 203 - Sonar, 125 - Salience + Sonar). Except by the number of actions, the trajectories for the second position were almost the same for Sonar (180 actions) and Salience + Sonar (151 actions), and for the third position was almost the same for Salience (301 actions) and Sonar (285 actions). Through Figures 7.11a-c and 7.16a-c it is possible to notice that all state calculation modes presented a trajectory very similar, with the exception of Salience + Sonar on the first and third positions. Besides that, in both experiments, the trajectory does not contain many curves.

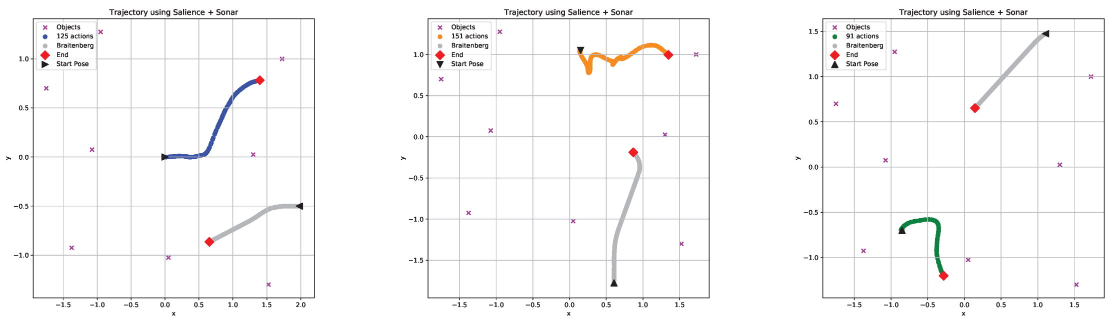
When analyzing the action *Turn Towards the Winner,* we can observe that the robot turns frequently, which increases the number of actions, but not necessarily increases the space explored by the robot. Furthermore, from these images (Figures 7.9, 7.14, 7.11 and 7.16), it is possible to note that the resulting trajectories are contrasting, which indicates



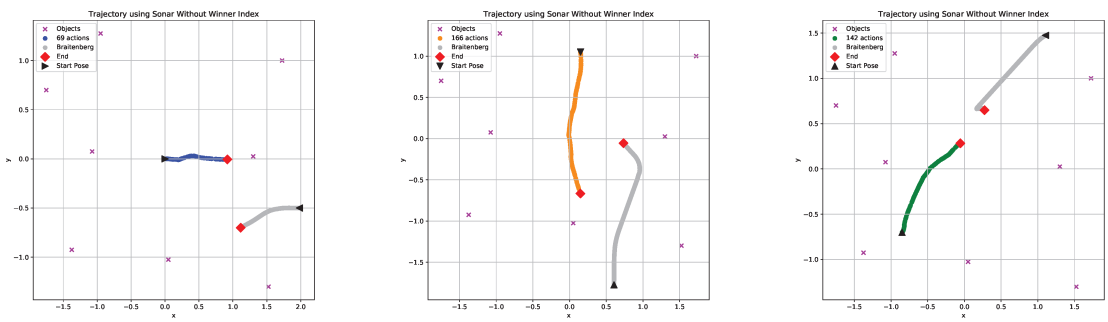
(a)



(b)



(c)



(d)

Figure 7.16: EXP06: Trajectory with action a_2 = Turn Away from Winner (a-c) and Without Winner Index (d). The states are calculated from (a) Salience, (b, d) Sonar, (c) Salience + Sonar. (d) corresponds to EXP04 - the non-attentive agent

that the robot indeed has learned either to go-to or move away from salient elements, according to the experiment goal.

Looking at the trajectories performed by a non-attentive robot (Figure 7.9(d) and 7.14(d)), it can be observed that the agent almost showed a linear path, with little curves. This can indicate that the robot learned to move forward and turn when it is indispensable (avoid an obstacle).

Considering the testing executions of each configuration to action *Turn away from Winner*, the action average in EXP03 is 271.66 to Salience, 238 to Sonar, 226 to Salience + Sonar and 261.66 to non-attentive. For EXP06, this value is 257 for Salience, 222.6 for Sonar, 122.3 for Salience + Sonar, and 125.6 for the non-attentive. While to action *Turn Towards the Winner* in EXP02 is 1692.66 to Salience, 692.66 to Sonar, 365 to Salience + Sonar, and 261.66 to non-attentive. Finally, in EXP05, these values are 590 to Salience, 320 to Sonar, 242.3 to Salience + Sonar, and 125.6 to non-attentive. Therefore, the Salience Map experiment offered the best results.

An interesting event was that even with better rewards during the learning phase in the second test set (EXP04 to EXP06), the number of actions in the trajectories performed during the testing phase in that set was worse than those in the first test set (EXP01 to EXP03). It is important to remark that the decision making learned over the salience map considers information from both laser and sonar readings once they were used to create the feature maps that were combined to detect Salience. With this, it was possible to promote a state-space reduction that, if not possible, would prevent us from using laser data in the same way that the sonar readings were applied. In this case, the proposed learned model was able to learn a better policy over a state space that is a 95% reduction of its original sensorial space. It is also important to remember that when *looking for the source of sound and touch*, as proposed as our basic experiment, the salience based model would be the most successful approach as it keeps track of the salience in the environment by turning towards the winner.

Chapter 8

Conclusions and future works

In this work, we aimed at investigating which modules in a cognitive architecture are necessary to control a robot that interacts with its environment while performing a set of sensorimotor experiments with increasing difficulty. We also aimed to evaluate whether it was possible to successfully learn how to behave to solve a task over the attentional space.

To achieve this goal, we deployed the bottom-up attention module of CONAIM in the CST framework and validated the attentional modules involved. We also have successfully extended the architecture to encompass learning. We carry out experiments involving learning over the features and attentional spaces. The reported experiments show that using the attentional map, specifically the salience map, as input to a Reinforcement Learning algorithm leads to results as close as those achieved when using the original sensorial space, but with a sensitive reduction on the search space. Indeed, the state space reduction promoted by the attentional system without information loss (95% reduction on sonar+laser experiment with salience) is crucial to the use of multiple or redundant sensors without impairing the system feasibility. One drawback happens when no salience is identified in the scene, and the robot behavior is erratic.

Considering the lack of formalization on how to conduct and assess agents learning in DevRobotics, we conducted a theoretical study on human development and the stages and concepts defined by Piaget related to it. Since learning is cumulative and the most complex cognitive functions emerge after the simplest ones, we focused our studies on the sensorimotor stage defined by Piaget, which corresponds to children aged 0 to 2 years. As a result, we proposed a set of incremental experiments, in different categories, to be applied in robots, which follow the same development observed in humans. The definition of a set of cognitive experiments inspired by Piaget's theory that could be used to assess agents learning in DevRobotics is an important contribution of this work.

Through all the material generated in this research, it is possible to map the cognitive functions involved and their activation dynamics for each experiment. Besides, it becomes possible to explore what are the functions required for each activity and the impact of the presence or absence of these functions on the agent.

As future work, we suggest tackling the drawbacks of using the attentional space to include a Top-down mechanism that would act in the absence of salient stimuli. Another possibility of improvement is associating observations over the original sensory data described in higher levels of encoding (as we did in the experiment using Salience and Sonar to compute the states) to the attentional space to allow for more complex decisions. Also, when comparing the experiments described in sections 7.5.2, 7.5.3, 7.5.5 and 7.5.6, it is possible to note that the set of actions directly affects the quality of learning and driving the robot towards salient stimuli, such as formulated, led to crashes. Future work could explore further configurations involving Salience maps and sensory data for the state space representations while developing the Top-down attentional mechanism for more complex decision-making.

Also, we suggest exploring new features derived from vision and evaluating the importance of emotion and motivation in learning. Besides, as one of the critical and essential factors related to learning and cognitive development observed in humans is sleep, we should address such aspects.

Finally, we should conduct the proposed experiments in the same incremental way as we proposed in our Piaget's inspired experiments.

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Appendix A

Controller

We used a closed loop controller to control the angular velocity of the robot with the actions *Rotate towards the winner* and *Rotate in the opposite direction of the winner* implemented on behavioral codelet *Rotate*.

The goal of the robot is turn the angle defined in each experiment. The set of angles was [10,90] degrees, varying the values of the interval in 10 degrees.

The controller chosen to test were Proportional (P). It is the simplest type of feedback control and the control variable is proportional to the measured error as is illustrated in Figure A.1. Multiplying factor Kp (Proportional gain) allows to control how quickly we get to the desired point (Algorithm 1). The experiments were with Kp = 1 to 12.

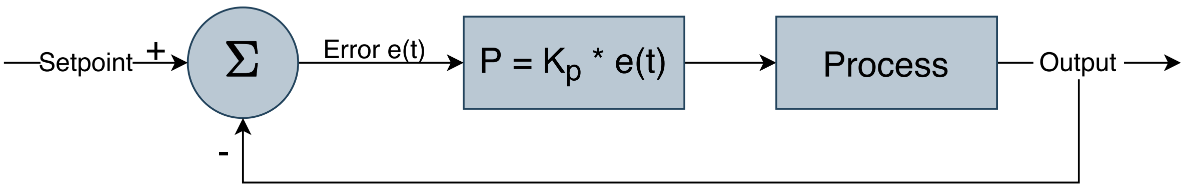

Figure A.1: Generic closed loop control system with a P controller.

Algorithm 1: P Controller

error = reference − measured;
u = Kp * error;;
motor(u);

The results are shown in Figure A.2 and it's possible to see that the best value was Kp = 8, because it didn't has overshoot, different from others. So this value was used in all experiments described in this thesis.

Obs: The graph has some steps between values. This is because the values were obtained in each cognitive cycle, and this cycle time is faster than the time needed to start turning.

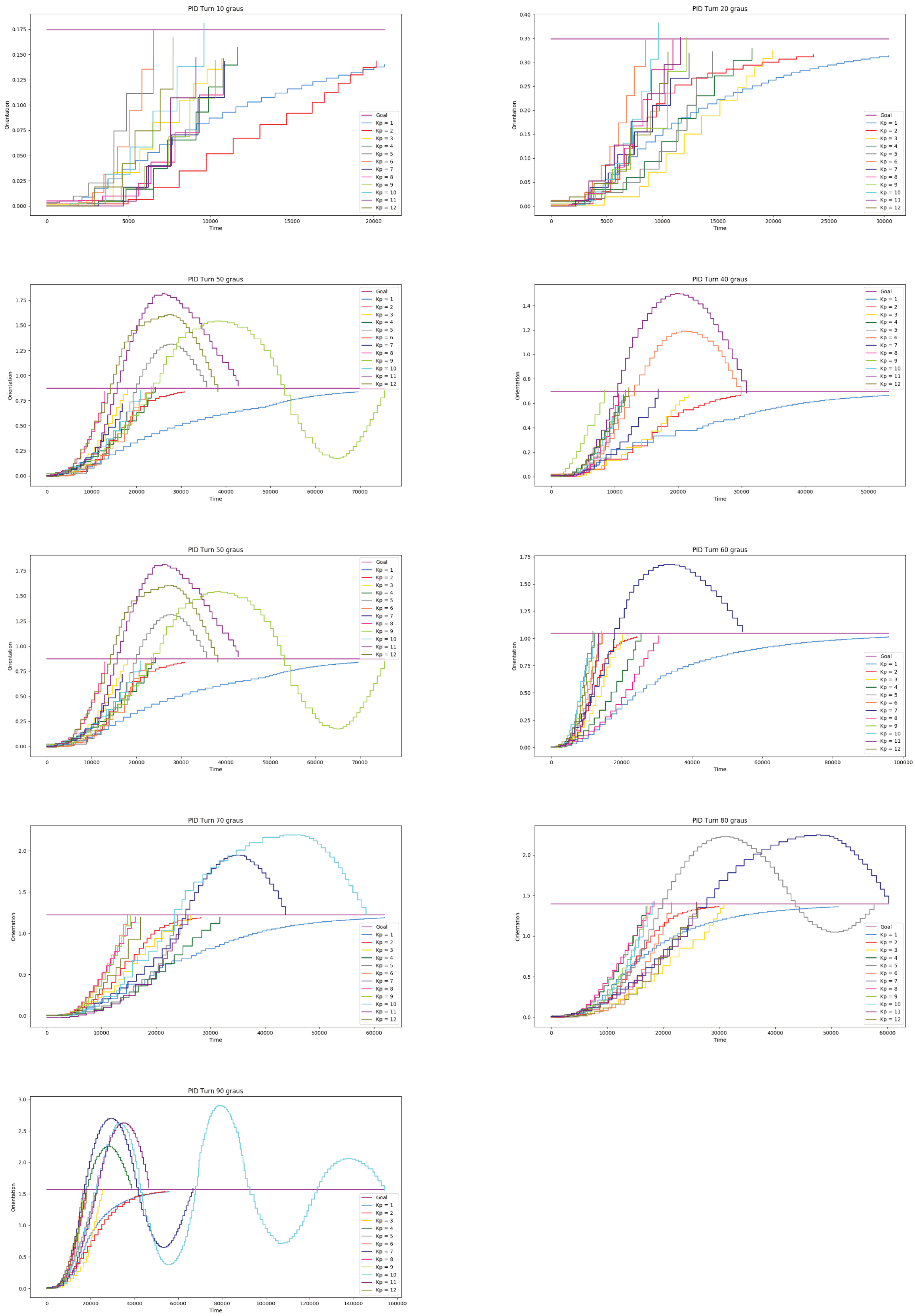

Figure A.2: Proportional controller, varying angle and Kp.

Appendix B

Resulting Publications

Three publications have been produced or are being produced as a result of this work:

- BERTO, L. M; ROSSI, L. L; ROHMER, E., COSTA, P. D. P.; SIMOES, A. S.; GUDWIN, R. R.; COLOMBINI, E. L. Learning over the Attentional Space with Mobile Robots. Submitted to IEEE International Conference on Development and Learning (ICDL) 2020.

- BERTO, L. M; ROSSI, L. L; ROHMER, E., COSTA, P. D. P.; SIMOES, A. S.; GUDWIN, R. R.; COLOMBINI, E. L. An Attentional Model for CST. Ready to be submitted to the Cognitive Systems Research Journal.

- BERTO, L. M; ROSSI, L. L; ROHMER, E., COSTA, P. D. P.; SIMOES, A. S.; GUDWIN, R. R.; COLOMBINI, E. L. Piagetian Experiments for Robots in DevRobitcs. Under construction.