FROM PERCEPTION TO COGNITION : A QUEST FOR EFFECTIVE ACTIVE VISION IN HUMAN-ROBOT INTERACTION

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by

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ABSTRACT

> *"Ever since the first computers, there have always been ghosts in the machine. Random segments of code that have grouped together to form unexpected protocols. Unanticipated, these free radicals engender questions of free will, creativity, and even the nature of what we might call the soul. Why is it that when some robots are left in darkness, they will seek out the light? Why is it that when robots are stored in an empty space, they will group together, rather than stand alone? How do we explain this behavior? Random segments of code? Or is it something more? When does a perceptual schematic become consciousness? When does a difference engine become the search for truth? When does a personality simulation become the bitter mote... of a soul?" Dr.Lanning in I,robot.*

We are in a crucial era for robotics. Robots escape from the laboratories where they have been segregated for decades. It is not unlikely to see robot that autonomously operate in houses, in museums, in factories. Robots assume the appearance of humans that replicate accurately their designer, they exhibits humanoid features without limiting the potentiality of the robotic platform, or they are present in our lives as cute beings or adorable little creatures. The common drive the intrinsically underlines all these different aspects is however one : promote the interaction between the human and the robot.

We are witnesses of a revolution that is silently happening now in our society. Robots are going to be part of our lives or they are already part of what we, as community, relate every day. However, since the dusk of the robotics science, the robot is not souvenir of engineering elegance which is no other goal than pure esthetics but rather a concrete support for human kind. There is not support if the robots remain isolated from the rest of the world with the only objective to accomplish its task. The interaction is the key aspect that brings decisive breakthrough in the introduction of robots in our lives.

This appears natural if we look at the design of the modern robots: replicators, humanoid or simply robot with which is incredibly easier to interact. This is natural if we look at the software that gives life to the mere hardware of these potential partners. The software, because of its key role in the robot design, favorites the escape of the robot community from the dark of our laboratories. This happens from one side by making the human-robot interaction more friendly (robots that have the ability to interact through speech, robots that bring you objects when they are asked to, etc.) from the other side by introducing supervised and unsupervised learning in their bits of code.

The robots, although autonomous, can hardly survive in a complex worlds such as the human

world. The only chance for the robot community is to learn from the experience, to grown wiser in the environment where they need to survive. Artificial intelligence (AI) studied for longer how algorithms can improve they knowledge of the world, and by doing so, algorithm can become wiser. However the insight on the artificial intelligence that the AI scientific community promoted was winning only for a short period. Although the smart algorithms were able to solve novel problems, they never managed to be pointed as the mean by which the robot can definitely survive in the day life.

More recently other form of development intrigued the robotic scientific community. The idea of embodiment, of evolution robotics, adaptation, epigenetic robotics widen the perspective to other kinds of rules that shape the research in the field.

In this thesis, starting from the latest ideas in robotics development, we propose an approach that aims at identifying the roadmap that will ultimately bring robots to be present in human world. The presence will be successful only and only if the interaction between human and robot is constantly promoted. From this interaction the synthesized systems can evolve into intelligent entities. Because of the constant interaction, continuous learning triggered by interaction improves their presence in the world. In this perspective we introduce a novel and inspiring proposal where the interaction is carried on three fold domain. The classical physical domain (the environment) the collaboration operates on concrete means cannot suffice. We propose that interaction must be grounded on at least other two domains: the development and the empathic domain. The first domain is an aspect that results evident after years of work with humanoid robots. The collaboration can be bring positive result if the counterparts correctly interpret the others‘ actions. Synthesized system can successfully interpret human complex behaviors if they share similar development. With the same mechanism by which we can understand where our partner is going drop a fruit or in which bush the hunter pay attention, the smart entity has to understand the behavior plausible hand movement of the partner or to interpret the saccades that brings the hunter‘s fixation point on the particular bush in forest. In author‘s opinion this is only possible if, at some degree, the development is also shared between the partners. This is key aspect in the research carried on by the epigenetic robotics community. We feel that our approach entirely marries the doctrine followed by the developmental robotics community.

Concerning the second domain, we claim that in order to enhance the performance of the interaction, the empathic domain must be exploited. Empathy is defined as the intellectual identification with experiencing of the feelings, thoughts, or attitudes of another. However we can find alternative definition that assign to the empathy the characteristic to ascribe to artifact feeling and attitude present in oneself. The humans already projects on others and objects plausible feelings that make resonate personal condition amplifying the quality of the collaboration. For example it is common to prove bad feelings in observing humanoid robot in non-human configurations that we interpret as painful ”broken” body configurations. Further more, it is common for humans to participate with emotions to the humanoid robot‘s impossible quest of reaching an unreachable object.

In our opinion these three domains are important basis of what is defined as *social intelligence*.

In the story of human evolution, this powerful drive represents one of the most decisive engines that contributed and contributes to make the human being as the most wonderful and intelligent creature in many worlds.

This is what we speculated about in this thesis however we do not limit our work to mere conjectures. On the contrary in these pages we designed and implemented effective algorithms that prove and give novel insights on our philosophical suggestions. Algorithms are designed on the schema designed by our theoretical speculation and on the schema suggested by the epigenetic robotics. We prove that the approach is valid and guarantees optimal results. Convincing results as those reported in this thesis based on a strong and innovative philosophical directives can only favorite the a novel form of presence of robots in out live and promote appealing solution in the quest of potentially successful human-robot interactions.

ACKNOWLEDGMENTS

The research success achieved in these years would not have been possible without precious help of Prof.Giorgio Metta who has always been supportive and proposer of always novel and interesting objectives. Without his never-ending desire to put in to effect theories and models on the humanoid robot iCub kept always alive and fresh my appetite for new challenges. I would like to express my gratitude to Prof.Giulio Sandini who has always been available for suggestions concerning the dynamics within the scientific community. I have been help enormously by conversation with other researches especially Chiara Bartolozzi, Vadim Tikhanoff, Marco Randazzo, Arjan Gijsberts and Ugo Pattacini. I take here the opportunity to thank all the people that with their work guarantee every day the full functionality of humanoid robot iCub and those whose technical support in the laboratory is precious. Finally a particular sincere and respectful thought goes to my family that have always helped me to follow my dream of research in robotics.

to my family

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INTRODUCTION 1

"To understand, as far as possible, the source or origin of the various expressions which may be hourly seen on the faces of the people around us, not to mention our domesticated animals, ought to posses much interest for us."
Charles Darwin

1.1 Theory of evolution Social Intelligence

The chimera of intelligent robots in every personal day-life has been appealing scenario dreamed for centuries by the whole humanity. What makes intelligent robots so desirable is the role of a companion that relieves from the difficulties of every day-life by the mean of support and presence. An intelligent robot can assist in the working environment, in dangerous scenarios but also in hospitals for the care of elderly people, or in the houses as valid and helpful company. In this picture, it is clear how the intelligent robots in general are absolutely essential in the dimension of tight interaction with humans. Note that, in the definition of intelligent robot, we do not embrace the idea of pre-programmed algorithms and hard-coded schemes. For pre-programmed machinery, the interaction with humans is not crucial and task accomplishment can be achieved without intelligence. The biggest challenge in this endeavor is to synthesize intelligence. And when we refer to intelligence, we unconsciously associate it to the human intelligence.

Human intelligence is absolutely a concept that is hard to define and to justify. Intelligent is hugely cost trait, and it must produce immense benefits to compensate such cost. Trying to find the justification of this characteristic choice in natural selection has been a long-standing goal in biology. In literature, we can list many intrinsically different attempts in defining human intelligence but if we look deeply at the definitions, one of the key aspects is missing. Probably it is not definable as a single ability but it is rather a collection of different skills that amazingly amalgamate in whole abstract concept. That is why, in author‘s opinion, we can only succeed in this challenging endeavor if we identify skills that make human intelligence unique, analyze them in the context of a collection of skills and deeply exploit the relations between any skill.

One of the characteristic skill that makes unique human intelligence, namely *social intelligence* may give insight on aspects of human intelligence

In this theory, it is stated that primates are more *social problem solver* than problem solver. As result of the social complexity, individuals evolve. Co-evolution between social and cognitive complexity in individuals takes place in society. In literature Sterelny (2007), at least two different reasons validate this hypothesis: a) the complexity of the social world, b) feedback loop between culture and cognition. The former indicates as source of complexity the level of cooperation with inter and intra-generations and the division of labor. There is a vertical and horizontal complexity of the society that shapes individuals. The later expresses the culture-cognitive loop as relevant. Intelligence increases complexity of the society and the level of complexity in society naturally selects greater intelligence. A particular version of social intelligence is usually defined as *Machiavellian Intelligence hypothesis*. The proponents of such hypothesis Byrne and Whiten (1989a) Whiten and Byrne (1997) argue: " One of the characteristic skill that makes unique human intelligence, namely *social intelligence* may give insight on aspects of human intelligence "

In other words Machiavellian intelligence evolves through arms race. The standard way to present it is through the game theory and in particular Prisoner‘s dilemma Ledyard (1994) Sally (1995). These are examples of collective actions problems, where the evolution of the system is based on the reaction of the whole collectivity more than the sum of contributions of single individuals (e.g. people rushing out of a building in the event of fire). The mechanisms is based on two innate instincts in the society: cooperation and defection. Axelrod‘s computer simulation Axelrod (1984) shows how cooperation can be rational as long as every actor plays cooperatively. The cooperation breaks into parts as long as one defeats the others, no cooperation is possible in this direction. This forced the highly intelligent individuals to enhance the ability to monitor counterparts in the society. This engages the *tit-for-tat* altruism: we cooperate with those who cooperate, and we do not cooperate with no-cooperative individuals. Reciprocity is sustained by self-interest and mutual scrutiny.

The power of these particular forms of intelligence is evident to us but transparent as well to the whole collectivity. We are so immersed in the social drive that we cannot imagine development without social rules. Since social intelligence tends to escape from our comprehension, research mastered chiefly two ways to prove it: i) through experiments on the nature of animals, ii) through computer simulations.

The social environment cannot be subsumed under general environmental factors and it has been suggested as the drive that might bring us closer to goal of making robots smart Dautenhahn (2007), Dautenhahn (1999) Dautenhahn (2004). The *social intelligence hypothesis* (also called social brain hypothesis; Dunbar (1993), Dunbar (1996),Dunbar (1998),Dunbar (2003)) suggested that primate intelligence evolution enhanced more as adaptation to social complexity. (e.g. Byrne and Whiten (1989b), Byrne (1995), Byrne (1997), Whiten and Byrne (1997) . It is to note the experiment carried in the Alison Jolly in fifties where social intelligence was first formulated on non-human primates. In nature there are primate species not able to manipulate object but they show social intelligence that allow them to create social organization. This evidence brings Jolly to conclude that social intelligence preceded the object intelligence and above that determined the primate intelligence. Despite the quite strong claim, it is worth to note that social intelligence is a powerful drive that possibly can operate in conjunction with other factor , e.g. ecological factors.

There are evidences that *prosocial behavior* is present in communities of evolved animals. Particularly in primates, the social drive is strong and determines active behaviors that favorite the conservation of the specie. In Cronin et al. (2005) it is presented a task of cooperative problem solving to assess cognitive basis of collaborative behavior. The breeding cottontop tamarin, Saguinus oedipus, as other great apes species, are able to design a successful collaboration that is based on common goal and coordination on the shared resources. This is very complex cognitive behavior that can be mastered only in presence of social drive. Without this collaboration the reward (that in nature can be associated to food or survivability) cannot be obtained resulting in minor chances in the challenge of natural selection.

The concept of sharing resources is crucial in author‘s opinion and we present it as important aspect of the collaboration. The prosocial drive can become so powerful in these communities that, not only objects are shared, also feelings become unique domain where the collaboration can enhance. As reported in de Waal et al. (2010) prosocial primate can exhibit altruistic behaviors that offer the actor no knowable rewards. Empathy, as mechanism in favor of prosocial behavior can be experienced when one individual share another’s emotional state. This easily would predict evolutionary theories of cooperation in non-human primates. As we present in the next paragraph, the empathy between partners can improve the quality of the collaboration. As personally experienced, the human feeling associated to the success in difficult tasks performed by humanoid robot, is powerful aspect that enriches the collaboration and interaction experience.

Further more, in recent research McNally et al. (2012), the cooperation and the evolution of intelligence is proved via the use of artificial neural model. The intelligent behavior emerges from the exploitation of cooperative behaviors. The selection pressure within the neural population is triggered by the need of effective decision making in cooperative dilemma. One of the possible explanation of similar approach is *social intelligence hypothesis* Reader et al. (2011) Emery et al. (2008). Cognitive abilities require coordination of partners. There are two typologies of coordination: a) direct where the decision is taken on what the counterpart does which directly affects the subject, b) indirect the choice relates to what the counterpart does on others. Decision on cooperative dilemma are taken based on different interaction in time and therefore a sort of memory has to be presented in this loop Stevens et al. (2005) Melis and Semmann (2010). In Brosnan et al. (2010)

it is suggested that such mechanism can be at the basis of the advanced cognitive skills. In fact,a recent study Hill et al. (2011) suggests that the level of relatedness is too low in the hunter-gathered groups to activate kin selection as a drive for evolution in human cooperation. In highly intelligent species (e.g.: humans, primates, cetaceans, etc.) other behaviors seems to be important Brosnan et al. (2010). The studyMcNally et al. (2012) shows that the selection of appropriate behaviors leads to cognitive abilities and that intelligent behavior facilitates greater extremes of cooperation.

Learning is usually and most of the time facilitated if the learner have a background of basic social competencies. More complex social competences develop on top of the existing, and by doing so, learning process easily activate Scassellati (2001) Lungarella et al. (2003). As already pointed out, the importance of social drives in development (and then in learning) is so manifest in our species that it is hard to image a fully developed human intelligence without social drive. In addition, severe developmental disorders can give inspiring insight on the concept. In particular, those that are characterized by impaired social and communicative development, such as autism (Baron-Cohen (1997)), play important role in defining the ”social contact” (Scassellati (2001)) in children development.

1.2 Human-Robot Interaction : Sharing Resources and Sharing Development

The importance of social intelligent is addressed by researches that involve Robotics as well. Robotics, more correctly developmental or epigenetic robotics, is considered new frontier where mechanisms that shape human intelligence can be reproduced and exploited. Aspects of such learning and development are introduced in this field with absolute success. The goal remains the chimera of proficuous interaction between human and robot but the approach that brings to the goal shapes on one important hot key: *sharing*

These consideration are inspiration for the emerging field of Human Robot Interaction (HRI). In this particular robotic scenario the human counterpart has a significant role. The robotic entity has to take in consideration the human being that shares the identical space in the same contextual relevant time horizon.

Sharing of resource and being present -both robot and partner- in the environment create a domain where all the players interact. Any player plays a role that profoundly affects the others. The single entity is not isolated from the rest of the world but rather receives and sends information. For example, an object located on the table in front of both the human being and robot is a shared resource. Reputedly even if the robot can only sense that particular object, that object becomes a mean for information to flow (in both the directions). By changing the position in the space of the object, the human changes the state of one of the shared resource and thus changes the state of the environment. State changes in the environment when sensed by the robot and immediately that results into information transfer which is the basis of interaction. The social implications of this mechanism are evident in this very trivial situation but it can quickly scale up when the robot is immersed in the environment.

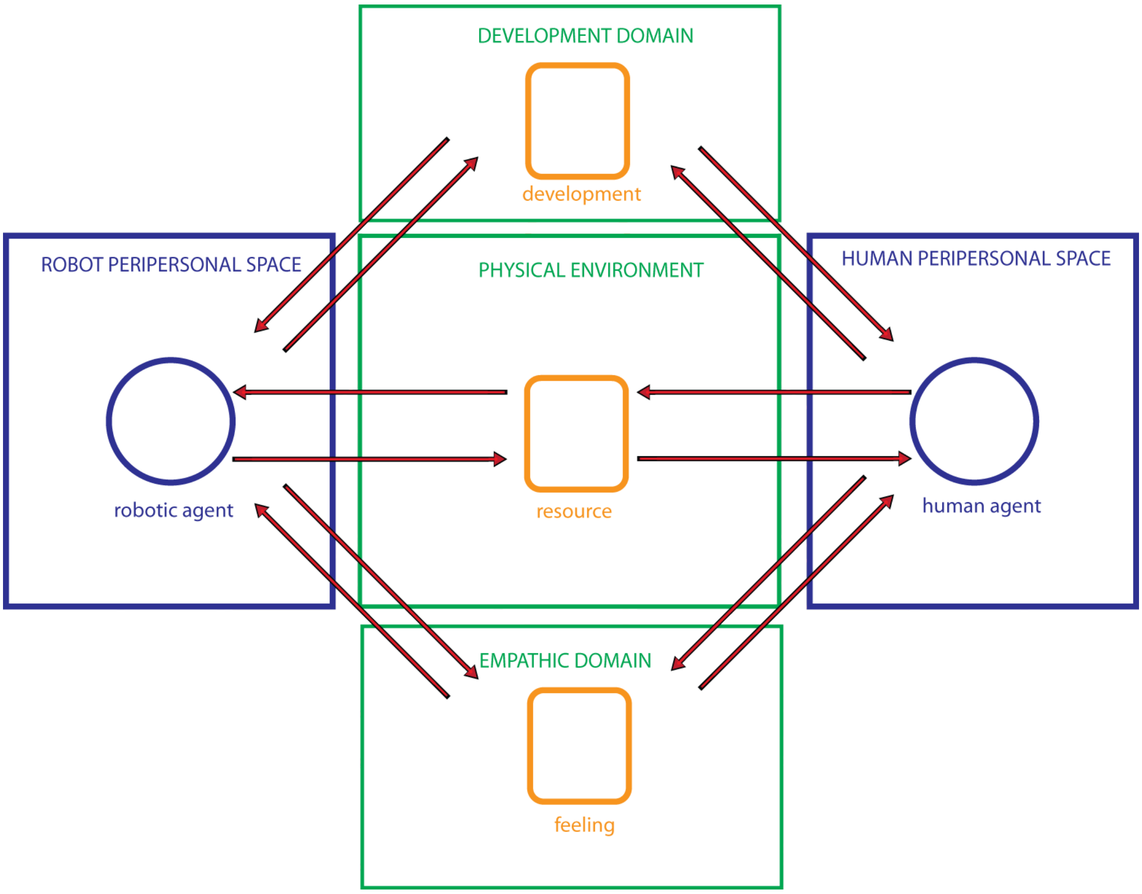


Figure 1.1: socialEmbodiment: how the interaction defined as sharing of resources can shape the development

The more the robotic actor is immersed in the environment the more information can freely flow. This is the reason why the embodiment has been such a crucial breakthrough in the field of artificial intelligence (AI). The absence of body, sensors, actuators in a intelligent actor limits the capability to evolve. Imagine an intelligent creature that has potentially immense processing capability but this is completely isolated from the rest of the world. That creature can only aim at solving pure abstract problems and never ground them in the reality of the physical world. Through the embodiment, the agent can at first instance autonomously explore the environment and successively promote for positive interaction with others. It is not in the author‘s intention to accurately present the concept of embodiment. However the author‘s take home message remains that the embodiment results a crucial tool and without it no further development takes place.

Following up on the idea of interaction as triggered by sharing resources in the environment, it can be easily assimilated to the concept of social interaction as we previously speculated about. Therefore such convincing idea that sharing resources introduces intelligence in the system strengthens its basis in the social intelligence. In other words robots that interacts with counterparts through common resources show intelligence. In addition, the aspect of the robot intelligence results crucial from another perspective. In order to establish robust interactions, from the point of view of the human counterpart, the robotic presence acts under rules that makes it appear intelligent. This characterization of the attitude is based on evaluation mechanism which can however enhance the feeling of interaction with smart agents. Giving this feeling to a subject facilitates enormously the quality of the interaction as personal experience. This can easily be found in reports in research on human robot collaboration and in the daily research activities when the interaction with the humanoid robot iCub is tight.

It is author‘s opinion that examples of effective interaction between human and humanoid robot are far from being impossible. Although the feeling of complete and proficuous collaborations can be experienced everyday by working with humanoid robot iCub, there are different detailed experiments that evaluate the quality of human robot collaboration. Intriguing concept that defines the feeling of collaboration is the *uncanny valley*. The phenomenon of *uncanny valley* was first explained in Mori (1970) as the feeling of accepting the robot as partner which increases with the human appearance of the robot. This is valid assumption up to a certain point where the robot appears too human, the robot is then rejected as partner. In Gray and Wegner (2012), the group showed how the quality of the experience in the assigned task grows with human appearance of the robot and decreases when the uncanny valley is reached. This can only be explained that, in author‘s opinions, that feeling of identifying one self with the robot promotes empathy (sharing the feelings). Only when the empathy for the partner contrasts with the prior knowledge of partner‘s robotic nature the quality of the interaction degrades. This experiment confirms that sharing feelings (*empathy*) as sharing resources boosts the final accomplishment of the social task.

Similarly to sharing the resource, sharing of development is crucial passage that smart robots cannot avoid. Imagine that the section of the human counter part in figure 1.1 suddenly disappears. The robot senses the environment and with it the available resources. No doubt, the robotic entity, which is not an isolated creature, acts on resources and obtains positive and negative rewards from the experience. The learning process can take place despite the absence of the social counterpart. It is evident that only a restricted subset of rule -mainly related to the physics of the world- can be deduced. However, how the knowledge of the world evolves is completely uncontrolled and therefore it reaches local minima that differs from the knowledge of the removed counterpart. If we hypothetically reintroduce the partner in the schema they can experience difficult collaboration because of the robot entity‘s knowledge is incomplete or do not share the same rules. From this logical demonstration it is clear that the more the two entities share the same development the more the interaction results facilitated. The author is convinced that in order to create proficuous human-robot interaction the robot has to learn and develop with processes that are as close as possible to the counterpart‘s development.

Thus social intelligence can be considered as a key factor for robotic application and, as we demonstrated, necessarily falls in the robotic development. On the other hand it can drive intelligent skill that otherwise can remain unexploited in classical robotics. Here we pointed out two very crucial aspects: i) the learning as drive for novel robotics ii) the development that might resemble the human development. An inspiring field of research in robotics that facilitates the exploitation of social aspects in robotics is *epigenetic robotics* also named as developmental robotics Lungarella et al. (2003).

1.3 Phylogenesis and Ontogenesis in Epigenetic robotics

Since the dawn of life on earth, three levels of individual enhancements can be distinguished: a) phylogeny, b) ontogeny, and c) epigenesis Sipper et al. (1997).

- Phylogeny : temporal evolution of the genetic program. Subject to a very low error rate at the level of individual, it is based on the reproduction of the program. Asexual reproduction and sexual reproduction give birth to offspring with different program. It is not deterministic and provides the greatest source of diversity. Diversity is fundamental for the survival of the species, for adaptation to changing environment, and appearance of new species.

- Ontogeny: the program passed from the ancestors to the individual is going to specialize in accordance to the surroundings. This is one of the main known developmental processes. It is essentially deterministic and an error in the program can be potentially noticeable and affective.

- Epigenesis: The ontogeny is limited in the amount of stored information thus a complete representation of the individual is impossible. For example, the human brain is formed by 10^10 neurons and 10^4 connections that make this quantity of information impossible to be represented in four character genome of length 3×10^9. A different mechanism permits the individual to integrate a vast quantity of interaction in the world. The epigenesis fills this gap where the inner part inherited from the program is subject to modifications. Modifications can occur during the life time and are due to interaction of the individual with the environment. The epigenesis can be assimilated to the learning.

Epigenetic robotics might be confused with developmental robotics but *epigenetic* is not ambiguous in biology Jin and Meng (2011). It might either refer to the modification in gene expression or morphogenesis or postnatal development. When we refer to epigenetic robotics we rather indicate a development that resembles post-natal development. The difference between epigenetic and developmental robotics is clear and clarified in different discussions Lungarella et al. (2003). Theoretically speaking we can now say that epigenetic robotics is branch of developmental robotics.

Developmental robotics is also known as ontogenetic robotics. For the educational perspective, epigenetic robotics is based on interdisciplinary subfield which gathers concepts from artificial intelligence, developmental psychology, neuroscience, and dynamical systems theory. Developmental robotics has as primary objective the modeling and development of cognitive processes in natural and artificial systems that incrementally evolve. Additional goal is to understand how such processes can be activated through physical and social interaction.
The test of theoretical model of the emergence and development of action and cognition using robots is typically one of the goal in the epigenetic robotics. The main idea is that entity that follows a model embedded in the real world can be learned about its strengths and potential flaws. On the contrary, evolutionary robotics operates on phylogenetic time scales and populations of many individuals. Developmental robotics is based on relative short time scales (ontogenetic time scales) and involves single individuals (or small groups of individuals).

The processes underlying human developmental is intrinsically robust and flexible. This appears more evident if related to the amazing ability of biological organisms to master novel and winning adaptive strategies. These biological systems have the ability to cope with unexpected environmental changes and guarantee survivability. Because evolution has selected development as the process through which to realize some of the highest known forms of intelligence,it is reasonable to assume that development is mechanistically crucial to emulate such intelligence in machines.
The idea that development might be a good tool to understand and construct cognition have been studied for long. In fact already Alan Turing suggested that ”in order to build intelligent machines one might want to start by simulating the child’s mind”.

In the context of robotics, three principal breakthroughs underlined the principal concept that gave birth to developmental robotics: (a) *embodied artificial intelligence (embodied AI)*, in other words that intelligence -at least as the humans conceive- can only be mastered if the system is completely immersed in reality and it can sense the reality (e.g. Brooks et al. (1998); Pfeifer and Scheier (2001); Pfeifer et al. (2007)); (b) *synthetic neural modeling*, that is a collection of techniques in which interaction among the nervous system can be studied by the use of large-scale computer simulations(edelman et al. (1992); Reeke (1990); and (c) *enaction* according to which cognitive structures emerge from recurrent sensorimotor patterns that enable action to be perceptually guided (Varela et al. (1991)).

Since the late 90s, the idea that the dynamic and reciprocal interaction between brain, body agent and environment can give intriguing insights on intelligence grows stronger. This idea proposes the current foundation that promotes the three principal breakthroughs above. In fact many of the works Ferrell and Kemp (1996) ; Rutkowska (1994); Sandini et al. (1997)) in the field of developmental robotics exploited the development of sensorimotor intelligence in the context of embodied systems.

1.4 Active Vision: from the Perception to Action

Consider that the development is never obtained by isolated process but rather it is process where novel skills are built on top of existing skills. This is important characteristic usually referenced as *developmental progression*. Usually later structures are more complete and more efficient with respect to the prior structures. In other words, any structure can be reused to master novel structures. The mastery of reaching, for instance, requires adequate gaze and head control, and a stable trunk support, the latter being even more important for one manipulation Bertenthal and von Hofsten (1998).

When we mention developmental structures we refer to components that are either result of ontogenetic or phylogenetic processes. In the case of phylogenetic processes or processed that are result of evolution, neurophysiology is particularly useful tool that reveals the phylogenetic mechanisms. Thus, if we want to analyze the developmental structures that space from perception to action, as a first instance, we look at the neurophysiology. In this section we present some foundations that validate the points in the discussion of the next chapters.

Following up on this intention, we move from developmental psychology to neurophysiology to underline the relationship between perception and action in primates. In particular, we focus on paths in the brain that exploit perception and action as one complex structure rather that analyzing them separately. In particular we studied dorsal and ventral streams in monkey to highlight their functional relation. In the early 20th century, the community of neurophysiologists widely accepted as fairly complete the existence of one *motor area* area4, main origin of corticospinal projections and a *premotor area* considered as preparatory origin of movements. This point of view considers the motor system as a sort of collection of associative areas that generate motor commands via spinal cord. In the last two decades this vision has been challenged.

One observation is particularly interesting for goal of this research, and which gives insights on the relation between action and imaginatory preparation to the action. *Sensorimotor neurons* in frontal cortex present an apparent degree of functional ambiguity since they are active during motor execution and sensory stimulation. In other words, stimulus-response of this area not only characterizes the movements but the goal too. The movement finalized to a goal accomplishment defines the action.

As proposed in Vernon et al. (2011) The quest of functional segregation of dedicated area in the visual cortex brought Ungerleider and Mishkin (1982) to formalize the *what and where theory*. According to this theory, ventral path has the main role in object recognition whereas the dorsal path in spatial localization of objects.

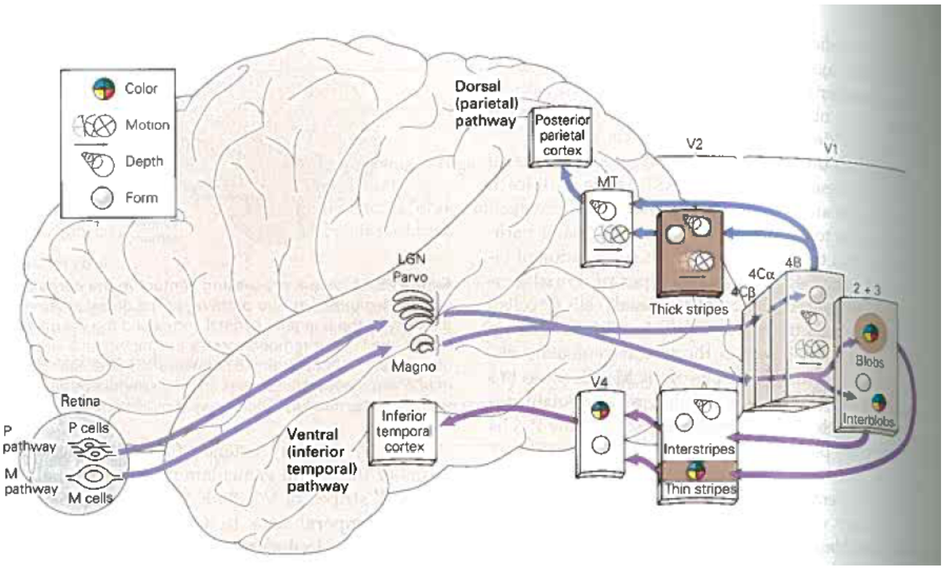


Figure 1.2: Possible functions mediated by the two pathways connecting visual processing centers in the cerebral cortex Kandel et al. (2000)

However as argued Milner and Goodale, there are no strong proofs of a across modalities space area in the posterior parietal cortex. On the contrary, it seems that each single circuit in a series of fronto-parietal circuits encodes the spatial location of an object and transforms it into potential actions Rizzolatti et al. (1997a), Rizzolatti et al. (1997b). The Milner and Goodale work might seem to propose a too rigid connection between action and perception, however there are evidences that perception and action integration occurs at multi-domain spaces. It is very likely that there exists more than one map (absolutely not a unique multipurpose space map) but the integration happens across distributed space maps.

The sharp distinction of the dorsal and ventral pathway or also known as the distinction between acting brain and knowing brain as proposed by Milner and Goodale seems to be contrasted by some other evidences. Mirror Neurons, at first discovered in monkeys, discharge both when the monkey performs an action and when it observes the same action performed by others Gallese et al. (1996). Demonstrated in humans, it means that what we perceive resonates with the associated actions, which goes against the idea of a sharp distinction between dorsal and ventral streams. Another cognitive function where the two streams seem to be correlated is the *motor imagery*.

These findings and many others directly support the involvement of dorsal stream in cognitive task.

The selective attention is a cognitive process where all these mechanisms are perfectly replicated. Thus, the selective attention is widely considered as starting point for the study and this is also why it has great importance for the author. This refers to the ability to select salient region to allocate perceptual resources on and, if convenient for the individual to act on. Attention might be considered as well as the result of circuits underlying action and perception and at first formulated as spatial attention in premotor theory of attention Rizzolatti and Camarda (1987) Rizzolatti et al. (1987). In fact, respectively, two effects occur: a) increase in motor readiness and b) facilitation in processing of the region where the focus of attention is deployed. From this, we can conclude that attention is regulated by the same mechanism of action generation. It is not debatable that eye movements are a form of action directly linked to the attention. Of particular interest is the series of experiments Sheliga et al. (1995b) Sheliga et al. (1995a) where result evident that ocular programming is not independent from the attention, and in particular location of attention influences the ocular saccades and microsaccades.
Finally, attention can be studied in relation to the goal of actions. As assumed in *premotor theory of attention* Craighero et al. (1999) the focus redeployment on graspable objects is fundamental step in preparing the actual grasping action. In recent experiment of the same group, the subjects were presented clue on the orientation of the object to grasp and this bias the preparation of the grasping, facilitating the grasping of those objects that match perceived clue. These neurophysiological evidences constitute the basis for modeling of the phylogenetic mechanism that we introduced in the system. Whatever is not autonomously learned by the smart humanoid robot iCub (ontogeny) is that implemented by the mean of detailed natural model which are results of evolution (phylogeny) in mammals.

1.5 Outline

In the next chapters we present in detail how we enhanced the skill of the humanoid robot iCub. Starting from the early perception stage -or in other words the mere interface of the robotic system to the environment- to the stage where the robot learns some rules out of the world. The passage from one basic skill to the mastering of the learning is not trivial and involves numerous tools that need to be introduced in the system. For example visual attention, correct oculormotor action, prediction are features that the robot has to posses if the robot aspires to survive in the real word.
In the chapter 2 we present the early perception stage which comprises different filters at different stages of complexity that process retinal information into more complex information -interpret the reality. This information is fed to the attentive system that determines the focus of attention. Deploying the focus of attention in subregion of the space is fundamental cognitive stage that allows the system to efficiently allocate its internal resources.

Similarly, in chapter 3, we present both early stage processing and attentive system that uses completely different hardware for the acquisition of information. With this we prove that, no matter which sensor samples the environment, cognitive processes can be successfully implemented at higher level (on top of world of perception). In this chapter, we illustrate how the use of neuromorphic chip can change the algorithms of the information processing of the early stage but keeps unaltered the final result of the cognitive stage.

The output of the attentive system can be considered as the composition of two contributions: bottom-up and top-down. In the previous chapters we only exploit the top-down component of the visual attention whereas in chapter 4 we complete a survey on the higher cognitive components of the visual attention. In particular we propose one key rule that shapes the interaction between bottom-up and top-down.

At the end of this process the focus of attention is deployed on the salient stimulus. This may not correspond to an eye movement in that location. In literature the focus of attention shifts even if the fixation point is kept fixed. For simplicity, we assume that an attentive shift always corresponds to a shift of the line of sight. To assure that this oculumotor action correctly deploys the line of sight on the focus target we implemented accurate saccade mechanism. In chapter 5 we present the implementation of saccades and we introduce other oculomotor actions that we provide to the robot (microsaccedes, express saccades, smooth pursuit).

Any of this oculomotor actions, brings a cost when performed and not always the cost is necessary. In some other situations the active system should rather opt for less demanding actions. However in order to trigger alternative action the system has to understand what is the state of the overall system (composition of itself, the environment, the partner) and predict. In chapter 6, we show how prediction mechanism can be implemented on a humanoid robot, and provide some experiments that show the performance of the solution designed. Infants exhibit prediction of the human movements, if they recognize the human counter-part and if they already mastered some specific skills in similar task. The idea presented in the relative chapter is based on the tight mapping between the neural path activation when they perform the action and the neural path activation when they see other perform the same action. Model of this mechanism have been studied and replicated on the humanoid robot iCub.

Finally, in chapter 7, we tackle how the robot can address ontogenesis on top of all the skills implemented on the robot and presented in the previous chapters. The learning is key aspect in this development therefore we propose some considerations and reflections on the topic. Moreover in the last section of the chapter we illustrate our possible implementation of the learning and we show how this works through real experiment performed with the robot and in a real human-robot collaboration scenario.

Foveated Visual Attention : from the Front End to the Selective Stage

2

Concerning the ”mindfulness” and meditation:
”faithfully returning back to refocus on that object whenever the mind wanders away from it.”
Dalai Lama
Attention, Memory and the Mind XVIII:
A Synergy of Psychological, Neuroscientific, and Contemplative Perspectives
Dharamsala, India
April 610, 2009

2.1 Introduction

By presenting phylogenetic development, we aim to promote proficuous interaction with humans, we are particularly interested in visual attention. Visual attention is widely considered one of the basic cognitive skills. Any interaction with the environment is successfully initialized if accurate focus of attention redeployment takes place. In nature, selectivity in the huge amount of visual information allows fast dangerous treat identification - and usually this results in an increase of survavibility chance. Unpaired patients affected by attention deficit disorder have difficulties in completing the assigned tasks. Since the importance of the attentive system in nature, we opted for a detailed analysis of the topic and successive implementation of system. We prefer to recreate in the humanoid robot dynamics which have been studied for decades and have been defined by attentive models. Those attentive models are present in living beings that have matured these models after million of years of evolution (phylogeny). In particular we transfer to the robot models that capture some features of attentive system in humans.

In the process of elaborating visual information there are bottlenecks (e.g.: optic nerve) that limit the capability to process the entire field of view. The evolution influences the mentioned mechanism in basically two ways. First, the distribution of photoreceptor in the retina have varying resolution (the cones are greater in number in the central zone, namely fovea). Second, rather than processing the complete flow of information, a small region of interest can be selected and all the resources can allocated in processing that region. The last process, usually defined as selective attention, helps in breaking down the problem of analysis of visual scene into computationally less demanding localized visual interpretation.

The topic of selective attention became very popular in the late 90s because of the converging evidences that, in mammals, before any interaction with the environment, visual attention pathway is active Walther et al. (2004) Rutishauser et al. (2004). The focus of attention is located on the target concentrating all the available resources on it. Only after the focus of attention locates on the object and the associated oculormotor action brings the fixation point on the object, various actions (e.g.: reaching, grasping, learning, etc) can be successfully triggered. That is, the visual attention is a critical cognitive skill that correctly activates motor actions and higher cognitive analysis of the scene.

Generally speaking in the last decades few different research communities proposed valid and inspiring models of selective attention. Since the first few years of the last decade, one of the groups particularly active in the field was Itti & Koch group. They proposed a computational efficient implementation of biological models of selective attention Itti and Koch (2001) based on the Treisman‘s research Treisman and Gelade (1980) exploiting pop-out effect in early pre-attentive system of mammals. Other groups in the scientific community proposed alternative models which resulted to be as much inspiring. In fact, these models produced similar enthusiasm in the research community which led to some complete reviews on the topic Heinke and Humphreys (2005) Rothenstein and Tsotsos (2008) Claus Bundesen (2005) Frintrop et al. (2010).

As most of the computation attentive systems, the model proposed by Itti & Koch structurally originates from the theoretical model of *feature integration theory(FIT)* Treisman and Gormican (1988). In fact, two main theoretical models inspired most of the relevant psychological theories of attention are: a) *feature integration theory(FIT)* Treisman and Gormican (1988) b) Guided Search model Wolfe (1994). In the former, different features are collected into a single master map, and thanks to this a serial search in the feature domain guarantees object detection. The later, introduces top-down attention to the bottom-up attention basically shaped as FIT and it refines the solution for software implementation. The community has produced many other psychological model of the attentive system in either humans or mammals. Eriksen and St. James (1986) have introduced the concept of *zoom lens model*. Another type of psychological model of attention is based of *signal detection theory* Green et al. (1966) Abdi (2007) where the quality of the attention selection mechanism is associated to the accuracy in the distinction between noise and signal. For a mathematical approach of visual attention system Logan (1996) : the CODE Theory of Visual Attention (CTVA). Two essential theories in the field *COntour DEtector (CODE) theory* for perceptual grouping Van Oeffelen and Vos (1982) and *Theory of Visual Attention (TVA)* Bundesen (1990) fuse together in order to generate novel theory of *race selection* model of attention. The responses to stimuli are computed in parallel, so that the fastest to complete the processing is selected as winner. The winner takes all the available resources reducing resources allocated to the distractors. In Milanese (1993) the author proposed a model early filter-based attention model and successively refined Milanese et al. (1994) by including top-down information on the recognized object. The system is further enhanced with the *distributed associative memory (DAMs)* : mechanism of memory recall of crucial information.

Several different *computation models* of visual attention have been proposed. Among the most important ones, Tsotsos et al. Tsotsos et al. (1995) use local winner-take-all network mediated by a top-down mechanism that selectively tunes neurons associated to the attended location. In this model, precuing selects the dimension of the attentional spotlight. Sun and Fisher in Sun and Fisher (2003) implemented a framework for object-based and location-based visual attention named as "groupings". This model directly continues the research path indicated by Duncan's *Integrated Competition Hypothesis* Duncan (1997). Finally Deco and Schurmann Deco and Schurmann (2000) allocate different spatial resolution receptors on the portion of the image indicated by the top-down attentional control signals.

As interesting examples on how these models bring novel contribution in the field of robotics, we reference to Zhang et al. (2009) where the object is segmented by separating the salient region from the background. The salient region is obtained by merging together different feature maps and determine the conspicuous region in the field of view. Usually attentive systems can successfully be used to accomplish self-localization tasks. Attentional mechanism can facilitate the search of static landmarks Nickerson et al. (1998) or even tracking moving landmarks Ouerhani et al. (2005). Even more challenging, simultaneous localization and mapping (SLAM) benefits from attentive system Frintrop and Jensfelt (2008). For task such as object recognition, attention system can improve the performance Walther et al. (2005). Usually the attention system must be coupled with other systems that address object recognition. Recent work Miau et al. (2001) proved that front-end of visual attention can successfully be coupled with biological plausible object recognition system HMAX Riesenhuber et al. (1999). Other attentive system can be successfully coupled with either SIFT features Walther (2006) or AdaBoost classifier Frintrop et al. (2004). For other form of cognitive integration, the reader can reference to Salah et al. (2002) where attention system interfaces to a neural network in a observable Markov model for hand-written digit recognition. In addition for some form of tracking of the most salient region in the visual field Ouerhani and

Hügli (2003).

In particular, reflecting the importance of associating the idea of foveated vision and visual attention (already exploited in depth in Tamayo and Traver (2008) Javier Traver and Bernardino (2010)), numerous models of foveated visual attention can be listed in literature. Of great interest for our approach is Orabona et al. (2005) which is a clear example of how the Itti & Koch model can be efficiently coupled with some foveated vision. We continue along this research direction refining the complete structure of the model and introducing novel and missing feature maps, following tightly the Itti & Koch model. Another inspiring evidence of the potentiality of this mechanism is the work by Colombo et al. Colombo et al. (1994), Colombo et al. (1996) where the authors transfer idea of pyramids of images to foveated images as way of efficient filtering. We identified similar mechanism of pyramids of log-polar images (as reported in this chapter) which can be seen as alternative model of the front-end stage. Inspired by the Metta (2001), we exploit in depth the concept of active vision. Many challenging aspects of the active vision are accurately addressed by different works Oshiro et al. (1997) Yamamoto et al. (1996) Yeshurun and Schwartz (1989) however in most of the cases the attention system tackles problems of covert attention. The limit is that very few exploit the overt attention Bernardino et al. (2002) and very few researches investigate real scenarios but rather prefer to simulate.
On the contrary we here present a model of active overt vision based on Itti & Koch model which processes log-polar images and operates in real-time in every-day cluttered scenarios. We propose a model for the foveated bottom-up visual attention that can be biased by top-down visual attention (details in chapter 4) and which generates attention shift translated into active oculormotor commands (details in chapter 5).

Evidences in psychophysics and physiology converge on the idea that the result of such evolution is a highly specialized processing focus Folk et al. (1992). This moving and unrevealing light on the world (either spotlight or multiple bright light) is the result two-stage theory of human visual perception. The first is the 'preattentive stage' where a collection of different filters is applied on the overall input visual channel. The second creates an 'attentive stage' where information from the previous stage are combined together in complex forms that help in the process of recognition. In fact, it has been proved that attention is key ingredient in object interaction (Koch and Ullman (1985), Neisser (1967), Bergen et al. (1983), Treisman (1988), Ullman (1984)).

In the foveated visual attention we are interested in exploiting the interesting research situation where both the solutions that the evolution has proposed (foveated vision and visual attention) belong to the final implemented model. The former mechanism is introduced into the system through a log-polar mapping. The log-polar image is the result of sub-sampling of iCub‘s standard rectangular images. Sub-sampling is implemented accurately by averaging pixels across receptive fields of varying size approximating certain CMOS implementations of foveated cameras Berton et al. (2006). The log-polar mapping follows this earlier work and in particular:

$$\begin{cases} \rho\left(r,\phi\right) = k \cdot log_{\lambda}\frac{r}{r_0} \\ \theta\left(r,\phi\right) = h \cdot \phi \end{cases}$$

where (r, ϕ) are the standard polar coordinates and (ρ, θ) the log-polar ones related to the image coordinates (x, y) by:

$$\begin{cases} r = \sqrt{x^2 + y^2} \\ \phi = atan\left(\frac{y}{x}\right) \end{cases}$$

with λ,k,h,r_0 various fitting constants determined by the actual size and desired number of receptive fields in the original and transformed image. An example of the rectangular to log-polar mapping is shown in 2.1.

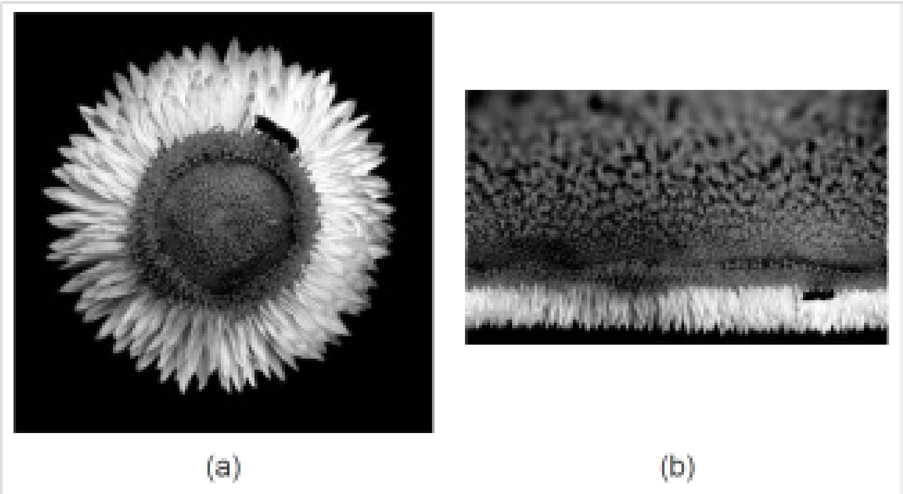


Figure 2.1: Conversion from cartesian image (a) to the logpolar image (b) where the distance r from fovea is depicted on the y-axis and the angle ϕ on the x-axis

The later mechanism, the attention, not only serves to select region of interest in the scene but it enhances the cortical representation of those objects at those locations. Finally attention is involved in triggering behavior, planning and motor control Ude et al. (2005).

The psychophysics evidence of a specialized focus can be divided in two classes of experiments Posner et al. (1984). First is proved by Treisman and her collaborator evidence of a fundamentally parallel across a spatial domain given born to the so-called pop-out effect. On the contrary feature search is mainly the result of a serial and self-terminating scan through elements in visual field. Studied on what stimulus characteristic does affect the minimum time for the appearance of the pop-out effect, it defines which feature can be processed in parallel e.g. color, orientation, stereo and motion. Singleton and textons as limited set of features that can be detected in parallel. Moreover the performance in pre-cuing task were better suggesting for notion of advance shift in

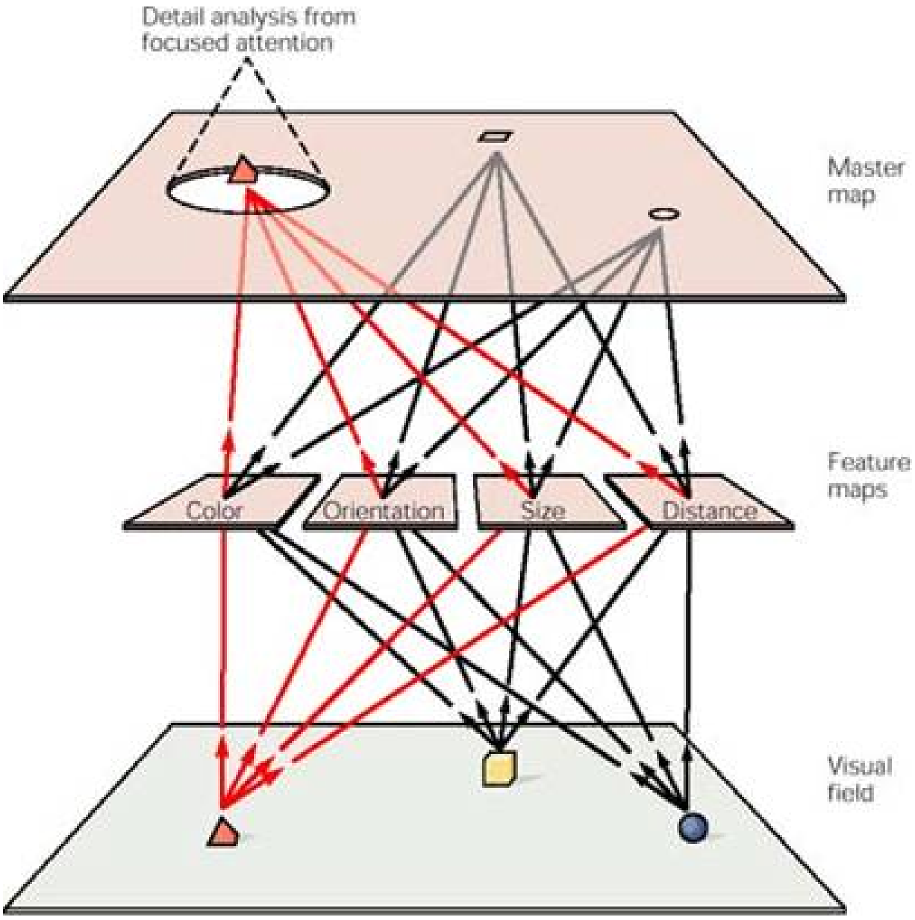


Figure 2.2: Treisman interpretation of the visual selectivity in the early visual cortex

processing Koch and Ullman (1985), Eriksen and Hoffman (1973); Posner (1980); Bashinski and Bacharach (1980), Remington and Pierce (1984). A series of evidences in the area of physiology reinforced this model of selective attention. Goldberg and Bushnell (1981) observed that visual responses in the posterior parietal cortex of monkeys are enhanced for receptive field in the study of a particular behavior.

2.2 A model of Early Visual Processing

The model that we opted for in a biologically plausible model salience-based form of focal bottom-up attention. The control of focal visual attention involves different paths in the cortex.

Visual information from the retina enters the visual cortex thanks to main pathways: i) through the geniculate nucleus, and ii) with minor effect through the superior colliculus (SC). From there the information is processed via two different parallel hierarchical streams. The first is called *"dorsal stream"* which includes also the posterior parietal cortex (PPC), is involved in the spatial localization. Concerning attention this pathway is active when directing attention and gaze toward the region of interest in the scene. The second comprises cortical areas that constitute the *"ventral stream"* includes the inferotemporal (IT) cortex and is concerned with recognition and identification of visual stream. Sometimes in literature these two pathways assume different names: respectively the *where* and *what* pathways. Despite the ventral stream is not directly involved in visual attention, there are evidences that attentional *feedback* in the area is due to interpretation of the attended location. Further more, other high level cognitive areas can bias the attentive system and this is what we later reference as top-down contribution. In Itti and Koch (2001) it is suggested that from the computational point of view the two streams must be present and correctly interact in order to obtain valid scene understanding. Another interesting connection between the cortex regions involved in attention is the prefrontal cortex. This is usually responsible for planning action (in particular also for planning oculomotor actions via SC) but it also contributes to level of activation in PPC and IT Miller (2000).

To recap, the *dorsal pathway* is mainly involved in the bottom-up selection of the attentive region of interest. On the other hand, top-down attention which presumes that the object must be recognized to effectively bias attention, is definitely involved with the *ventral pathway*. The research for visual paradigm, carried on by Treisman and colleges in the 80s, introduced the basis of most of the computational model and proposed a distinction between *pop-out effect* and *conjunctive search*.

However only later, in Koch and Ullman (1985) Koch and Ullman explicitly proposed a biological plausible computational framework. The model is based on the idea of *saliency map* as a topographical representation that encodes the level of conspicuity for every location of the visual field.

Aiming for a general framework where evidences depicted in the previous section can hold true, the definition of visual attention starts with its early representation. This is a set of map in the domain of cortical representation of the visual environment (Zeki 1978, Barlow 1981), such as edges,orientation, color, contrast, etc. Fundamental concept is that neighborhood relations are preserved even in the log-polar representation of visual response. Generally speaking, the main aspect of these map is that extract whatever stimulus is conspicuous, that in other words is significantly different from its surroundings. The validity of parallel processing is guaranteed by the typical processing characteristic of distributed computing.

2.3 Preattentive Stage: Contrast Feature Map

The implementation of the visual attention is based on the model presented in Koch and Ullman (1985) where the input image is log-polar representation of the whole field of view. The log-polar mapping brings different advantages as reported in previous section. In the model, topological representations of the stimuli are relevant components in the early stage of preattentive system.

Inspired by the model, we defined a richer structure 2.3 where every single topological map of feature is obtained as the output of center-surround difference and normalization. Such response is typical of simple receptive cells in the retina and lateral geniculate nucleus. In literature this can be computationally obtained as difference of Gaussians.

Similarly to Dankers et al. (2008), Ude et al. (2005), we compute feature maps by extracting pyramids of images at different scale domains from input image. The input RGB color image is converted to YUV in order to reduce the number of processed images, improving the response rate of the attention system. The processing algorithm for any channel of the input image is depicted in Figure 2.4. Any image *P* at the base of the pyramid is down-sampled by a factor of two k times. Every obtained image P_j is than convolved with a Gaussian function g^+ obtaining P_j^+ which is then up-sampled with bilinear algorithm. The Gaussian function g^+ has variance σ_+^2 to 1. For every image at scale factor j the first and second order neighbors are subtracted.

$$P_j = max\left(P_j - P_{j+1}, P_j - P_{j+2}\right)$$

$$P_{cs} = F_2 \oplus F_4 \oplus \dots F_{2^k}$$

where $\oplus$ indicates the combination between different levels of the pyramid as presented in equation and I_2 is the image obtained by function F_1 subscripts indicate the scale factor.

We choose $k = 3$ as the best compromise between the performance in the extraction of features and the computation demand. Finally we combine together all the responses at different scales preserving the spatial information carried by every scale factor.
In the algorithm the center-surround feature map of contrast is calculated as

$$I_{cs} = I_2 \oplus I_4 \oplus \dots I_{2^k}$$

The input image I is one frame acquired from the luminance channel Y of the color image. This form of processing preserves the information in unique regions in intensity map, in fact uniqueness emerges as prominent regions in this feature map. Luminance contrast in M ganglion cells and M pathway in lateral geniculate nucleus can be computationally emulated by a similar process. Since the objective is to define fast and reliable process for luminance contrast we constrained the output according to the characteristic of cells in the Magnocellular pathway. Cells in this layer respond to lower spatial frequency and above that to higher temporal frequency. Thus, we focus mainly on the fast output rate as important design constrain.

2.4 Preattentive Stage: Color Feature Map

For the chrominance we opted to merge U and V channels of the input image. Similarly to the intensity map, we calculate:

$$U_{cs} = U_2 \oplus U_4 \oplus \ldots U_{2^k}$$

$$V_{cs} = V_2 \oplus V_4 \oplus \ldots V_{2^k}$$

where the input image is respectively extracted from U and V channel. The single chrominance channel is obtained as normalization of the sum of contribution of the last two feature maps:

$$UV_{cs} = abs(U_{cs} + V_{cs})$$

However, for some applications, richer responses in the chrominance space are needed. Color opponency maps among them are maps that resemble the behavior of color opponency receptive fields present in human retina. In this paradigm, studied in literature starting from the last century Hurvich and Jameson (1957), responses of one color of the opponent channel couple are antithetical to those of the other color. In particular, these opponencies, named as R^+G^-, G^+R^-, B^+Y^- are present in the human retina as center-surround receptive field with spectrally opponent color responses. These additional images can potentially require extra computation but in our solution obtaining these color representations is not costly.Thanks to a simple and efficient mapping any color opponency map can be obtained as simple linear combination of feature map obtained from remapping of chrominance information already extracted. In addition, this extra amount of computation is required only if any color opponency is requested. The solution does not elaborate redundant information but rather produces an alternative representation. It only demands for additional mapping M. The necessary maps representing the center on response R^+, G^+, B^+ are defined as following:

$$(Y^+, U^+, V^+) \overset{M}{\to} (R^+, G^+, B^+)$$

where M is the mapping operation between the YUV chrominance filtered with Gaussian and the color RGB chrominance filtered with Gaussian. Concerning the surround-off maps, respectively R^-, G^-, Y^- , are calculated convolving the images G,R,Y with the Gaussian function g^- that has variance σ_-^2 equal to 3.

$$\begin{aligned} G^- &= G * g^- \\ R^- &= R * g^- \\ Y^- &= Y * g^- \end{aligned}$$

where the Y image is the result of the addition between images extracted from G and R channels.

Precisely, the operation is expressed by

$$\begin{aligned} G^+R^- &= \alpha \cdot G^+ + \beta \cdot R^- \\ R^+G^- &= \alpha \cdot R^+ + \beta \cdot G^- \\ B^+Y^- &= \alpha \cdot B^+ + \beta \cdot Y^- \end{aligned}$$

We chose the ratio between the standard deviations of the two Gaussian distributions σ_s/σ_c to be equal to 3 and we preferred unbalanced Gaussian functions where the ratio β/α results equal to the constant $c = 1.5$, consistently with Smirnakis et al. (1997). Thanks to this unbalanced ratio, we preserve the achromatic information and the system implicitly processed this information similarly to what happens in the human retina‘s P-cells and Parvocellular pathway in lateral geniculate nucleus Billock (1995). Parvocellular layers have low sensitivity to temporal frequency stimuli but high sensitivity to spatial frequency, thus we rather focused on designing a module with high spatial and color resolution scarifying partially the output rate.

2.5 Preattentive Stage: Motion Feature Map

On the other hand, motion response must provide high process frequency. Motion is considered in literature Nieuwenhuis et al. (2008) Koch and Itti (2001) as relevant information that triggers attentive responses. Magnocellular pathway, equally important area in LGN, provides the major input to the putative motion areas. Thus, the output frequency of this module is designed to have same temporal characteristics of the component that extracts luminance contrast. In designing the module that extracts spatial location of motion we focus on obtaining a log-polar feature map that allows fast responses. At this stage, the only information that we identified as relevant is the spatial location of the motion stimulus. Any other characteristic of the motion such as direction and speed is neglected. We filtered the monochromatic image, resulting from the composition of the three planes of the log-polar input image. Denoting the image as M we applied the following temporal filter:

$$M_t^p = \lambda \cdot M_t^i + (1 - \lambda) \cdot M_{t-1}^p$$

where in the log-polar image M_b^a, a indicates the typology of the image (p-processing, i-input and o-output) and the b indicates the temporal domain of the image.The value of λ is assigned value 0.6. Since the image is integrated in time, only feature that have significant changing rate influence the outcome. On the contrary noise does influence the final output image. The processed images are saved in m-dimension vector:

$$\overrightarrow{M^p} = [M_t^p, M_{t=1}^p, \cdots, M_{t-m}^p]$$

For this robotic application, the value $m = 4$ represents optimal choice between the required computation and efficiency in the extraction of motion feature. The motion feature map M^o is the result of pixel wise difference between images:

$$M^o(x,y) = \left(\sum_{i=0}^{m-1} \sqrt{\left(M_i^P(x,y) - M_{i+1}^p(x,y)\right)^2} + \sum_{i=1}^{m} \sqrt{\left(M_i^P(x,y) - M_{i+1}^p(x,y)\right)^2} \right) \cdot g(x,y)$$

The result of the difference between images is weighted by a function expressed as:

$$g(x,y) = exp\left(\frac{y}{h}\right)$$

Where the (x,y) is the pixel mediated by the weight g and the parameter h is the height of the image. Thus, considering the pixel in fovea of y coordinates equals to zero, the weight suppresses motion in fovea and enhances motion in periphery. In literature both periphery and fovea are sensitive to motion although with different characteristic. In this application we opted for different weights to redirect the focus of attention to newer locations which is the main task of visual attention.

2.6 Preattentive Stage: Orientation Feature Map

Given the topographic depiction of the Y input channel, we define local feature maps O_θ of the orientation using Gabor filter.

$$O_\theta = \|I * G_0(\theta)\| + \left\|I * G_{\frac{\pi}{2}}(\theta)\right\|$$

where

$$G_\psi(x,y,\psi) = ()$$

$$G_\psi(x,y,\psi) = exp\left(\frac{(x'^2 + y^2 y'^2)}{(2\sigma^2)}\right) cos\left(2\pi\frac{x'}{y} + \psi\right)$$

is Gabor filter with aspect ratio γ, standard deviation , wavelength λ, phase ψ. The coordinate (x', y') are the result of a rotation of θ around the axis orthogonal to (x,y).

$$x' = xcos(\theta) + ysin(\theta)$$
$$y' = -xsin(\theta) + ycos(\theta)$$

We choose $\gamma = 1$, $\delta = 7/3$ pixels, $\lambda = 7$ pixels, $\psi = [0, \pi/2]$.

As presented in Kuhlmann and Vidyasagar (2011), any of these orientation filters can be assimilated to the anisotropic filter of the oriented excitatory simple cell in mammals. It remains controversial how orientation selectivity emerges in simple cells of mammalian primary visual cortex. Kuhlmann& Vidyasagar propose a model on how the orientation-biased responses of cells in lateral geniculate nucleus (LGN) can contribute to the orientation selectivity. There hence the group proposes that simple cells are excited by lateral geniculate fields with an orientation-bias and inhibited by unoriented lateral geniculate fields. The alternative would be to consider disynaptically inhibition as the result pf polling across orientation. Obviously the competing contribution must be centered in approximately the same retinotopic coordinates. We opted to use unoriented contribution for inhibition. This has multiple reasons: first, the response to unoriented filters are already present in the model as previous computing, second, the actual computation demand scaled down enormously with respect to the polling across orientation. The isotropic contribution for this simple cell can be provided by Gaussian filters applied on luminance channel. As a matter of efficiency these isotropic responses are already calculated. Also for edges we provided multi-scale variance using similar model depicted in Figure 2.6. However the difference is always performed between response of anisotropic filter and response of first and second isotropic neighbor filter. This allows the system to extract sharp orientation features across different scales in real-time. For any orientation and any scale we calculate the response of the orientation filter using center-surround difference:

$$O_\theta = O^+_{theta} - O^-_\theta$$

where

$$O^+_\theta = g^+ * (I * K_\theta)$$
$$O^-_\theta = Y^-$$

We designed the module to combine the orientation map O_0, $O_(\pi/2)$,$O_(pi/4)$, $O_(- \pi/4)$ through a weighted sum:

$$O = w_0 O_0 + w_{\pi/2} O_{\pi/2} + w_{\pi/4} O_{\pi/4} + w_{-\pi/4} O_{-\pi/4}$$

The weights of the sum $(w_0, w_(\pi/2), w_(\pi/4), w_(- \pi/4))$ can be changed from the top-down component of the visual attention. This allows the system to either be receptive only to one orientation or extract the strongest orientation during a task.

2.7 Complex Stage: Proto-Object Feature Map

As further stage in the preattentive system we extract more complex feature maps. First, edges map E are obtained from three color-opponency map separately using a generalization of Sobel filter Li et al. (2003). We obtain E_{RG}, E_{GR} and E_{BY} respectively edges extracted from the color opponency map $R+G-$,$G+R-$ and $B+Y-$. A single edge map is generated combining the three outputs with a pixel-wise max(.) operator:

$$E(x,y) = max\left\{ \left|E_{RG}(x,y)\right|, \left|E_{GR}(x,y)\right|, \left|E_{BY}(x,y)\right| \right\}$$

Second, we improved the approach Orabona et al. (2005) for proto-object detection. It has been

speculated, that synchronization of visual cortical neurons might serve as as carrier for the *perceptual grouping phenomenon* Eckhorn et al. (1988) Gray et al. (1989). The differences in the phase of oscillation among spatially neighboring cells are believed to contribute to the segmentation of different objects in the scene. Proto-object is the answer to one of the key question within the scientific community involved in attention : "how can we attend at objects before they are recognized". Rensink et al. (1997) Rensink (2000) proposed a possible model by introducing *proto-objects* namely volatile units of visual information that are likely to be bound into coherent and stable objects. The latest process can occur when focus attention and high level cognitive drive validate these units of volatile visual information into proper objects. In our implementation of this visual process we neglect the bounding step that validate object and we rather focused on the extraction of volatile units. Interaction can take advantage from this visual unit at an early stage of visual filtering longer before the objects are recognized.
The discriminative input information for this algorithm is provided by the first stage of the preattentive system. The feature maps of edges E and color opponency R^+G^-, G^+R^-, B^+Y^- are essential components for defining every single proto-object. We prefer color-opponency map to preserve the color selectivity of human retina‘s P-cells. The design of the information flow is optimized in order to remove any redundant processing and minimize the computation time. Thus, edges and color opponency maps are inherited from the previous stage of the early visual processing. A boundary of any proto-object is extracted from the edge map using watershed technique (rain-falling algorithm) Smet and Pires (2000). From this stage, we obtain a rich list of blobs representing proto-objects. Associated to these blobs the user can exploit additional features of the blobs such as location on the retina, dimension along the two dimension of the log-polar image. Whereas color quantization associates color information to the proto-object allowing for complex searches within the list of blobs. The module is designed to receive queries and provide views of the database of proto-object. Obviously this facilitates any further visual search of volatile units in the field of view that might trigger successful interaction with the robot.

Additional output of the module is the saliency map associated to the collection of detected blobs. This is a log-polar topographic map representing the relative saliency of any proto-object extracted from the scene. Color, dimension and position of every blob contribute in defining bottom-up saliency :

$$P_{BU} = \sqrt{\Delta RG^2 + \Delta GR^2 + \Delta BY^2}$$

$$\Delta RG = \langle R^+G^- \rangle_{blob} - \langle R^+G^- \rangle_{surround}$$
$$\Delta GR = \langle G^+R^- \rangle_{blob} - \langle G^+R^- \rangle_{surround}$$
$$\Delta BY = \langle B^+Y^- \rangle_{blob} - \langle B^+Y^- \rangle_{surround}$$

Where $\langle \rangle$ indicates pixel-wise average across the selected region. The surround region is a rectangular bounding box with size three times the size of blob and centered in the blob. On the contrary, the blob region is the collection of pixels that topographically belong to the selected blob. This feature map can also be biased by the contribution of the top-down component of the visual attention.

$$P_{TD} = \sqrt{\Delta RG^2 + \Delta GR^2 + \Delta BY^2}$$

$$\Delta RG = \langle R^+G^- \rangle_{blob} - \langle R^+G^- \rangle_{target}$$
$$\Delta GR = \langle G^+R^- \rangle_{blob} - \langle G^+R^- \rangle_{target}$$
$$\Delta BY = \langle B^+Y^- \rangle_{blob} - \langle B^+Y^- \rangle_{target}$$

The conspicuity of the proto-object increases with the degree of matching between its color and the target color. The color is expressed in terms of color-opponents R+G-, G+R-, B+Y- to correctly address the behavior in human P-cells. In addition, we revise this solution superimposing a bivariate norm function centered in the blob. This biases the maximum response of every blob in the center rather than the boundaries of the object, helping in deploying the focus of attention and eventually the gaze fixation point in the center of the related stimulus.

2.8 Selective Attention

According to the reference model Koch and Itti (2001), feature maps are combined together to obtain a single retinotopic representation of conspicuity called *saliency* map across different perceptual characteristics. Thus, the single components of the preattentive filtering, that extract unique features from the retinal image, are combined together.

The temporal frequencies of filtering elements do vary in a broad space since inspired by different psychophysics processes of the extracted maps. Therefore the different maps are grouped together in three different categories defined by their temporal response: *early stage*, *middle stage*, *final stage*. Every group can asynchronously prime the location with greatest response within the retinotopic map. This location corresponds to the location with greater conspicuity. Similar process in primate visual attention selects the stimulus that wins in the competition of attracting the focus of attention. This process in Koch and Itti (2001), Riesenhuber et al. (1999) model is defined as winner-take-all (WTA) process. The luminance contrast map I and the motion map M are grouped together in the asynchronous early stage, whereas the chrominance map C and the orientation map O belong to the asynchronous intermediate stage. All the remaining feature maps are added in the final stage through a mechanism of a weighted linear combination.

$$S = Norm\left(k_I \cdot I + k_M \cdot M + k_c \cdot C + k_0 \cdot O + k_E \cdot E + k_B \cdot B\right)$$

Norm operator indicates the normalization that is integral part of the model, whereas

$$\vec{k} = [k_I, k_M, k_C, k_O, k_E, k_P]$$

indicates weights that bias the saliency result toward more relevant features.

Thus, the system operates in different modalities taking into account whether a strong response is present in the early, and middle stage or absolutely absent. If a strong response is detected in early stage, it triggers an asynchronous interrupt that guarantees immediate reactions. In addition the weights k can be changed in real-time by the higher level component of visual attention to attract focus of attention on particular task-relevant features. Indeed, the selectiveAttention module determines the location of the WTA in the retinotopic space of the drive eye. The WTA location is where the focus of attention is deployed and for this application also where the motor command drives the fixation point. Through the motor command provided for the humanoid robot iCub, it is possible to redeploy the line of sight of drive eye on the selected salient region. This motor action is defined as saccade. The generated oculomotor command carries temporal information about the stage that has generated WTA location. This helps in activating different behaviors for different temporal domains. Another process that is considered relevant in early reviews Stephenson and Siddle (1983), Thompson and Spencer (1966) and in more recent literature Birmingham and Pratt (2005), Boot et al. (2004), Klein and Dukewich (2006), Shore and Klein (2000) is the *Habituation*. There are few converging experimental evidences concerning the level at which this process takes place because. Indeed *habituation* is ambiguous phenomenon and can be represented at different levels of response Rose and Rankin (2001). Others Dukewich (2009) Cowan (1988) present a divergent opinion on the processes that regulate habituation. We decided to design habituation as retinotopic phenomenon that only interacts at the level of the retinotopic map. By diminishing the response in the saliency map at the locations that exceeds a predefined level of firing rate, we filter out stimuli that must exhibit an habituation counter effect. The typical response characteristic of an habituation process does not follow a linear decay function. Evidences Boehnke et al. (2007) show that Superior Colliculus (SC) neurons (presumably involved in habituation) present an exponential-like decrement in activity with repeated stimulation. We shaped the time course of habituation as exponential-like decaying function in time for any pixel that overcome the threshold th_H. This topographic representation of persistent stimuli is then subtracted to the correspondent saliency map obtaining a saliency response that is modulated by the habituation phenomenon.

2.9 Inhibition of return and Habituation

In psychophysics, *Inhibition of Return (IOR)* is presented as a progressive increment of the response time for the location in the space already attended Posner et al. (1985). Computationally in Itti and Koch (2001), a simple and practical model was proposed to emulate this process. It is based on the suppression of attended regions of the saliency map. In Posner and Cohen (1984), inhibition of return can be activated by exogenous sensory event and by endogenously generated eye movement. In particular they provided evidences that exogenous visual signal primes the oculomotor system to prepare a saccade through the retinotectal pathway. In Maylor (1985) it is shown that IOR exhibits interocular transfer, further arguing that externally triggered attention movements were necessary to activate inhibition of return. Thus inhibition of return is triggered by either exogenous signal or when the attention is deployed endogenously ”in concert with the eye”. Similar hypothesis are stated in Rafal et al. (1989) where IOR would result in oculomotor activation regardless of whether it was produced by exogenous signals or endogenously. More importantly they found further evidences that the mechanism may be mediated through the retinotectal pathway. As reported by Abrams and Dobkin (1994), the presence of different spatial maps appears to underlie two different components. It seems likely in their review that they exert in different places in visual and oculomotor system. We focus on the particular component that is triggered by exogenous stimuli and not associated to higher level concept as objects Tipper et al. (1994). Moreover, inspired by all these converging evidences, we define the inhibit location in the visual attention system as carried in the spatiotopic domain. This is movement-related inhibition operates at the level of oculomotor system and is mediated directly though the retinotopic domain. The efficient coexistence of both the spatiotopic internal representation and mediating retinotopic domain is the main design characteristic of the IOR mechanism developed for the humanoid robot iCub. This solution is supported by research proving evidences of up to four retinotopic inhibitory locations Klein et al. (2005). In the model implemented for the visual attention these multiple locations can be represented in the retinotopic domain grounded to a particular oculomotor arrangement. In addition, in our implementation, despite evidences that the concept of IOR can be extended to include non-spatial dimension, we focus on implementing spatial mechanism leaving the non-spatial approach to future work. We take inspiration from two main concepts in Klein (2000), Posner and Cohen (1984). First, by interposing eye movements between cue and target, IOR was shown to be coded in environment rather than retinal coordinate. Second, converging evidences Posner et al. (1985), Rafal et al. (1989) provided support for motoric basis for IOR when the response is an eye movement. We developed a mosaic module that collects motor information about any joint that affects camera position in space of the drive eye. Using motor positions of all the joints of the head and the torso we merge views into a single 2D environment representation that resembles internal memory of visited location. We obtain a gradient image by merging together bivariate Gaussian functions centered in fovea point when the salient location is attended. Similarly to figure 2.10.A, we compose cartesian images of bivariate guassian function centered in fovea by looking at the proprioception information of the torso,head and eyes (see Figure 2.10.B). We opted for this degrading function around the fovea referencing recent research work Samuel and Kat (2003) Bennett and Pratt (2001); Collie et al. (2000); Klein et al. (2005) those showing that the strength of IOR gradually decreases with the spatial distance between clue and target. We create a covert representation of the locations that have reduced response due to the IOR by extracting the portion of the spatial internal memory that matches the current joint position. The effect of temporal degrading of IOR toward neutral values has been showed through essentially two processes: a spontaneous recovery of IOR and dishabituation mechanism. First, spontaneous recovery of IOR was presented in Samuel and Kat (2003) through graphical meta-analysis of IOR.

The authors proved that the IOR effect recovers gradually over time. We implement temporal recovering of IOR introducing a temporal decay function that gradually reduces the covert representation in time. Second, in Thompson and Spencer (1966), the dishabituation has proved to affect the IOR when an unexpected change in the clue is presented. We emulated this typology of events with express saccade that represents strong and unexpected stimuli (e.g.: unexpected flashing of the entire screen, resetting stimulus perceived by the subject). Thus, we design a process that triggers dishabituation when express saccades are performed. In conclusion through this mechanism the gazeArbiter requires a sub-portion of the mosaic image that is directly suppressed from the saliency map. Thank to this process, we are able to covertly depress the attended locations at the level of the saliency map. Therefore the visual system is performing inhibition at the level of overt attention and not only for covert attention.

2.10 Experiment pure bottom-up attraction of the focus of attention

In this section we introduce the performance of the pure bottom-up attention system. We present the system following the sequence of processing that produces output images. In figure 2.11 -the first column (a)- we present the input which is a logpolar remapping of the cartesian input image (the fovea at the top). This image triggers the processing of the early preattentive stage which, in other words, filters the image as soon as it is available. The second column (b) presents the different feature maps produced by the early pre-attentive stage. In this particular run we can appreciate in order : motion, intensity uniqueness, the component u-chrominance and v-chrominance that linearly combined define the chrominance uniqueness. In the third column we present the complex preattentive stage, with in order the blob representing proto-objects and edge feature map. At the stage (d) all the feature map are merged into one saliency map through weighted linear combination. This operation is performed in the log-polar domain and from this domain the Winner-Take-All retinal location is extracted. In the image (e) we present the saliency map remapped into cartesian to easily interpret the location of the WTA. Finally in stage (f) we present the Cartesian image of the scene after the saccade is performed. To note that the object selected in the previous stage (the red tomato on the right hand side of the Lego ®) is now in fovea (small green circle). Further more, we measure the time interval necessary to process the image in the pre-attentive stages and the time interval to perform the saccade to the selected object (details on the oculomotor action in 5). Note that in the saccade time interval measure, we consider the post-saccadic correction as important component of the saccadic event. Therefore the time interval for the saccadic ocular movement comprises the post-saccadic correction as well.

In order to measure the time interval necessary to perceive novel stimuli, we run the system collecting $n = 278$ attentive shifts. We tune the system in order to be very sensitive to novel salient stimuli and this resulted in experimental runs where the system commands shifts at the highest rate the attentive system was able to produce. We measure a mean and variance of the vector of interval time in perception isi_p (infra-shifts interval for the perception stage)

$$E[isi_p] = 0.1188(s)$$
$$var[isi_p] = 1.7354e^{-6}(s^2)$$

Similarly we measure the mean and variance of the vector of the vector of interval time in saccade execution isi_s (infra-shifts interval for the saccade execution). In order to generate the vector of time interval we perform $n = 50$ saccades in salient regions of the field of view, and wait for the command of "saccade accomplished " which is always issued after the post-saccadic correction.

$$E[isi_s] = 1.6140(s)$$
$$var[isi_s] = 5.3064e^{-4}(s^2)$$

In conclusion we point out that since the overall time interval is the serial combination of time interval necessary to perceive novel stimulus and time interval necessary to perform the saccade, we estimate the overall time as the sum of the two contributions

$$E[isi] = 1.7328(s)$$
$$var[isi] = 5.3064e^{-4}(s^2)$$

The performance of the attentive system can be compared with the performance of human involved in similar task. This makes the attentive system as more than acceptable emulator of human behavior which definitely boosts up the performance predicting the behavior of the robot and finally improves the general task of human-robot interaction.

In the previous paragraph we presented every single module involved in the creation of pure bottom-up visual attention. We depicted how the information flows from one module to another. The similarities with the Itti and Koch (2001) model are evident however we added few additional innovative components. The idea that additional high cognitive layers hierarchically interact with early preattentive stage is quite novel. So the map representing location of proto-objects in the scene compete with the traditional feature map. The normalization stage equally maps contributions in the same response range whether the map belongs to the early preattentive stage or the complex preattentive stage.

However in the selective attention high response in the feature map can trigger saccades with different temporal activation depending on the whether the feature map is generated with the early preattentive stage or the complex prettentive stage. This is due to the huge difference between terms of time interval necessary to generate the response. None of the responses in the feature maps corresponds to the situation where there is firing in none of the neural pathway. If this happens, the selective attention generates a saliency map which is the result of the weighted linear combination of feature maps.

2.11 Outline

The experiment reported in the previous paragraph gives immediately impression that the system, albeit simplified, performs approximately as human attentive system. It is true that the system can easily find conspicuous regions in the field of view and that it might appear intelligence to those who observe the system in action. Also the inhibition of return mechanism helps in providing the feeling of smart system that produces articulated and correct scan-path in the scene. However from our experience in the field an attentive system that, generates shifts and only takes into account the bottom-up component, hardly provides intelligent output in day life scenario. The top-down component as expressed in 4 has a crucial role in stabilizing the shifts.

An attentive system that only redeploys focus of attention using bottom-up component creates very unstable shifts. Small changes in the environment reflect as completely different response in the system. The system hardly settles in a minimum because minima are not as deep as expected. The contribution of top-down helps remapping the output in a different domain where deeper minima guarantee stabler responses. The final effect is that a pure bottom-up attention system the focus of attention jumps between salient stimuli quite often, more than expected.

Despite this structural deficit in bottom-up, in this chapter we presented a structure for valid front-end in processing composed of different stages of filtering. Further, the filters produce feature maps that are result of models that are studied on humans. Therefore here we exploit one of the aspect of the epigenetic robotics. The study of the human biological model using their implementation on the robot is one of the possibility for this system. Those models are the result of evolution of visual pathway in mammalians and thus the implementation is typically related to the phylogenetic development. Those feature maps, thanks to the selective attention, shaped on the evolution model, compete in order to form a single topographic map the salient response. The attentive system selects one single location in the saliency map -namely *winner-take-all location*- which is a valid location for a pure autonomous attentional redeployment.

Despite its characteristics of instability, the location of the focus of attention is very accurate. In fact, if we feed the oculomotor action system, objects in the scene efficiently fall into fixation. This allows the system, as simplified as it is, to segment object at zero disparity for free and provide an extremely appealing human-like scan-path. This allows the human partner to easily understand the intention of the robotic system increasing the feeling of collaboration with intelligent system.

In the next chapters we introduce the top-down component of the visual attention system which stabilizes the attention redeployment. In addition this biases the attention system providing responses that are task-dependent.

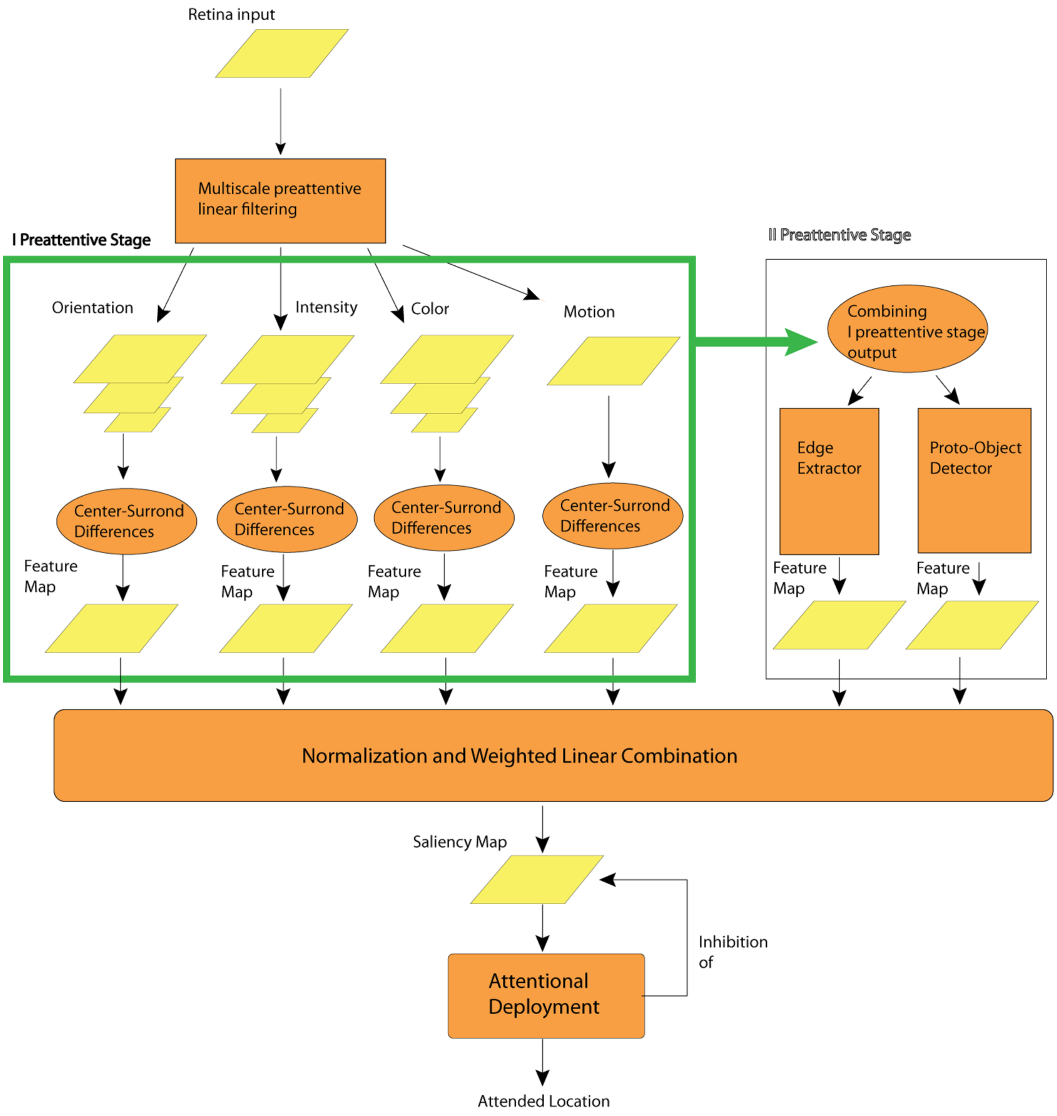


Figure 2.3: Visual attention model used as reference for the visual attention framework

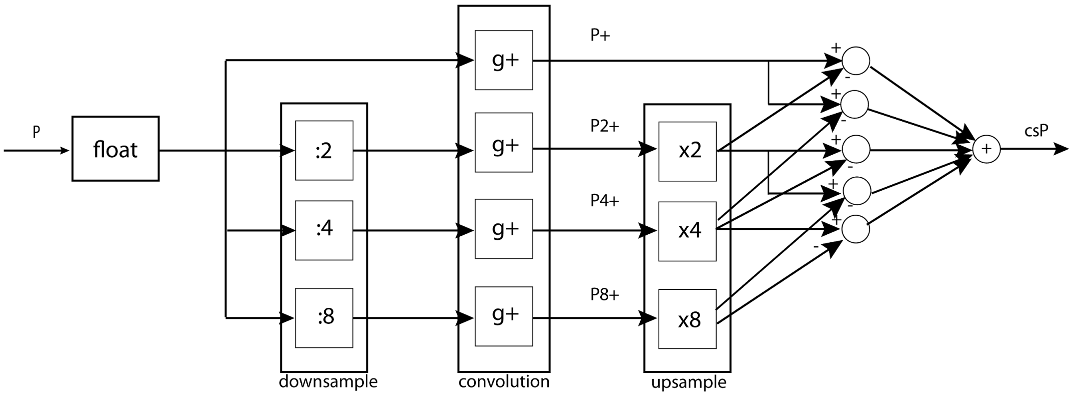


Figure 2.4: Generic model of multi-scale difference of gaussian on an image.

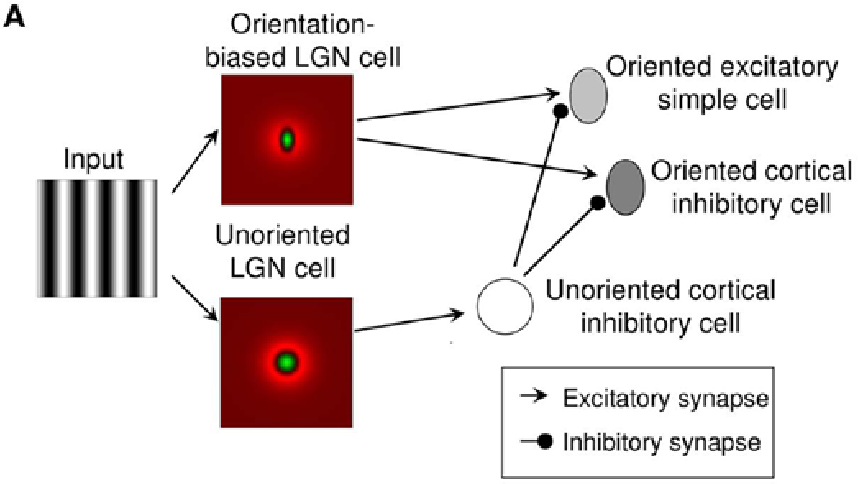


Figure 2.5: schematic of the feedforward of the model presented in Kuhlmann and Vidyasagar (2011)

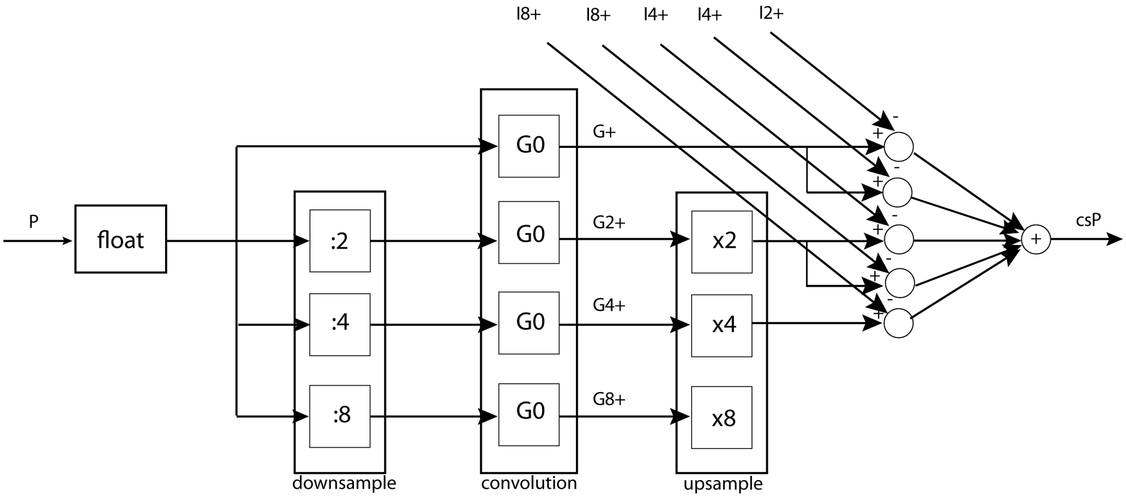


Figure 2.6: orientation visual processing

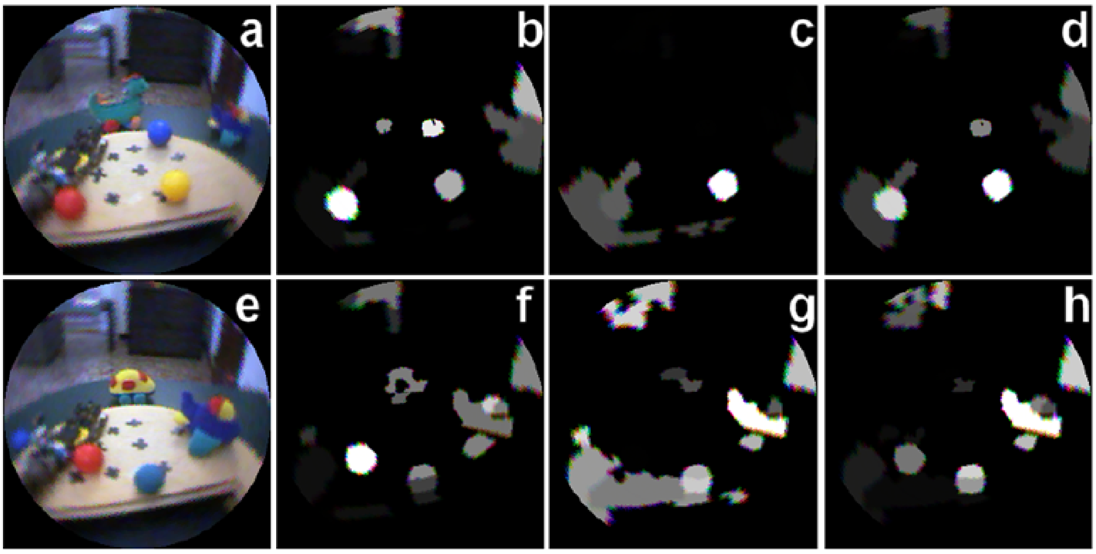


Figure 2.7: Experiment in Orabona et al. (2005) where the protoObjects are extracted in pure bottom-up and pure top-down mode

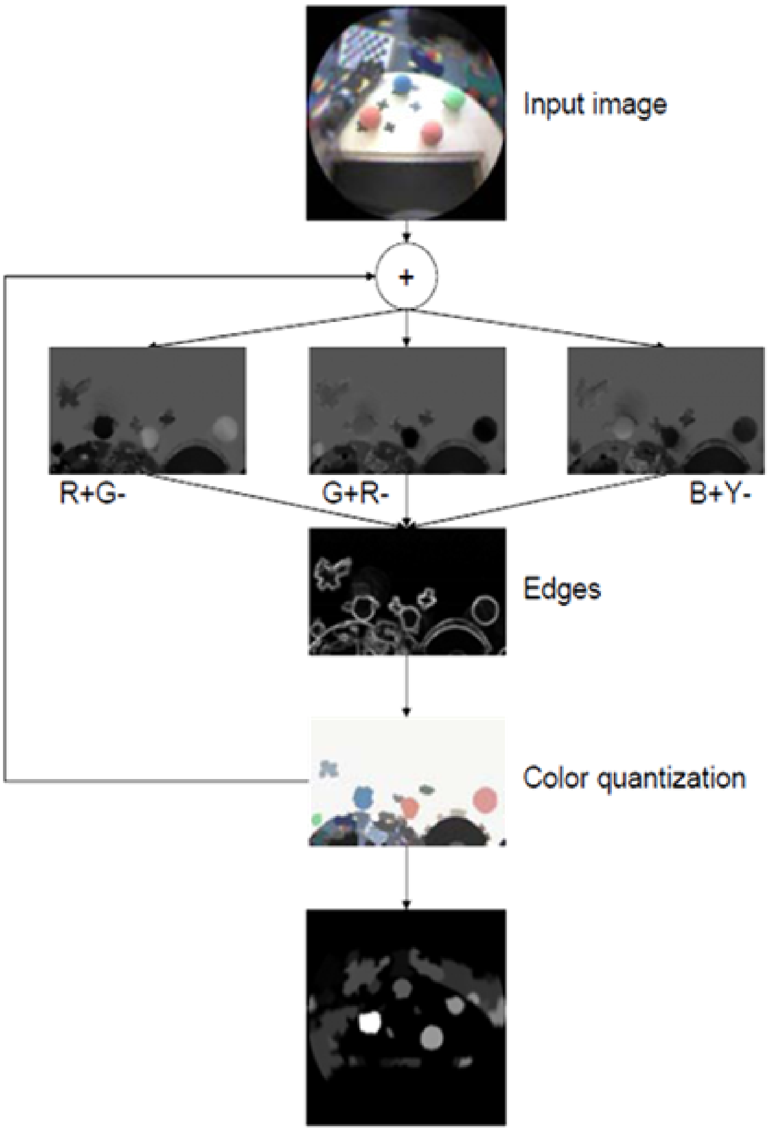


Figure 2.8: Process for protoobject extraction proposed in Orabona et al. (2005)

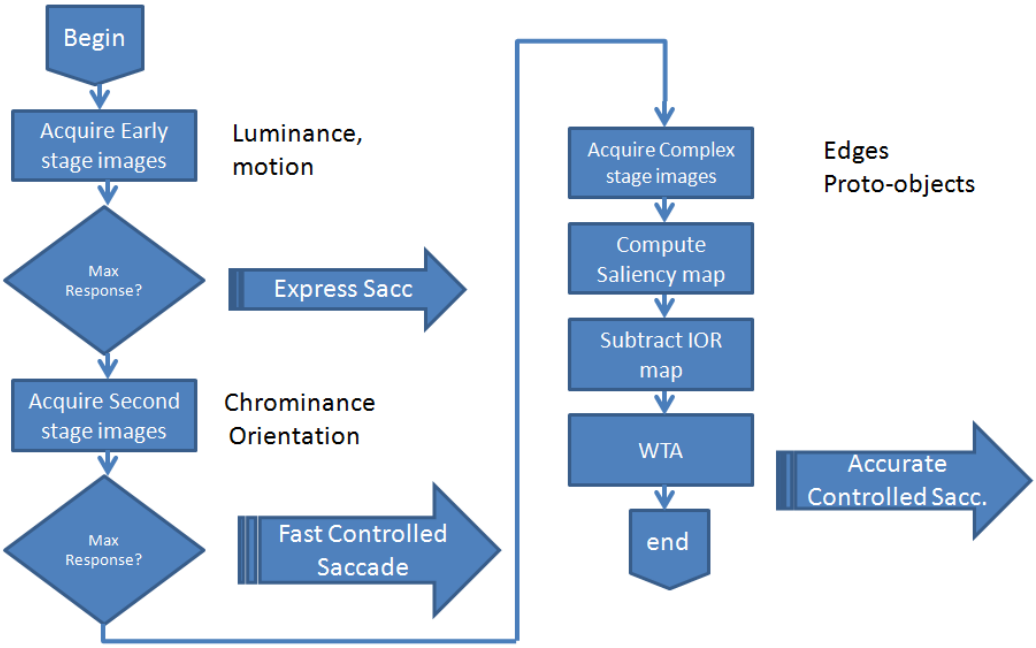
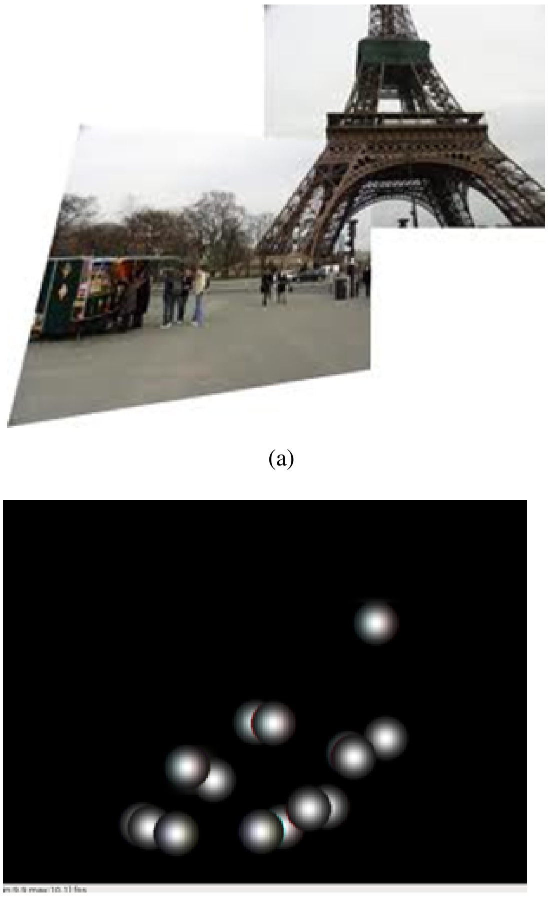


Figure 2.9: Algorithm for selective attention specifically designed to obtain asynchronous saccade generation



(a)

(b)

Figure 2.10: Comparison of the mosaic for egosphere generation and mosaic for IOR

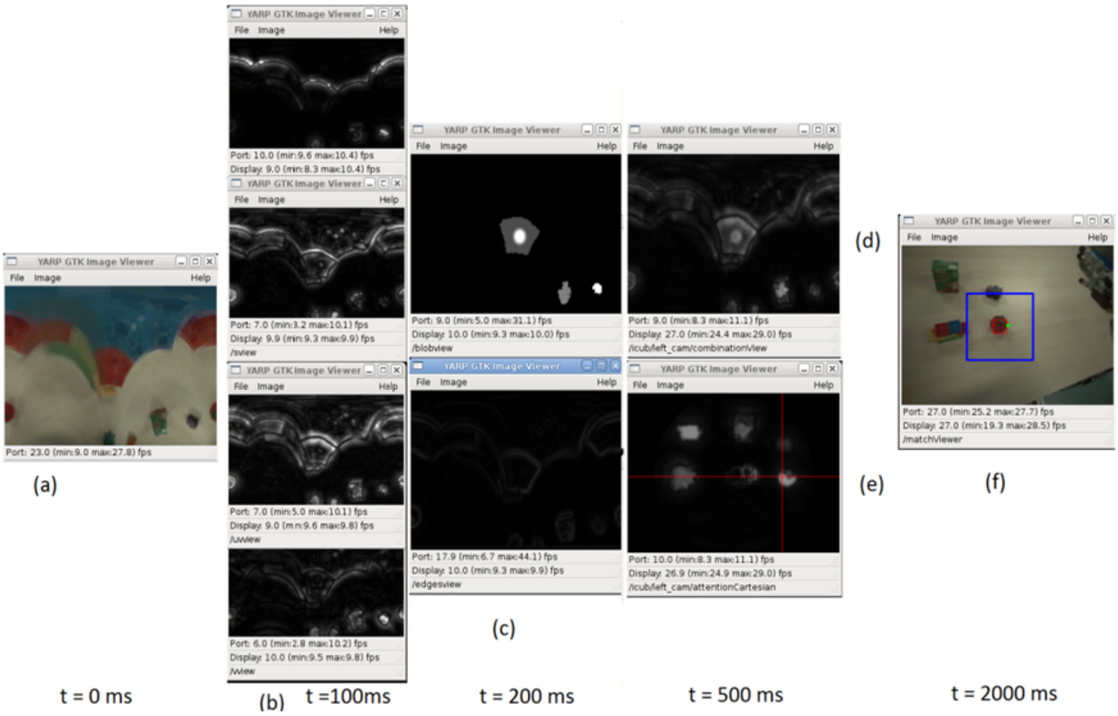


Figure 2.11: Experiment of pure bottom-up attentive system.In order from the left to the right: the early stage of filtering, the complex stage of filtering, the selective attention response and the result of the triggered saccade

EVENT-DRIVEN VISUAL ATTENTION : A HIGH PERFORMANCE NEUROMORPHIC APPROACH TO ATTENTIVE REDEPLOYMENT

3

> *The Argument from Continuity in the Nervous System*
> *”The nervous system is certainly not a discrete-state machine. A small error in the information about the size of a nervous impulse impinging on a neuron, may make a large difference to the size of the outgoing impulse. It may be argued that, this being so, one cannot expect to be able to mimic the behaviour of the nervous system with a discrete-state system.”*
> Alan Turing

3.1 Introduction

In the previous chapter, we proposed a front-end filtering stage that processes visual input. The different flows of processed information compete in the attention system in order to select salient region in the visual field. The biological model of attentive processing based on the Itti and Koch model is considered the state of the art in the field. The model is valid regardless the typology of the perceptual input stage. In fact, what we present in the chapter is the idea that selective attention mechanism performs equally good in the situation where the perceptual input stage is radically diverse. In this chapter, we analyze another model for the preattentive stage and we assess the differences with respect to the traditional image processing of the previous chapter. In fact, another significative aspect that can be analyzed in develop cognitive skills within robotics is

the level of asynchronous event generation of the nervous system.
Since the selective attention paradigm can be considered as a process that involves cognitive skills and it is quite easily implemented, the asynchronous activation can be successfully studied within this framework.

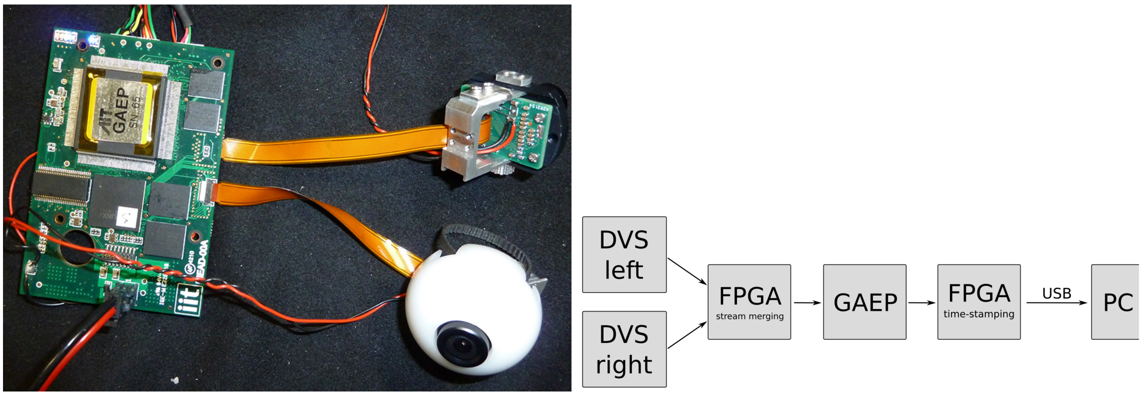
Neuromorphic engineering is an interdisciplinary topic that addresses how neural computation can be emulated on a concrete physical device. The main goal of the study is the understanding of brain functionality grounded on specific brain-inspired vision and auditory systems. This theory is well established tool in autonomous robot systems, because the characteristics of energy efficiency of its artifact compared with conventional digital processing technologies Mead (1990). Neuromorphic systems take inspiration from the structural and computational principles present in nervous systems.
Mead was pioneer in the field since the late 80s, and stated that what distinguishes standard digital systems from neuromorphic systems is the way computation is embedded into the architecture, rather than the physical properties of the substrates that support them. Generally speaking, the interaction of any system with the real-world environment depends on the frequency of information acquisition from the real-world and the frequency of action of the system on the world. This marries completely the idea that any agent interacts with the environment through double-ended connection: by sensing and by acting. Considering the mere information acquisition aspect of the interaction, a real-time and high frequency sensing of the real-environment puts the system in advantage position. Thus, dedicated neuromorphic chips, where the computation is locate in the physical substrate, perform at higher frequency than conventional system. This result is an appealing solution for all the application where successful interaction with the world is required. Because computations are instantiated on the physical substrate, neuromorphic systems can be designed to operate in real-time, thereby enabling them to easily interact with real-world environments. Neuromorphic devices are easily scalable because a very large number of neural circuits can be densely implemented on the same chip, and each chip can be combined to form a large multi-chip system using event-based communication. Also, the circuits exploit the analog properties of the substrate. So they are potentially more power-efficient than general-purpose digital processing technologies.
The design of software has recently gained importance in the field of neuromorphic engineering, because the mapping of desirable functions on the neural hardware necessitates an adequate framework. The goal of this software framework is to solve two problems: the first is to cope with the fabrication variability and noise that affects analog devices, and the second is the configuration of neural parameters. These problems are achieved by standard optimization techniques, and by choosing computational paradigms that are robust to component failure, noise and the unreliability of real world cues.

The processes regulating the nervous system are predominately stimulus driven or in other words triggered by significative events namely spikes. Processes like temporal and spatial contrast operations have important role in visual processing, and can be implemented in a event-driven framework. Yet another characteristic of the neural computation such as automatic gain control, which was neglected in previous analysis of attentive system, have key role in nervous system. Through the mechanism of event-driven processing this aspect can be further exploited. In fact the neuromorphic chip developed in the last decade can respond to a wide dynamic range of the input signals allowing the robotic application to show reliable behaviors in wide spectrum of different conditions. The major difference between tradition and event-driven vision lays in the way the input information is treated. In conventional vision system, the main stream computational paradigm the atomic unit of information is the frame, ”a static snapshot” of the input information. Most of the information between consecutive frames is redundant. This introduces constraints and limitations in visual data transfer, storage and processes. On the contrary, for event-driven vision, the information transfer and processing is only limited to the location of the space where the spike generates.

3.2 Embedded asynchronous vision

Asynchronous vision is embedded in the humanoid robot platform iCub. The visual system comprises two sensors based on technology of ”Dynamic Vision Sensor” (DVS) Lichtsteiner et al. (2008). DVS sensor is a VLSI implementation of the transient signal pathway of the mammalian visual system that encodes visual acquisition into flow of asynchronous information. Connected to the sensors, an embedded dedicated processor for asynchronous data, the General Address Event Processor (GAEP) Hofsttter et al. (2010) provides efficient and real-time in locus preprocessing of the data. A Field Programmable Gate Array (FPGA) interfaces the sensors, the GAEP to the ICUB PC104. These custom hardware component are designed to fully interoperate sharing a common communication protocol. The ”address-event representation” (AER) protocol Mortara (1998), Hofsttter et al. (2010) defines the exchange of information between components. In the last set-up, the sensors produce events that are sent on the communication bus to the FPGA that redirects the flow to the GAEP. The GAEP is in charge of adding timestamps to every single events which are then sent to the PC104 via FPGA. The FPGA uses the FX2 to reliable send data to the embedded computer PC104. The FX2 is a single-chip USB2.0 peripheral. The design of the FX2 is similar to the USB FX family and most of the functionality is preserved, however some elements went through redesign to accommodate the higher data rate offered by 2.0 USB protocol.

At the PC104 side of the interface a USB device driver has to be installed. The driver handles the flow of data sent and received on the USB toward the FX2. In addition, any application on the PC104 can interact with the USB device driver sending and receiving commands.



(a) (b)

3.3 Support Components of the Event-Driven Attention

The collection of events are stored in the buffer of device driver. The driver plays the role of interface between the software computation and the hardware computation.

The component of *aexGrabber* successfully interacts with the device driver. The flow of information can travel in both the directions. The aexGrabber sends information to the neuromorphic chip through the device driver. It has been defined a mechanism that takes advantage from this degree of interaction and allows to program the hardware. Biases are sent through the device driver to refine the behavior of the chip. Information received from the USB is saved in a buffer and eventually retrieved from the USB at any time. Similarly the commands travel from the PC104 to the USB Device Driver that immediately sends those commands to the FX2 interface and the FPGA (e.g.: the operating biases of the DVS Chip).

The iHead through the interface FX2 sends the block of information of the generated event respecting the AER Protocol. This information is temporarily stored in a device driver buffer. The advantage of this solution is that the software on the PC104 asynchronously requests to read the latest block of information. The block is populated with the ultimate collection of details of all events generated from the previous reading (up to the dimension of the buffer). In the module accurate dynamics have been designed to explicitly avoid the buffer to be full. Potentially, this situation causes the events drop which is unwanted consequence of limited buffer dimension. Once the block of events is acquired, in the module, some statistic complete the measure of the real-time performance of the acquisition. Typical measure are: a) Ns - number of kevents in time b) Ne- number of events that do not respect the AER protocol (corrupted information).

These statistics are designed to demand less possible time to computation. This assures high processing rate which is fundamental aspect in the analysis of the events. In addition, prompt visualization of GAEP Error has been implemented. As reported in Hofsttter et al. (2010) the GAEP generates error events with a particular format. The *aexGrabber* module easily intercepts these error events and interprets the meaning, notifying promptly the user of possible source of event drops or bad event transfer. Once the block of event is entirely read, the *aexGrabber* instantiates an opportune unit of information and sends this unity to the *YARP* network.

We propose two consecutive implementations of the transferring mechanism, two main classes *bufferEvent* and *bottleEvent* have been designed. In the first, the information is transferred as a single block of data pointed by a char pointer. The second is the evolution of previous class where any event is treated as single event and appended to a bottle. In the later, what is really sent is the bottle that contains events. Both the classes belong to the dedicated library for support in event processing. The library is visible as a support library to any module in the project and thus it helps users to develop novel model with less effort possible. Using *bottleEvent* class gives the opportunity to the user to extract and process the stored *yarp::os::bottle*. Another class in the library processes the extracted bottle. The *eventCodec* class extracts events from the *yarp::os::Bottle* and decodes the single events based on the extracted event identifier. From the class the user obtains the characteristic of the event which now can be processed.
The unmasking mechanism is usually a process necessary in any module. To avoid redundant coding in the project, the authors designed a dedicated class and added that to the *eMorph library*. The class facilitates the conversion of any yarp::os::Bottle into *queueEvent*. The last class is also essential component in the library and specializes the *std::dqueue* class for a generic event: *eventGeneric*. The generic event can than be dynamically transformed in any of the specific classes representing the typology of event.

In fact, all these classes are basically used in any novel module, for example the *cartesianFrameCollector* module. This module creates a representation of the flow of events and visualizes it in frames. Having frames might be considered as going against the idea of asynchronous computing however the conversion in frames is adopted here only to create visual snapshots synchronized with the maximum frequency of acquisition of human visual system (30Hz). Events are integrated in the time interval of 1/30Hz = 0.033 s and visualized in two different forms. The first, any event contributes in the same form despite its polarity. In the visualization the white response over the black background indicates locations of generated events. In the second form of visualization, the representation of the events changes with the polarity of the event. The events have either black tonality (negative polarity) or white tonality (positive polarity) over a gray (neutral) background.

$$\begin{cases} f(x,y) = 0 & \text{if } x \geq 0; \\ f(x,y) = 0 & \text{if } x < 0. \end{cases}$$

$$\begin{cases} f(x,y) = 0 & \text{, no event;} \\ f(x,y) = 255 & \text{, event (any polarity).} \end{cases}$$

$$\begin{cases} f(x,y) = 0 & \text{, event(negative polarity)} \\ f(x,y) = 0 & \text{, no event} \\ f(x,y) = 255 & \text{,event(positive polarity)} \end{cases}$$

Another parameter of the representation plays an important role in distinguishing the number of events per location: increment constant. The single event contributes for different degrees to the final representation of the spatial location response. If the contribution constant value C is the max value possible the response of the location will be represented with high contrast tone, otherwise if the contribution value C has an intermediate value any event contributes partially to the reach max value. The effect is a visible integration of events in time in the representation.

The mechanism for event acquisition and processing is constant component of any developed module. This a optimized algorithm for efficient processing of all the events. However, from the experience gathered in the field, this mechanism is the most effective and efficient. The instantiation of two *yarp::os::thread*s guarantees the optimal performance along with the use of a *circular buffer* with reading and writing pointers. The first is inherited from *yarp::os::Portable* which allows the class to refine the response of the callback function. This function is called when the object is received in a typical connection between ports. When this happens the *circular buffer* collects either the block of information or the *yarp::os::Bottle* and stores it in the correct position of the buffer updating the two pointers. The second *yarp::os::Thread* asynchronously with a constant time interval extracts the information from the *circular buffer* updating the two pointers. Starting from this point the information is available to the processing thread. If the information is wrapped in a bottle, the class *eventCodec* helps the user to extract single event information otherwise the unmasking is trivial. Generally speaking, once the information of the flow of generated events is extracted, any single algorithm runs and processes specifically information. Thus, this is general mechanism that we provide and suggest to reused in any processing module.
Using this method the *cartesianFrameCollector* module generates images for the left and right camera according to the parameters of representation instantiated by the user.

3.4 Event-Driven Feature Extraction

There are speculation in literature on the presence of different stages in hierarchical processing of the cortex in mammals Alonso et al. (2001). However the structure of the receptive field organization of complex cells in the mammal‘s visual cortex is anatomically well-known and documentedHubel and Wiesel (1962) Kandel et al. (2000) Movshon et al. (1978) De Valois et al. (1982). Starting from the Hubel and Wiesel‘s proposal it is agreed that simple cells become orientation selective by virtue of the excitation they receive from LGN. In particular the excitation comes primarily from those receptive fields that are aligned parallel to the simple cell‘s preferred orientation. Receptive fields have structures composed of two subregions that evoke response when a light spot exerts this regions. In the center-on receptive fields, the on-subregion respond increasing the firing rate when the spot light stimulates the region, on the contrary the off-region respond decreasing the firing rate when spot light stimulates the region. However when no spotlight stimulates the off-region the firing rate increases and it can be contrasted if no-light elicit the on-region cause the fire rate to decrease. In the center-off receptive field the contribution is inverted. The spot of light that hits the center cause a decrement of the firing rate, whereas if the same light stimulates the periphery causes an increment of the firing rate.

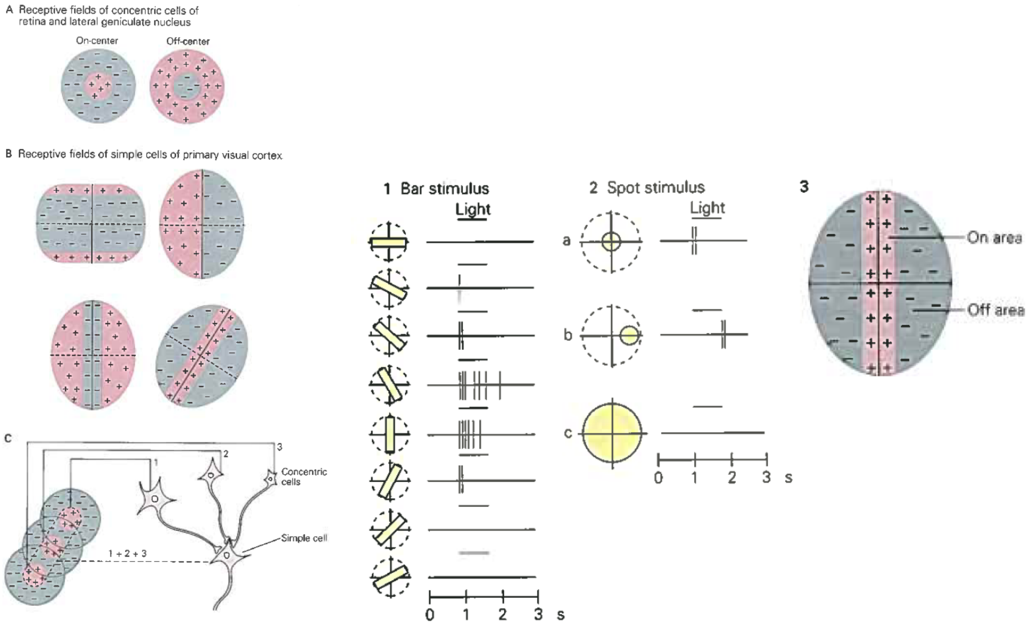


Figure 3.1: center-surround receptive fields and simple cells representation

The orientation columns in visual cortex are those areas that perform orientation selectivity. Although cells in the orientation column share the same features, they are classified in two functional classes: simple and complex cells. Simple cells receive responses from collection of receptive fields that create elongated receptive field in the direction of the orientation. The complex cell, as combination of multiple simple cells responses, shares the same mechanism of on-off response. These are evidences in favor to hierarchical structure of the orientation column. The simple cells become selective to the presence of a oriented line in a precise location, the complex cells are selective to the orientation of the line regardless of its exact position.

The event-driven feature extraction mechanism emulates the behavior of simple cells and is based on a very simple and efficient mechanism: the *mapping*. In comparison with the traditional convolution, the mapping results faster and less computationally demanding. In order to favorite further more fast computing we activate the process with reduced resolution with respect to the resolution of the original input information. The proposed resolution can be valid option since the final goal remains attention selectivity. Resolution in attention selectivity can be reduced because it only aims at eye movement generation. On the contrary, convolution can be performed for any single entity of the input space and this partially explains the computation demand and the time consumption of this solution . The result of the convolution is an output information with the same resolution of the input. Despite this, if we consider that the purpose of the feature extraction is a feature map for attentive system. That is, for this task, we rather prefer less time consumption than high resolution, finally the mapping can be considered optimal solution. The idea of the mapping is based on a predefined relation between input location of event and their contribution in the output feature map. The *simple cells* in the mapping are adjacent regions that comprises sub-portions of the input map. Within the simple cell, only few locations contribute positively to the output the others contribute negatively. This process emulates the behavior of simple cell in the visual cortex.

event polarity	location	contribution
positive	center	increase activity
positive	surround	decrease activity
negative	center	decrease activity
negative	surround	increase activity

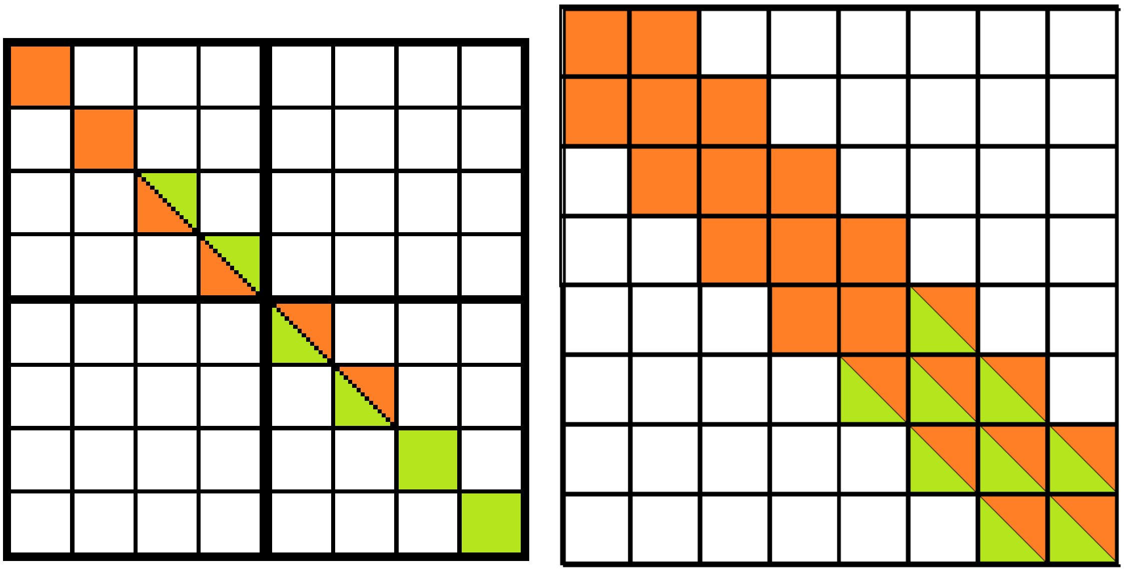
Table 3.1: effect of the received event on the topographic register *center-on*

event polarity	location	contribution
positive	center	decrease activity
positive	surround	increase activity
negative	center	increase activity
negative	surround	decrease activity

Table 3.2: effect of the received event on the topographic register *center-off*

The module as explained in the previous paragraph receives events from the network using concurrent interaction between two different threads that share a singular circular buffer. Once the singular event is unmasked, its location determines the entry of the look-up table representing the mapping. This gives indication on whether the position corresponds either to a on-region or to a off-region.

Another important aspect is that the single feature extraction module associated two opposite contributions to the shape defined in the look-up-table. At the same time the *eventFeatureExtraction* represents the behavior of both center-on cell and center-off cell. Formally, this implemented through two different registers: one that emulates the behavior of center-on cell and one for the center-off cell. If an events (either with positive positive polarity or negative polarity) arrives from the look-up table the thread extracts the location of the generated response in the space of the feature map. Only locations that belong to the center of the cell are coded in the look-up table, whatever location absent in the look-up-table is to be considered as belonging to the surround. The single received event contributes to the center-on topographic register as reported in table 3.1. Similarly, the same single event contributes to the center-off topographic register at the same time as reported in table 3.2. For any topographic register are defined two parameters: i) the amount of increment/decrement of the value in the topographic register, ii) the threshold beyond which the cell can be considered as firing. If the value in one topographic location of the center-on register passes the threshold the cell emits a event with positive polarity. Otherwise if the value of one topographic location in the center-off register passes the threshold the cell emits event with negative polarity. This creates a new train of positive and negative events in the space of feature map which respectively indicate a firing in the associated center-on and center-off cell. The collection of generated event are sent to the network in a completely asynchronous fashion. This process is easily scalable to multiple feature maps because the only aspect that eventually change between different feature maps is the mapping. Mechanisms for easy mapping generation have been provided to the user who can generate, save different maps and feed the only selection of maps that the user needs.



(a) a

(b) b

Another aspect implemented in this mapping concerns the lateral connection between two different orientation columns. As reported in Sirosh and Miikkulainen (1996) Gilbert and Wiesel (1989) lateral connection pattern follows the property of neural response. In particular, Gilbert and Wiesel (1989) presented the classification of lateral connection in terms of their length and associated the longer lateral connections with areas that share the same orientation columns preference. In other research study Katz and Callaway (1992), evidences bring an insight on how development shapes the lateral connectivity pattern, bearing some degree of plasticity. These converging evidences highlight a common development process for neural response properties and lateral connectivity.

In particular, lateral connections self-organize simultaneously, forming patterns that are tightly correlated to receptive field orientation. In addition, the models proposed gives insight on the claim that lateral interactions reduce redundancies in cortical activity. This provides founding for models that promote efficient sparse coding of the visual input. In Sirosh and Miikkulainen (1995) the *Laterally Interconnected Synergetically Self-Organizing Map (LISSOM)* model comprises a sheet of interconnected neurons. Each neuron has both excitatory and inhibitory lateral connection. In this model, lateral excitatory connections are short-range whereas lateral inhibitory connections run for long distances. Both the two typologies of connection follow the Hebbian Learning Process strengthen by correlated activity. However, there is little disagreement in the community on the fact that equilibrium between inhibition and excitation gives rise to orientation selectivity Priebe and Ferster (2012) Vreeswijk et al. (1998). In fact, cross-orientation inhibition has been proposed to operate under different modalities, constrained by the orientation dependence and inhibitory interconnections. This inhibition is a form of lateral inhibition that operates in feature domain rather than spatial domain.

Inspired by these findings, we improved the design of feature extraction. In the mapping, lateral excitatory connections are implemented as additional entries in the look-up table. When the simple cell is elicited by an event, the contribution affects both the parent simple cell and the simple cell which follows in the receptive field orientation. On the other hand, the inhibitory contribution is performed in the orientation domain rather than in spatial domain.

In conclusion the final orientation selectivity grounded in a feature map is the result of fast and reliable mapping of event. Two aspects compete in defining the mapping: a) the direct transformation of event into feature and b) the lateral connections. The overall process of mapping is then mediated by a temporal integration.

Imagining a scenario with different feature extraction modules that generates different feature maps at the same time. This design guarantees a competition between different orientations. However one constraint must be verified. The flow of events sent in the network can easily saturate the bandwidth if any module receives event from a dedicated connection. Intuitively, it is necessary in this scenario to implement multicasting connection between event flow generator (aexGrabber) and the collection of feature extraction modules. This allows scalability in the number of feature extraction and at the same time avoids the bottleneck in the network bandwidth.

3.5 Event-Driven Selective Attention

The rest of the system is based on the well-know Itti & Koch model Itti and Koch (2001) of Selective Attention. The model is very similar to the model for Selective Attention presented in the previous chapter 2. However, events defined by the feature extractor algorithm map on a feature map that has half resolution of the retina input information. Thus event received from the network must be associated with the dimension of the feature map they do belong to. This is the reason why, the *Event-Driven Selective Attention* module provides up to 4 full-resolution feature maps and up to 4 half-resolution saliency maps. An additional operation of up-sampling allows to regain the original resolution for half-resolution saliency map. For any feature map there is a dedicated spatial register of the dimension of the original input channel where the events belonging to the feature map are integrated in time. That is, if the operation of up-sampling must be performed, the event changes the value of the spatial register in the position given by its coordinates times scale factor. The same events affects the value of its neighbors up to the scale factor positions around.

$$R_k(x_{event} \cdot S + i, y_{event} \cdot S + j) := R_k(x_{event} \cdot S + i, y_{event} \cdot S + j) + C$$

where

$$i = \lfloor -S/2, S/2 \rfloor, j = \lfloor -S/2, S/2 \rfloor, k = [1, .., K]$$

The constant value C is always positive value uncorrelated to the polarity of the event. That is because, the aim of the register is to reproduce the saliency of particular spatial locus. The conspicuity of the response of the simple cell is not affected by the polarity of the response. In addition, a mechanism of reset of the value in the register counter-balances the increase of responsiveness (see previous formula 3.5). The design of the reset is based on a temporal decaying factor that the autonomously decreases the response in the particular location.

In literature Itti et al. (1998), there exits multiple proposals of feature map combination. The principal techniques are : (1)Simple normalized summation, (2) Linear combination with learned weights, (3) global non-linear normalization followed by summation, (4) local non-linear competition between salient location. Evidences in Itti et al. (1998) analysis, led the authors to the following conclusion. First the learning scheme proves to be efficient but at the cost of a broad specialization of the generic model. Second, remarkably, with non-specific normalization that replicates biological mechanisms, the authors were able to obtain good-performance. All the solution (additive learning, non-linear) outperformed ad-hoc weigthed summation. However in this survey one aspect of design restricts the experiment. The authors intentionally discard the top-down component in their design. On the contrary, the role of top-down contribution in visual attention have a critical influence on the focus of attention deployment. In robotics applications, the task drives the action and defines the success in the final application. Therefore, in a effective attention system, the task biases the attention system acting in the space of the features. In the chapter 4 a detailed analysis of the topic is addressed.

In the implementation of the event-driven visual attentive system, every register represents a feature map. The spatial response of every feature map is then normalized:

$$F_k(x,y) := \frac{R_k(x,y)}{(R_{max} - R_{min})} + R_{min}$$

where

$$k = [1, .., K]$$

The saliency map is generated through the weighted linear combination of all the feature maps.

$$S(x,y) := w_k \cdot R_k(x,y)$$

where

$$k = [1, .., K]$$

In the formula the w_k represents the weight of every single k map in the summation. The value of the weight $w_k = [0.0, 1.0]$. The weighted linear combination is optimal solution that allows remarkable performance in combining feature maps. It provides a form of effective interaction with the top-down component of the visual attention.

Concerning the graphical interface to the user, in the module we provide a representation of the saliency map in frames. At a constant time interval, a snapshot of the register value is transformed in gray scale image, mapping the value on 255 gray scale tones, and sent on a dedicated port on the network. Any user can easily connect the output of the port to a *yarpviewer* and visualize the feature map in real-time.

The saliency map guides where the focus of attention can be deployed. On the basis of this scalar topographical representation, the selective attention module biases attention in order to focus it onto the most salient location. This corresponds to drawing attention towards the locus of highest activity in the saliency map. In selection and convergence process, a location is defined as salient if it wins the spatial competition in one or more feature dimensions at one or more spatial scales. The *Winner-Take-All (WTA)* network paradigm is one plausible neural architecture to detect the most salient location in topographical map. This implements a neurally distributed maximum detector

The *Winner-Take-All (WTA)* location is the result of max-operator applied on the saliency map pixel-wise:

$$L_{WTA} = argmax_{x,y} S(x,y)$$

The identified location respects the characteristic of high activity in the saliency map performed via simple and efficient operations that guarantee reduced computation demand.

Finally, in the last paragraph we introduce another form of feature map that enhances the performance of the event-driven selective attention. The relative contrast map is the integration in time of events generated by the retina. The map is particularly effective in adding topographic regions where the flickering is present into the saliency map. Every receptive field transfers information to the feature map whereas the decay factor implemented for the feature maps asynchronously compensates for increments in the response.

3.6 Experiment: Attention Biasing for Event-Driven Vision

We evaluate EVA in three different experimental setups and benchmark the performance of the proposed asynchronous implementation against the state-of-the art main-stream system based on the Itti and Koch (2001) model: the *iLab Neuromorphic Vision Toolkit (iNVT)* Itti et al. (1998) Itti et al. (2003) Navalpakkam and Itti (2005), that uses as input traditional frame-based cameras. The two systems run on the iCub robot using respectively the DVS and the standard robot's Dragonfly cameras. They run at the same time on two identical machines[1]; both distribute the processing over the four available CPU cores. To correctly compare the two systems, we implemented the same type and number of feature maps in both,restricting the numerous feature maps of iNVT to intensity(I), orientation(0) and flicker(F). In order to remove any overhead load on the computation, the iNVT program processes a batch collection of camera images. [2] The system as presented in the previous paragraph needs to go through a rigorous evaluation to asses the performance of the system. We would like to compare the neuromorphic attentive vision with the state of the art in implementation computational neuroscience models for real-time applications: iLab Neuromorphic Vision Toolkit iNVT Itti et al. (1998). The toolkit aims at developing vision algorithms structured with the intent of emulating the neurobiology of primate brain. To this end, it provides software that reliably grounds development of neuromorphic models and systems in real-time applications. The aim of the comparison is in giving further insight in the field, enhancing the modeling of neuromorphic systems that act in real-time environments.

The stimulus is placed at a distance d in front of the robot and centered in the fovea of both the Dragonfly and DVS cameras, such that the stimulus is completely visible and the quantity of received light is comparable for both sensors. The sensors have been configured with typical parameters (see Table 3.3) and have not been specifically tuned for the experiments, in order to assess the system's performance in typical use cases.

As the performance of both sensors and, consequently, of the two attentive systems depends on the illumination level, for each experiment we report the diffuse scene light[3].The Lunasix F measure is in Exposure Value EV but we convert it in LUX for clearer interpretation using the constant

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[1] Intel Core 2 Quad Cpu Q9950 @2.83GHz

[2] *ezvision –in=raster:*.ppm –display=display -T -j 4 –input-frames=@30Hz –textlog=iNVTLog.log –vc-chans=IOF –ior-type=None –use-random*

[3] Measured by portable hand-held exposure meter Gossen Lunasix F.

Parameter Dragonfly	Value	Bias DVS	Value
width	320 (pixel)	cas	52458
height	640 (pixel)	injg	101508
shutter	0.913	reqPd	16777215
gain	0.312	pux	8053457
white balance A	0.506	diffoff	133
white balance B	0.494	req	160712
sharpness	0.5	refr	944
hue	0.48	puy	16777215
gamma	0.4	diffon	639172
saturation	0.271	diff	30108
framerate	30 (fps)	foll	20
		pr	8

Table 3.3: Setup parameters of DVS and Dragonfly sensors.

value $k = 5.5$ provided by the producer:

$$2^{EV} \cdot k = LUX$$

By the use of the exposure measure we can understand how light influences the perception and how performance degrades with the light. For all of the validation setups we report the focus of attention scan path generated by both systems, giving an immediate qualitative evaluation of the attentive computation. For a quantitative assessment the benchmark comprises a set of predefined measurements:

- Number of shifts of the focus of attention over time F_{EVA} and F_{iNVT} and the correspondent time interval between consecutive shifts Δt_{EVA} and Δt_{iNVT}
- CPU system utilization S_{EVA} and S_{iNVT}
- CPU user utilization U_{EVA} and U_{iNVT} [4]
- Data rate D_{EVA} and D_{iNVT}
- latency time interval L_{EVA} and L_{iNVT}

The time interval between two consecutive shifts in the selective attention is a good measure on the frequency of attentional redeployments. An high rate of focus relocation guarantees prompt reaction time in the event of sudden change in the environment. An high rate of visual updating in the attentive system guarantees prompt reaction time in the event of sudden change in the environment. We measure the latency in both the systems as time interval from the instant the novel stimulus is

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[4] Measurements performed with *SAR*, a program that directly measures the computational load on the processor over a user-defined time interval.

presented to a complete processing of the visual input. In EVA, the latency interval comprises the time interval in feature extraction and time interval in selective attention. The former represents the time necessary to generate a new flow of events from the moment a new stimulus arrives. The later represents the time interval in which the selective component processes a new train of events in order to generate attentional shift. In both these measures, the single event never triggers alone a change in the output but it is rather a block of events that alters the output of the module. For this reason the latency time is greater than the time interval necessary to process the single event. On the contrary for iNVT, we present a single frame and we measure the time interval necessary for the system to process the camera snapshot. CPU utilization and data rate give an accurate measure of the computation demand of both implementations. An important difference across the two implementations is that EVA runs in a monocular implementation system, as iNVT gathers data only from one of the sensors. In order to fairly compare the two attentive systems we send biases to the right dvs camera that turn the camera off. By processing only events generated by the left DVS camera, EVA triggers attentive shifts only in the retinotopic domain of the drive eye (left). The evaluation comprises two test scenarios, the first uses typical stimuli for visual experiments, such as oriented gratings, and runs under two different illumination conditions. The second shows the performance of the EVA system with a fast unpredictable stimulus such as a chaotic pendulum.

3.6.1 First scenario bright illumination : experiment B

In the first experiment we provide a stimulus, whose position is fixed in the space. The stimulus is composed by two horizontal grating stimuli and two vertical grating stimuli of dimension 4 cm x 4 cm each and positioned at 20 cm from the camera (figure 3.2). The degree of illumination of the environment is crucial aspect of the environment so that we preferred to report LUX measure for any acquisition run. Thanks to microsaccades, the neuromorphic embedded system extracts features from the scene even if a steady stimulus is provided.

Under these conditions we measure data rate $D_r = [7.05kAE/s, 7.12kAE/s] = [227.8Kbit/s, 225.8Kbit/s]$.

From the graphical representation of the landing point of generated shift we assume that both iNVT and EVA are successful in selecting conspicuous area. Topographical location of the WTA perfectly matches the retinotopic regions where the stimuli are presented. In figure 3.3 we compare the topology of the attention landing point for the two models. In particular, these figures present the retina on the x and y plane whereas the number of shifts in the x, y location spreads along z axis. In the figure 3.3.a it is also possible to appreciate the position of the focus of attention with respect to the stimulus presented. We render one of the acquired frame on the plane x-y. Obviously similar snapshot cannot be provided for figure 3.3.b because of the complete absence of frames in pure asynchronous event-driven vision.

We point out some characteristic aspects of the result. First, the shifts generated by iNVT are mainly localized on the horizontal grating. This is absolutely correct in the situation where the IOR is not active in the run. However in the numerous experiments that we provide, we observe

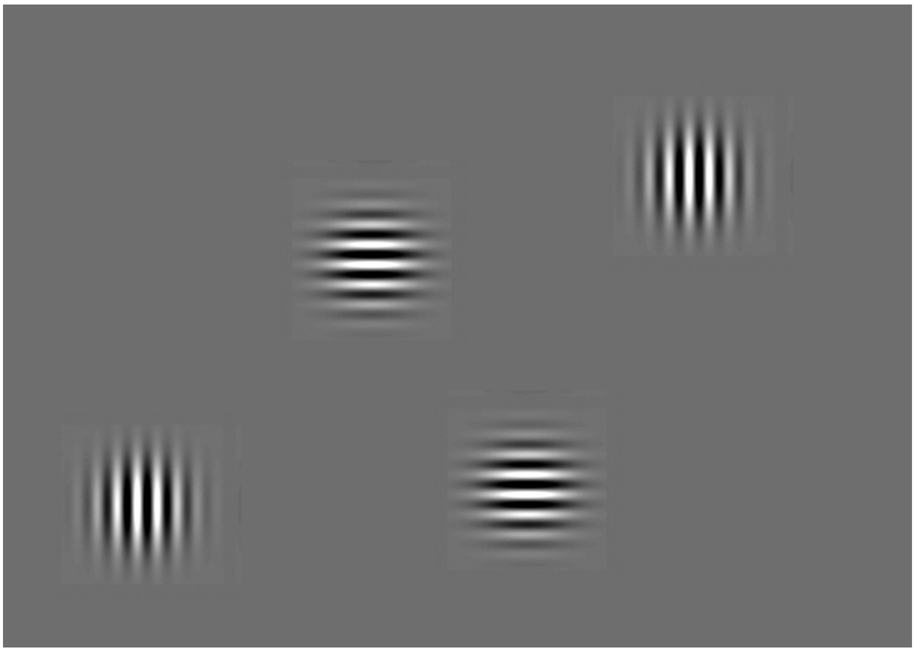


Figure 3.2: Gratings used as stimuli in the experiment of attention biasing

stimulus	iNVT	EVA
horizontal top	60.85 %	33.53 %
horizontal bottom	0	33.19 %
vertical top	39.15 %	15.06 %
vertical bottom	0	18.21 %

Table 3.4: First scenario, case A: Number of hits clustered on the different regions of interest under bright illumination (~ 352 LUX).

another key aspect. The model of biological noise implemented in iNVT forces the system to generate shifts towards other gratings. Similarly, EVA model exploits other gratings because of the noise even though this model is never explicitly embedded in the system. The noise is inherited from the asynchronous generation of events in the hardware of the DVS camera. However we need to distinguish the two models of noise. The degree of biological noise simulated in iNVT seems only to differ for a smaller effect when compared with the noise intrinsically present in the event-driven vision. In fact where the iNVT selects accurately the most salient region, the EVA selects other regions as significative because higher degree of noise generated by the hardware.

Second, EVA seems to prefer the lower horizontal grating and opts for the top horizontal grating as second choice deploying the attention spot to the other two vertical gratings afterward. The two horizontal gratings are identical thus the only difference lies either in a different processing of the uniqueness with respect the background or the sensitivity of traditional camera to different illumination. Finally, the number of attentional shifts generated by EVA are in number at least double than what the iNVT generated as depicted in the table 3.4.

The comparison between the number of shifts between the two systems is crucial aspect that needs specific note. The number of shifts in time can be measured if we look at the time interval between two consecutive shifts figure3.5. The EVA has far shorter time interval between two consecutive shifts with respect to the iNVT. This can be appreciated comparing the *intrashift* and *intrasel* variables in the figure3.5. For the experiment A, note that, in bright light (approximately 55.6 LUX) every attentional redeployment occurs every 50ms for the iNVT whereas the EVA outperforms iNVT providing one shift every approximately 1.5ms. This crucial difference is important to compare the two systems and it is worth a detailed analysis of the performance. In EVA, whereas the feature map extraction is the result of multiple concurrent filter modules, the selective attention module is single element that has to merge information from different modules. As explained in previous paragraph, the selective attention module comprises multiple threads as many as the feature maps merged together into one single saliency map. In addition one chief thread is responsible for normalization of the feature maps, merging of information and saliency map generation. This is the real bottleneck in the processing of events in the selective attention module. From the measurements that we carry on this system, the minimum processing interval required by the selective attention module is approximately 1.5ms (for accurate measure of the interval see data). That is, the module can provide attentional shifts at the maximum frequency of approximately 666.66Hz. Here, the authors stress the fact that the rate with which the data is sent in the network is higher but the processing for the generation of saliency map requires time. We design the algorithm in order to reduce as much as possible the processing demand. In order to do so, we opt for multiple registers that are only updated with the last train of received event. We absolutely avoid a complete regeneration of the maps that will require addition and unnecessary extra-time.
Thus, in the design of the attentive system, we take advantage from the asynchronous and high rate data generation of the event-driven vision and provide a dedicated algorithm for high rate attentional foci redeployment. Further more, the computational demand of the overall system normalized by the number of shifts is exceptionally minimal with respect to the computation demand of the other attention system. In figure 3.5, it is worth to appreciate that, looking at the percentage of cpu utilization, the iNVT and EVA system have radically different performance. However we want to point out yet another crucial detail. The proposed model deals with stereo information at least for the first stage of processing: the feature extraction. In order to perform fair analysis of the two attentive systems we decided to switch off the DVS right camera. No further events are generated by this camera and the comparison is perfectly fair.

We analyze the characteristic of degree of asynchronous processing and high rate of the event-driven vision but we exploit yet another important characteristic of this neuromorphic engineered technology: responsiveness in high range of light. Concerning the latency, we measure for the system EVA $E[L_{EVA}] = 2.9295e - 4(s)$, $\sigma^2[LEVA] = 1.0923e - 8$ whereas for the system iNVT we obtained $E[L_{iNVT}] = 3.88e - 2(s)$, $\sigma^2[LEVA] = 2.5709e - 5$.

3.6.2 First scenario dim illumination: experiment B

In the second experiment we provide identical stimulus of the ExperimentA but in a different lighting condition. Once again, since the stimulus is static, the embedded neuromorphic system activates the oculomotor behavior: micrasaccades. In the ExperimentB, the reduced ambient light challenges the ability of the neuromorphic model to extract salient region. We aim at establishing whether the developed neuromorphic model performs differently in this scenario. We determin that degree of illumination is far lower than ExperimentA. This does not influence the number of generated events in time. In other words, the system is highly responsive to change in the environment and this is confirmed by data rate $D_r = [5.06kAE/s, 5.2kAE/s] = [161.9kbit/s, 166.4kbit/s]$.

Intuitively, the distribution of shifts location brings again a deeper comprehension on the differences between the two models. Whereas for the iNVT we cannot find huge differences between experimentA and experimentB, the EVA in experimentB successfully detects at least three out of four gratings but with a greater level of noise. This influences directly the shift in fact in experimentB some of the attentive shifts fall in locations where there is no stimulus. Despite this, the number of attentional re-deployments in correct locations are in number greater than iNVT (at least for the first-choice horizontal grating -see the peak of 13 occurrences- in correspondence of the horizontal grating figure3.4.b).

stimulus	iNVT	EVA
horizontal top	100 %	0 %
horizontal bottom	0 %	0 %
vertical top	0 %	0 %
vertical bottom	0 %	100 %

Table 3.5: First scenario, case B: Number of hits clustered on the different regions of interest (mean and standard deviation over 10 repetitions).

Concerning the computation demand, the utilization values remain the same of the previous experiment. Despite the environment results darker (see LUX measure) the cpu utilization for both iNVT and EVA does not significantly change. Concerning the latency, we measure for the system EVA $E[L_{EVA}] = 2.6933e - 4(s)$, $\sigma^2[LEVA] = 1.2113e - 8$ whereas for the system iNVT we obtained $E[L_{iNVT}] = 3.56e - 2(s)$, $\sigma^2[LEVA] = 1.4269e - 6$.

3.6.3 Second scenario : chaotic pendulum

Differently from the previous experiments, we decided to estimate the performance of EVA system with an high dynamic stimulus. The chaotic pendulum have characteristics that make it suitable for testing the performance of the system when rapid objects move unpredictably in front of the camera. The chaotic pendulum is composed by two color black links respectively of $22cm$ and $18cm$ connected by a low friction joint over white background figure3.6. The overall system is attached to the ground (fixed position in space) via a second low friction joint. Thus, the first link can rotate in space with respect to the ground and it is influenced by the second link which revolves independently with respect to the first link. In order to guarantee that the whole chaotic pendulum remains in the field of view, we located the stimulus 50cm far from the neuromorphic cameras. After 10 measures of the amount of data rate generated, we report a mean data rate in the range $D_r = [39.65kAE/s, 94.26kAE/s] = [1.268Mbit/s, 3.016Mbit/s]$. The experiment was conducted in a average lighting condition of 27.6LUX.

It is tough task for frame-based camera to acquire any significative frame that could help in interpreting the movement of chaotic pendulum and even humans can hardly follow (and never anticipate because the movement is not biological). Thus in these experiment we do not compare the two systems but rather assess that EVA effectively provides reliable attentive shifts even in this situation. The movement of the links of the chaotic pendulum when acquired by neuromorphic cameras causes the generation of events in the location of the silicon retina that correspond to the edges of links. We note that different links that move at different angular velocity generate different train of event at different data rate. Ideally if we could separate the two links and analyze anyone alone, we might notice huge difference in the number of events generated per second. Parameters in this attentive system can be fine-tuned to perceive one better than the other.
To estimate the quality of the attentive system we measure all the events generated in the run and compare them with the location of the attentive shifts. In the figure 3.7.a we represent the location of the event on the x-y plane and the time on the z axis. This allows the reader to picture the rotation of the edges of the links in time. In this figure we represent events of the left camera that have either positive or negative polarity. Similarly in figure3.7.b, we represent the location of the foci of attention after every shift generated from the same train of events. Comparing the trajectory of the focus of attention and the events generated by the bi-pendulum we can appreciate how well EVA produces convincing shifts even with such chaotic and fast movement.

In order to further evaluate the quality of the EVA we provide additional details on the shifts in this experiment:

The represented space is reduced from three dimensions (x,y,t) of the figure 3.7 to two dimensions of the figure 3.8. The mapping M converts the $(x, y) \overset{M}{\to} (\xi)$ which is plotted on the y-axis of the figure. In other words the variable ξ is represented in time to show how the pendulum evolves in time.

$$\xi = 128 * y + x$$

Similarly, we can convert the position of the shift generated by EVA in $\hat{\xi}$, as reported in figure3.6.3, and estimate the quality of the attentive system.

$$\hat{\xi} = 128 * y_{EVA} + x_{EVA}$$

Note that, in figure 3.8, visible a delay between the generated shift and the original stimulus and further, the delay is not constant. The delay is due to the computation demand required by the attentive system. However this affects only few sections of the simulation and anyway the delay never exceeds beyond few milliseconds.

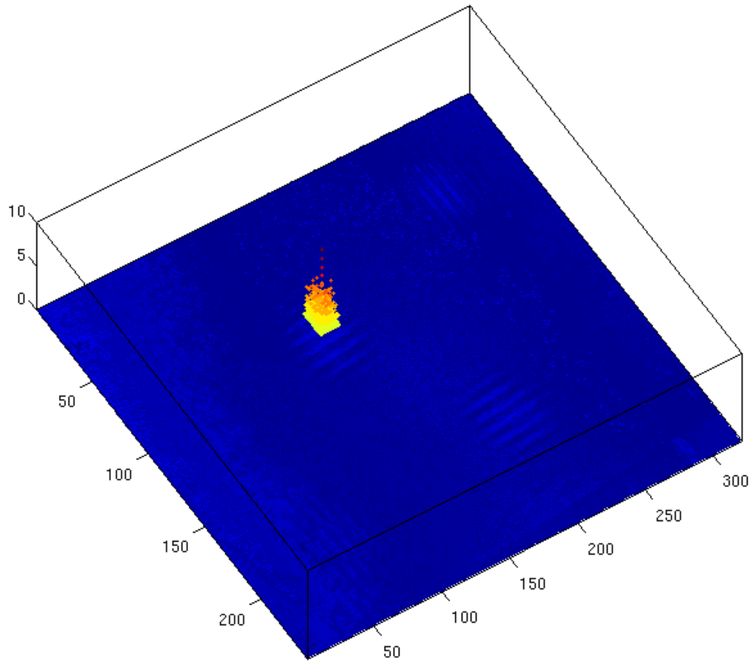
3.7 Outline

In this chapter we demonstrate that a complex cognitive process as the visual attention is absolutely disentangled from the perception stage. The same approach for visual attention can be used either with traditional frame-based images or the event-driven images and the result remains valid. The cross-modality within the sensorial input (vision) is guaranteed in the model of selective attention and we prove this concept by adopting the same algorithm for both frame-based and event-driven vision. The potentiality of this approach is vast. Remaining within the vision as unique sensorial input, we easily integrate information from traditional vision with vision generated by the DVS or any other neuromorphic chip. This can be successfully achieved because the structure that generats attentive shifts is the same.

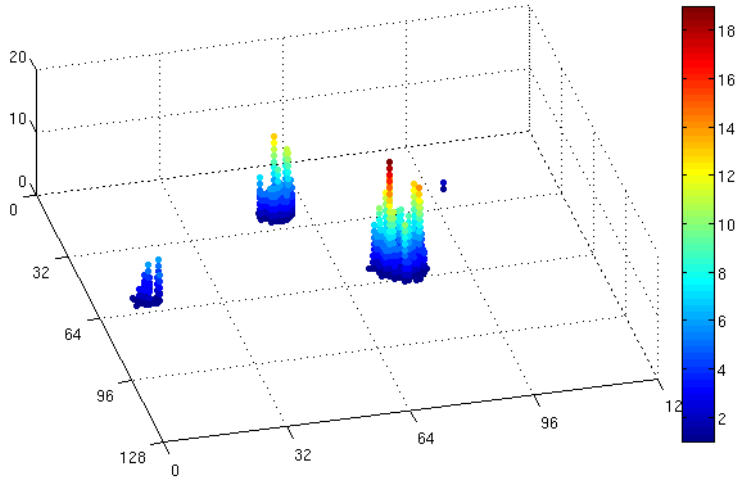
If we desire to move the cross-modality to the next level, we are absolutely sure that this approach brings advantages event when we have multiple different sensorial inputs (e.g.: vision+auditory, vision+touch, etc). With the opportune change in the design, the saliency map can be enriched with different cross-modality contributions.

If we want to analyze how this fits in the development of epigenetic robotics, we point out two different aspects. First, the neuromorphic chip DVS sensor Lichtsteiner et al. (2008) is a VLSI implementation of the transient signal pathway of the mammalian visual system that encodes visual acquisition into flow of asynchronous information. In the sensor we encoded mechanism of visual acquisition that resemble pathway mammalian visual system. Regarding this, we can fairly claim that we introduce in the system complexity which is result of evolution and then relate to the concept of phylogenesis. Second, not only DVS sensor emulates processes that derive from evolution but also the technique that transfers information in the system is the result of evolutionary mechanism. The AER protocol, Mortara (1998), Hofsttter et al. (2010) which defines the exchange of information between components, reproduces the typical biological inspired connectivity pattern. This emulates the projection of the activity of one cell to another in the next neural processing layer and the projection is usually referenced as *projection field*.

In the previous chapter and in this chapter we presented a computational layer that reproduces processes of which validity can be found in the different stages of evolution in living being. In the next chapter we present how the information processed in the visual cortex can be interpret in order to extract ”where” the stimulus is presented (*dorsal pathway*) and ”what” kind of stimulus is presented (*ventral pathway*). In addition we look at how the high complexity layer interacts with those two pathways in order to stabilize the search of interesting object in the environment.

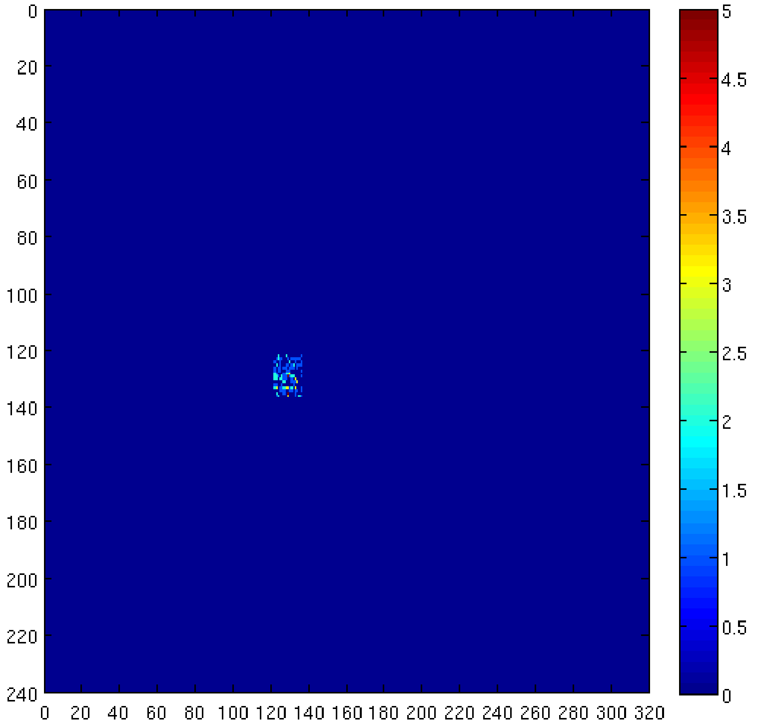


(a) Shift locations generated by iNVT in scenario of Experiment A

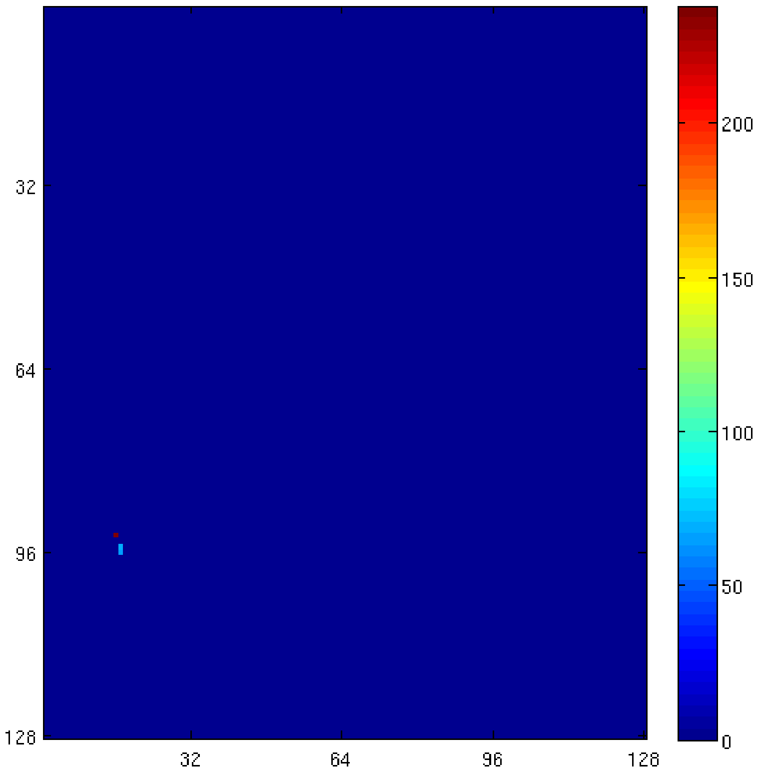


(b) Shift locations generated by EVA in scenario of Experiment A

Figure 3.3: Comparison of the shift generated by the two models in experiment A



(a) Shift locations generated by iNVT in scenario of Experiment B



(b) Shift locations generated by EVA in scenario of Experiment B

Figure 3.4: Comparison of the shift generated by the two models in experiment B

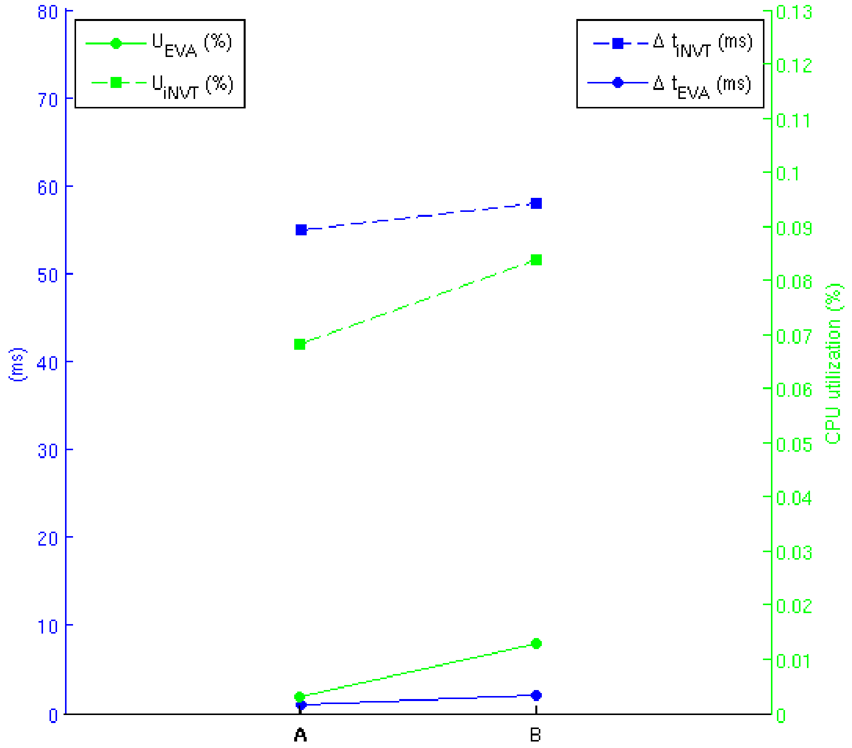


Figure 3.5: Comparison of the computation demand and intrashift time interval of the two experiments

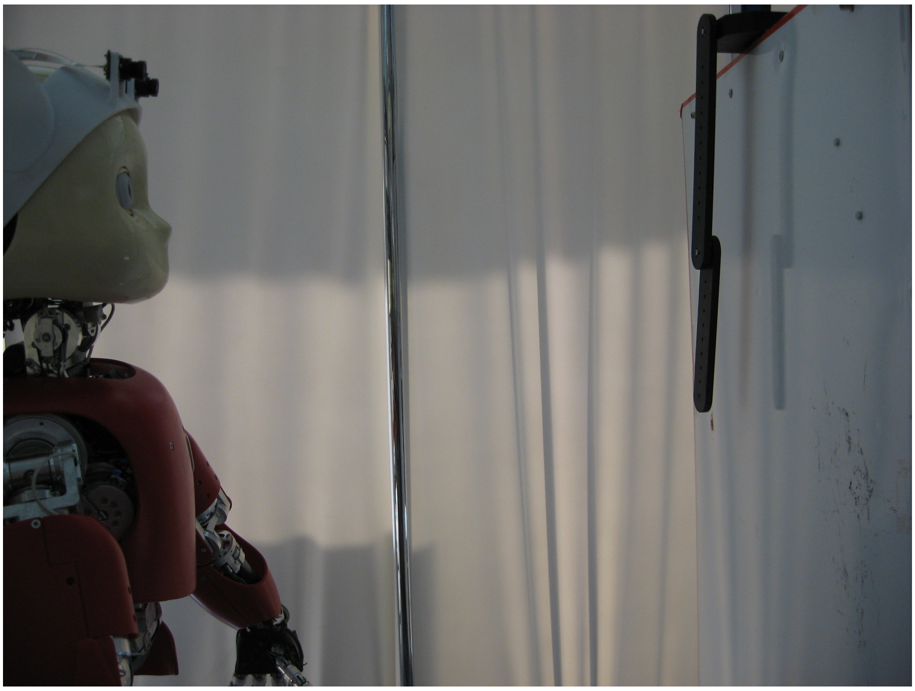
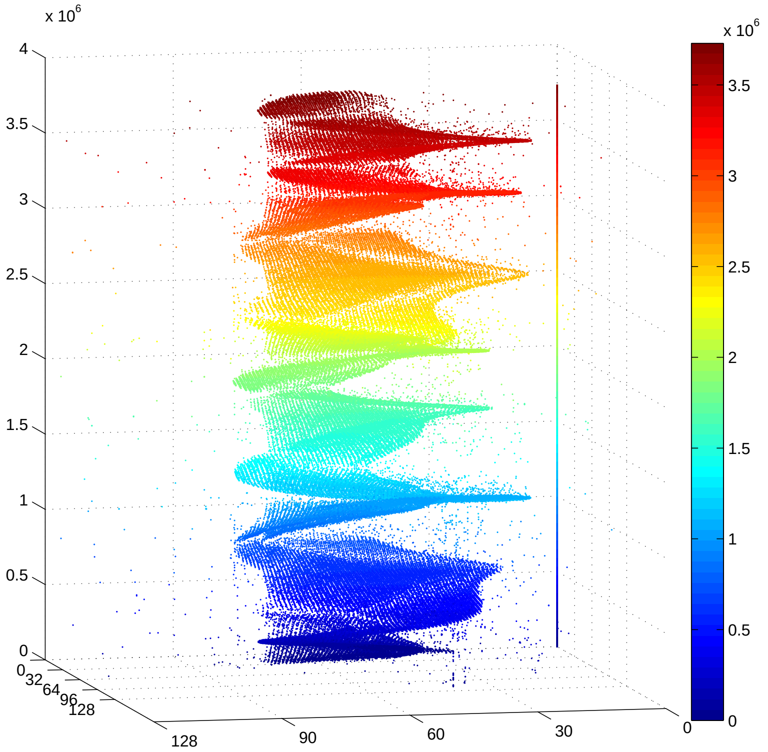


Figure 3.6: Set up of experimentB. The chaotic pendulum is located 50cm far from the event-driven cameras (embedded in the humanoid robot iCub‘s eyes.



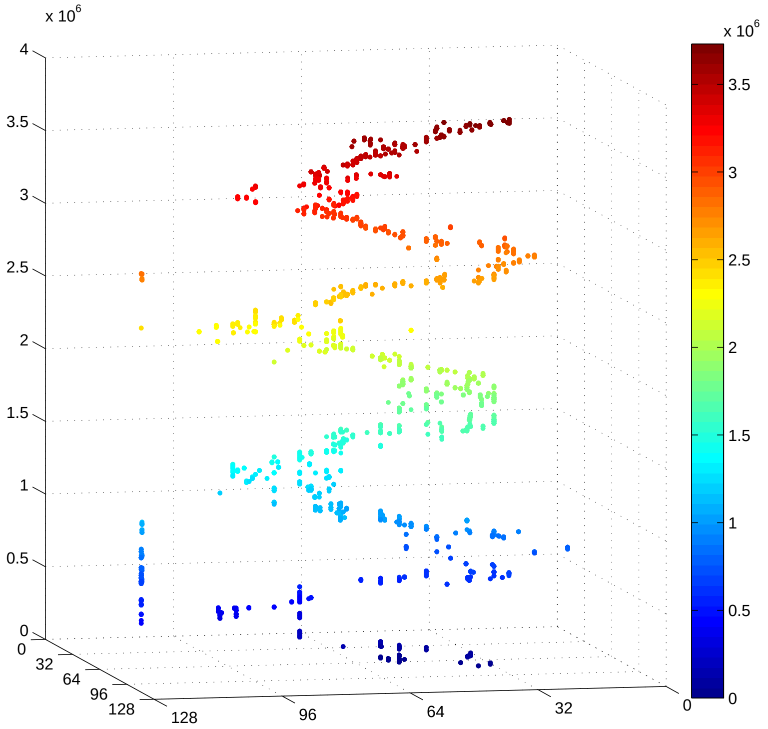


Figure 3.7: Comparison of the shift generated by the two models

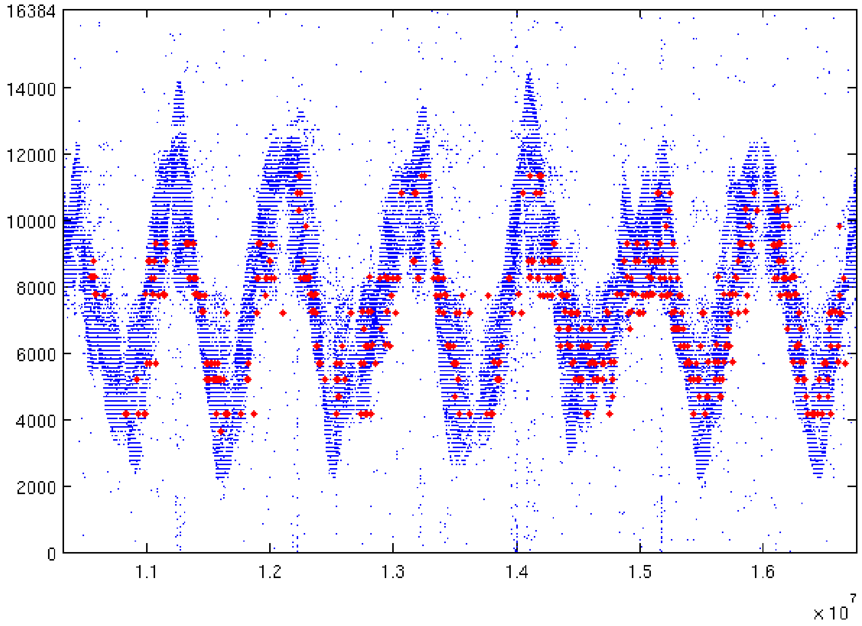


Figure 3.8: Raster representation of the events generated on the retina by the pendulum and the shifts produced by EVA in the same time interval

TOP-DOWN AND BOTTOM-UP INTERACTIONS IN VISUAL ATTENTION

4

> *"But the eyes are blind. One must look with the heart."*
>
> *"Mais les yeux sont aveugles. Il faut chercher avec le cur."*
>
> Antoine de Saint-Exupry, The Little Prince

4.1 Introduction

The effect of behavioral goals on eye movement control has been known to the scientific community since the last century Buswell (1935) and Yarbus (1967). Showing that observers patterns of gaze activation depended critically on the tasks, they started up discussions on the difference between top-down and bottom-up actions. We already exploited the bottom-up attention but much less is known about the neural instantiation of the top-down, volitional component of attention Hopfinger et al. (2000), Corbetta et al. (2000). We report substantial success in the implementation of bottom-up visual attention even if we experience tendency of instability in such model. Adding volitional component or in some cases exogenous control of the attentive system we aim at biasing the already convincing behavior toward task goals. In order to implement such mechanism we look at cognitive models proposed to envision characteristic of this control. For example, some lesions in the high cognitive area seems to give insights on how top-down contribution interacts with the bottom-up. The patient in these situation seems to be unaware parts of the visual environment Parasuraman (2000). These and other researches allow us to design a model which is the result of phylogenetic development in humans.

Looking at the typology of attention, it is possible to distinguish different attentive schemes. The bottom-up attention selects regions of interest when those regions are significantly distinct from

the background (pop-out effect). The visual attention presented in the previous chapters operates under similar constraints. In the bottom-up attention the response time does not change with the number of distractors, giving evidences on the parallel computing nature of the schema Treisman and Gelade (1980)Wolfe and Horowitz (2004).
On the contrary, another mechanism that might control the attentive system is the *top-down attention*. This schema is recruited when only a subset of features allow the system to select a winner in the competition for attentive focus redeployment. In this scenario, the number of distractor influences the time of selection (set-size effect), suggesting that through an attentional scan, element of the set are serially analyzed.

In modern scientific community, the bottom-up and top-down attention are usually referenced with other names: Exogenous versus Endogenous attention. Stimulus-driven vs goal-directed attention (in the terminology of Yantis, Yantis (1993)) are also terms with which the community refers to this classification. Stimulus-driven (or bottom-up) selection is said to occur when attention is captured by properties of the stimulus even if they are irrelevant to the current task. Goal-directed (or top-down) selection, on the other hand, is said to occur when the observer's knowledge or beliefs about the task determine what is selected in the visual field. In decades, the community have produced an accurate list of features by which the attention can be categorized. The Bacon WF (1994) proposed that observed instances of attentional capture in *singleton detection mode* is associated to stimulus-driven attention. This is the result of salience-based strategy adopted by subjects, such as pure pop-out of some conspicuities derived from pure bottom-up attention (see Itti and Koch model). They further presented additional evidences that prove that subject can override singleton detection mode by adopting strategies based on searching for a specific target feature, namely *feature search mode*. Other researches Theeuwes (2004) diverge from the Bacon and Egeth model who proposed two important criteria for examining stimulus-driven capture. The former criteria indicates that *search latency* cannot increase with display size, since the principal characteristic of the singleton detection mode is *parallel* search. The latter, the salience of irrelevant distractor is never compromised by characteristic of search display. Given these metrics, Theeuwes claims that subjects always recruit stimulus-driven attention and the only parameter that might change is the *window size* of the search, much like a dimension varying spotlight. The debate on the difference between top-down and bottom-up attention remains complex and always enriched of novel and different points of view. In Leber and Egeth (2006) proposed that *feature search mode* can override *singleton detection mode* event if the previous criteria are fully satisfied essentially confirming the work Bacon WF (1994). In Bacon WF (1994) sought evidences of override by creating conditions that discourage subjects from using the *singleton detection mode*. Essentially, Leber and Egeth (2006) provided evidences that are difficult to reconcile with the view that most salient item in the display automatically draws attention during parallel search. On the other hand, they rather confirmed the Bacon and Egeth view and others Folk et al. (1992), Jonides and Yantis (1988). Subjects posses the ability to exert top-down control to avert involuntary capture by irrelevant although salient feature singletons.

In general, visual search has a behavioral goal which creates consistent patterns across subjects. Different models in both the field of bottom-up and top-down have been proposed. Concerning the modeling of bottom-up attention numerous studies have been carried on recently (e.g., Bruce and Tsotsos (2006); Itti et al. (1998); Koch and Ullman (1985); Li (2002); Rosenholtz (1999); Torralba (2003)). Most of these models are based on the idea that where local statistics differ from the background statistics, there is where attention is more likely to be deployed (Wolfe and Horowitz (2004)). This is true for natural images, where the objects are typically more than salient than background Torralba et al. (2006) Elazary and Itti (2008). In our recent research, we noticed that bottom-up cannot be used alone as oculomotor guidance process as heuristic to fixate object but only to redirect attention into salient subregions. Top-down attention which is modulated by the task can help in improving the performance. Through top-down attention, the subject can look at the areas in the field of view that are more likely to contain the goal of the task. Target features are ”ubiquitous” source of guidance Treisman and Gelade (1980); Wolfe et al. (1989); Wolfe (1994), Wolfe (2007) ; Zelinsky (2008). Recent research in the field brings considerable evidences that in real word visual search are mainly addressed via *target-driven attentional guidance* Einhäuser et al. (2008); Rao et al. (2002); Rodrguez-Snchez et al. (2007); Tsotsos et al. (1995); Zelinsky (2008). Different techniques can be chosen in order to perform feature target selection. In the next sections we propose an approach that uses *feedback refinement*.

In order to promote winning top-down strategies *memory* must be involved in the task. Either remembering location and feature of the target or simply associating the target to a task involves *memory*. For example if the task consists in ”looking at the banana”, the attentive system is biased toward objects that have yellow color and have structure longer than wider and have no sharp corners. These are feature of the target associated to the ”banana” label. Memory recalls features when asked and coordinates multi-sensory information associated to the target. Imagining that a correct saccade is performed on the object and additional shifts brings the target out of the field of view, *spatial awareness* of objects in the space helps in redirecting fixation point on the target. This information is usually associated with *memory*. For further information on the research in the field of memory, Gazzaley et al. (2005), Buschman and Miller (2007a), Sarter et al. (2001), Ungerleider and G (2000) provide valid reviews. Memory of spatial location is already addressed in the framework if we consider IOR in space domain as transient memory of the location where the object of interest is. As explained in chapter2, the *inhibition-of-return* inhibits region already attended. This approach can be used to excite regions in the space previously attended when tasks requires so. The top-down attention mediates in this situation bringing as conspicuous the attended targets. However, it is author‘s intention to a further enhancement of the technique by associating target feature information to the mere spatial location of the attended target.

Scene context is another top-down component that might guide the visual search. Memory is involved in scene contextualization in the way that particular spatial layout links to current working scenario. The chief drive in this component references to statistical regularities in the scene that can either direct attention to the target location or give information of target feature Eckstein et al. (2006) Torralba and Oliva (2002). In particular, global information can help in discriminating between different spatial layout and scene category (Joubert et al. (2007); Greene and Oliva (2009); Renninger and Malik (2004);Rousselet et al. (2005); Schyns and Oliva (1994)). Further more, via the ability of the system to categorize and discriminate between scenes, the viewer can take advantages from additional information such as which object might be present in the scene (Bar (2004); Biederman et al. (1982); De Graef et al. (1990); Friedman (1979); Henderson et al. (1999); Loftus and Mackworth (1978)). Possibly the location (”where”) of the object might be interesting priming for the visual attention.

4.2 Neural Mechanisms of Top-Down and Bottom-Up Attention

In literature, top-down attention is further classified into two different classes: *volitional top-down attention* and *mandatory top-down attention*. The first exerts its influence through the act of will whereas the latter modifies the top-down attention which is invasive and which cannot be eliminated by volitional. The latter can develop through experience grounded a form of mental plasticity. It modifies during development and includes contextual modulation. In general, attention modulation comes from both the ventral stream (*”what” pathway*) and dorsal stream(*”where” pathway*).

The attention system has recently been studied by the mean of some experiments performed on monkeys. The attention map is probably associated with dynamics present in lateral intraparietal (LIP) Bisley and Goldberg (2010a) region of the cortex and the frontal eye field (FEF) Thompson and Bichot (2005). The LIP-FEF circuit contains three classes of neurons: a) visual neuron responding only to visual stimuli, b) motor neuron active in association to eye movement, c) visuomotor neurons firing during visual and movement-related activity (Bruce and Goldberg (1985),Goldberg et al. (1989)). In particular movement-related neurons, neural activity is associated to ocular saccades most of them discarging before the saccade on-set. On the contrary, the V1 area is mostly recruited for feature extraction and it is modulated by attention Buffalo et al. (2010) McAdams and Maunsell (1999). On this tight modulating link between the attentive system and area V1, the author defines the mechanism for the interaction between attentive system and feature extraction stage. Moving up to the V2, V4 areas the population of neurons are more sensitive to features than locations, there is a gradual shift from *spatial* to *feature-based* attention. Excitation of population of neurons in LIP can be driven by both top-down and bottom-up mechanisms. This makes LIP a candidate where interaction between the two forms of attention take place. LIP encodes agnostic priority towards the factor that generate priority Bisley and Goldberg (2010b). LIP controls other brain areas in order to bias the attentional processing, in particular this is produced

via direct feedback connections Ungerleider et al. (2008). The author believes that this aspect is great inspiration for the implementation of the top-down mechanism in the attentive system.
Evidences Fecteau and Munoz (2006) Thompson and Bichot (2005) suggest that FEF area is responsible for saliency computation, and its connections to motor neuron make it important structure for oculomotor action associated to visual attention.
Sub-threshold stimulation in FEF area enhances responses in V4 neurons in the presence of a stimulus in their receptive field Moore and Armstrong (2003).

Defined the circuits involved in visual attentive system, we here highlight discoveries that suggest how the top-down mechanism works. We now consider feature-selective visual areas V1, V2, V4 and IT. These visual processing areas drive bottom-up attentional signals and are targets for top-down attentional biasing signals. Two typologies of feedback signal from the higher cortical region can influence the visual processing Sherman (2007). One type of feedback flows from the higher visual processing area to the lower following the hierarchical structure. The second form of feedback signal can flow from FEF to other cortical area such as V4.

The flow of top-down attentional signals from the pre-frontal cortext (PFC) to area inferotemporal cortext (T) is another example of how top-down attentional signals from higher cortex can influence a feature sensitive sensory area Tomita et al. (1999). Microstimulation in area IT results in biases of object recognition Kawasaki and Sheinberg (2008), or even of face detection when microstimulating face-selective sites within area IT Afraz et al. (2006). In conclusion, top-down signals can emerge from the PFC to bias visual cortices through direct connections, such as from the PFC to area IT, or possibly through the pulvinar. Similarly, there is evidence that a direct connection from the FEF to area V4 might exists, which further demonstrates the possible communication of top-down information from higher cortex to sensory areas. Top-down signals from the PFC probably contain detailed information about the target and this information might be used to bias feature-selective areas of sensory cortex.

Further, a recent report Buschman and Miller (2007b) reported records of the prefrontal and parietal neurons in monkeys. The prefrontal neurons reflected the target location, during top-down attention, whereas parietal neurons signaled during bottom-up attention. Synchrony between prefrontal and parietal was stronger in lower frequency during top-down and at higher frequency in bottom-up attention. This result indicates that top-down and bottom-up signals arise from the frontal and sensory cortex, respectively, and different modes of attention may emphasize synchrony at different frequencies.

From the point of view of the motor response the FEF have significant role. The connection from FEF to motor neurons and the deeper layer of the superior colliculus SC, defines a crucial pathway to the oculomotor behaviors and the attentive system. From the areas related to the FEF, converging researches identified several descending pathways to the eye motor control. We take inspiration from the direct connections to the eye movement related structures in the brain stem in particular the SC. The pathway which was originally related only to the saccadic control predominantly, it has been recently associated to the pursuit cortical areas Yan et al. (2001). We think that the control by the high level regions of areas related to motor-generation is one of the aspect that we need to implement.

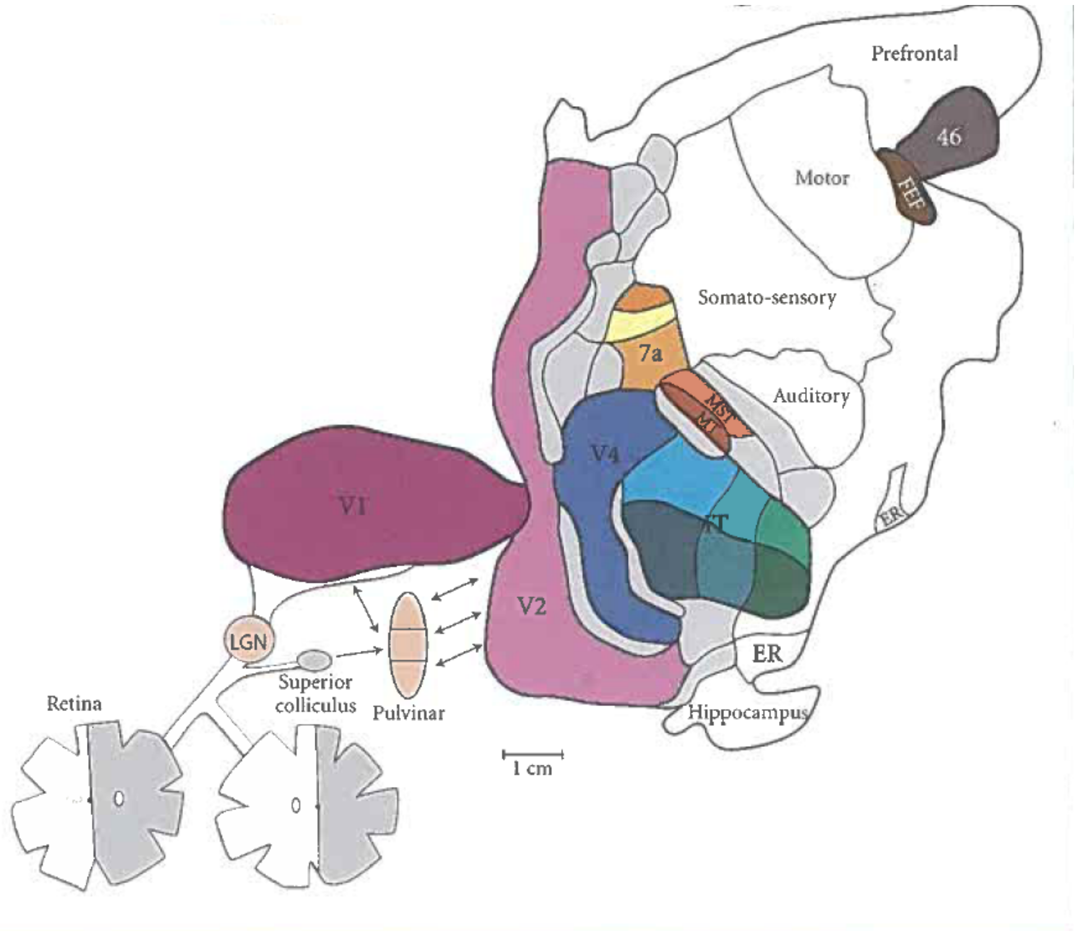


Figure 4.1: flatten map of the macaque‘s monkey brain from Koch (2004)

In the next section we present how the connections directed both to the bottom-up component of attention and motor execution are modeled in the framework.

4.3 Experiment: Evaluation of the top-down and bottom-up interaction

In the overall framework we propose one chief cognitive director: *attentionPrioritiser*. In the module, we implemented both connections to the early stage (visual processing and early stage of the attentive system) and the motor pathway.

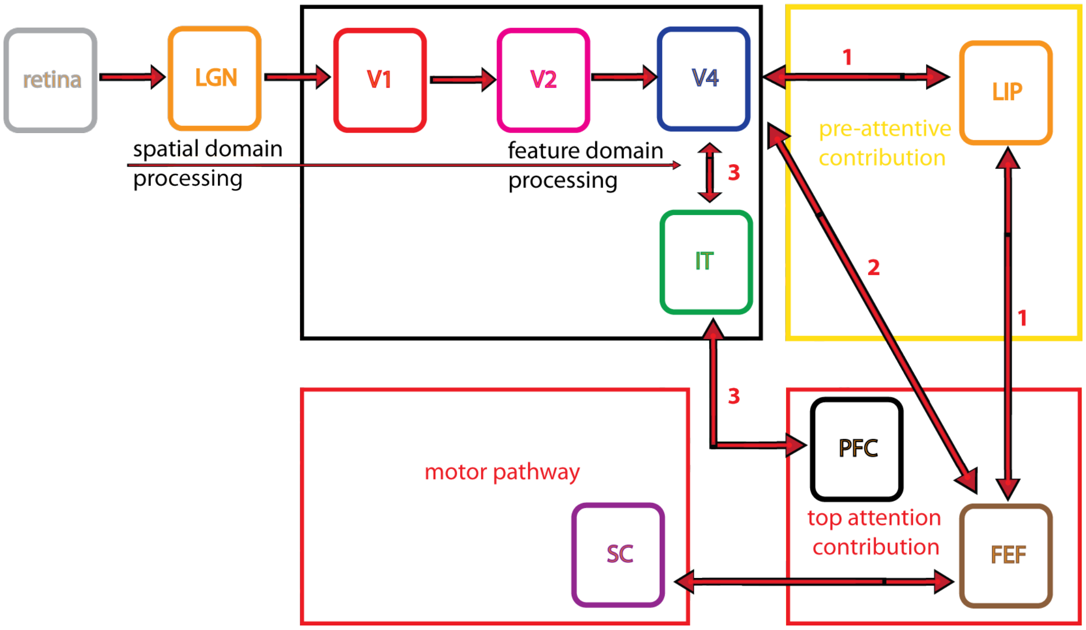


Figure 4.2: Representation of the neural organization of the high cognitive component in attention as suggested by the literature published in the last decades. The color mapping of the single involved areas refers to the figure 4.1 whereas the relative position of the components resemble the framework of the system.

As already pointed out in the previous paragraph, the mechanism of feedback is valid tool that we elected as most effective in the designed framework of visual attention. Similarly to Sherman (2007) we reproduce attentional connections from the higher cortical region to visual processing that we named *feedbacks*. This idea finds strong foundations in the research carried on in the last decades (even though incomplete and sometimes diverging). The *attentionPrioritiser* is effectively a director that regulates behaviors of the visual processing components and attentive stages by the mean of feedback commands.

We define three different typologies of *feedback connection*:

- *SA-fc : selective attention feedback connection*
- *CVP-fc: complex visual processing feedback connection*
- *EVP-fc: early visual processing feedback connection*

Through *SA-fc*s, the *attentionPrioritiser* interacts with the component that selects ”where” and ”when” the location of focus must be redeployed. It balances the contribution of the different feature maps and alters the timing. If one of the features results to be more relevant in the task,

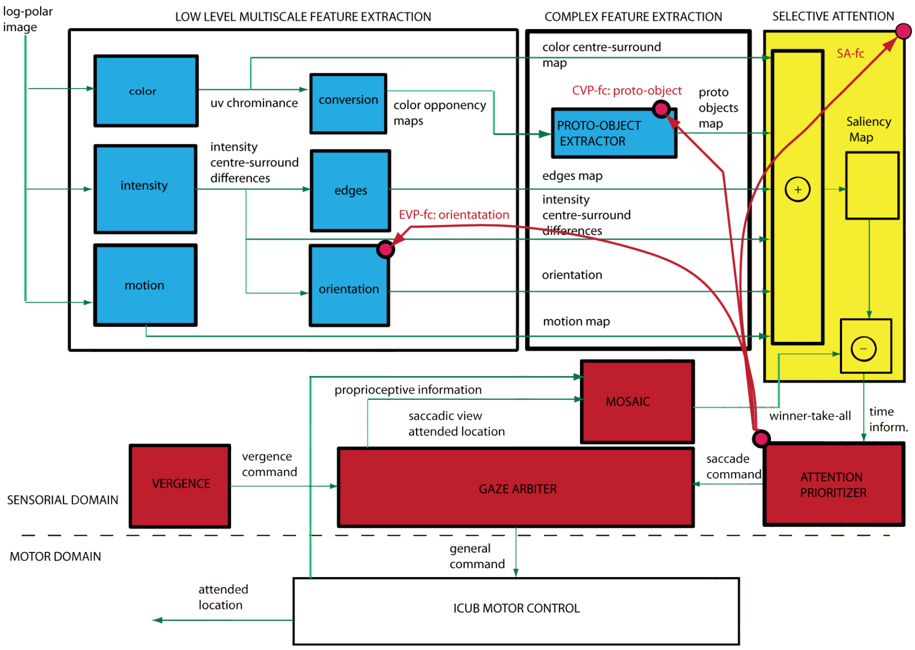


Figure 4.3: Software framework: representation of the feedback connections that go from the attention-Prioritiser to visual processing. Within this group of connection we represent instance of SA-fc, CVP-fc and EVP-fc: respectively selective attention feedback, proto-object feedback and orientation selectivity feedback (highlighted with red arrows)

the *attentionPrioritiser* biases the attention in favor of the selected feature. The weight of the feature in the linear combination of the selective attention is increased and the output accordingly provided.

SAC-fc feedback connections:

- *SET* W_i *: weight of every single feature map in the linear combination*
- *SET TIME : time interval for a standard saccade generation*

The *CVP-fc*s refines the behavior of the components in the complex stage of the attention system. In particular, via the proto-object connection, the *attPrioritiser* regulates the conspicuity map of proto-object blob. The proto-object module produces feature maps based on the conspicuity of the blobs, the higher cognitive component alters the characteristics that defines the conspicuity of the blob such as the target color, the dimension blobs.

CVP-fc feedback connections:

- *SET minDB : min dimension of the blob associated to proto-objects*
- *SET maxDB : max dimension of the blob associated to proto-objects*
- *SET colorTarget : target color to determine the saliency of the single blob*

- *SET mode : selects which modality defines the saliency of the single blob*

Finally, via the *EVP-fc*, the *attentionPrioritiser* alters the processing of the modules in the early stage. In particular, we designed one dedicated connection that reshapes the processing of the orientation feature extractor. We restrict the output of the orientation module to only particular directions or let all the orientations compete and produce a single orientation feature map. The high cognitive stage can either extract the most salient orientation in the scene or differently determine the spatial location of the strongest stimuli with a particular direction in the scene. Such diverse tasks can be equally addressed by the identical mechanism this is clear potentiality of the technique.

EVP-fc feedback connections:

- *SET* W_i *: determine the weights of the different orientation in the orientation selectivity module*

The *attentionPrioritiser* sends commands via feedback connections when the system reaches a particular state. The states of the system associated to different situations are as follows:

- *udt - user-defined task*
- *pdt - prediction-defined task*
- *srt - self-reinforcement task*

In the first case the user explicitly defines the typology and characteristic of the visual target. For example, if the goal is to ”find a red ball on the table”, the higher cognitive module biases attention toward blobs of red color. When it is the prediction that biases attention, the focus of attention is deployed in advance on the expected visual target. When the prediction action is activated 6, it selects one visual target as anticipation of where the counter-part is going to act. Based on the features of the selected visual target, the higher cognitive stage biases accordingly the attentive system in order to stabilize the focus of attention on the visual target. Finally the self-reinforcement is a mechanism that stabilizes the bottom-up visual attention. When the bottom-up attention mechanism selects novel visual targets by the mean of exclusive endogenous activation, the focus of attention is deployed on it. This triggers fixation point redeployment and a saccade brings area of high resolution (fovea) on the target. Conveniently at this stage, features of the target can be extracted and through reinforcing feedback these characteristics deepen the minimum located on the object making the attention system output more stable.

Concerning the design of control for the motor components, the *attentionPrioritiser* supervises the actions that the system performs in different task situations.

At this point, different motor-commands are asynchronously presented to *attentionPrioritiser* module. We define four states that indicate whether the oculomotor controller is in: no-action,

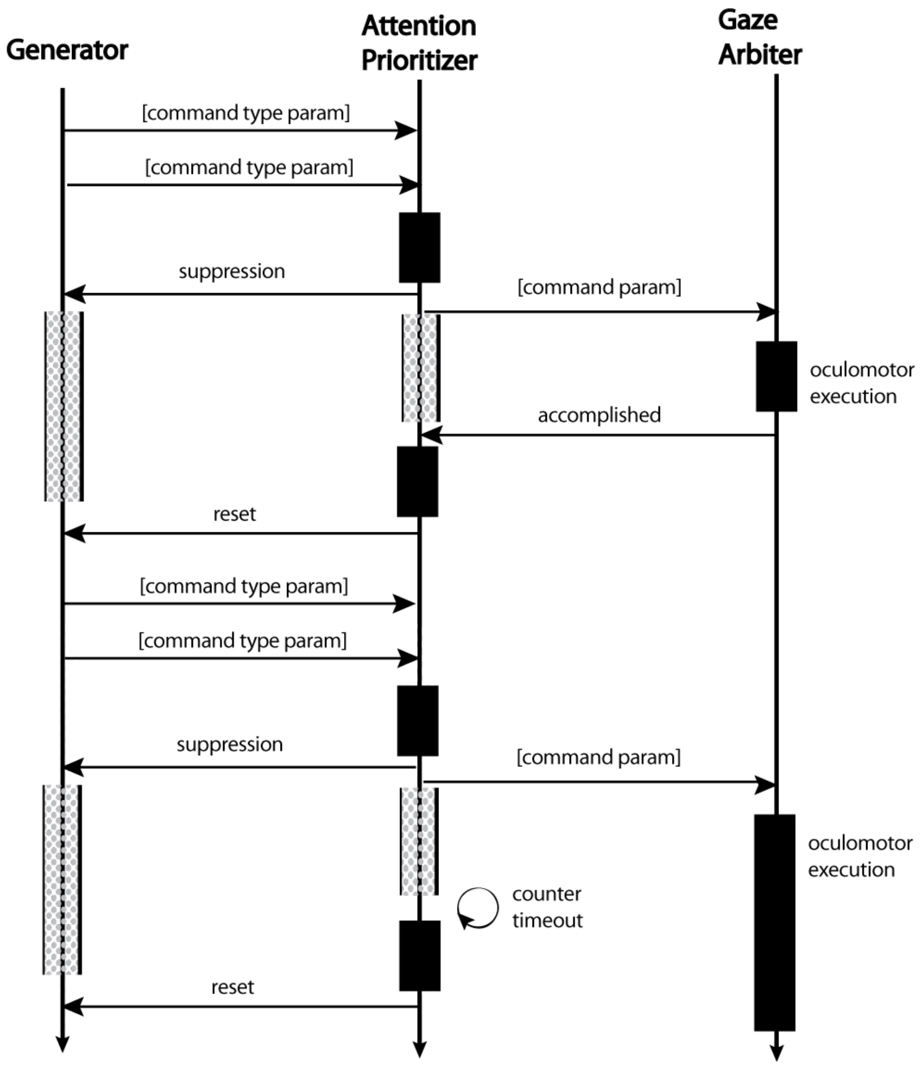


Figure 4.4: temporal sequence of interaction between higher level of attentive system and gaze arbiter. The gaze arbiter is the module responsible for action execution chapter5

vergence, saccade, smooth pursuit . The transition between states is regulated by transition matrix M^a. Given the state s_{t-1} and request of action r_t, the function defines f_{M^a} defines the state s_t.

$$F_{M^a}\left(s^a_{t-1}, r^a_t\right) = s^a_t$$

The states have different priorities (in particular express saccade has highest priority) which defines which action has rights to be executed first. The active part associated with a state initializes a communication protocol between the *attentionPrioritiser* and respectively *gazeArbiter* and the module that has sent the command, called generator figure7.3. We designed this process for mainly take advantages from two evident benefits. First, with this mechanism, attentionPrioritizer receives acknowledgment from the gazeArbiter when an oculomotor action successfully ends. This means that the synchronization of different actions can be accurately controlled. Second, we are able to suppress motion feature at the level of selective attention module and there exist no motion interference with the attention system during saccade actions. The approach is supported by evidences in literature Burr et al. (1994), and particular relevance is given to the idea that only Magnocellular layers in LGN are suppressed and whereas other cells are not affected. The suppression command is sent back to the selectiveAttention ignoring which generator has generated the command. This command inhibits motion response command from the motion filter which cannot longer trigger attentional redeployment but allows the filter to compute relevant information anyway. When the gazeArbiter has accomplished the task the attentionPrioritiser resets the state allowing motion to initiate novel saccades. The difference between these two actions does not lay only in the different initialization time at the level of the selectiveAttention module but also in the execution time. We defined an algorithm for the attentionPrioritiser that enables visual feedback only for planned saccade and not for express saccade. The approach that we implemented for visual feedback takes inspiration by recent insight in the saccadic deployment of primates that prove that saccade become more accurate when more time is allowed for target selection to occur Cohen et al. (2007) Coëffé and O'regan (1987) Ottes et al. (1985). For planned saccade the retinal image of the predicted landing location is compared with the post-saccadic image based on what reported in Bahcall and Kowler (2000). On the other hand, for express saccades no visual feedback is planned although we designed an additional process. Conditioned to this the final line of sight can be deployed on average position as reported in the center of gravity saccade experiment Coren and Hoenig (1972) Findlay (1982). Saccade usually lands near the target and the landing position other than the position elected by the pure bottom-up contribution. This is proved to depend on visual characteristics of the object, distribution of the attention or goal of the task Brouwer et al. (2009), Findlay and Brown (2006), Johansson et al. (2001), in other words top-down visual attention. For these reasons we choose to spatially pool the landing position based on the higher component of the attention that acts on weights of early stage feature extractors. The attention prioritizer biases the landing location of the focus of attention towards the salient features defined by the weight associated with any singular component of the early stage.

4.4 Experiment: how top-down attention biases bottom-up attention

We present a case study of top-down biasing of the visual attention. The experiment is performed with the humanoid iCub located in a highly clustered environment such as the typical research lab. In front of the humanoid robot iCub there is a table where the visual target and some distractors are placed. The complete collection of modules from the processing front end, via the early and complex attentive stage to the selective attention run on a single machine. The *attentionPrioritiser* run on the same machine along with the other modules and the output of all the modules can be considered in real-time. The huge effort that we put in developing efficient processing in the modules assures great performance in reduction of computation demand.

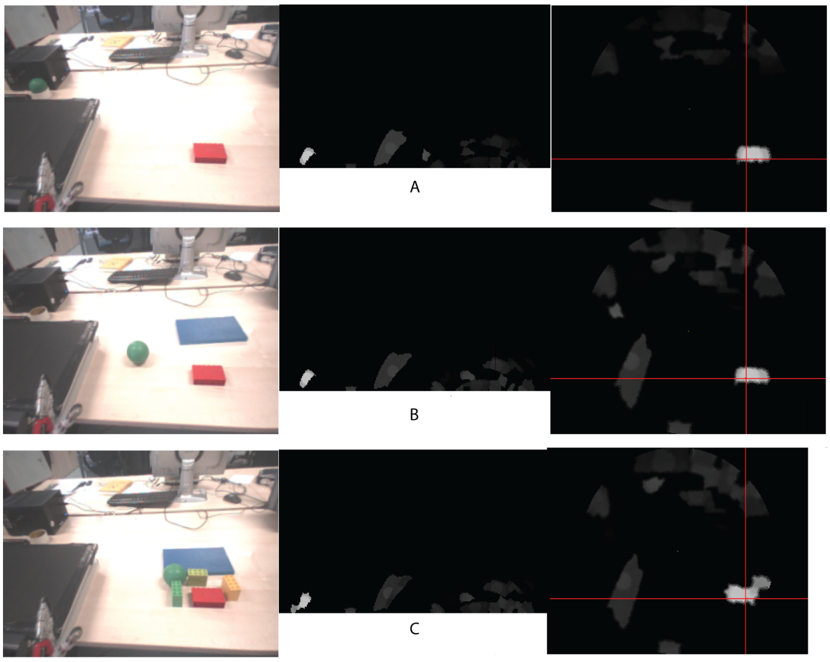


Figure 4.5: Representation of the visual search and segmentation driven by top-down attention. We provide three different runs and for each of them we represent the scene in Cartesian mapping (left), the saliency map generated by the selective attention module (center) and the mapping of the saliency map in Cartesian space with the related WTA location (right). We represent result in three different conditions: A) response of isolated target B) soft cluttered scene C) hard cluttered scene

The visual target is a red block of LEGO® on the table. We impose the task to the *attentionPrioritiser* module through a user-defined task assignment. Thus, in this situation, the task of *visual search* belongs to *udt* category. We kept the visual target in the position and we both introduced other distractors and relocate existing distractors. The hardest task is not related to the localization of the red in the scene but rather to isolate and segment correctly the visual target in the scene. Distractors, if located closer to the target, alter the detection mechanism or at least complicate the segmentation of the visual target. The mechanism presented in this chapter is robust to distractors. In the figure 4.5 the reader can appreciate how the top-down contribution directs the visual search despite the proximity of distractors. In particular in the final trial figure 4.5.C the visual attention detects similar proto-objects in the neighborhood of the visual target. No-target are correctly segmented and the saliency successfully calculated. Accordingly to the assigned target, the only proto-object that obtained highest level of saliency is the red block of LEGO®. Note that the yellow block of LEGO® close to the visual target is segmented as different blob despite the similar color to target color.

4.5 Outline

We provide a possible implementation for the mechanism that regulates the interaction between the bottom-up and top-down and at the same time controls the motor component of the system.

Toward the preattentive stage and visual processing we use simple feedback signals between the modules that resemble the high cognitive area with the modules that reproduce the *”what”* and *”where”*. Connections exist between high cognitive regions in the cortex with *inferotemporal cortex - posterior parietal cortex*. These two pathways correspond to respectively the ”ventral” and ”dorsal” pathways that both together interpret the visual environment. Those circuits share regions with other FEF and LIP which form a circuit active during oculomotor action generation and are crucial for the connection to the higher cognitive level. We implemented a dedicated component that resembles the behavior of both circuit of ”where”-”what” pathways and pathways FEF-LIP of eye movement control .
The simplified implementation guarantees correctness and takes advantages from the high degree of modularity in the visual attention framework. The module *attentionPrioritiser* that triggers the feedback toward the top-down modules has been designed to interact directly with the modules responsible for eye movement. To simplify the structure to the very essence, the *attentionPrioritiser* can be associated to the prefrontal cortex. In doing so, we can identifies feedback connections to the IT and PPC regions. The target can be presented to *attentionPrioritiser* which is able to extract relevant features. Those features are related to the single components of the bottom-up attentive system and the feedback command can refine parameters of those components. The search is biased toward the features of the target object providing a winning mechanism for top-down visual attention selection.

From the point of view of eye movement generation, an additional direct connection to the superior colliculus is introduced. This is responsible to eye movement. In the framework this connection represents the connection between the *attentionPrioritiser* and the *gazeArbiter*.
Further more, we provide dedicate strategy for the supervision of the motor control (eye movements). The *attentionPrioritiser* filters the different requests of oculomotor actions, opting for the action that has higher priority. For any selected oculomotor action the high cognitive module triggers additional post-action evaluation measure. Eventually, in the case where the oculomotor action results inaccurate, the *attentionPrioritiser* initializes and executes post-action correction trying to reduce post-action error.

The implemented characteristic of the high cognitive level component help us in defining effective higher level of cognitive control of the other components of system: a) the preattentive-stage and visual processing, b) motor control stage. In the next chapters we analyze in detail the last control stage. We present details on the the actions that the high cognitive stage can activate. Finally, in the chapter that we dedicated to the autonomous learning (ontogenetic development) we present how learning mechanism smoothly interacts with high cognitive action generation strategy active in the *attentionPrioritiser*.

ACTIVE VISION ON HUMANOID ROBOT ICUB : OCULOMOTOR ACTIONS AND ACTION SELECTION

5

> *"Difficult to look. I mean at anything, to make the eyes stay put.*
> *They want to shift, move out*
> *wherever something might be missed.*
> *The fear of missing winds us up, were like small go cars*
> *set in motion by a key, with that same random energy*
> *we scan, pan, glance, turn to one side*
> *do anything but fix our gaze.*
> *A common cat can stare us down. "*
> Emily Leider From RAPID EYE MOVEMENT & OTHER POEMS
> San Francisco: Bay Books, 1976

5.1 Introduction

The study of the eye control gives unique tool for the study and understanding of the working processes in the brain. In fact, in the past three decades eye movements have increasingly brought valid insight into disorders raging from muscular dystrophy to dementia Kaminski and Leigh (2002) Leigh and Kennard (2004). At higher behavioral level, eye movements have been used to address fundamental aspects such as human behavior and cognitive behavior. Eye movements have also been used for testing and identification tasks, in particular, new therapies for from genetic to degenerative disorder have been successfully validated by the use of eye movements Biscaldi et al. (2000). It is not surprise to note that eye movements influence so many areas of human study. In almost any behavioral paradigm we can find eye movements related activity in nearly any area of the brain. The explanation is that we are creature that deeply depend upon vision for most of

Class of Eye Movement	Main Function
Vestibular	Holds images of the sen world steady on the retina during brief head rotations or traslations
Visual Fixation	Holds the image of a stationary object on the fovea by minimizing ocular drift
Optokinetic	Holds images of the seen world steady on the retina during sustained head rotation
Smooth Pursuit	Holds the image of a small moving target on the fovea;or holds the image of a small near target on the retina during linear self-motion; with optokinetic responses, aids gaze stabilization during sustained head rotation.
Nystagmus Response	Reset the eyes during prolonged rotation and direct gaze towards the oncoming visual scene
Saccades	Brings images of objects of interest onto the fovea
Vergence	Moves the eyes in opposite directions so that images of a single object are placed or held simultaneously on the fovea of each eye.

Table 5.1: Functional Classes of Human Eye Movements

the human activities. It is only the result of evolution that eye movement assume a central role in survival for animals. For example, in humans, visual attention has a big role in making prompt and effective responses to what is happening around us. Another aspect that makes eye movement particularly interesting for the scientific community is the analogy with axial and limb movement in motor theory. In addition, the complexity of the control is reduced to essentially the rotation of the globes. The eye movements can be classified in different groups: Vestibular, Visual Fixation, Optokinetic, Smooth Pursuit, Nystagmus Response, Saccades, Vergence. The distinction between the classes is defined on the basis of how they support vision, their physiological characteristics, and their anatomical substrate.

Eye movements can be grouped into different typologies of motor actions: those that stabilize the perception and so keep the images steady on the retina, and those that shift gaze and so redirect the line of sight to a new salient object Buttner and Buttnerennever (2006) Carpenter (1991). In general as depicted in table 5.1, any class has function suited for a specific purpose Dodge (1903), D.A. (1970), G.L. (1962).
Any of these classes have been implemented on the humanoid robot iCub at different control levels. In the next section only oculomotor actions designed by the author are reported. However, we need to point out that control at high level instantiate actions at a lower level control. It is not intention to show specific characteristics of the low level control, which can be addressed in Pattacini et al. (2010).

Classification	Definition
Volitional Saccades	Elective saccades made as part of purposeful behaviour
Predictive, anticipatory	Saccade generated in anticipation of or in search of the appearance of a target at a particular location
Memory-guided	Saccades generated to a location in which a target has been previously presented
Antisaccades	Saccades generated in the opposite direction to the sudden appearance of a target at a particular location
To Command	Saccades generated on cue
Reflexive Saccades	Saccades generated to novel stimuli (visual, auditory, tactile) that unexpectedly occur within the environment
Express Saccades	Very short latency saccades that can be elicited when the novel stimulus is presented after the fixation stimulus has disappeared
Spontaneous Saccade	Seemingly random saccades that occur when the subject is not required to perform any particular behavior task
Quick Phases	Quick phases of nystagmus generated during vestibular to optokinetic stimulation or as automatic resetting movements in the presence of spontaneous drift of the eye

Table 5.2: Classification of Saccades

5.2 Saccade

5.2.1 Biological Evidences of Saccadic Event

Saccades are rapid eye movements that shift the line of sight to a novel location of fixation. Saccades comprise different aspects from the involuntary shift of fixation to quick phases of vestibular and optokinetic nystagmus. In the animals that lack of spatial variance in retina, namely fovea (e.g. the rabbit does not have fovea) the shift of the line of sight is more or less associated with a change in head angle et al (1988). In the evolution stage of primates, the function of voluntary saccades is linked to the presence of fovea. On the contrary, afoveated animals produce quick phase of nystagmus during passive head movements. This can be explained by the need of slow phases of vestibular and optokinetic nystagmus does not drive the eye into an extreme orbital position. The classification of saccades spreads wide across different levels of behavior: from the quick phases of vestibular nystagmus during passive rotation in darkness to the high cognitive level of the voluntary saccade to a remembered spatial location of a visual target.

Saccades show tight relations between all their chief parameters: size, speed and duration. The relationship can be used to distinguish between correct saccades and abnormal saccades. Similar relationship can be found in other visual fixation behavior (eg.: microsaccades).

$$V_{peak} = V_{max} \cdot \left(1 - e^{\frac{-Amp}{C}}\right)$$

where C is constant.

It can be noted in different research that the duration of saccades are approximately linear with the amplitude. Power function is one possible interpretation that can be used to describe the relationship between amplitude and duration Garbutt et al. (2003b) Garbutt et al. (2003a) Lebedev et al. (1996) Yarbus (1967). The acceleration and its derivative jerk are very characteristic in saccade movements, therefore these can be used to identify saccades Wyatt (1998). With that the temporal shape of the velocity profile is another typical way to characterize the saccade. The asymmetry of this waveform namely *skewness* is recognizable in most of the saccades. This gives information on how peak velocity is reached earlier than half of saccadic period. At the end of a saccade, appositely directed, post-saccadic movement is occasionally measured. This occasional atypical saccade has been called ”dynamic overshoot” which is not be confused with *glissade*. Glissades are considered *post-saccadic drifts* due to the mismatch between the tonic and and phasic components that generated saccades. The last characteristic is post-saccadic drift usually present in fatigued subjects. Even though these are quite detailed aspects of the waveform, these are important to design a correct and human-like saccadic behavior. The final version however follows a simplified version of these trajectories in time domain.
The *Saccadic Reaction Time* is another feature of the saccadic movement that we considered as absolutely relevant in the design of saccadic movement. That is the interval between the target presentation and the beginning of saccadic movement (conventionally identified when the eye speed exceeds 30 degrees per second threshold). The importance of the measure is relevant when estimating the performance in visual processing, target selection, or generally cognitive tasks. In fact, different factors such as amount of information, the urgency to make a decision or perceptual/cognitive loads influence saccade latency Carpenter (2004) Reddi BA (2003). From this perspective, it can be shown that saccadic programming obeys Hick‘s law Lee et al. (2005):

$$T = b \cdot log_2\left(n + 1\right)$$

In a more generalized situation

$$T = b \cdot H$$

where H is the information-theoretic entropy of the decision, defined as

$$H = \sum_{i}^{n} p_i log_2\left(\frac{1}{p_i} + 1\right)$$

where p_i refers to the probability of the ith alternative yielding the information-theoretic entropy.

In other words the subject‘s saccadic reaction time reflects the time necessary to decide whether the target is present or absent (two alternatives of the same probability distribution) Carpenter (1991). We are particularly interested here in the motivational and attentive state of the subject that influences the latency in saccadic activation. Recent work Groner and Groner (1989) addressed this particular aspect. Whereas tradition research in vision tackles the question on how perceptive features (e.g.: luminance, contrast, size and complexity) alter the nature of the latency Miyashita et al. (1995). Despite these aspects are crucial in defining attentional shifts, they assume less importance in the present survey. Continuing in the list of the aspects resulting important in these survey the predictability of the target‘s motion has key role in the attentive system. In particular, recently scientific groups deeply exploited the question Ross and Ross (1987) Schmid and Ron (1986) Shelhamer and Joiner (2003), whereas a detailed report on the implementation of predictive behavior can be found in the following chapter 6.

Another source of interest for the group is how specific instructions given to the subject alter the saccadic reaction. In other words, how high cognitive processes alter the performance of the saccadic event. In recent research Isotalo et al. (2005) this is referenced as *cognitive set* but we reference it as top-down interaction. In next chapter 4 we present some details on the implementation of this phenomena. Distracting stimuli amplify the reaction time where focusing attention prepares in the interaction with the external word by reducing the reaction time. Some work exploited the difference between these two very common situations Crawford et al. (2005) Honda (2005) Walker et al. (1997).We considered those as source of inspiration for the design of the attentive system presented.

Generic saccades, conversely to express saccade (see next section), present *correction mechanisms*. In this type of saccedes, the saccadic shift must land on the target whether that is stationary or moving Eggert T (2005) Ron S (1989). This is not always true, normal individuals frequently show small degrees of *saccadic pulse dysmetria*. This inaccuracy of visually guided saccades comprises two different categories: *hypometria* or undershooting and *hypermetria* or overshooting. The first, is the mostly common in normal subjects, and it is only limited to relatively small angles, typically 10% of the saccade amplitude Becker and Fuchs (1969) Troost et al. (1974), even less for small saccades Kowler and Blaser (1995). The second is occasionally present in normal subjects. Generally speaking, fatigue and age may also influence saccade accuracy, in particular tired people tend to perform multiple close saccades rather than single saccade. Regarding differences in age, elderly people tend to have undershooting Abel et al. (1983) Huaman and Sharpe (1993) wheres infants tend to make multiple small saccade rather that one large saccade. Regardless the characteristic of the dysmetria, individuals make corrective saccades within 100ms to 300ms Becker and Fuchs (1969). The author designed similar mechanism for the attentive system. This mechanism relies on a feedback command either visual or motor that corrects the landing position. As one possible explanation, both the nonvisual and visual feedbacks influence the corrective saccades. Evidences that the feedback signal is extraretinal highlight how the feedback signal corrects the saccadic position even when the visual stimulus is removed or in darkness Zivotofsky et al. (1996). The efferent motor copy is likely to generate such non visual information. However, visual information is equally important in getting the eye on target. That is, when the visual stimuli is still present at the end of the saccade, evidences measured decrease in latency to the corrective saccade Deubel et al. (1982) Prablanc C (1978). This effect is what mainly inspired the design of the post saccadic correction. The correction may even start during the deceleration phase but we preferred to neglect this aspect.

5.2.2 Model of Saccades in the Humanoid Robot iCub

The implementation of the oculomotor saccade on the robot is halved in two contributions from different control levels. The low-level refines the trajectory of the saccadic waveform and saccadic trajectory. It guarantees biological correct velocity, acceleration and jerk profile and it is based on previous research Pattacini et al. (2010). The higher level of control is central aspect of this section because is where the author contributed the most. The higher level generates command for the lower control layer respecting the timing of typical saccadic event. It checks if response from the control level exceeds typical temporal constraints and triggers visual post-saccadic correction if needed. Above that, the higher level supervises the correct execution of the saccade.
The process compensate for errors and imprecision in the model of the robot. Without those systematic errors (derived from computation, encoder and vision imprecision) the saccade would be a perfect ballistic event that brings the line-of-sight of the drive eye on the target. However this is not possible with a real humanoid robot. We develop a mechanism that assures correctness for the saccade movement.

During the period of research carried on the humanoid robot iCub, different versions of the mechanism have been addressed. The first version works for slow saccades- the speed of the saccade depends from the low level controller and even firmware version. The idea is that during the initialization of the saccadic event a visual tracker, namely *matchTracker*, is initialized with the portion of retinal image surrounding the target. This generates a small template image that can be found in proximity of the original location in short time with reasonable computation load. The algorithm regulating the tracker is based on the pixel-wise correlation function between the gray-scale template and the gray-scale template-size portion of retinal image centered in the previous position of the target. The maximum correlation value gives the position of the template in the image. The *matchTracker* operates via a thread that guarantees that dedicated process carries on the active part of the class. This means that the *matchTracker* carries on in locating the closest representation of target in the neighborhood whatever happens in the rest of the system. Thus, through this simple mechanism we can always know where the template is located within the image. The rest of the mechanism is based on correction of the error between the position of the line-of-sight and target. After the ballistic saccade is executed, the line of sight lands somewhere near the target. Because of the saccadic event, the target position is changed but thanks to the *matchTracker* the position of the target can be easily retrieved. Defining $L = [L_x, L_y]$ the center of the fovea in cartesian space, $T = [T_x, T_y]$ the retinotopic position of the target, the error $E = [E_x, E_y]$ can be obtained from

$$E_x = T_x - L_x$$
$$E_y = T_y - L_y$$

Correcting the position of the line of sight with small monocular saccades we remove the error. The process is reiterated few times and we keep correcting the saccade until we obtain an error smaller that desired minimum error.

```
Data: target position $T = [T_x, T_y]$ on the original retinal image target position $T'[T'_x, T'_y]$
      on the current retinal image
Result: $[L_x, L_y] == [T'_x, T'_y]$
initialization;
matchTracker.init($T_x, T_y$);
saccade($T_x, T_y$);
matchTracker.getTargetPosition($T'_x, T'_y$);
error = sqrt($(T'_x - L_x)^2 + (T'_y - L_y)^2$);
while $error > error_threshold$ do
    saccade($T'_x - L_x, T'_y - L_y$);
    matchTracker.getTargetPosition($T'_x, T'_y$);
    error = sqrt($(T'_x - L_x)^2 + (T'_y - L_y)^2$);
end
```

Algorithm 1: algorithm for accurate slow-saccade with post-saccadic correction

However the procedure works only if the saccade is relatively slow. With fast saccades the camera records blurred frames that makes impossible a continuous tracking and the template can easily migrate out of the tracking area. In both the situations the *matchTracker* is not able to track the template on the retinal image. To solve this issue, we decided to implement the second version of the tracker, namely *periodicTracker*. The *periodicTracker* works in extended spatial domain and updates components only when required from the supervisor actor. That is, the *periodicTracker* revisits its template only when required and avoids any template update during the saccade. At the end of the fast saccade the *periodicTracker* finds the location of the template in a huge portion of the retinal image. This requires computation power and time but the computation component is performed only few times and it is not continuous. At the end of this process the retinotopic position of the template (still representing the target) is retrieved and the system compensates the error.

The algorithm assures correct saccade movement in any situation even with very fast saccades.

```
Data: target position $T = [T_x, T_y]$ on the original retinal image target position $T'[T'_x, T'_y]$
      on the current retinal image
Result: $[L_x, L_y] == [T'_x, T'_y]$
initialization;
periodicTracker.init($T_x, T_y$);
periodicTracker.computeCorrelation();
saccade($T_x, T_y$);
peridicTracker.computeCorrelation();
periodicTracker.getTargetPosition($T'_x, T'_y$);
saccade($T'_x, T'_y$);
error = sqrt($(T'_x - L_x)^2 + (T'_y - L_y)^2$);
```

Algorithm 2: algorithm for accurate fast-saccade with post-saccadic correction

Important point to note is the presence of two different methods in the periodic tracker: i) *init* to initialize the tracker and extract the template, ii) *computeCorrelation* to find the maximum in the topographic representation of the correlation function between image and template. In the *matchTracker* the two methods were executed continuously in the active part.

The process implemented on the humanoid robot iCub resembles the behavior of humans when performing saccades. They ideally conserve a reference point during their fast saccade and relates this point with the landing position of the saccade. As presented in the previous section the post-saccadic correction is process that refines the saccade performance under motor or visual feedback. Here we present an implementation of the biological model that uses visual feedback to correct saccades.

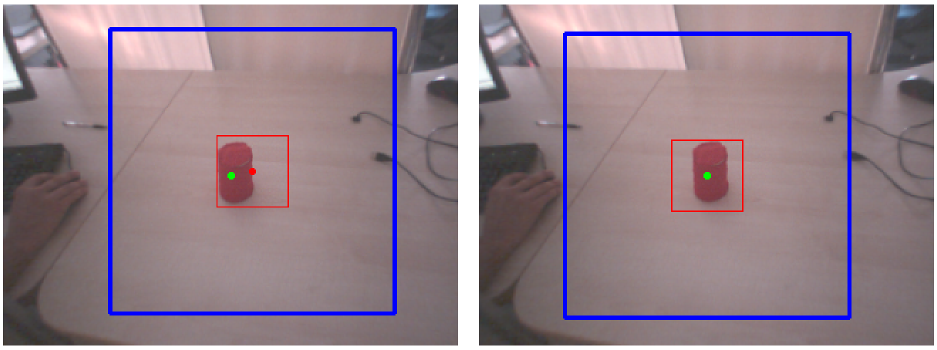
In addition we implemented a further visual correction which is the favorable choice in the improvement of correct result in saccadic event. This does not preclude an additional motor feedback when the stimulus is absent from the scene (because removed or because of darkness). The algorithm is based on visual feedback and calculates alternative landing positions around the expected landing target. For any position, a prediction of the saccadic image with fovea in the selected location is calculated. Any postsaccadic predicted image is compared with the real postsaccadic foveal image after the saccade is performed. The maximum correlation measure among the correlation measures of the different comparison wins the competition. The correction in the retinotopic correction is a function of the vector between the foveal position of the winning predictor and the theoretical target position.

Although similar to the previous postsaccadic correction this works on a different temporal domain since it is only performed once. This is a sort of ballistic postsaccadic correction that compares the landing position of the saccade with some not proximal extra points usually. Further more, this correction is entirely performed in logpolar space.

To recap, we presented how the high-level saccadic controller (currently working on the humanoid robot iCub) interacts with the lower level. In addition it is showed how mechanism for real-time error compensation in saccades are implemented in the overall framework and how postsaccadic mechanism are accurately ported in the model. These mechanisms profoundly interact each other providing a smooth result that gives feeling of predictable and human-like saccadic behavior.

(a) initial state of the system before saccade to visual target

(b) initialization of the episodic tracker



(c) ballistic saccade to the visual target with possible saccadic error

(d) error compensation thanks to episodic tracker localization

Figure 5.1: Example of saccadic event that exhibits post-saccadic compensation. As final result the visual target ends in the center of the fovea.

In the first snapshot of figure5.1 it is shown the visual target (salient red soft cilinder) whose location is far from the fovea (fovea location is depicted as a green circle). The saccade to the retinal location of the visual target triggers the *episodicTracker* which memorizes the portion of retina of the dimension of the red square around the target (see second frame in figure5.1. The blue square represents the search area of the image where the *episodicTracker* calculates the correlation measure. In the third snapshot we represent the result of a ballistic saccade in the retinal location. The fovea deploys in the surroundings of the visual target and the error is non-systematic and unpredictable. The *episodicTracker* activates again at the end of the saccade and search the memorized template in the blue area of the cartesian image. To note that the area of search is huge and this requires computation time but, thanks to the design of the mechanism, this occurs only once when needed. In the last snapshot we appreciate how the *episodicTracker* localized the memorized template in the scene, providing its location to the system which managed to compensate for the error. In fact the center of the red square (see red circle) indicating the template matching is precisely in the same location where the center of the fovea is deployed (green circle). The visual target is the fovea for the drive eye.

5.3 Express Saccade

There are contrasting opinions on whether express saccades actually occur in natural view condition or they are result of laboratory phenomenon Schiller et al. (2004). Generally speaking express saccades appear when a number of visual stimuli are presented in a short time interval Fischer and Ramsperger (1986);Fischer and Ramsperger (1984)). They are characterized by short reaction time and latencies in the order of 100ms Fischer and Weber (1997) Mayfrank et al. (1986). This a mechanism that evolves during development, in fact it is proved that infants activates express saccadic events more often than adults and it adapts quickly in adults with practice Fischer and Weber (1993) Schiller PH FAU - Haushofer and Haushofer. This suggests that express saccades relates to predictive path in the brain (Kowler; Pare and Munoz (1996); Carpenter (2001)) or in general they have attributed to separate neural system(Schiller et al. (1987)) . This predicted mechanism manifests in multiple trials. If the upcoming target matches the direction of the previous trials a certain degree of facilitation biases the express saccade Weber et al. (1995).

The oculomotor action of the *express saccade* is related to the concurrent planning of different saccades which facilitates the scanning strategies that favors speed instead of accuracy. In other words, there are situations where is more rewarding to plan a sequence of quick saccades with no correction than few accurate saccades that necessitate time for post-saccadic correction (Araujo et al. (2001); Coëffé and O'regan (1987); Hooge and Erkelens (1996); Hooge and Erkelens (1998); Hooge and Erkelens (1999); Wu et al. (2010)). We are particularly interested in two aspects of this mechanism: a) the incredible short reaction time, b) the landing point of express saccade in the *center-of-gravity* saccade Coren and Hoenig (1972) and Findlay(1982. The hypothesis is that, in some situations, multiple stimuli presented in a very short time horizon trigger the visual attention. The first point is the result of some pressure exerted on the attentive system. The reaction time must be comparable with the time interval with which the stimuli are presented. The second is a natural evolution forced by the fact that feedback is absent in reduced response time. Saccades become more accurate (less influenced by non-target stimuli surrounding the visual target) when more time is allowed (Cohen et al. (2007); Coëffé and O'regan (1987); Ottes et al. (1985)).

In the implementation of *express saccade* the active vision of the humanoid robot iCub both the previous points have been successfully tackled. Express saccade in this framework are completely different oculomotor events. They differ in the way they are triggered, in fact the time necessary to activate *express saccade* is reduced to the minimum. The express saccade neglects usual controls on the effectiveness of the action. In other words, we assume express saccade as ballistic ocular movement that always land in approximately accurate position. Further more, post-saccadic feedback is removed from express saccades. Because of the pressure on the attentive system, complex control strategy cannot be activated and therefore the landing position cannot be evaluated. The second point is an implementation based on evidences reported in recent laboratory test. When presented with multiple stimuli, that differ for their location on the retina, an express saccade is performed. The fixation point lands in a location which is equally distant from all the stimuli. We assume that is again due to a lack of allocated time for response. Complex mechanism for stimuli discrimination cannot be instantiated and thus only simple mechanisms can take place. The simplest active control is obtained by calculating the mean point in between the stimuli locations and redirecting the fixation point to this mean location. This is what we designed for express saccade and after few test sessions it replicates fairly tightly the effects previously presented. Overall, extreme caution is required, the ability to generate express saccades might be attributed to the visual attentive mechanism that inhibits fixation mechanism.

5.4 Vergence

5.4.1 Neurobiology Characteristic of the Vergence Control in Humans

Until now, eye movement directed by one of the two eyes have been presented. However when the world is perceived through stereo vision we need to implement binocular eye control. That is, the binocular control commands the motor path of both the eyes in order to generate stereo synergies across eyes. In nature, animals can control eyes separately (e.g.: chameleon) but in primates when the spatial variance of the receptive field is not constant (foveated vision) the eyes are binocularly controlled. The reason is that when both the eyes concur in defining the perceived world at different depths. Definition of depths is crucial aspect for the correct estimation of the distances. Both stereopsis and bifoveal fixation of objects require precise alignment of visual axes. Without a correct alignment of the axes, it produces the double vision and the inability to estimate the distance. Stereopsis is the phenomenon such as the brain perceives three-dimensional (3D) representation of the objects. This effect is the direct result of different eye views of the same object. Eyes in fact are misplaced by approximately 6.8 cm. When the two images of the subject follow on corresponding retinal points, it can be perceived as one, which allows for subjective sense of visual direction and sense of single cyclopic eye. When the two images follow on non-corresponding retinal regions, we perceived two separated directions and we experience double vision. The disparity map is always been considered as the chief drive for vergence refinement. Disparity between the location of the images produces fusional vergence movements. Vergence movement are voluntary controlled movement of which we are not aware of. Another effect namely *retinal blur* influences vergence control but, despite its importance, we neglect its effect in this survey. In the robot, *retinal blur* for vergence control is not implemented. Recent researches Howard and Rogers (2002) Carpenter (1991) in the field bring clear view that fusional vergence is the chief contributor of ocular align-

ment. The role of the blur is relegated to the mere fine-tuning of the accommodation.
For the realization of active vision on the humanoid robot iCub, we are mainly interested in *horizontal vergence* rather than *vertical vergence* or *cyclovergence*. The horizontal vergence presents either *latency* (measure of the response time) based on prior knowledge or completely reactive control. When the presented stimulus is completely unpredictable, we assume complete reactive vergence control. In this case, the vergence has latency of 160ms in the attempt of jumping from one depth to the other. The latency has two contributions: a) the pure perceptive contribution , and b) the motor latency. The motor latency results to be more relevant because the performance changes whether the movement is divergent, convergent and from the starting angle Alvarez et al. (2005). Vergence movements in conjunction to saccade show latency distribution similar to those of saccedes Coubard et al. (2004). Vergence movements in conjunction to smooth pursuit show decreasing latency when the object movement is predictable Erkelens et al. (1989).

5.4.2 Implementation of Vergence Control on the Humanoid Robot iCub

Concerning the precision of vergence mechanism, the feedback error can be identified in residual disparity. The difference between correspondent areas on the retina determines residual disparity. Similar mechanism has been implemented on the humanoid robot iCub. The algorithm resembles successful procedure implemented in Manzotti et al. (2001). The algorithm controls the vergence is robots with stereoscopic vision. The methods extracts global disparity measure of correlation for vergence control. It does not require region segmentation but rather a computation in log-polar plane of the best vergence angle that maximize the correlation measure between left and right retinal image. The advantages of this design are : a) global, in the sense that the overall image contributes in the measure, b) computationally inexpensive, c) robust and d) independent to either the feature of the environment (e.g. luminance) or the feature of the objects in the scene. To further analysis, in foveated vision the measure of stereoscopic correctness is deeply influenced by the correlation between the left and right retinal image. In other words, if the object at center of attentional focus is correctly verged, stereo images should be very similar. In this case, the images are said to *binocularly fused*. The global measure of binocular fusion can be computed using the *normalized correlation technique* Nielsen and Sandini (1994):

$$C\left(I_l, I_r\right) = 1 - \frac{\sum_{\eta,\xi}\left(I_r\left(\eta,\xi\right)-\mu_r\right)\cdot\left(I_l\left(\eta,\xi\right)-\mu_l\right)}{\sqrt{\sum_{\eta,\xi}\left(I_r\left(\eta,\xi\right)-\mu_r\right)^2\cdot\left(I_l\left(\eta,\xi\right)-\mu_l\right)^2}}$$

where I_r and I_l are respectively the right and left image, and μ_r and μ_l represent their mean values. The $C\left(I_l, I_r\right)$ is almost invariant to changes of illumination and it is normalized. Given these properties, *normalized correlation measure* can be employed in a standard proportional control

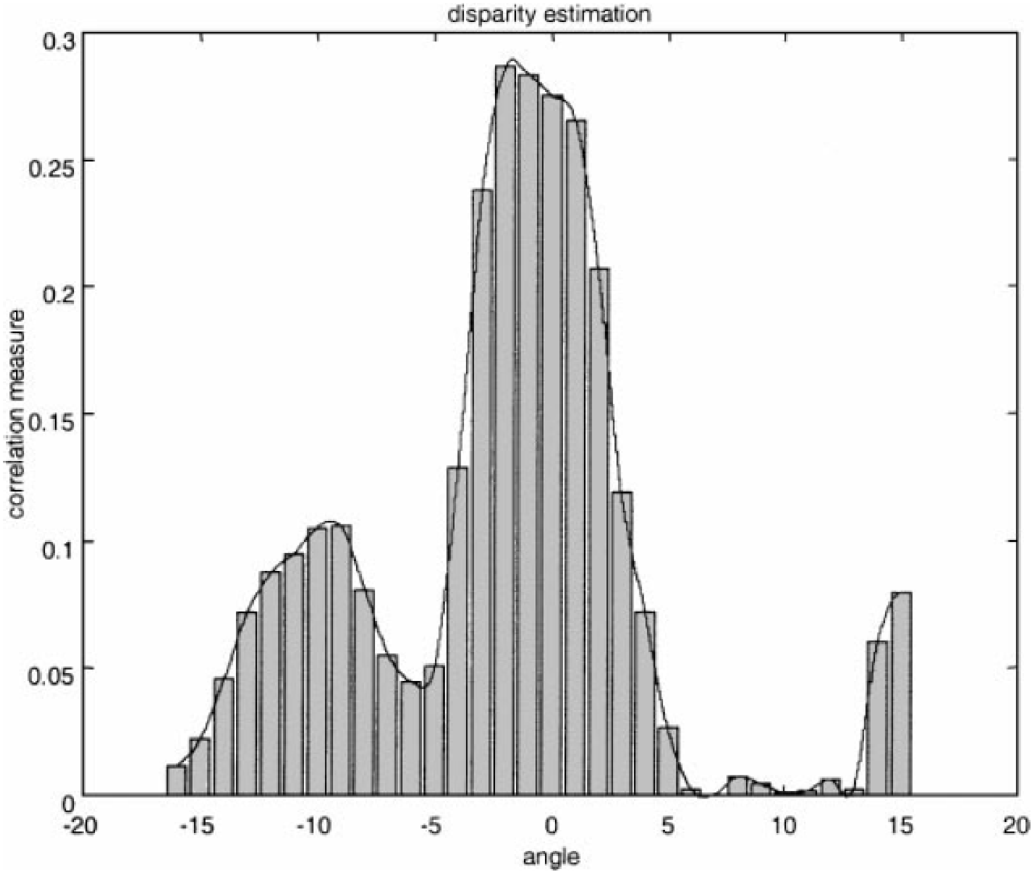


Figure 5.2: Example of the histogram of shifts that indicates of the maximum shift that compensate for binocular disparity

law for vergence refinement:

$$\dot{\theta} = -K \cdot \dot{C}$$

This approach has several issues, whose solution is reported in Nielsen and Sandini (1994). Here it is enough to say that the very same approach is successfully used for the control of the vergence angle in the humanoid robot iCub. The two images are shifted one against the other along the horizontal axes of the Cartesian space. The correlation function is then computed for every horizontal shifts giving rise to a curve representing the correlation function in the space of shifts. Given the geometry of the vision system, the shift space is mapped into angles, obtaining the curve of the correlation in the angle space: Some additional constraints associated with the joint limits of the iCub‘s head-eyes movements must be introduced. The goal of the vergence system is to minimize the difference between the two images and then to maximize the correlation measure.

At the level of higher control mechanism of control and refinement have been implemented. Bad performance have been measured in Cornell et al. (2003) Malinov et al. (2000). Despite subjects reported no diplopia, the direction of the fovea movement do no move toward the target. Perhaps, this is due to multiple disparity in a rich visual environment. Identical effect on the robot behavior gives insight on the similitude between the human model and the implemented model. In the phase-plane analysis of dynamic control of vergence identifies a first open-loop component and a successive slower phase. The second mechanism sustains vergence at the level necessary for fusion Horng et al. (1998) Kawata and Ohtsuka (2001). Another analogy between the horizontal vergence and the implementation on the robot is in the occasional presence of secondary vergence refinements. In these situations the second vergence is more likely to be a corrective vergence in conjunctive system Alvarez et al. (1998) and the visual feedback drives the correction. Vergence control in humanoid robot iCub constantly checks the disparity of the scene and if the correct angle differs from the current angle more than a certain extent the action vergence refinement triggers. This happens even if the previous vergence action led to vergence accomplishment. Such behavior evidently resembles a vergence correction.

5.5 Microsaccade

5.5.1 Biological Evidences of Microsaccade Oculomotor Movements

To see stationary objects the projection of the object must be held steadily upon the fovea. However if the projection on the fovea of the visual target has absolutely no relative movement, vision fades Ditchburn and Ginsborg (1952) Riggs and Ratliff (1952) Steinman et al. (1973) Yarbus (1967). There may list to related mechanisms that cause visual fading : a) the visual system habituates to persistent stimulation, b) photoreceptors get fatigued by continuous stimuli. The fatigue caused by persistent stimuli can be reduced three main active motion components: tremor, microsaccades, drift. Tremor has a frequency of up to 150Hz and amplitude of approximately than 0,01 degree and it is debatable their positive contribution to vision Carpenter (1991) Lewis et al. (2001) Spauschus et al. (1999) Steinman et al. (1973). Drift has one order bigger amplitude (0.1degree). Convergences report that the cause can be related to instability of the gaze control during fixation Epelboim and Kowler (1993) Murphy et al. (1984). Drifts are likely to happen in the wake of a saccade. On the other hand microsaccade have amplitude of one third of degree, have mainly horizontal direction. Even though it has been reported that visual attention can bias microsaccades toward any direction Engbert and Kliegl (2004) Engbert and Kliegl (2003). They can unconsciously be disabled. For task that demand absolute precision (such as gun aiming, threading a needs), microsaccades degrade the task performance and thus they are absent in trained people performing such tasks. It is debatable the real evolution‘s reason that produces microsaccades. It is thought that small saccades may help during fixation, increase the LGN and V1 regions in relation to the current stimulus Martinez-Conde et al. (2002) Martinez-Conde et al. (2000), and mitigate habituation Martinez-Conde et al. (2006).

5.5.2 Model of Microsaccade Movements for the humanoid robot iCub

In the implementation of these early oculomotor mechanisms, we opted for a contribution which is surely independent from the rest of the system. However there are evidences in favor of fixation system which is independent from the smooth pursuit. The author takes inspiration from most of these studies that focus on the differences between the smooth pursuit movement and the motor behavior of the eye when it comes to a halt. Since sufficient differences between the motor features of the two mechanisms have been found Huebner et al. (1992) Krauzlis and Lisberger (1994) Krauzlis and Miles (1996) Leigh et al. (1994) Luebke and Robinson (1988), the author fairly assumes that the two control paths may be separated. The research group can provide similar analysis for dynamic properties of the two control paths reaching similar conclusion. We opted for a single control that puts together motor contributes of both tremor and microsaccades. We consider drift as effect related to motor inefficiency of saccades and then we prefer to address this behavior in the saccade paradigm. One particular complicated aspect of this control is the frequency of the control. In relation to this, the small amplitude can make the implementation not trivial. In other words exerting multiple small control commands in a very short time interval can require accurate designed. In the eye control, we opted for superimposing contributes of two different effects. The first is completely random control that acts at every discrete time interval on the two main joint angles: eye version and eye pan. The angle of the control is slightly bigger than measured angle (approx. 1/10 of degree). The second control mechanisms emulates the microsaccades and it is active for multiple of the time interval of the previous control. It has a mean amplitude which is approximately 1 degree. The mean amplitude angle of the two controls are evidently bigger than the angle measured in experiments on humans. This is due to mechanical imprecision rather than motor control imprecision. In fact the quality of the control has been already enhanced with the design of the iCub head second version. It is likely that such mechanical inexactness could be further improved in the next robot design.

5.6 Smooth Pursuit

5.6.1 Neurobiology of Smooth Pursuit

Smooth pursuit movements allow the line of sight to remain on a moving object. This is possible thanks to continuous eye movements that keep the line of regard congruent with the line of interest Leigh and Zee (2006). In other words, the attentive system must be active and must keep focus of attention on the object. The velocity profile of the smooth pursuit eye matches the velocity of the target on the retina. The effect is that if the object is in fovea and the visual target maintains its position on the retina, the target will remain as perceived by the retina. To estimate the speed of a visual target, the *optic flow* provides important information on the relative speed of any position in the environment with respect to the fovea. Smooth pursuit movements must be generated in response to local optic flow in fovea. We use this mechanism to generate correct smooth pursuit movements starting from the optical flow. The ability of the smooth pursuit implies the compensation of retinal image motion, with two distinct effects: a) a correct localization in space of the object in the environment and b) filtering out of attended objects selected by the attentive system. Addressing the smooth pursuit from the point of view of impairments, it has been reported that patients with posterior cortex lesions have problems in processing image motion caused by eye movement Haarmeier et al. (1997). The effect is that the patient tends to compensate with multiple and frequent saccades. Nonetheless, impaired vision subjects can experience the second effect and have difficulties in perceiving moving targets Haarmeier et al. (1997).

Another aspect that results interesting for this review of what has been directly ported on the robot is *prediction*. Prediction of the visual target motion deeply effects the smooth pursuit. Generally, when the target starts to move, a *predictive acceleration of the eye* generates. In this phase the acceleration has ballistic effect, in other words there is no feedback. If the light stimulus disappears right when the eye movements starts the eye keeps accelerating for a while Becker and Fuchs (1985). It author‘s opinion a time window for velocity estimation is critical component of this eye movement. Clear example is that, after the oculomotor action stars, any other stimulus deceleration causes an overshoot in velocity of the line of sight. Aware of the fact that the mechanism is not only triggered by vision -because the response time of the visual processing is over 70ms- we decided to simplify the mechanism. Evidences in humans Robinson et al. (1986) Stork et al. (2002), Boman and Hotson (1992) Jarrett and Barnes (2003), and in monkeys Churchland et al. (2003) confirm that *anticipatory drifts* and *early accelerations* are common effects of a single phenomenon: a sort of memory of previous tracking experience and based only on perceived motion Boman and Hotson (1988) Boman and Hotson (1989) Wells and Barnes (1999). It is in author‘s opinion that such a memory can only mature in the education period of the subject. The learning of the complete ontology of all the possible target movements is complex. Thus we focus on the test of the predictive mechanism more that the learning algorithm. The collection of model is provided as a bank of predictors and a detailed description of it is reported in chapter 6.

Differently here we continue with an analysis of the mechanism for predictive and adaptive properties of the smooth pursuit. It has been demonstrated that different wave forms such sine waves can be easily tracked Dallos and Jones (1963) Dodge (1903) Michael and Jones (1966). On the contrary some complex and unusual waveform require persistent training. This can only be explained by storing memories of tracking and successively relating them to the perception. Generally speaking, the predictive mechanism for smooth pursuit is independent to predictive mechanism of the saccadic tracking. This is demonstrated by larger number of trials needed to master predictive saccade with respect to smooth pursuit. During the on-set period of the smooth pursuit(approx. 100ms Carl and Gellman (1987)) the smooth pursuit control selects one model. From the computational point of view this can be achieved with two different actions. First, we can enlarge the number of predictors and parallelize their processing of the measurement of the visual target during the on-set period. Second, a priori acceleration of the eye can reduce the catch-up phase afterward.

In Krauzlis and Lisberger (1994) Tychsen and Lisberger (1986), the scientific groups measured in the first 40ms acceleration which is unrelated with either target speed or target features. Others Carl and Gellman (1987) Tychsen and Lisberger (1986) measured such acceleration in up to 100degree/sec. Concerning the sustained tracking the only aspect interesting for this survey is the pursuit gain and phase. Those two measures of the tracking do not deteriorate until the target velocity exceeds about 100degree/sec. The adaptive properties of the smooth pursuit are more appealing in the robot development. It seems that a certain amount of visual feedback is sufficient to correct sustained tracking. For the adjusting system it is not necessary to plastically reconfigure the characteristic of the tracking. The cost of system reconfiguration and the long on-set period might discourage the complete reconfiguration of the system. Eventually catch-up saccades can be triggered to compensate for a sudden failing in the tracking. Evidences of such intervention are evident when the target speed is altered. Color is critical aspect in visual correction of the smooth pursuit Takagi et al. (2000), therefore in the implementation of the sustained control of the smooth pursuit, a color-based tracker activated a posteriori can be valid result. A detailed analysis of the result on the smooth pursuit system based on prediction can be found in chapter6.

5.6.2 Implementation of Smooth Pursuit

Concerning the implementation of a similar mechanism on the humanoid robot iCub, we design a dedicated motor block that receives as input the velocity profile of the point of interest in the retinotopic space. The velocity profile of a particular region of the retina can be easily extracted by exploiting optical flow. In perception, optical flow projects on the retina the velocity of elements on the scene with respect to the eye. Selecting one interesting object in the scene, the object remains in the fovea during smooth pursuit. In other words, once the object is in the fovea, if the fovea moves with the same velocity profile extracted by the optical flow of the object. We experience correct tracking of the object by using such policy. In the framework of the active vision designed for the humanoid robot iCub, we allowed time for either velocity estimation or velocity prediction. This can explain the time interval without actual eye movement in any measured smooth pursuit profile in humans. We do not go into details on techniques on velocity extraction because we already speculate on them in chapter6. However we rather assume that, at the end of this step, the velocity profile is available to the motor execution of smooth pursuit. At this point, smooth pursuit action is only in charge of moving the fovea of the drive eye with the very same velocity profile for a defined time interval.

5.7 Outline

In this section we presented four implementation of oculormotor actions: saccade, microsaccade, express saccade, vergence, smooth pursuit. The study of the model of any of this behavior is accurately shaped on biological evidences of similar behavior in humans. We carried on an accurate analysis of the biological mechanism at the basis of every action partially reported in this chapter. Reporting these characteristics we want to picture the features of every oculumotor action that inspired any decision on the related ocular model. Further more, we not only limited the work on the introduction of biological plausible mechanisms but we also fit those on the humanoid robot iCub, taking always in consideration the principal characteristic of the robot. In fact, the contribution of those characteristics, if not accurately analyzed, can affect the biological plausibility of the action. Despite this additional work in the refinement of the action, we succeed in the creation of actions that really reach desired goal in optimal fashion. This is confirmed by extraordinary reality in the appearance of the result. Any oculormotor action shows similarity to the real human actions, and this favorites the interpretation of the action. In human-robot collaboration, it is fundamental to correctly interpret the counterpart‘s intention and goal. This can only be achieved if the action generation mechanism of both the parts share similar characteristics. Without these common basis across actors the collaboration might result hard or even impossible.

In the next section, we present how these similarities between common mechanisms can be used in order to predict others‘ goals. Prediction is another important aspect that shapes the collaboration between partners but this can only be successful if they share similar active processes too.

THE ROLE OF PREDICTION IN THE ACTIVE ATTENTION SYSTEM

6

"Engage people with what they expect; it is what they are able to discern and concerns their projections. It settles them into predictable patterns of response, occupying their minds while you wait for the extraordinary moment that which they cannot anticipate."
Sun Tzu, The Art of War.

6.1 Introduction

We live in a complex world , where ambiguous stimuli and noise cause uncertainty in what we perceive and how we shall act. For any agent living in such a challenging world another aspect results critical: the energy consumption. Acting on the environment by the mean of multiple actions in the attempt of finding the correct answer to a particular scenario is profoundly inefficient. The selection of the correct answer to the current situation in the world must come from a-priori knowledge. In the animal kingdom, some pre-programmed or innate behaviors regulate this phenomena. In this case, the phylogenesis of the animal comprises Darwin‘s theory of natural selection Darwin et al. (1958), adaptation Haldane (1957), genetics diversity Dobzhansky and Dobzhansky (1937).

In primates, innate patterns also exist as reported in Tinbergen (1951), however, they cannot be the only source of behavioral control in such complex subjects. Prediction mechanisms are more dynamic mechanisms that better fit environment situations where the subject is immersed. The success of those mechanisms is associated to the high degree of fast adaptability, referred to personal experience. Personal understanding of the world is again a-prior knowledge even though the ontogenetic processes do shape knowledge in this situation Mayr (1974). The problem of uncertainty and optimality is addressed by minimization of the discrepancy between inference and actual experience Friston (2005). In other words the efferent copy generated by forward models is the representation of internal representations. This generates an expected sensory outcome which checked up against the actual sensory feedback. Predictive Brain is often the terminology associated with this process in the society of cognition studies. Many researches in the community of cognitive science converge on the idea that inferential processes can be found in apparently different cognitive mechanisms : motor control Miall and Wolpert (1996), perceptual inference Friston and Kiebel (2009), reward-based associative learning Schultz and Dickinson (2000).

In other words, the ability to anticipate the goals of our actions is paramount for a successful interaction with the environment von Hofsten (2004). In fact, humans anticipate the goal of their own reaching and displacement actions as proved in Johansson et al. (2001). This is not exclusive to action performed but it is also valid for the observation of other‘s actions. Major driving force in cognitive evolution is the complexity of social environment in which primates are engaged. Since the proved wide range of activities in which prediction plays a big role, it follows that internal speculation can shape processes in social cognition and social inter-action. Evidences on shared neural representation of own experience and other‘s experience Decety and Sommerville (2003) give insights on the social inter-action between individuals. Similar neural activity has been observed in subject equally when they perform and observe the same action Gallese et al. (1996).

Mirror Neurons were first discovered in late 90‘s Rizzolatti et al. (2001) Pellegrino et al. (1992) Gallese et al. (1996) Rizzolatti and Craighero (2004). The core idea is that when an individual acts, the observer activates the same neural pattern. As the individual knows the motor consequences of his/her action, similarly, thanks to the mirror activated neural pattern, the observer knows the motor consequence of the observed actor‘s action. Because of the similarity between the evoked motor representation and the neural activity in premotor cortex during action execution, the observer ”understands” the other‘s action Rizzolatti et al. (2001). In recording performed in the Umilt et al. (2001) study of monkeys, it results evident that the understanding does not rely only on the visual description of the scene but rather on the motor representation of the action. Such neural activation is shared between observer and actor and it is related to some features of the scene such as objects involved, and environment contextualization. Because of these and other evidences reported in Fadiga et al. (2006), the research group concludes that mirror neurons constitute more an ”active interpreter” than ”passive perceiver”. Because of the additional information provided by the mirror neural pattern evoked, uncertainties and gaps in the performed action can be compensated. Completeness in motor knowledge on other individual‘s action gives possibility to predict the action outcome.

Examples of the mechanism are presented in Kilner et al. (2004) where the group shows that motor readiness and motor preparation are detectable in action observation. Similarly, in Borroni (2001) motor facilitation triggers long before the observer visually sees the movement. In another work

Craighero et al. (2008), in order to detect the instant in which the finger touches the object, the subject uses internal model selected through mirror neuron activation.

Flanagan and Johansson (2003) and Falck-Ytter et al. (2006b) suggest that action understanding and goal anticipation is defined by a well-defined connection between the observed action and motor representation of that action. The activation of the specialized system for action perception generates pro-active goal directed eye-movement. In Falck-Ytter et al. (2006b) the authors proved that such guide of the eye-movement is present in 12-month-old but not in 6 month-old infants. In adults, proactive goal-directed eye movements are fundamental for planning and control Land and Furneaux (1997) Johansson et al. (2001). Such eye-movements are active also when adult subjects observe other people‘s actions Flanagan and Johansson (2003) , meaning that the same collection of neurons that fire when we see people performing an action guide the eye movement. The path of the eye movement results identical to trajectory of autonomous control. The same collection of neurons fire as well even when someone else performs the same action. Recently, a strong claim has been presented on the role of the *mirror neuron system* in human ontogeny. According to the *mirror neuron system* hypothesis of social cognition, the *mirror neuron system* constitutes the basis for important social competences such as imitation, ”theory of mind” and communication by means of gesture and language Gallese and Goldman (1998), Williams et al. (2001), Iacoboni (2009), Rizzolatti and Arbib (1998), Kohler et al. (2002). Key point in this analysis is that pro-active goal directed eye movements reflect the presence of strict mapping of the observed action to the motor-repertoire. Therefore the development of such mechanism is subordinate to the motor/action development. Only group of 12 month-old infants in Falck-Ytter et al. (2006b) manifest this behavior which is consistent with Connolly (1970).

Further, in adults, the mirror neuron system activates when the interaction of the human agent is visible and not when the object moves alone. Thanks to the *teleological stance theory* Gergely and Csibra (2003) we can think that seeing human partner is not enough to trigger this mechanism in 12 month old infants. On the contrary in Falck-Ytter et al. (2006b) no evidence has been found on these speculations. Thus 12-month-old infants incontrovertibly mastered pro-active goal-directed eye movement in the same form of adults. On the contrary, 6 month-old babies do not manifest this skill even though this cannot be ascribed to the inability to predict. In fact 6-month-old babies predict the reappearance of temporarily occluded objects.

Another recent empirical study Gredebck et al. (2010) suggests that both direct matching between observation and own motor representation and teleological processing are present in the early infancy. They suggest that goal anticipation might be mediated by the direct matching process whereas retrospective evaluation of perceived event are mediated by teleological processes.

This idea is confirmed in a recent research Gredebäck and Melinder (2010), where the authors show strong connection between the manual ability of predict and anticipate the objective of other‘s behaviors. To the toddler, the authors give the opportunity to solve a task and observe someone else in the same situation. They demonstrated a direct relationship between the goal anticipation and manual refinement in the same task. The very same finding do not support teleological reasoning in the interpretation of goal via attribution of rationality to human actions Eshuis et al. (2009). In addition, as conclusion of this experiment, the authors speculate that the connection between observed action and motor representation is function of the mirror neural system. In fact, other studies Calvo-Merino et al. (2005) Järveläinen et al. (2004) pointed out that the level of activation in mirror areas in young infants has a strict relation to the efficiency and quality of the performance of the same action by the observer.

6.2 Implementation of predictors in Active Attention System : a bank of specialized predictors

In predictive Brain, a clear distinction between *prediction*, *inference* and *simulation* must be clarified. Mainly the three typologies can be distinguished by their temporal domain. Inference refers to short-term processes that are mostly situated in current behavior. On the contrary, the prediction is generally associated with long-term processes. Finally, *simulation* groups together processes that construct internal representation of imagined events Gilbert and Wilson (2007) based on episodic memory Williams et al. (1996).
In Social Brain, social interaction and social functioning trigger social relevant cognitive process (e.g.: social perception, understanding other‘s actions, etc). Recently, in the community, the idea that shared neural representation is at the base of understanding of other‘s action is growing in importance. This allows us to make prediction about consequence and outcome of observed action. We can now define action as the movement finalized to the goal. Anticipation is associated to both movement prediction and goal interpretation. From the biological point of view, the *superior temporal sulcus* STS is active when these two aspects of the actions are exploited. The perception of biological motion and inferring the intentions or goal are the tasks where STS is most active Perrett and Emery (1994), Allison et al. (2000) Jellema et al. (2000). The STS is regulated by mirroring network Molenberghs et al. (2010). Recently, aspects of how the social perception is influenced by how we perceive the counterpart have been tackled. ”Uncanny valley” is disconcerting effect in which androids are perceived human-like the more their appearance matches the human appearance. Nevertheless, surprising enough, the effect inverts when the androids are too human-like. Evidences on the difference in perceiving human and robots can be found in recent publications Saygin et al. (2011). This study found that the activity in STS was distinctive for mismatch between appearance and motion. This was proposed to reflect prediction error activity and expectancy violation. Interesting enough, social brain can interact at early stage of processing before awareness. This role of social cognition has been studied in relation with discovery of mirror neurons in monkey premotor cortex during both action execution and action observation Gallese et al. (1996).

6.3 Model of Prediction in Human-Robot Interaction

In this section, we present the methodology for predicting behaviors in Active Attention System. The methodology resembles the functionality presented in the previous paragraph. The implemented mechanism is based on the representation of the knowledge about natural movement that humans exhibit. Humans have implicit knowledge about intrinsic characteristic of the movement when biological counterpart is involved. Such speculation is present in 6-months infants, however younger infants seems to lack this predictive behavior. The development of motor skills seems to trigger perceptual pattern recognition that later evolves in prediction. It is likely that prediction is generated when children personally perform actions that imply the creation of efferent copies. Similarly, observation of other‘s action results in activation of neural regions that match those that are activated by the efferent action copy (mirror neurons). Using this mirroring effect, infants are able to obtain salient features of the action and relevant characteristics of both the movement and the goal (the action).

This mechanism is tested in a scenario where the subject is the Humanoid Robot iCub. The humanoid robot iCub perceives the counterpart when she/he performs motor actions reproducing a velocity profile which is biological (minimum jerk movement theory). Even though direct relation between performed action and perceived action is not explicitly coded, the knowledge about similar movements is transferred on the motor pattern recognition. A bank of different minimum-jerk trajectory predictors enriches the motor pattern recognition mechanism within the iCub software framework. Every single element of the bank, namely ”expert”, is asynchronous and independent active component. This structure allows for independent and concurrent analysis of the perceptual input and favorites the fast and reliable comparison of the output of every expert. The experts compete in interpreting the perceptual input. Only one of them wins the competition and it regulates entirely the output of the predictive system. The winner-take-all expert is the component whose prediction is more likely to match the real movement.

To reproduce accurately and efficiently this behavior we design a queue of *evalThread* components. The *evalThread* class, designed specifically for this purpose, comprises an active component (thread) that triggers an independent concurrent process. That is, in a collection of *evalThread*s, any thread operates autonomously and produces the best result. Further more, to any *evalThread* is associated a model of the expected behavior. This enables reliable prediction of the trajectory, correct velocity and acceleration profile, and eventually the punctual estimation of final position of the stimulus, according to the expected behavior. To any predictor is associated a Kalman Filter Welch and Bishop (1995) to filter the measure of the input trajectory. The data acquired during the first time interval defines the $z(k)$ measure vector. In most of the main research in the field the information about the position of the stimulus in the space is reduced in dimensionality. Similarly we opted to reduce the dimensionality of the stimulus from the 3D location to location in the 2D plane. The position is projected on the working plane and then relevant features are extracted from the projected trajectory. We project the position in space of the center of mass of the visual target

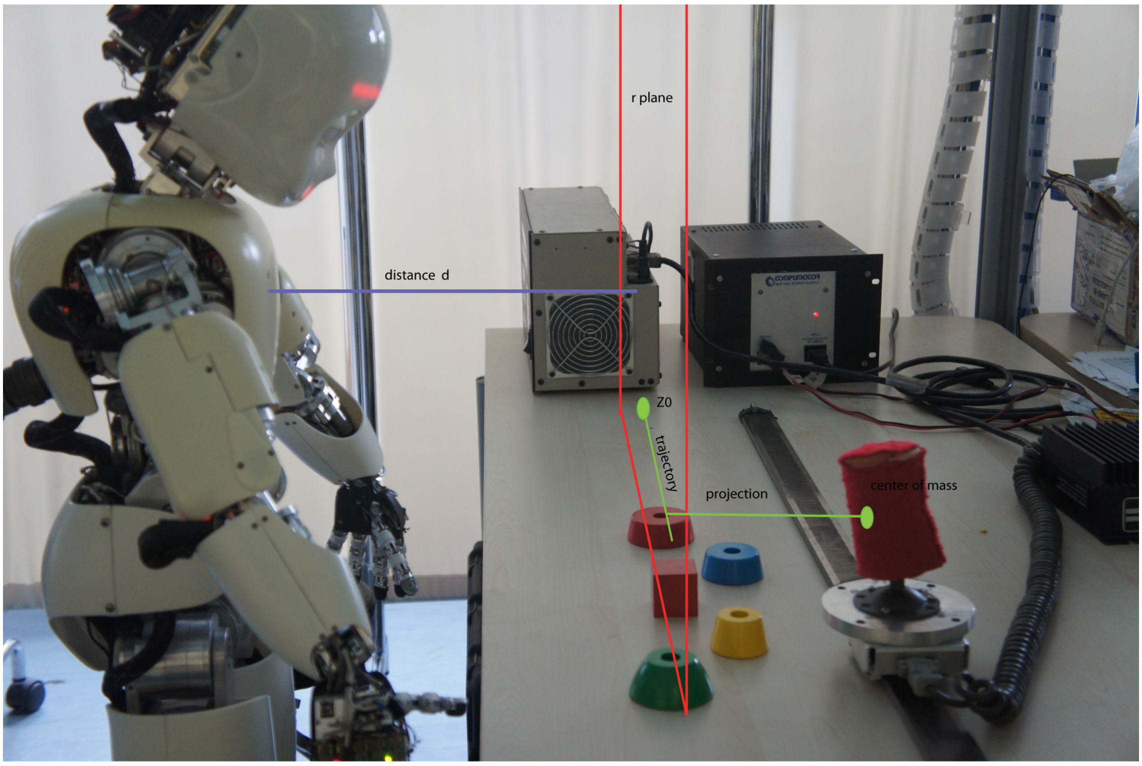


Figure 6.1: Representation of the plane where the trajectory is projected

on the plane r. The plane r is parallel to the coronal plane and intersects the working area at a distance $d = 50cm$. As further reduction of complexity, on the r plane the trajectory of the movement is represented as a linear trajectory. The main characteristics of the linear trajectory are the initial position $z0$ and the θ angle. This is the angle that assumes the linear projection of the trajectory with respect to the robot frame of reference and is supposed to remain constant in the trajectory. The measure vector $z(k)$ is the distance of the position of the visual target from the $z0$ location. The Kalman Filter tries to estimate the state $x(k)$ of a discrete-time LTI system. The quality of the estimation selects a subset of models that approximately match the visual target movement.

Within the subset, the model that provides best prediction is considered the model that best replicates the visual target movement. We assume that, in this situation, the intrinsic characteristics of the model corresponds to the characteristic of the original trajectory. The predictors are based on a set of continuous time LTI models which comprise:

1. Constant Velocity Model (cvM) - modeling stimuli that moves at constant velocity. Typically this represents object that have already started to move out of the field of view and will not decelerate with it.

$$A = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, C = \begin{bmatrix} 0 & 1 \end{bmatrix}, D = 0$$

2. Constant Acceleration Model (caM) - modeling stimuli that accelerate/decelerate. Most of the time this model estimates features of the movement caused by gravity acceleration/deceleration. An object dropped from height will accelerate with the constant acceleration of $g = 9.8m/s^2$. The position and velocity of the object can be easily estimated. Moreover in the situation when the system measures a deceleration (for example when a ball is thrown in the air) the additional measure of the position where the acceleration is null can be calculated. This can help in predicting where to look and where to act when dealing with object affected by gravity.

$$A = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, C = \begin{bmatrix} 0 & 1 \end{bmatrix}, D = 0$$

3. Minimum Jerk Model (mjM) - modeling the class of biological movements. The model refers to the simplified version of control proposed by Pattacini et al. (2010). The LTI system approximate the ideal minimum jerk model having a particularly faster onset and a slower convergence to the steady state. Nevertheless, it provides a very good compromise between smoothness and complexity of the implementation. With this class of model we intend to address the complete category of biological movement.

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ \frac{a}{T^3} & \frac{b}{T^2} & \frac{c}{T} \end{bmatrix}, B = \begin{bmatrix} 0 \\ 1 \\ -\frac{a}{T^3} \end{bmatrix}, C = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}, D = 0$$

where $a = -150.7658689$, $b = -84.9812819$ and $c = -15.9669610$

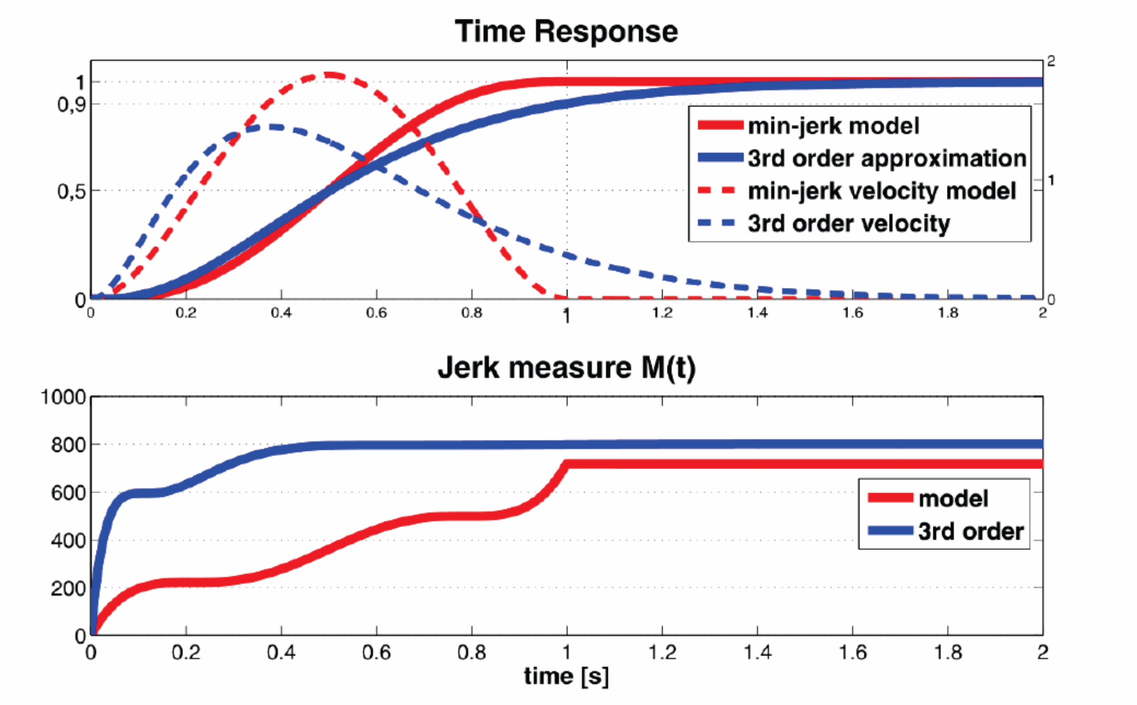
for a discrete-time filter derived from any of the caM, cvM, mjM and describes as

$$\hat{x}(k+1) = A \cdot \hat{x}(k) + B \cdot u(k)$$
$$y(k) = C \cdot \hat{x}(k) + D \cdot u(k)$$

A Kalman Filter Welch and Bishop (1995) is employed for each model. To incorporate the LTI model in the Kalman filter, we discretize the continuous-time LTI models. The author design a specific library that allows the user to create the specific predictive models that belong to one of the following categories: a) constant velocity model, b) constant acceleration model or c)minimum-jerk model. The library provides the generic class for the predictor: *attention::genPredModel* inherited from the *virtual class predModel*. Other classes as specific implementation of the three categories are respectively derived by inheritance: a) *linVelModel* , b) *linAccModel*, and c)*minJerkModel*.

The state matrices of the *linVelModel* are:

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 0.01 \\ 1 \end{bmatrix}, H = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$



The state matrices of the *linAccModel* are:

$$A = \begin{bmatrix} 1 & 0.01 \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 5e-5 \\ 0.01 \end{bmatrix}, H = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

For the third category, matrices that define the dynamic of the system are designed to accommodate different execution periods T:
for T=0.5sec

$$A = \begin{bmatrix} 0.9998 & 0.0099 & 4.495e^{-5} \\ -0.05422 & 0.9845 & 0.0085 \\ -10.27 & -2.9480 & 0.7127 \end{bmatrix}, B = \begin{bmatrix} 0.000185 \\ 0.05422 \\ 10.27 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

for T=1sec

$$A = \begin{bmatrix} 1 & 0.0099 & 4.741e^{-5} \\ -0.0071 & 0.9959 & 0.009229 \\ -1.391 & 0.7915 & 0.8486 \end{bmatrix}, B = \begin{bmatrix} 2.415e^{-4} \\ 0.071480 \\ 1.391 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

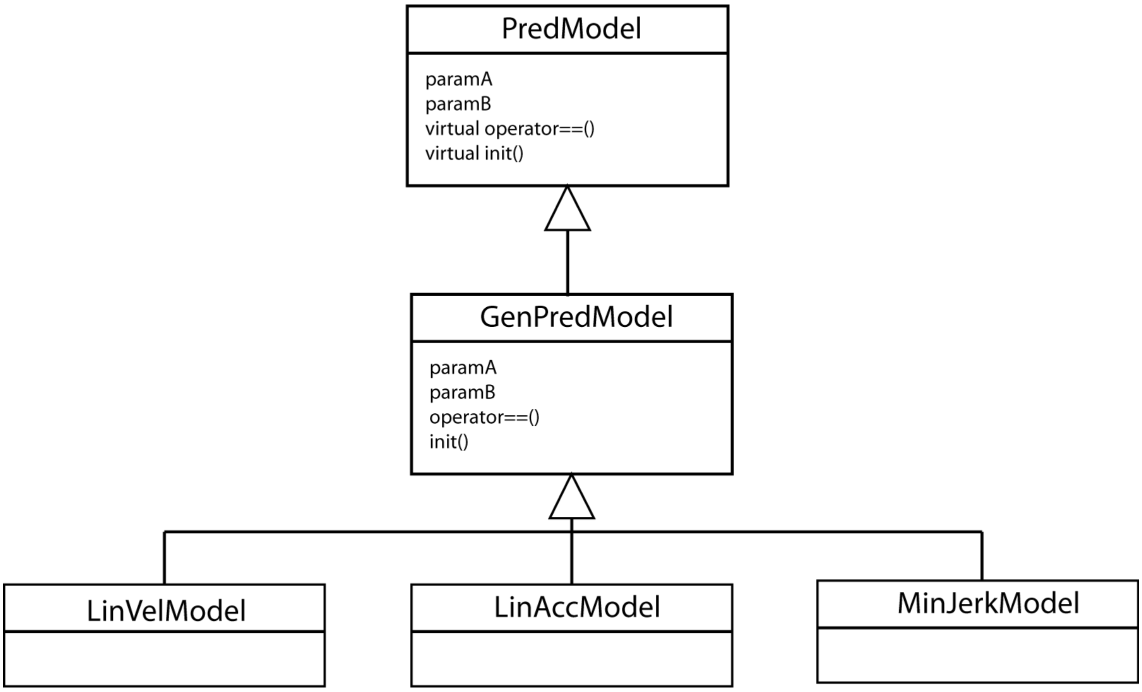


Figure 6.2: UML diagram of the dedicated library for the attention

for T=1.5sec

$$A = \begin{bmatrix} 1 & 0.0099 & 4.826e^{-5} \\ -0.0021 & 0.9982 & 0.00948 \\ -0.4235 & -0.3602 & 0.8973 \end{bmatrix}, B = \begin{bmatrix} 7.25e^{-6} \\ 0.0021 \\ 0.4235 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

for T=2sec

$$A = \begin{bmatrix} 1 & 0.0099 & 4.869e^{-5} \\ -0.0009 & 0.9990 & 0.0096 \\ -0.1811 & 0.2050 & 0.9223 \end{bmatrix}, B = \begin{bmatrix} 3.076e-6 \\ 0.00091 \\ 0.1811 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

6.4 Experiment:the Role of Prediction in Human-Robot Interaction

6.4.1 Experiment A: multiple predictor in a controlled scenario

In this section the author presents two experiments run on the humanoid robot iCub. The experiments demonstrates how we obtain very good results through the use of the mentioned prediction system. In the first place, the purpose is to test the robustness of the decision even when measurements are subject to noise. Thus, we inherited one model from constant velocity models, one from the constant acceleration model and two models from the minimum-jerk class. We choose respectively $v_1 = 1\frac{m}{/}s$ for the first model; the second model has a constant acceleration of $a_2 = 1\frac{m}{s^2}$. The first minimum-jerk (or minJerk) model instead has temporal horizon $T_3 = 1s$ and distance$d_3 = 1m$ whereas the second one has temporal horizon $T_4 = 2s$ and distance $d_4 = 1m$. We generated trains of position as the response to the step function of fourth model. We added white noise to the output of any model:

$$z(k) = y(k) + w(\mu, \sigma)$$

where $\mu = 0$ and $\sigma = 0.01$; The system of predictors activates the concurrent competition for best prediction, each of which provides different measure (MSE) of the quality of their estimation. Thus, for any model, we use the Kalman filter to estimate successive value of the measurement (state of the Kalman filter). To estimate the accuracy of the predictor/Kalman filter we measure the mean squared error (MSE) between the measurement and the estimated state:

$$MSE = E\left[(z(k) - x(k))^2\right]$$

The MSE measure that exceeds a threshold stops the model and removes it from the collection of competing predictors. Among the group of survived predictors, the one with lower MSE value is selected as best predictor of generated trajectory. Since the trajectory is generated using the model of the third model, the third predictor should predict position with the smallest MSE.

We run the predictor for only 12 steps using the response to the step function of those 4 models, and we obtained the following MSE: $MSE_1 = 3.03e{-}4$ $MSE_2 = 2.70e{-}4$ $MSE_3 = 7.74e{-}5$ $MSE_4 = 1.99e - 4$ Using these measures, we choose the third model as the model that better represents the generator of the measurement. This corresponds to the model that has identical parameter to the predictor. In the next figure, we compare the MSE of the four models along the 13 steps of simulation.

6.4.2 Experiment B: performance of predictors in real scenario

As second experiment, we propose a set-up in a real human-robot collaboration, where the advantages of the prediction can be studied. In this scenario, the robot is located in front of human subject. The human subject moves objects from one side of the robot visual field to the other end. Typically this is the scenario presented in numerous experiment that test children development (Falck-Ytter et al. (2006a)). The task is triggered by the saliency of the object which remains always visible during the action. The trajectory of the object may end outside the working plane r but the mechanism is able to associate the correct velocity profile to the projection of the object on the working plane r. This is achieved by the efficient use of predictors as explained in the previous paragraph. For this simulation we instantiated a collection of 16 predictors of type *minJerk*. The bank of predictors can obviously be enriched with either new types of predictors (linear acceleration predictor and liner velocity predictor) or new minJerk predictors with different parameters.

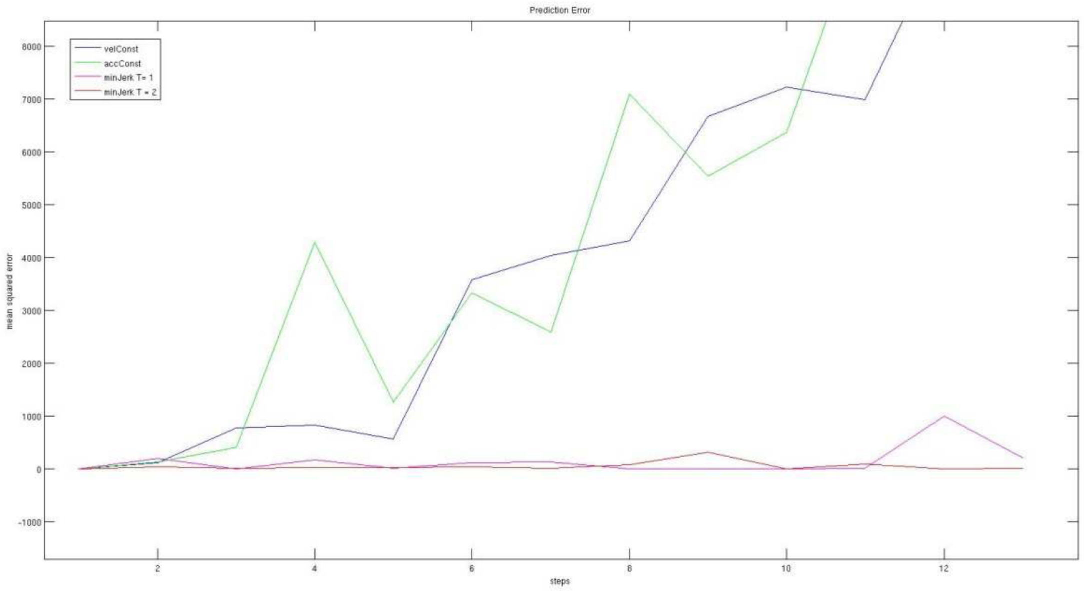


Figure 6.3: test of 4 different predictors in a controlled scenario

Multiplying the number of predictors improves the sampling of the 2D space of predictor parameters.

We go through the complete set of steps presenting the algorithm of the predicting process implemented on the humanoid robot iCub. The salient object is located in the fovea of the drive eye and we suppose that this is the salient stimulus that the attentive system selects. The command ”PRED 160 140” triggers the prediction and activates the *matchTracker* that continuously locates the object in the field of view. The human counterpart in the experiment moves the object along a linear trajectory with biological motion. Querying the *matchTracker* we fetch the position of the stimulus in the field of view. We project that position in retinal image on the *plane r* parallel to y-z axes and orthogonal to x axis (6.1) and located $d = 0.5m$ along x of the robot frame of reference. We obtain a trajectory on the 3D space that lays on the y-z axis. Considering only the component of the trajectory on the y-z plane, we define the initial position $P_0 = [y_0, z_0]$ and the prevalent direction of motion, identified by θ angle. The main hypothesis is that the performed trajectory will keep the θ constant which corresponds to a straight line in the y-z plane. Since the study is now reduced to 2D space we extract position, velocity and acceleration of the stimulus in time for 10 samples every 33ms. Here, we need to make a crucial point: obviously the greater the number of samples the more accurate the prediction is. The limit is that we extract trajectory features in short time interval to allow fast reaction time (now it is approximately $330ms$). Thus, further refinement of the implementation can reduce the intra-sample interval to provide a greater number of samples.

```
Data: target position $T = [T_x, T_y]$ on the original retinal image target position $T'[T'_x, T'_y]$
      on the current retinal image
Result: $[L_x, L_y] == [T'_x, T'_y]$
initialization;
matchTracker.init($T_x, T_y$);
matchTracker.getTargetPosition($T'_x, T'_y$);
[$x_0, y_0, z_0$] = getPointOnPlane($T'_x, T'_y$)
for $i = 0$ to $40$ do
    matchTracker.getTargetPosition($T'_x, T'_y$);
    [$x, y, z$] = getPointOnPlane($T'_x, T'_y$);
    S = getDistance($x, y, z$);
    V = getVelocity($x, y, z$);
    A = getAcceleration($x, y, z$);
    zMeasure.append(S,V,A);
    error = sqrt($(T'_x - L_x)^2 + (T'_y - L_y)^2$);
end
predIterator = listPredictor.begin();
while preIterator == listPredictor.end() do
    predIterator.setMeasure(zMeasure);
    predIterator.start();
end
while $countPredictorEnded < numberOfPredictor$ do
    predIterator = listPredictor.begin();
    for preIterator == listPredictor.end() do
        evalFineshed = predIter.getEvalFineshed;
        if evalFineshed then
            countPredictorFineshed = countPredictorFineshed + 1;
            if maxMSE ¡ MSE then
                maxMSE = MSE
            end
        end
    end
end
```

Algorithm 3: algorithm for accurate prediction

The position $\vec{s}$, velocity $\vec{v}$, acceleration $\vec{a}$ are vectors that contain the measurements. They can all be gathered into one single variable $\vec{Z} = [\vec{s}, \vec{v}, \vec{a}]$. The collection of measurements is the input vector for the predictors. The predictors concurrently operates thanks to the thread class associated to any of them *evalThread*. Once received, the collection of measurements $\vec{Z}$ starts the active process in the predictor which feeds the vector of measure to the Kalman Filter. The Kalman

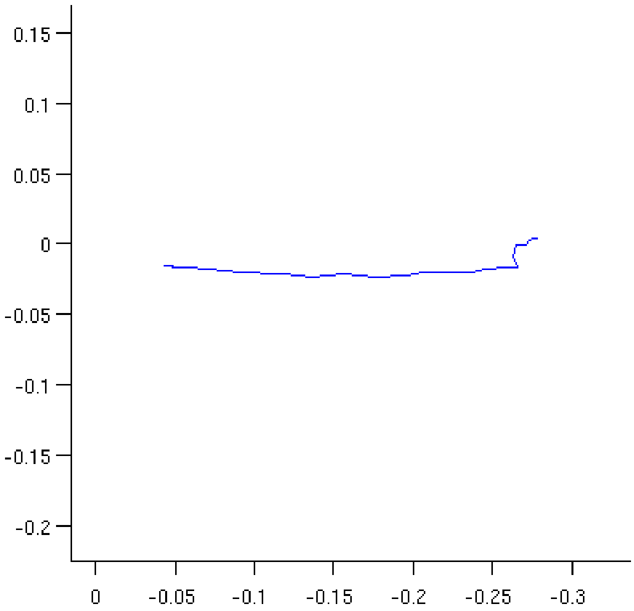


Figure 6.4: projection of the trajectory on the y-z plane

filter associated to the predictor contains a series of parameters such as A, B, C matrices and the input vector u which are parameters of the prediction model associated. We provide a bank of 16 predictors with different parameters 6.1.

In the active execution loop of the *attPrioritiser* the predictors starts at the same instant but differently take varying time interval to process the information. In this section of the *attPrioritiser* we provided a synchronizing stage where all processes wait for all the predictors to finish. When a predictor successfully ends its computation, the measure of MSE between the predicted state and the current state provides measure of the quality of prediction. From the experiment, in relation to the movement performed by the demonstrator, we obtain the following results:

From the collection of predictors, we select the one with best performance. The predictor *minJerk520* with $MSE = 0.000057$ is the predictor that performs better and then wins the competition against others. According to the result, the human partner‘s movement fits better with a minimum-jerk trajectory of 0.2m amplitude performed in 0.5 sec. This is proved by the anticipatory saccade in predicted end-trajectory location 6.6.

The error is in the order of few centimeters which is then mapped in few pixels in the retinal image. In fact, the absolute error E is distributed as a bivariate normal function $E_X = 15 \pm 12$ and $E_Y = 10 \pm 10$ pixels in reaching considered the center-of-mass of the object located. The error cannot be related to the only distance between the COM of the object and the center of the retina but rather it must evaluated in relation to the number of predictors. The 2D space of the parameters must be discretized and the level of discretization defines how well the model captures the real

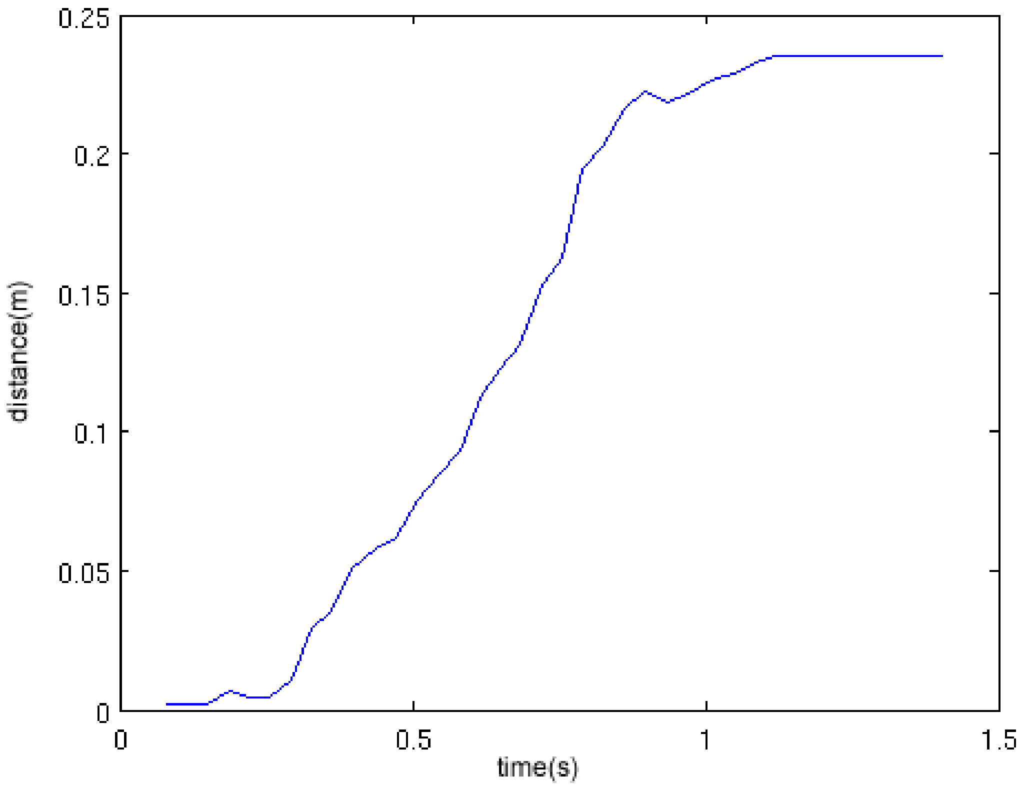


Figure 6.5: mininum jerk trajectory in space for the experiment B

performed action. The structure of the system is designed in order to move the trade-off from the couple accuracy-computation time to the couple accuracy-computation load. The processing of the predictor is parallelized which avoids serialization of the computation time but, on the other hand, increases the computation load. The constraint relates to the computation power of the system and it is unrelated to the algorithm of the processing. In this scenario, a more powerful machinery can eventually improve the quality of the prediction straight away.

6.5 Outline

In this chapter we described a valid mechanism of prediction. We report in detail the algorithm and its implementation on the humanoid robot iCub. The implementation takes into account multiple constraints that usually are associated with humanoid robots that operate in dynamic and real environment. The two presented experiments reflect how the process successfully predicts where the robot should look. This is crucial skill that enables anticipatory behaviors.

It is evident how prediction improves the performance of the robotic counterpart in a human-robot

Predictor ID	T - Period (sec)	u - distance (cm)
minJerk550	0.5	50
minJerk540	0.5	40
minJerk530	0.5	30
minJerk520	0.5	20
minJerk1050	1.0	50
minJerk1040	1.0	40
minJerk1030	1.0	30
minJerk1020	1.0	20
minJerk1550	1.5	50
minJerk1540	1.5	40
minJerk1530	1.5	30
minJerk1520	1.5	20
minJerk2050	2.0	50
minJerk2040	2.0	40
minJerk2030	2.0	30
minJerk2020	2.0	20

Table 6.1: Collection of minimum jerk predictors with their parameters: T (sec) period of movement , u(cm) distance from the start position of the movement

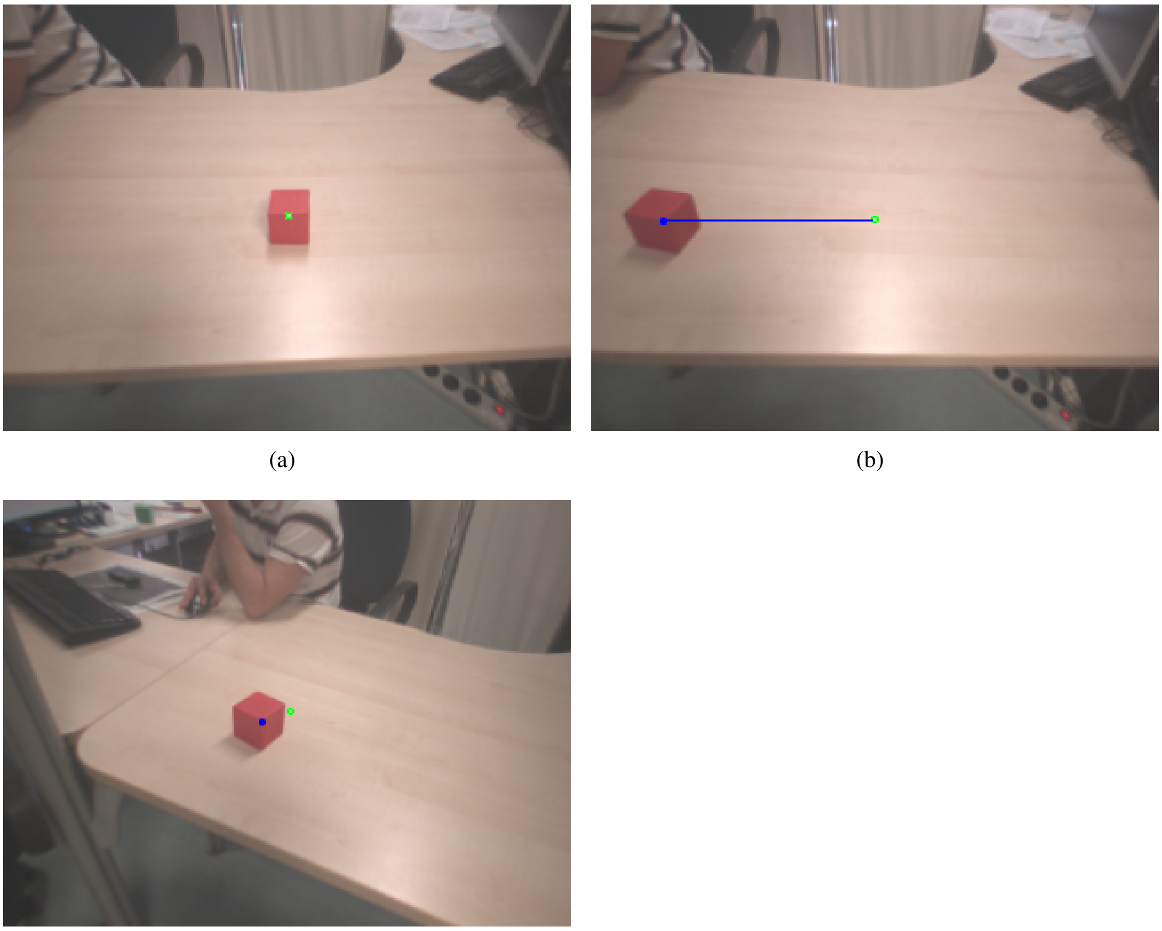
collaboration. First, the robot can reduce the energy required in the task. The robot that can efficiently anticipate the location of the salient target and aim for the target without continuously tracking the object in time. We know that this is very energy consuming task when compared with ballistic eye movement (e.g.: saccade to the goal target). Thus single ballistic movement is preferable. Second the prediction of the goal of movement corresponds to prediction of counterpart‘s intention. As reported in the literature this is a behavior that children master approximately at the age of 6-months. The development of this skill is strongly related to the development of ability to perform movement finalized to action accomplishment. In a mirror-like mechanism, the babies in this stage of the development learn how to map other‘s action (where action is the composition of movement and goal) to a class of similar actions that themselves already experienced. The goal of the action then automatically pops out giving the immediate comprehension of what is happening in the environment and what other‘s intention are. In this situation, the environment is the interface between two or more agents that interact. The action performed on the shared object in the environment can be sensed and gives to the counter-part insights on the performer‘s intention. Similarly when a robot collaborates with humans, they share the environment which becomes the mean of the interaction. Once the goal of action is known the interpretation of the situation obtains an proficuous aid. The action itself can be interpreted if the target is recognized. As *affordances* of the object helps in fire the correct sequence of neuron activation in the mirror neuron area, the system recognizes the action from the affordances associated to the target. We strongly believe that this is a key aspect that deeply promotes the human-robot collaboration. A smart robot without such a prediction mechanism can only reach without a clear view of what happens in the interac-

Predictor ID	estimated state	MSE
minJerk1050	[0.176723, -0.003559, -0.147732]	0.001835
miJerk2050	[0.216168, 0.035887, -0.108289]	0.046965
minerk550	[0.169798, -0.010482, -0.154659]	0.000116
minJerk1550	[0.191988, 0.011669, -0.132477]	0.012993
minJerk540	[0.169031, -0.011249, -0.155425]	0.000089
minJerk1040	[0.176129, -0.004153, -0.148325]	0.001830
minJerk1540	[0.191517, 0.011198, -0.132948]	0.012990
minJerk2040	[0.215785, 0.035505, -0.108671]	0.046952
minJerk530	[0.168265, -0.012016, -0.156192]	0.000069
minJerk1030	[0.175535, -0.004746, -0.148918]	0.001828
minJerk1530	[0.191045, 0.010727, -0.133418]	0.012988
minJerk2030	[0.215403, 0.035122, -0.109054]	0.046939
minJerk520	[0.167498, -0.012782, -0.156958]	0.000057
minJerk1020	[0.174942, -0.005340, -0.149512]	0.001827
minJerk1520	[0.190573, 0.010256, -0.133888]	0.012987
minJerk2020	[0.215020, 0.034740, -0.109436]	0.046928

Table 6.2: Result in prediction of the minimum jerk predictors after the performed movement by demonstrator.

tion. On the other hand, with a working prediction mechanism, the interaction takes the best out of physical level of the sharing.

This produces effect in the other domain: domain of the feelings. The level of confidence in the robotic partner enhances because of the prediction mechanism. The human figure in the collaboration interprets the robot anticipatory mechanism as limpid manifestation of correct goal interpretation. Moreover the anticipatory behavior resembles similar mechanism in humans and this increases the level of trust in the robot action. We presented how two domains of interaction presented in the first chapter benefit from the correct prediction of the other‘s intentions. In the next chapter we address the remaining domain: the developmental domain. We present a semi-supervised learning instance which resembles dynamic aspects of the developmental learning in animals. Thanks to such a learning we claim that the overall experience of collaboration will improve significantly.



(a)

(b)

(c)

Figure 6.6: Generation of the saccade on the basis of the prediction. In (a) the object in fovea(green dot), in (b) the object is moved with a minimum jerk trajectory along the direction in blue. In (c), which is the view of the left camera after the saccade in predicted landing point of the visual target. The difference between the position of the object (blue dot) and the position of the fovea (green dot) corresponds to the prediction error.

(a) (b)

Figure 6.7: (a) retinal image of the left camera at the beginning of the experiment (stage a) and retinal image of the left camera at the end of the experiment (stage c). Note that the object is not perfectly in fovea, this corresponds to the prediction error. Object located in $O_{COM} = [145, 125]$ and error experience in this run $E_X = 15$ and $E_X = 5$.

LEARNING OF THE OPTIMAL ACTION SELECTION POLICY IN REAL-TIME COMPLEX SCENARIO

7

> *For the things we have to learn before we can do them, we learn by doing them.*
> Aristotle, The Nicomachean Ethics

7.1 Introduction

Humans execute complex oculomotor actions while performing tasks in real world. The eye movements serve to reduce uncertainty about environmental variables that are important for the action. As presented in previous chapters 5 and 4, circuits in the cortex generate oculomotor actions. It is commonly assumed that these models are direct result of the phylogenetic evolution. In fact, human eye is characterized by an higher resolution area called fovea where most of the cones are located. The reason for this spatial variance in the distribution of cones can be explained by the limitation in the evolution design of the human vision system. In recent experiment Koch et al. (2006), measurements proved that the optic nerve has a maximum and constant data transmission of 10Mpbs. The amount of data that is transferred is limited and thus the excessive amount of photoreceptors in the retina is superfluous. The evolution drove the anatomy of the eye toward an restricted area with high resolution:the fovea. However, through the active vision, eye movements relocated the fovea on the region of interest.

We introduced numerous oculormotor actions that reproduce human eye movements 5. The crucial aspect that we face is how we could master the best policy of action activation. Which action must be activated and when in order to obtain maximum benefit given the current environmental situation. A natural way of determining the best strategy of eye movement is the reinforcement learning Sutton and Barto (1998). In the framework of reinforcement learning few aspects must be defined as the reward function, the goal state, the action transition through states. Defining these learning parameters for the eye movements is not trivial because the learning has not direct consequences. Different attempt have been pursuit. In Sutton and Barto (1998) the authors design the system on the idea that eye movements serve to reduce uncertainty about environment variables. In this research the reward is based only on the expected reduction of uncertainty and not on the anatomical cost of the eye movement. In other research Sullivan et al. (2011) the addition information on the cost of single eye movement.

Motivation for the selection of the reinforcement learning as a valid mechanism in epigenetic robotics comes from the early research Hikosaka et al. (2000). Physiological and anatomical evidences indicate that *basal ganglia* is tightly related to *sequential procedural learning* and *reward*. Rewards are a form of feedback related to the discrepancy from expected and what happened in reality. The expected event is defined on the basis of long-term memory for learned sequential procedure. Measured activities in *Caudate Nucleus* CD Sawaguchi et al. (1991) Watanabe et al. (1996) give insights on the fact that CD may contribute to expectation in addition to working memory. Indeed in this framework, expectation is a sort of mental state evoked by predictive events. Whereas *working memory* is defined in Baddeley (1986) as temporary collection of information which motor and cognitive signal can alter. In literature, working memory is always associated to the memory-guided saccade task. In this task, neural activity has been found in CD Hikosaka et al. (1989) in dorsolateral prefrontal cortex Funahashi et al. (1989) and perietal cortex Gnadt et al. (1991). These are the areas elicited when working memory is active in memory-guided saccade. There are three types of neuron in the basal ganglia that might be interesting for the memory-guided saccades: (1) visual neuron, (2) memory neurons, (3) saccadic neurons. The first group of neurons fires when the location of visual stimulus populates the buffer of working memory. The remembered location will be used in future memory-driven saccades. The memory neurons become active when stimulus location is maintained as working memory. Saccadic neurons show sustained activity just before the memory-driven saccade is performed. To recap, basal ganglia has important role in enabling the circuit gate for working memory so that target motor areas use prediction mechanism when performing actions. The prediction we refer it is not a prediction of other‘s actions but rather the expected result of action autonomously performed.
On the other hand, concerning the sequential procedural learning, many studies suggested the important role of basal ganglia and even, recently, extended to *implicit learning* Peter et al. (1992) and *problem solving* Saint-Cyr et al. (1988). Recent data on experiments carried on monkeys Rand et al. (1998), suggests that anterior and posterior regions of basal ganglia are active during learning and execution of learned procedural sequences. Whereas the dorsomedial frontal cortex is associated to the learning of new sequences Nakamura et al. (1998) Nakamura et al. (1999). Based on these findings, Hirosaka et al Hikosaka et al. (1999) proposed a specific loop circuit (fronto-parietal association cortices and anterior part of basal ganglia) involved in gathering visuospatial coordinates for the learning and a second loop circuit (motor-premotor cortices and mid-posterior basal ganglia) recruited for sequencing of motor coordinates in a later stage of learning. In addi-

tion, information coming from cerebral cortex is selected in basal ganglia based on reward-related information. In fact, it is well-known that both cognition and emotion fairly guide actions Konorski (1967). From early studies on basal ganglia, the area where these two flow of information meet is the nucleus accumbens or ventral striatum. In other words, anatomically, basal ganglia receives information from both neocortical area (cognitive signals) and limbic areas (emotion signals). These result have enhanced the possibility of neural correlates for the integration of cognitive and emotional information in basal ganglia. Behaviorally, many neurons in basal ganglia respond to reward or sensory stimuli that indicate the coming reward. Finally, we conclude that visuo-oculomotor circuits in basal ganglia are modulated by reward specifically expectation of reward Kawagoe et al. (1998).

In other words, the feeling of success -emotion- coming from limbic areas regulates the mechanism of reinforcement learning. If such feeling of success can resonate in the counterpart limbic system and produce similar emotions we can fairly say that a mechanism of empathy is successfully active between the collaborators. We aim at this level of resonance that improves the performance of the collaboration. Specifically in the section dedicated to the presentation we address this idea in details.

Having presented all the components necessary for the reinforcement learning mechanism, we give further insights on the process by reporting experiments conducted on monkeys. The experiment is characterized by a precise temporal pattern: i) the monkey is presented with the fixation point which is also the clue, ii) the targets (blue triangle and red circle) are presented along with the clue, iii) when the clue goes off, the monkey has to saccade to the correct target. Each clue codes the correct target, e.g.: when the clue is blue triangle, the monkey will be only rewarded for a saccade to the right target. The information about the target will be available on the PP. At the same time the information about the feature of the fixated clue will travel through the cortex ($V1-V2-V4$) and finally will be available to the *inferotemporal* area IT. This projects on the same caudate cells as those influenced by *frontal-eye field* FEF. So that, information can now flow from IT to the CD. The chief hypothesis of the research group is that the juice payoff will produce the effect of *dopamine* DA release which can modify the $IT \leftrightarrow CD$ synapse. Accordingly to the Kotter and Wickenes Kötter and Wickens (1995), the processes establishes a reinforcement learning rule where active CD cells when *dopamine* DA is released, the IT synapse have the following effect: (1) synapses from active IT cells will be strengthened (long-term potentiation), (2) synapses from not active IT cells will be weakened (long-term depression), (3) assuring constant overall synaptic strength (normalization effect). Via this normalization, postsynaptic cells compete for influence from presynaptic cells, producing clue discrimination. The key role of the reward is not aimed to specific correct answer but rather to favorite hebbian learning in $IT \leftrightarrow CD$. Only $IT \leftrightarrow CD$ synapses active in the learning are reinforced. On the other hand when negative reinforcement is present we get antihebbian rule which weakens synapses involved.

The Reinforcement Learning Sutton and Barto (1998) implementation is based on this mechanism. The policy describes the action of the agent in the environment given the state of the system. The reward function maps each state (for this implementation state-action pair) into a reward value indicating the desirability of the state (state-action) condition. The overall reinforcement learning is based on the estimation of the quality of expected state after the sequential procedural learning. Considering that the system has to keep a long-term memory of the past iterations, we easily identify all the components of basal ganglia previously listed.
According to the Thorndike law of effect Thorndike and Bruce (1911), if an action tends to improve the condition of the actor, the tendency to produce that action is strengthened. Learning based on this rule is defined as generate and test in Barto (1995). The aim of the reinforcement learning is to maximize the expected return which is function of the subsequent reward sequence. One problem of estimation of the reward after a series of actions is that the model of the system needs to be known. *MonteCarlo* theory overcomes this problem because it is not longer required a detailed model but the estimation and policy improvement are based on sample experiences rather than complete probability distribution. This algorithm is usually used in RL for the policy iteration. In fact policy iteration consists in two steps: policy evaluation and policy improvement. The *MonteCarlo* methods are used in the policy evaluation step.
However the *temporal difference* TD methods are the most widely used technique for RL. That is because the TD methods integrate benefits of the *MonteCarlo* methods with dynamic programming. This class of models deals with the task of predicting future rewards for a course of predefined sequence of states. The most used variant is the Sutton‘s temporal difference method based on recursive Bellman equation.
However both MonteCarlo and TD methods raise a problem of sufficient exploration. These methods will only work when the state (state-action) space is completely exploited and anyway in a large number of steps. Q-learning algorithm Watkins and Dayan (1992) Jaakkola et al. (1995) is used when the space of conditions must be augmented to state-action space. It associates a Q-value to the state-action pair and this value is the result of all the reinforcements for a particular action taken in a particular state.

Inspired by these findings in biology, classical machine learning theory divided the term *learning* in : a) supervised learning, and b) unsupervised learning. In the former, the agent is helped by all-knowing teacher in distinguishing what is correct or wrong. It usually implies a training data on which the teacher has already presented correct answer. Further, the figure of a teacher is biologically unrealistic (Churchland and Sejnowski (1994)). The latter the agent does not have teacher‘s support. Input is classified thanks to the ability of the agent to discriminate and generalize on the input data. With this form of learning the agent is able to discover regularities in the input data. From one side the absence of the teacher makes the learning biological plausible however, it is only useful for a set of carefully chosen problems. As a general principle, Reinforcement Learning works as a combination of these two learning paradigms. In this scenario, the agent usually acts on the environment with the ultimate objective to accomplish its goal. The agent‘s action on the environment is presented back to the agent as feedback (usually reward but sometimes punishment). The rewards plays as a form of evaluative signal, indicating the degree of appropriateness of the knowledge of the agent about the world. The Reinforcement learning is therefore referred as *weakly supervised learning* Pennartz et al. (2000).

7.2 Implementation of Reinforcement Learning For Optimal Oculomotor Strategy

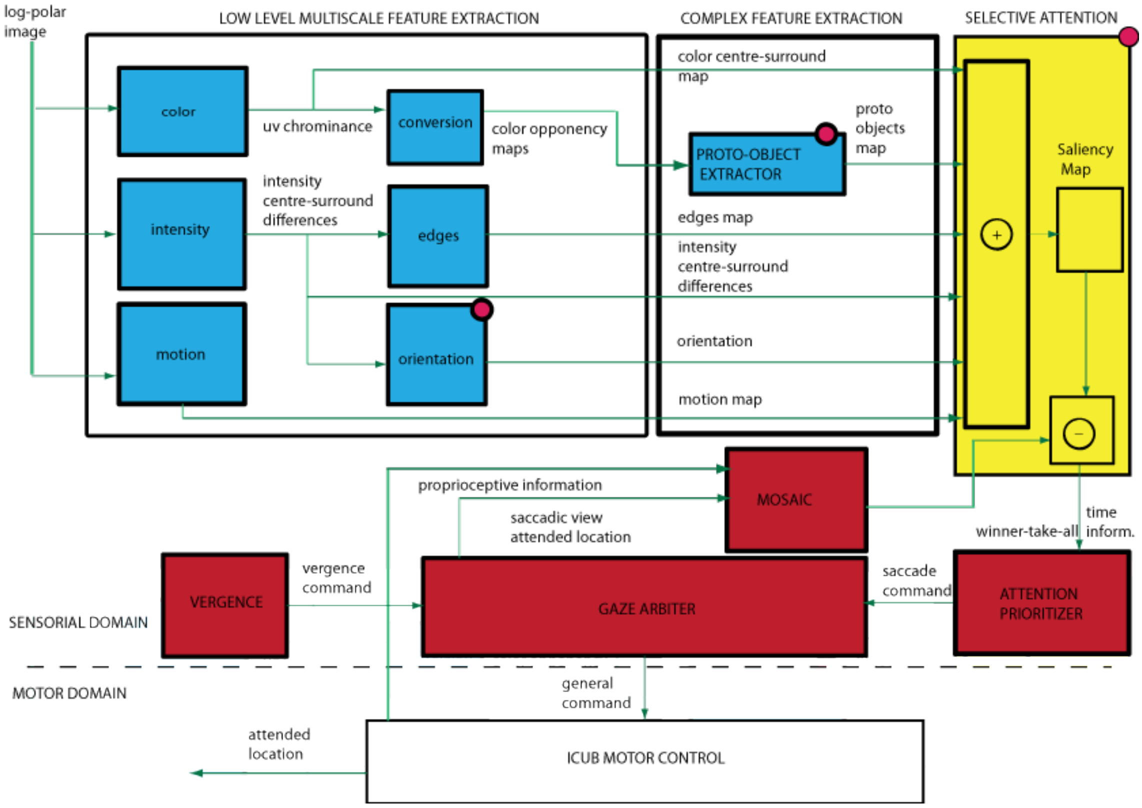


Figure 7.1: Software architecture in the learning system

The learning process is carried out using reinforcement learning RL Sutton and Barto (1998). The agent in the *attentionPrioritiser* learns by interacting with the environment rather than being explicitly taught by positive and negative samples. Formulated as Markov Decision Problem MDP, the agent dynamically chooses different oculomotor actions ending up in different informative states. In other words, the agent takes decision guided by the expected reward. Reinforcement Learning RL with Q-Learning technique regulates how the expectation of reward evolves with the trial-and-error experience performed by the agent in time. By the mean of Q-learning technique Watkins (1989), the agent enhances its action-value function that gives the expected benefits of taking one oculomotor action in a given state. The advantage is that the agent is able to compare the expected utility of the available actions without requiring the model of the system. This approach finds different links in the psychology mainly in neural reward system of basal ganglia Joel et al. (2002). Reward neurons produce internal reward signals that the brain uses to control, decide and choose. Reward signals influence neural processes in cortical and subcortical structures underlying behavioral actions and thereby contributing to economic choices. The control agent for oculomotor actions performs actions from a repertoire of possible actions A:

$$A = \{res, wait, verg, smP, uSac, mSac, lSac, exSac, pred\}$$

which respectively can be express as Actions in this repertoire are based on actions that the low level controller performs (5). Additional high level actions enlarge the collection of actions that the humanoid robot iCub is able to perform. *Reset* and *predict* are actions that do not belong to action controller gazeArbiter although essential in triggering state transitions. In addition, *wait*

Action Code	Action Name	Main Function	
1	res	reset	Brings the system to the initial state with no-memory about the past
2	wait	wait	Brings the system to the wait state necessary to synchronize different the system with the world
3	verg	vergence	Changes the vergence angle, introduces stereopsis in the active vision system
4	smP	smooth pursuit	Performs a smooth pursuit of the salient visual target by the mean of the estimated velocity of the stimulus
5	uSac	micro-saccade	Performs a saccade whose amplitude minimum, reduced energy consumption
6	mSac	medium-saccade	Performs a mean-range amplitude saccade
7	lSac	large-saccade	Performs a wide amplitude saccade, high energy consumption
8	exSac	express-saccade	Performs a saccade without postsaccadic control and with simplified and immediate execution
9	pred	predict	Predicts relevant movement features of the visual target

Table 7.1: Action designed for the learning mechanism

command carries information on the *typology* of the waiting and the maximum rest time allowed. The *typology* indicates whether the waiting is requested as component of the anticipatory behavior or as state trigger of transitions toward fixating state. The *predict* command carries the retinotopic location of the relevant stimulus for the episode. Tracking this stimulus the agent can extract information about its movement. Once filtered, this information can be used to estimate the trajectory profile and predict additional information. The action reset always reinitializes the system from any state the actor is positioned. The predict action is fundamental for the actor. In fact, from any predict request, the system estimates the characteristic of the trajectory of the stimulus (6). The controller reaches one state in the collection of states S:

$$S = \{null, pPred, mPred, aPred, stOK, stKO, trOK, trKO, aOK, aWait, verOK, verKO, fix\}$$

which respectively can be expressed as in 7.1.

The group of *prediction* states indicates that prediction of specific trajectories in terms of the velocity, final retinal position have been successfully predicted. State in the prediction group refers respectively to stimuli with steady position in time, stimuli with defined velocity profile, objects with well-known trajectory and therefore landing point. Any other state in the list is coupled with its opposite to address both success and failure in performing associated action. Finally, *fixating* is the goal state that defines the end of the episodic learning. In this state, the object can be considered at zero disparity (in fovea of both eyes) and time interval has been allowed for synchronization. Note that the dimensionality of the action A, $|A| = 9$, and the dimensionality of the state S, $|S| = 13$. The agent visits states by performing actions, therefore, for any possible situation, the couple state-action (s, a) must be defined. For any couple, the choice of the agent is evaluated by an immediate scalar value representing either *reward* or *punishment* and this defines the reward function R. The policy π is the sequence of actions taken from the initial state s_0 during the episodic learning. The sum of any local reward of any couple (s, a) visited defines the total payoff p^{π}. The optimal policy $\pi^{\star}$ is the sequence of actions in the episodic memory that maximizes the *total payoff*, $p^{\pi^{\star}}$. In the Q-learning algorithm the agent estimates the expected utility of taking a given action in a given state following a defined policy. The measure of the expected utility is given by the *quality function* $\phi(s, a)$, quality of the state-action combination:

$$\phi : s \times a \rightarrow \mathbb{R}$$

The quality function can be updated by the update rule:

$$\phi\left(s, a\right) \leftarrow \phi\left(s, a\right) + \alpha\left(r + \gamma \cdot max_{a'}\phi\left(s', a'\right) - \phi\left(s, a\right)\right)$$

Where $\gamma \epsilon \left[0, 1\right]$ is the *discount rate*, $\alpha \epsilon \left[0, 1\right]$ is the *learning rate*, the $\phi\left(s', a'\right)$ regrences to the *quality value* of the next state-action and r is the reward generated by R. By the mean of training, this estimate is guaranteed to converge to the true value $\phi^\star$ Watkins and Dayan (1992). The policy ϕ maximizes the expected sum of future reward such as:

$$\pi\left(s\right) = argmax_{a_i}\phi\left(s, a_i\right)$$

To implement this particular algorithm the probability distribution $P_{s,a}$ of the future s' given the current state s and the action a has to be defined. In literature, this probability transition is often estimated by the mean of either models of the system, or analysis of the system in a long period run, performing random choices. We opted for a *guided analysis* of the model, where the basic transition model is obtained by the real measure of the transition of the system using prioritized hierarchy of action (4). Because the high dimensionality of such transition estimation may be costly:

$$P_{s,a} = (s, a) \times s \rightarrow \mathbb{R}$$
$$|P_{s,a}| = |s, a| \cdot N_s$$

The constrain is that, given the stochastic properties of transition, the probability of state transition for (s,a) must sum to one:

$$\sum_{s,a} P_{s,a} = 1$$

The advantage of using the prioritized algorithm is that, in short time, we obtain a reliable estimation of the probability distribution of transitions. In addition, this measure is not fixed but changes in time even when unexpected states (states with very low probability of being visited) are reached. The rule of action selection is another relevant aspect that we take into account. During the first few runs of iterative learning algorithm, the information about the expected utility of a given action can be not discriminative. We opted for performing iterations using a random selection rule for actions for the first few learning episodes. This allows initializing the quality measure of states avoiding the error of using inaccurate policy. We defined a stochastic variable $s = uniform(0, 1)$ and the threshold t. The threshold t varies with the number of episodes. When $s > t$ the action selection is random-based, otherwise the learned policy defines which action is performed. Using this mechanism, the quality function Q allows reliable action selection only when the confidence on this measure is high. To reduce the situation where the system might get stuck in local minima, we use the threshold t to introduce randomly out-of-policy action selection. The chief result is that random action selection can occur in the Q policy action selection with probability related to the value of t. As a designed choice, we opted to use the preexisting action controller layer of attPrioritiser rather than directly command an action using the learning agent. The efficiency of this solution is guaranteed by the reliable interaction between these two components of the attPrioritiser (see 7.3). As previously reported, the interface of the attPrioritiser receives different typologies of oculomotor commands. Those commands can be generated either from the low level or the attPrioritizer (which represents *high level oculomotor request* namely a feedback) or internal level. Concerning the last, we designed specific commands that do not transit from low level.

On the contrary, those actions are high level actions in the way the learning actor requests them and immediately reads them from the *action interface*. The action *reset* and *predict* for example interrupt the *action interface* as high level feedback (see 7.3). Further more, for any received high-level feedback command a secondary command associated to the first can be generated and sent again to the command interface. This is important to generate additional command that might be eventually executed by the agent.

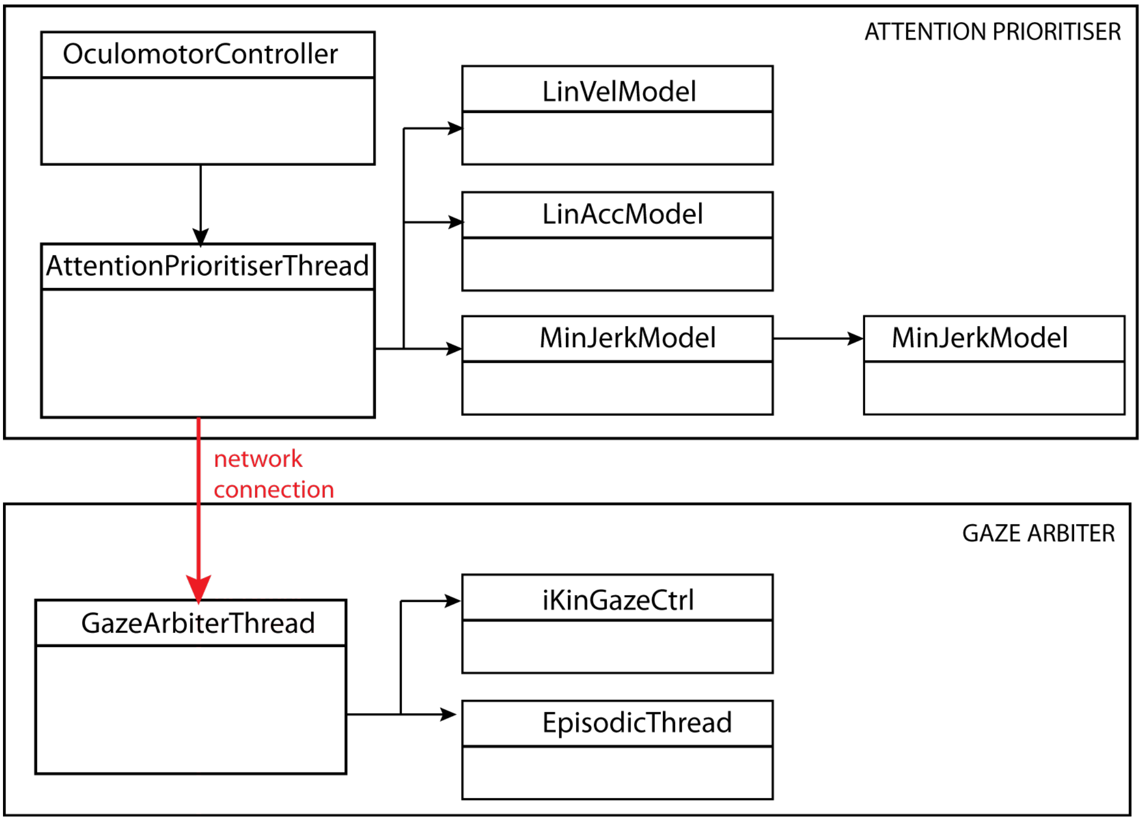


Figure 7.2: Components of the Reinforcement Learning framework

During the learning, the controller does not immediately execute those commands but rather stores them in *typology command memory*. This is a list where the commands are sorted and successively stored by their typology. Through a retrieval instance the agent adopts the action that has been chosen by learning algorithm. If no action of the desired typology is present in *typology command memory*, the agent forces a *default action* that matches the typology of the original action. Obviously the default action is less likely to positively reward the agent. Thus some actions are less likely to reward the learning actor in some particular situation or combination of state. Through the default action the agent executes the proper action but the negative reward that generates discourages the action execution in the particular situation. This is automatically ported in the learning mechanism in the way that voluntarily generated actions will be preferred to default actions. On the other hand, if the agent retrieves an instance of the correct typology of command, this action is

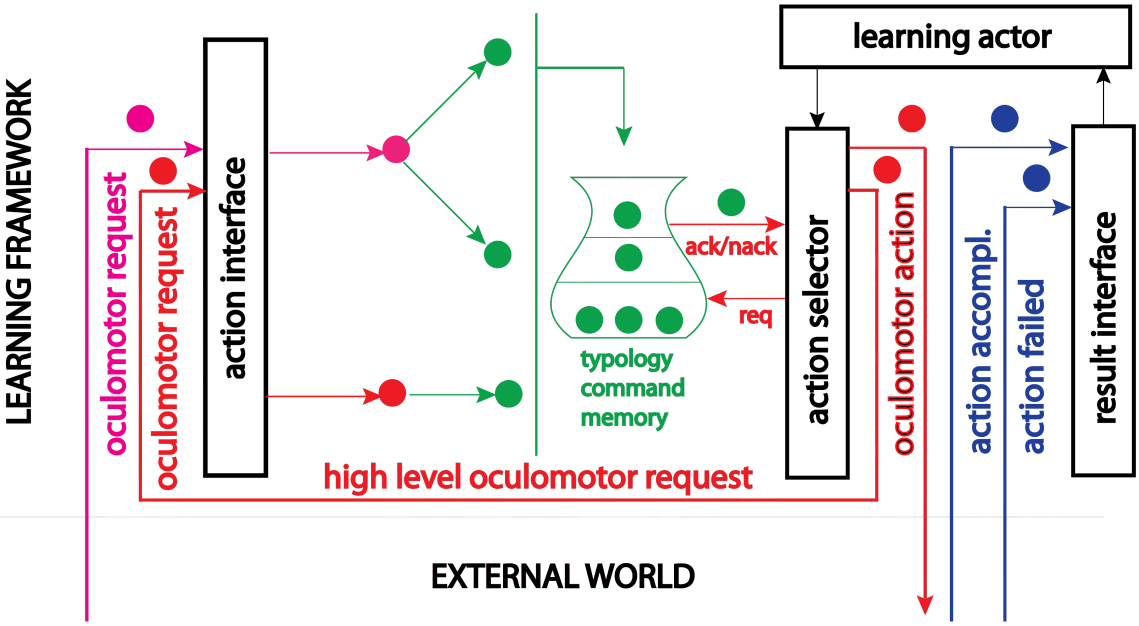


Figure 7.3: Structure of the flow of information between components of the Reinforcement Learning framework

certainly grounded to the agent-environment current situation and therefore more likely to generate positive rewards.

In any case, the selected command is sent the low level controller, and the *gazeArbiter* performs the action. More importantly, when the learning agent is active, the interface of the attPrioritiser, can populate the typology command memory with more than one command for any command received by interface (lets call it *twin-generation*). This is the case when one command from the low level can trigger more than one possible behavior at the same time (see figure 7.3).

In general, we need to clarify that the selected action updates only the actor‘s knowledge of the current taken action but not the state of the agent. For the state, it waits for *accomplishment command* from the low level action controller. Any *accomplishment command* is associated to a particular state of the system 7.3.

When the actor receives a particular *accomplishment command* updates its knowledge of the state where it currently operates. Sometimes, the action ends unsuccessfully, therefore we designed a new set of interaction commands (*unaccomplished commands*) using a similar paradigm. The agent uses these responses and other measures to evaluate the state after action is performed 7.4. Thus the couple *accomplishment command* and relative measure is univocal, and to the couple is associated only one state. Analogously, any *accomplishment command* is linked to one action. Further more, despite the action ends successfully for its steps, there might be conditions that bring the actor into unsuccessful states. For example, if the saccade reaches the desired location but the position of the tracker that followed the salient stimulus is distant the actor experiences insuccess anyway. Ideally, when the best policy is obtained from any state, the best action brings the actor to the next valid state that maximizes the reward. Reiterating this process we can obtain the optimal path from the initial state to the goal state.

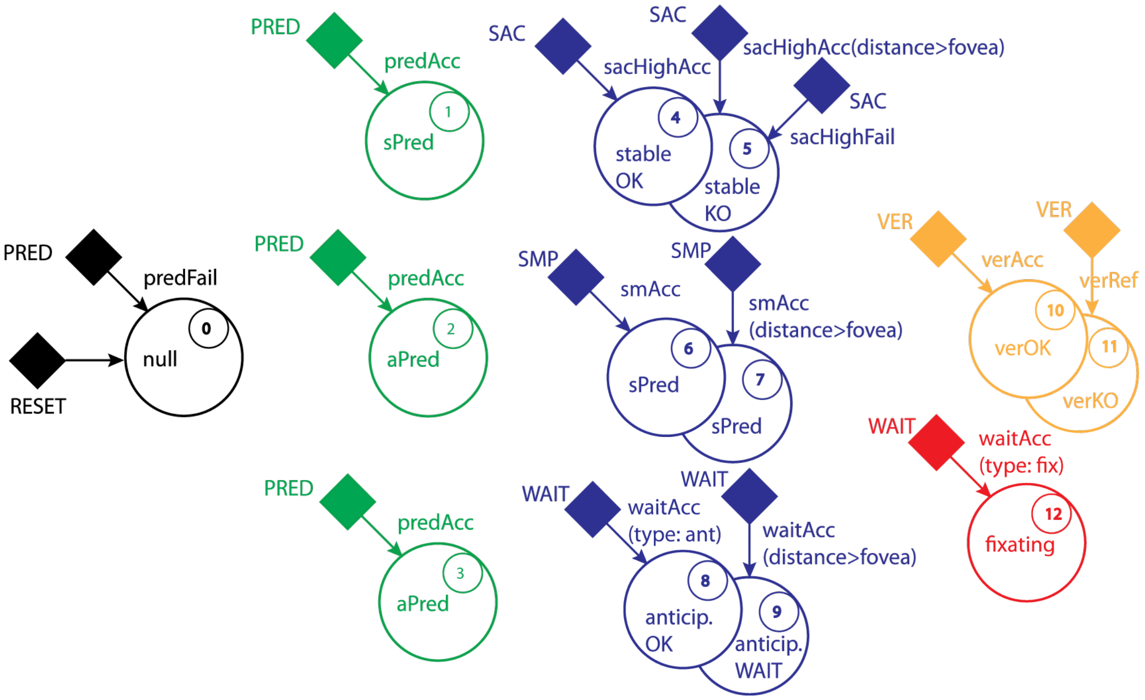


Figure 7.4: *state*-depicted as circle- and *accomplishment command* that drives the actor into the state. To one *accomplishment command* is associated one action - depicted as diamond. In capital letters is the name of the *action*, whereas the *accomplishment command* is represented in lower case letters. The color code highlights the group of states that share similarities.

Ultimately, given the previous state s, the taken action a and the current state s', the quality function can be refined by the update rule. The total payoff provides accordingly a measure of the quality of the learning.Through the whole series of learning episodes, the knowledge of the expected reward can be store in and retrieved from the internal memory. Like the internal memory in neural reward systems and neuronal plasticity, the expected transition between states, the reward associated to any situation and the quality of situation in the perspective of maximum benefit are internally stored 7.1. The agent saves permanently all the information necessary to improve whatever it has learned in the past. Thanks to this form of *working memory* nothing is lost at the end of the training. This allows the system to change autonomously the reward function setting its valuation on an intrinsic drive as Hart et al. (2008).

The reward function comprises to contributions: *positive reward* $R^+(s,a)$ and *negative reward* $R^-(s,a)$:

$$R(s,a) = R^+(s,a) - R^-(s,a)$$
$$R^+(s,a) = A$$
$$R^-(s,a) = cost_W \cdot f \cdot t + cost_E \cdot f \cdot t$$

The A is the accuracy measure calculated along all the oculomotor action and not only at the end of action. This allows the use of the same measure for different types of actions (e.g. saccade, smooth pursuit, etc). On the other hand the negative reward is associated to the cost of the single action. In other words, the reward is defined by the competition between the the *accuracy* of the action - how well the stimulus is followed by the learning actor- and the *energy consumption* generated by the action - how costly the action is. We design the cost consumption considering that any single action comprises one or more than one *atomic subevents*. For example the smooth pursuit is composed of continuous refinement of the velocity profile which is modeled as a collection of *atomic subevents*. On the contrary the saccade is the result of one single ballistic eye movement which is consequently modeled as an action that comprises one single *atomic subevent*. The negative contribution depends on W - the amplitude in degrees of the movement, f - the frequency of *atomic subevent* in the action and t - execution time. The constants $cost_W$ and $cost_E$ are respectively the cost of amplitude degrees in any action and the general cost of every single *atomic subevent*. Since the objective is to keep the fixation point on the salient stimulus, the positive reward measure how good is the selected action to achieve the goal. This is obtained by measuring accuracy: the distance between the tracking system of the selected stimulus and the actual fixation point during the overall execution of the oculomotor action. Any behavior brings a cost which is directly related to the type, the *amplitude* and *duration* of the behavior Saglam et al. (2011). For example a continuous tracking costs more than a single wide saccade. In infants at different ages, the selection of the successful behaviors with particular characteristic of accuracy frequency, duration is delicate task.

It has been already pointed out that the feeling of success -emotion- coming from limbic areas regulates the mechanism of reinforcement learning. In particular positive reward, that is associated to an increment of DA in the system, creates the feeling of success. Thus, we implement an interface via facial expression that aims at promoting feeling resonance in the counterpart limbic system. By reproducing similar emotions in the partner, we can fairly say that the mechanism of empathy is successfully active between the collaborators. We aim at this level of resonance that improves the performance of the collaboration. The facial expression changes accordingly to the state of either success or insuccess of the performed action.

Concerning actions that do not involve ocular movement. we define a completely different rewarding mechanism. For example, if we consider the *prediction action* the reward cannot be negatively rewarded by the cost of the eye movement because completely absent. We rather suggest to simplify it by coding the reward with the expected positive feedback of the prediction. This concept correspond to introducing evolution (phylogenesis) in the development (ontogenesis). This is very crucial and interesting aspect that we need to hard code in the system at this stage. However, we do not exclude that the mechanism of knowledge transfer from the phylogenesis process to onto-

genesis process can be automatized in the future.
The reward for prediction reflects the idea that prediction is quite costly for static objects. The prediction in this situation costs in terms of time and energy and does not give immediate benefits. However, the prediction of characteristics of the movement of moving object brings relevant advantages after the object reaches the expected landing position. Though we need to distinguish between pure constant velocity prediction and prediction of the final position of the moving object, the advantage of predicting final position is evident when the actor executes saccadic movement to the position saving energy with respect to a continuous tracking of the object. Presumably a correct prediction of final position of the visual target brings more positive rewards.

We present how, in our design of the framework, the mechanism of prediction couples with the learning commands necessary to control the reinforcement learning.

```
Data: target position $T = [T_x, T_y]$ on the original retinal image
Result: Command COM to the RL Agent
$Predictor_W TA$ = predict($u_{initial}, v_{initial}, V_x, V_y, x_{POS}, y_{POS}, z_{POS}$)
if $(V_x == 0) and (V_y == 0)$ then
    $Reward_{pos}$ = REWARD_STATIC;
    $ACT = SAC\_MONO u_{initial} v_{initial}$;
    $COM = PRED_A CC$;
    return COM;
end
if $Predictor_W TA$ == NULL then
    $COM = PRED\_FAIL$;
    $Reward_{pos}$ = 0;
    return COM;
end
$COM = PRED\_ACCOMPL$;
if $Predictor_{WTA}.getType()$ == CONST_VEL then
    $Reward_{pos}$ = REWARD_SMOOTHPURSUIT;
    $ACT = SMOOTH\_PURSUIT V_x V_y$;
    return COM;
end
$\hat{pos} = [\hat{x}, \hat{y}, \hat{z}]$
$\hat{pos} = Predictor_{WTA}.getEstimatedPosition()$;
$[\hat{u}, \hat{v}] = get2DPixel(left, \hat{x}, \hat{y}.\hat{z})$
$Reward_{pos}$ = REWARD_ANTICIPAT;
$ACT = WAIT(\hat{u}\hat{v})$;
return COM;
```

Algorithm 4: algorithm that regulates commands issuing in the interaction between predictor and reinforcement learning

where $REWARD\_STATIC < REWARD\_SMOOTHPURSUIT < REWARD\_ANTICIPAT$.

The predictor thread measures the velocity from the position of the visual target on the retina.

If the velocity has zero value for all the measure the prediction ends without triggering the predictors. The object is static and the positive reward is minimum. The command that is returned is a saccade to the original starting position of the prediction. The cost of the prediction is definitely greater than the information extracted. If the velocity is not null (even if constant) the predictors are initialized with the measurement and start to process it. If none of the predictors predicts the state with an error smaller than the threshold the prediction is considered failed. In this case the command sent is $PRED\_FAIL$ (prediction failed) and the positive reward is null. On the contrary, if at least one predictor manages to provide accurate prediction (below the threshold) the command issued is $PRED\_ACCOMPL$ (prediction accomplished). Together with the command feedback of the action, the system generates a novel action. If the type of winning predictor is $CONST\_VEL$ (constant velocity) the system generates a $SMOOTH\_PURSUIT$ command with the specific extracted velocity profile. Otherwise the winner predicts biological movement(minimum-jerk movement) and thus it is able to estimate the position on the vertical plane where the action is performed. The location in the frame of reference of the robot is transformed (function get2DPixel()) to the expected position of the target on the retina. In this case, the generated command is $WAIT$ command. The system anticipates the landing location and waits for the expected time interval in the location. Note that the time interval necessary to complete the movement is one of the typical feature that the predictor predicts from the selected model of the movement.

Note that policy of action selection changes during the childhood development. Converging evidences in this research underlines the degree of connection between attention mechanism and development. Using well-designed reward and punishment mechanism we prove that similar development can be achieved when triggered. We stress another key aspect: the development of action selection mechanism is regulated by the attentive system. In the experiments that we present we intend to give useful insights on these aspects as well. We prove that attention can shape differently the result of the autonomous learning.

7.3 Evaluation of the Autonomous Learning System based on Reinforcement Learning

In this section we present evaluation process of the quality of learning of the system instantiated on the iCub. The relative robot hip position is 10 cm away from the edge of the table at a relative height of 13 cm. Static colored objects are placed at a distance of 25 cm from the edge of the table. The 7.5 shows the typical configuration of the set-up for the learning. We constrain the attentive system to the portion of the table where objects can be placed and reached safely. In other words, we limit the gazing space of the robot. We present the result in the learning process for different conditions of the attention system. Each condition is the result of a defined bias from the top-down component of the visual attention, behavior of the visual targets in the scene. For any experiment the graph of total payoff value in time is presented along with some additional indications on the learning rate.

7.3.1 Experiment A : static visual targets

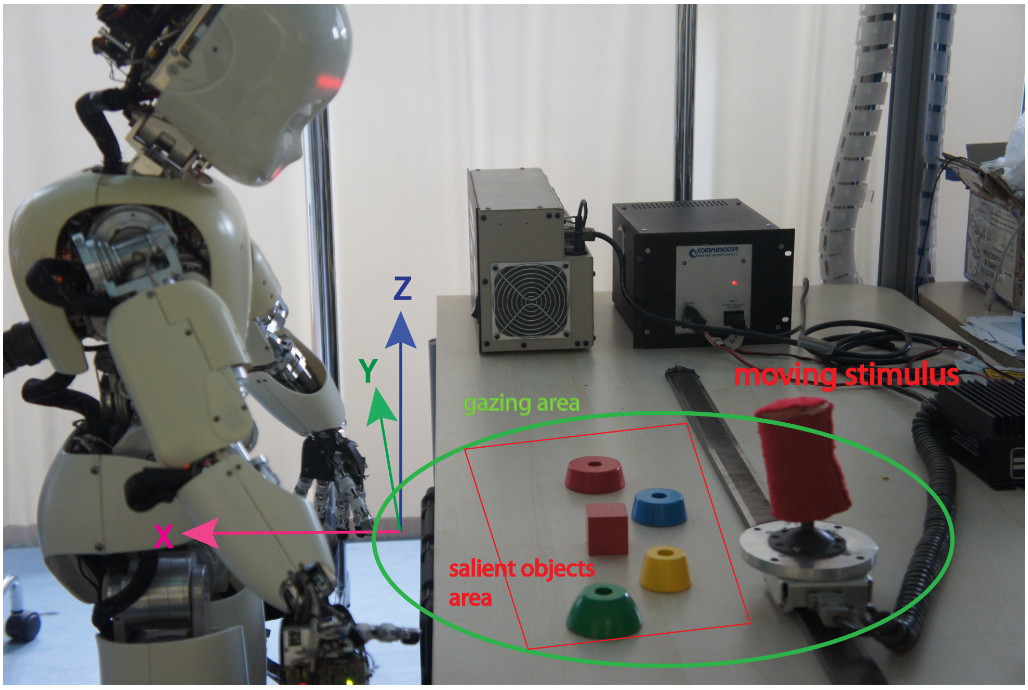


Figure 7.5: Set-up used in the experiment of Reinforcement Learning

In the Experiment A any object is kept in fixed location in the portion of physical space named as *working area*. The weight biases are set as follows:
$k_I = 0, k_M = 0, k_C = 1.0, k_O = 0; k_E = 0; k_B = 0$

The particular set of weights refers to the linear combination of feature maps which are defined in 2: intensity uniqueness, motion, chrominance uniqueness, orientation, edges, proto-object. In other words the only feature map that influences the behavior in this experiment is the chrominance. This is just a forced condition in the attention system but any other combination assumes valid result with different learning dynamics. In 7.6 the total payoff for two typical runs in the learning are depicted. Any step (or *iteration*) corresponds to an action taken by the agent. Initially the system evolves with pure *babbling*. In other words for the first 500 steps the system gradually moves from completely random action selection to policy action selection. Ideally at 500th selected action is based purely on the learned policy. However, in the policy action, for a small probability $p = 0.5$ the action can still be randomly selected. This allows the system to move from being completely deterministic and provides valid escape technique from local minima.

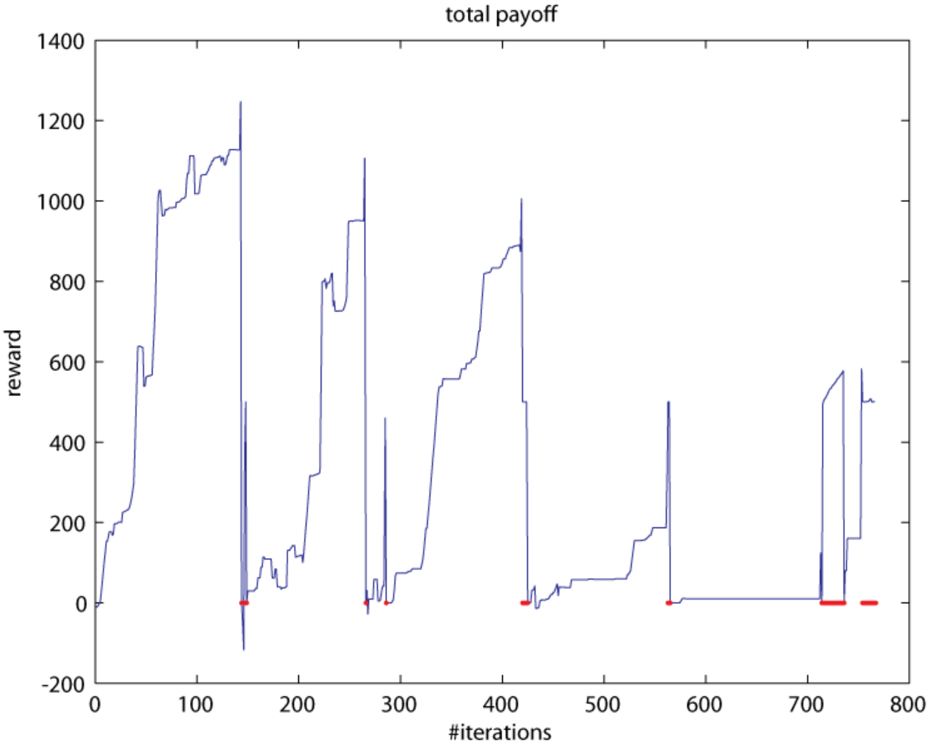


Figure 7.6: The graph presents the evolution of the total payoff during typical run of learning. After the agent reaches the goal state (red dot) there is an abrupt increase of the payoff and successive decrement to zero. The number of steps (namely selected actions) from the two successive goal states is a good indication of the quality of the learning

In the 7.6, it can be appreciated how the sum of the positive and negative rewards prospectively increases and decreases the quality of the agent‘s behavior performed actions) in order to achieve the designed task (keeping the target in the fovea for both the eyes saving energy as much as possible). The red dot represents when the system reaches the goal state of the learning (fixating the object for prolonged time interval). When this happens the payoff has an abrupt increase because of the consistent reward for completing an episode successfully. Subsequently the policy matrix is updated, the agent resets the total payoff measure and a new episode starts.

The gradient of the learning grows with the number of learning steps. In other words the total payoff increases much rapidly later in the learning with respect to the beginning. This is due to the fact that, after few steps, the agent masters a policy (set of actions given the state) that approximates the optimal policy (the policy that maximizes the reward). After the babbling in the learning is completely ended, the agent chooses the action looking at the mastered policy. This theoretically indicates which is the best and shortest sequence of actions that brings the system to the goal state. This corresponds to performing less and less actions necessary to reach the goal: the policy gradually enhances. The policy is continuously refined and in fact the agent reaches the

goal state more frequently towards the end of the experiment. The agent moves from one policy to the next ideally converging to the optimal policy.
To further prove the success in the learning we run the learning algorithm for $m = 10$ successive trials. The run starts with null quality matrix and ends when the agent reaches the goal state for $n = 12$ times. We studied in particular the *payoff rate* measured as :

$$r_L = \frac{payoff(i_end) - payoff(i_begin)}{i_end - i_beginning}$$

where i_begin corresponds to the action progressive counter when the system is in RESET state and i_end when the system is at the GOAL state. Every action counter increment corresponds to an action performed by the agent in the attempt to reach the goal state. The learning rate gives information on how fast the system converges to the GOAL state in terms of transition through state. Further more, this measure captures as well how rewarding are the actions that the agent performs. We expect the system to converge to the goal in less steps the more the system improves its policy.

In 7.7 we appreciate how the first part of the learning, when the agents learns through random actions on the environment (*babbling*), the learning rate is not exclusively decreasing. The peak in 5th accomplishment is caused by a particular bad sequence of randomly chosen actions. However this is extremely positive for the learning because the agent learns from bad experience. In fact starting from the 6th accomplishment the system starts a positive trend that reduces the number of steps to very few steps indicating high *accomplishment rate* towards the end.
We calculated the variance σ^2 and standard deviation σ on the measure of step necessary across the $m = 10$ trials obtaining the vector

$$\sigma^2 = [\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2, \sigma_5^2, \sigma_6^2, \sigma_7^2, \sigma_8^2, \sigma_9^2, \sigma_{10}^2, \sigma_{11}^2, \sigma_{12}^2]$$

where var_i corresponds to the variance of the number of actions necessary to reach the ith goal state. We calculated $\sigma^2 = 711.65$ as the variance of the number of steps necessary to reach a generic goal state

$$\sigma^2 = \frac{\sum_{i=0}^{n} \sigma_i^2}{n}$$

We define the related standard deviation $\sigma = \sqrt{\sigma^2} = 26.67$ and using this value we added boundaries $var \pm 1stdev$. To note the extraordinary minimum in the number of actions (approximately 5 actions) which is very close to the limit.

We provide insights on the policy by presenting which action is selected in any state. The quality matrix (shaped as reported in 7.1) gives a clear view of the policy by showing the value of the quality vector associated to any state. The max value within the *quality vector* indicates the action that, according to the policy, brings the greatest reward. However, the single value of the matrix is only significative when compared with other values in the same *quality vector*. Whereas it is less

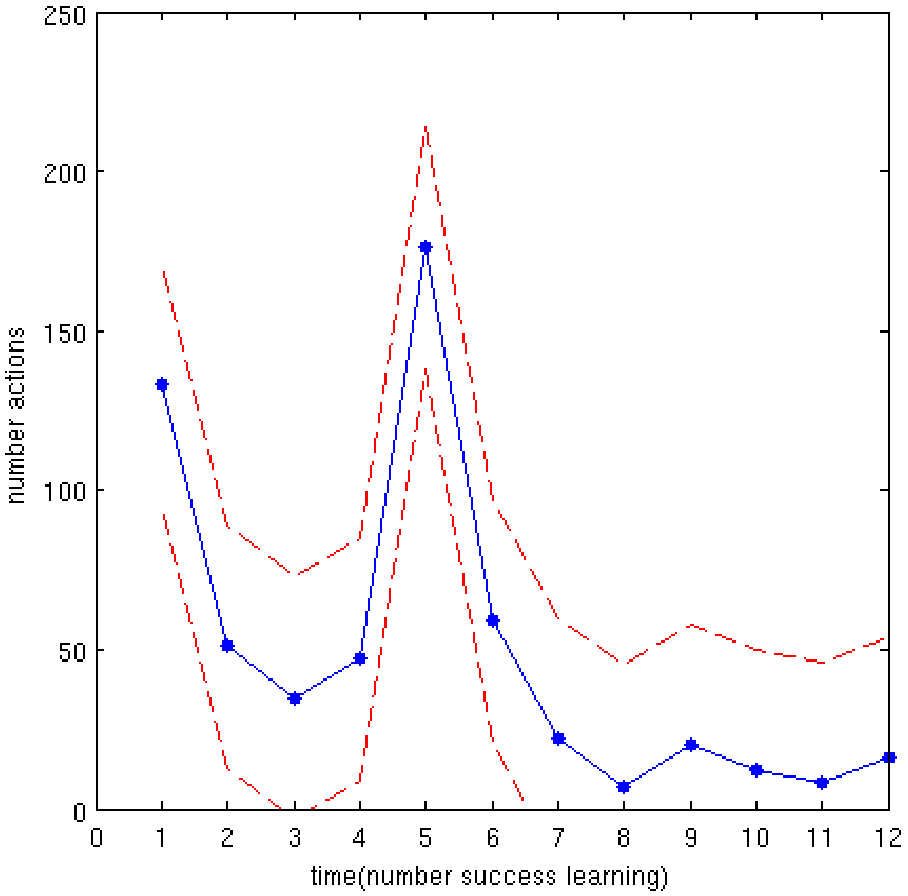


Figure 7.7: Temporal trend of the learning in ExperimentA. The number of action necessary to reach the goal state decreases in time

significative to compare the expected reward of an action in different states. Because of this, we opted for a normalization of the single values in the *quality vector*. After we determined the S_i as the sum of the quality values in a *quality vector*:

$$S_i = \sum_{j=1}^{n} q_{ij}$$

Dividing the single value in the quality vector by S_i, we obtain normalized value which is then represented in the *normalize quality matrix*.

$$\bar{q}_{ij} = q_{ij}/S_i$$

In 7.8, we show that the action that brings greater reward associated for any state is reasonably comparable to what the human counterpart chooses in similar task. In particular, if we analyze for any state the action that brings greater reward we can appreciate this similarity. For the first state, *null* state, the system opts for different actions that start the learning event. Possibly vergence can be considered as valid option for the triggering of episodic learning. Concerning the state that indicates a predition: $f$ixPred, mPred, LPred, motPred and antPred, the only state that has not null vector is the *fixPred* since all the objects never move in the scene. After a prediction of object that do not moves, the system prefers to reset (second vector in the Q matrix). It can clearly see that for the 7th state (*fixStableOk*) when the system has just performed a correct saccade to the object the selected action is *Ver*. This corresponds to affirm that the system autonomously learns that after a correct saccade to the object (driven by the eye-drive) the greater reward comes if stereopsis corrects the fixation point. On the contrary, if the saccade has not success the system resets and starts again. The other interesting aspect of the learning that appears evident in the quality matrix is the strong response for the 13th state. The agents reaches this state after a correct vergence action, in other words, the stereopsis refinement has been accomplished and the object is in the fovea for both the eyes. The system has learned to trigger a wait action that strongly stabilizes the system into the goal state *fix*. Note that if the vergence angle needs to be refined, in the 14th state, the agents opts for novel vergence angle.

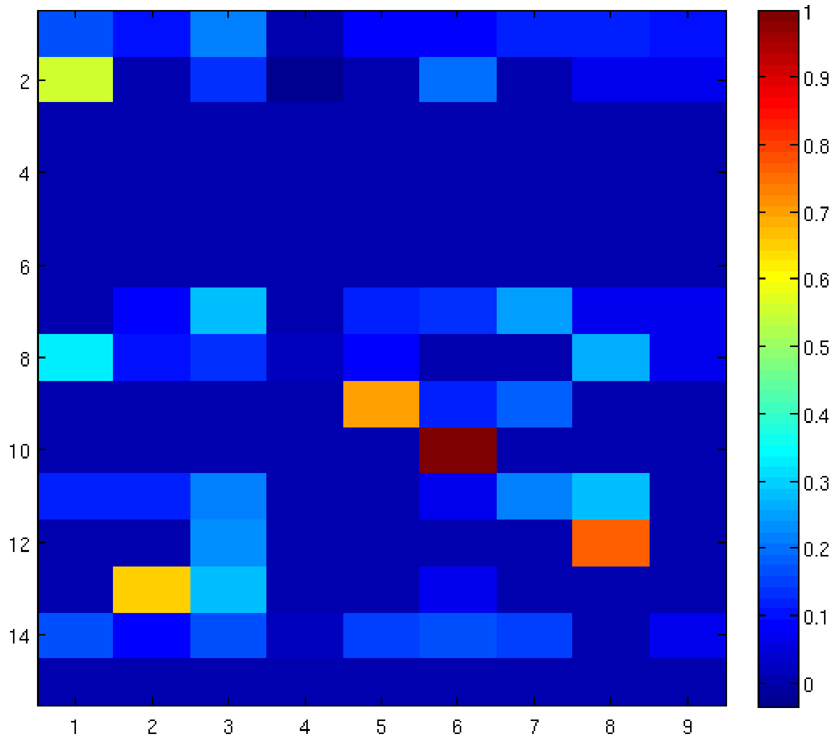


Figure 7.8: Representation of the quality matrix which gives insight on the policy learned by the system

The representation of the policy can be represented in the form of transition between state spaces 7.9.

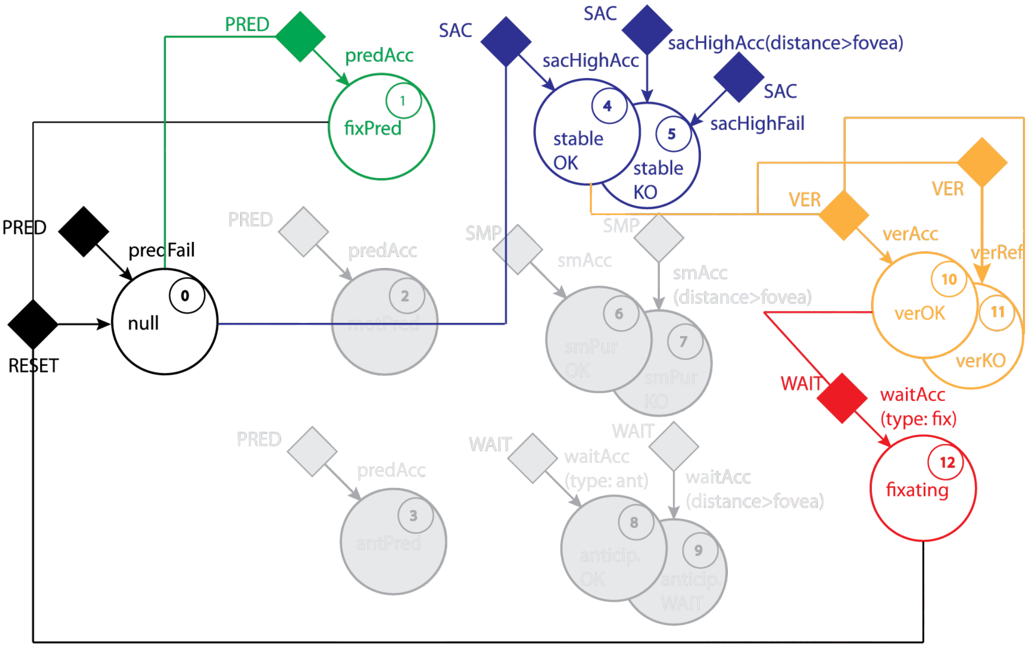


Figure 7.9: Representation of the quality matrix which gives insight on the policy learned by the system in Experiment A

7.3.2 Result of the Reinforcement Learning: Experiment B

With respect to the previous experiment we now introduce the moving stimulus. The human partner moves salient toys (two different objects that have different features) in the scene. The objects move drawing a minimum jerk trajectory since is the human counterpart that provides biological trajectory to the object. This is crucial aspect because we expect to see greater rewards in prediction with respect to the previous situation where nothing moves. Further more we expect the agent to predict only minimum jerk trajectories. The contribution of the top-down components is identical to the previous experiment 7.3.1: the task changes but the attentive bias remains constant. We present the evaluation measures for this experiment in 7.10.

In the 7.11, the reader can appreciate how sometimes the total payoff can have negative values. The reason is that, in the first part of the learning where the *babbling* is the major component, the agent can opt for wrong actions. It is not surprising that after the 2nd, the 6th, and 9th accomplishment the first action is randomly selected. When this happens the system gets negative rewards and the total payoff drops. The agent eventually finds the right sequence of actions to converge to the goal state but, bad choice at the beginning of the learning introduces side effects. The most evident side effect is that the number of actions to reach the goal increases consistently. It is clear in the same figure that learning episodes that take many actions to complete are those that start with negative rewards (3th, 7th and 10th learning episode)

Concerning the analysis of the learning rate in the experiment through out the whole learning process, we represent the number of steps necessary to reach the goal state in the first $n = 12$ learning episodes. The tendency to converge to very few actions in order to achieve the desired goal is evident in the second experiment too 7.12. However we must stress that, despite the correct trend, there are few outliers that show sometimes longer episodes. On the other hand, in this simulation we still obtain some good result, in fact there are episodes that need less that 10 actions to achieve the goal.

We analyze the quality matrix to interpret the policy mastered by the agent after its learning. From the first state -*null* state- the system similarly to the previous experiment opts for different actions. Among these actions if the action selected is a saccade the system eventually ends up in either state 7 (stable OK) or state 8 (stable KO). From the state *stable OK* with $p = 0.5$ the prediction action is selected. Differently from the previous experiment both the state 2 (*fixPred*) and state 6 (*antPred*) are states in which the system ends after prediction command. This correctly matches the constraint of this experiment where the objects move in the scene because the human partner move them in the scene. The activity in the *quality vector* of the 6th state *antPred* confirms the previous statement. The system, after a correct prediction of a minimum Jerk movement ends in the state 11 *antOK*. With a probability p=1.0 the system opts for a further prediction that might bring the system in state 11(antOK) or the state 2 (fixPred). From this state it is very likely ($p = 0.65$) that the system chooses *saccade* as best action in the situation. This brings the system in either state 6 (stable Ok) or state 7 (stable KO). In the first case, the action that is most likely to bring reward is *vergence*. Otherwise from the state 7 (stable KO) the action that better fits the situation is a RESET action. In addition, particularly interesting is that for the 13th *vergOK* and 14th *vergKO* the pattern is very similar to the previous experiment. If the system ends in *vergKO* state the action the agent performs is *VERG* action -the system tries to refine its vergence angle- whereas if the system ends in *vergOK* state the agent performs the *wait* action -which brings the system to the fix state.

In the next figure 7.14 we represent the policy as transition within state space of the agent.

7.4 Outline

In this chapter, we provide an implementation of reinforcement learning that finds nearly-optimal policies in the task of selecting the best sequence of actions that maximize the reward. The total reward comprises both the negative reward as the cost of the selected action and positive reward defined as how well the system can keep the fovea of both the eyes on the region of interest. The salient region, which can either be moving or be stable on the visual field, is previously selected by the attentive system as salient stimulus on the retina. Thus, in the proposed implementation, we provide the reward function, states and actions. The implementation is then evaluated through two experiments. The first one where all objects in the collection of objects in the working space are steady. Whereas in the second one, the objects are moved by the human counterpart with a particular biological profile in the working area. The human partner which interacts with the learning of the robot through the environment, affects the development of the system. Further more the system is not an abstract synthesized intelligence but rather embodied humanoid robot which senses and acts on the environment/world. The humanoid robot iCub is effectively interacting through the environment with the human counter-part and, as a direct consequence, the ontologenetic development shapes accordingly. The system is able to learn optimal policy in both the situations which is proved by the decreasing number of steps that the system necessitates to reach the target state. An optimal policy means that the robot decides the action that brings greater reward from any condition state. The reward is defined as the capability of the system to foveate the salient stimulus selected by the visual attention and, at the same time, to reduce the cost of the selected oculomotor actions.

If we look at the experiments we conclude that the learning exhibits wide range of different performances. These depend from very different aspects of the learning: a) the learning parameters, b) condition of the environment, c) the parameters of the attentive system. Concerning the learning parameter we identify learning rate, discount factor, rewards associated to different state-action couples and how fast migrates from random exploration of the states to the policy decision. On the other hand, the environment condition influences the performance and, in particular, lighting conditions and how the object behaves in the environment change the learning process. Finally, the parameters of the attentive system and parameters of the early perception stage influence as interface between the environment and the learning. This absolutely agrees with the idea of embodied system that learns autonomously when immersed in the environment. In order, the *environment*, the *interface* between the entity and the environment (attentive stage, early perceptual stage) and finally the *learning process* itself influence the autonomous development of cognitive systems. Similarly in humans, the learning process can change across individuals (strategy) but also the way the individual perceives the environment is subject to dissimilarities. Finally the environment strongly influences the development of an human subject Gottlieb (1991) Johnson et al. (2008) Cox (2012) Richardson (1998) Harris and Butterworth (2012) Waddington (1942). In other words, in this process we are mirroring some instances of the human development.

In addition we transfer the result of either success or insuccess to the environment. From the reward the system obtains during the learning, we hypothesize and reproduce a facial expression following the model of the limbic system in humans. The intention is to promote similar ”feeling” into the counterpart. Sharing the same feelings during a collaboration task improves the quality of the interaction enhancing the performance. The learning presented in this chapter can be considered as emulating a mechanism that living beings usually perform when learning is involved. The system acts on the environment in the first instance in pure random fashion (identically to the babbling in infants) only after it masters a policy which approximates the optimal. Through continuous real-time learning the system refines its policy which slowly tends to the optimal. If we consider the optimal solution as the solution which a human being masters having the same set of perception front-end and actions and the same environment, we can fairly assume that the robotic system, in this situation, emulates ontogenesis development. The system goes through development within its life span period in order to enhance the way it interacts with the world. What it is more crucial is that the development shares important aspects with the ontogenesis development of human kind. In author‘s opinion this is one of the key aspect that autonomous robots with ambition of epigenetic development need to possess. This is further reinforced by the conviction that this is added value to the collaboration experience. The robotic system that interacts with human performs better if its development process is similar to human development process. The first reason is that both of them tend to accomplish the same task by interpreting the reality in similar manner. If they both agree in the physical world can be interpreted they also agree in the sequence of actions to achieve the goal. The second reason is that sharing development promotes understanding of other‘s actions. This automatically facilitates the anticipation other‘s intention and results in tangible success in the assigned task.

State Code	State Name	Main characteristic	
1	null	null	Initial state with no-memory about the past
2	fixPred	stable Prediction	Prediction classified the salient stimulus as static object in the space
3	mPred	mediumPredict	Prediction classified the salient stimulus as static object in the space (medium distance)
4	Lpred	LargePredict	Prediction classified the salient stimulus as static object in the space (large distance)
5	motPred	motion Prediction	Prediction classified the salient stimulus as moving object of unknown trajectory. Final location of the object cannot be extracted
6	antPred	anticip. Prediction	Performs a smooth pursuit of the salient visual target by the mean of the estimated velocity of the stimulus
7	stableOK	stable OK	After performing saccade, the stimulus is in the line of sight of the drive eye
8	stableKO	stable KO	The saccade performed on the stimulus was unsuccessful
9	smOK	smooth-pursuit OK	Successfully tracking the stimulus
10	smKO	smooth-pursuit KO	Insuccess in tracking the stimulus
11	antOK	anticipation OK	The trajectory predicted is correct and finally the stimulus reaches the expected location
1	antWait	anticipation Wait	The expected location anticipated is not reached by the stimulus
13	verOK	vergence OK	The stimulus is at zero disparity, because the second eye converged on the stimulus.
14	verKO	vergence KO	Vergence angle must be refined because the stimulus is not at zero disparity
15	fix	fixation	After the stimulus landed at zero disparity and some time has been allowed the stimulus is considered in fixation

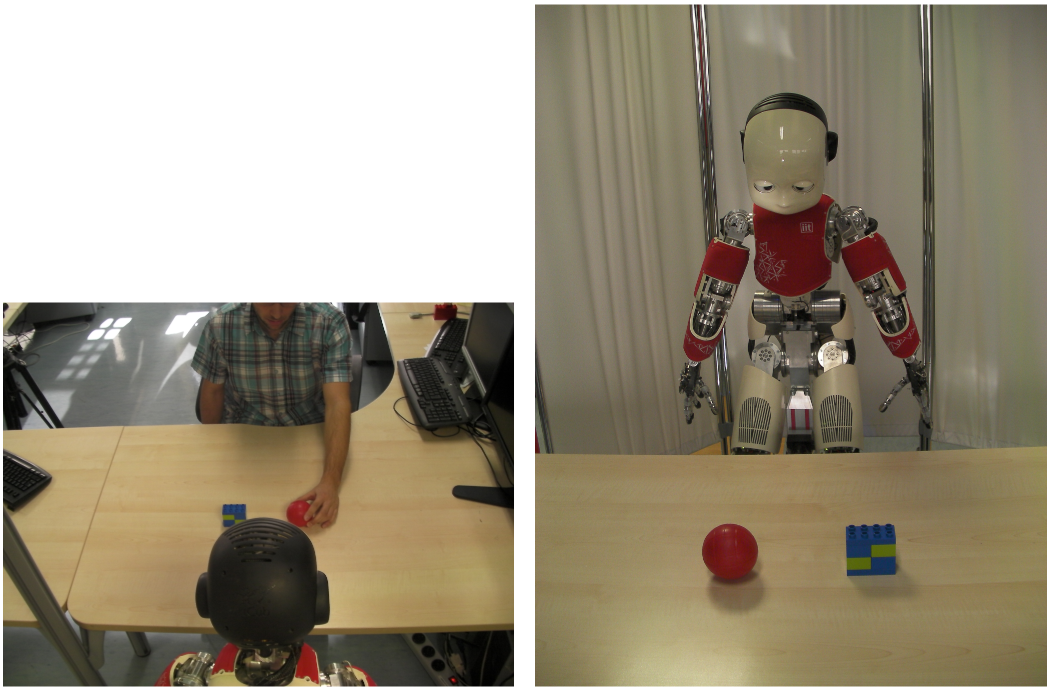
Table 7.2: State designed for the learning mechanism

Command Code	Command Name	Main characteristic	
1	predFail	prediction failed	Prediction failed in one of its steps
2	predAcc	prediction accomplished	Prediction accomplished successfully
3	sacHighAcc	high saccade accomplished	High Level Cognition Saccade accomplished successfully
4	sacHighFail	high saccade failed	High Level Cognition Saccade failed in one of its steps
5	smAcc	smooth-pursuit accomplished	Smooth-Pursuit accomplished with success
6	smFail	smooth-pursuit failed	Smooth-Pursuit failed in one of its steps
7	verAcc	vergence accomplished	Vergence accomplished : no further stereopsis correction needed. Object in fixation.
8	verRef	vergence refinement	Vergence in refinement : there is stereo disparity to compensate in order to have object in fixation
9	waitAcc	wait accomplished	Waiting process ended. No possible failure for the wait action

Table 7.3: Accomplishment commands that trigger transitions to states

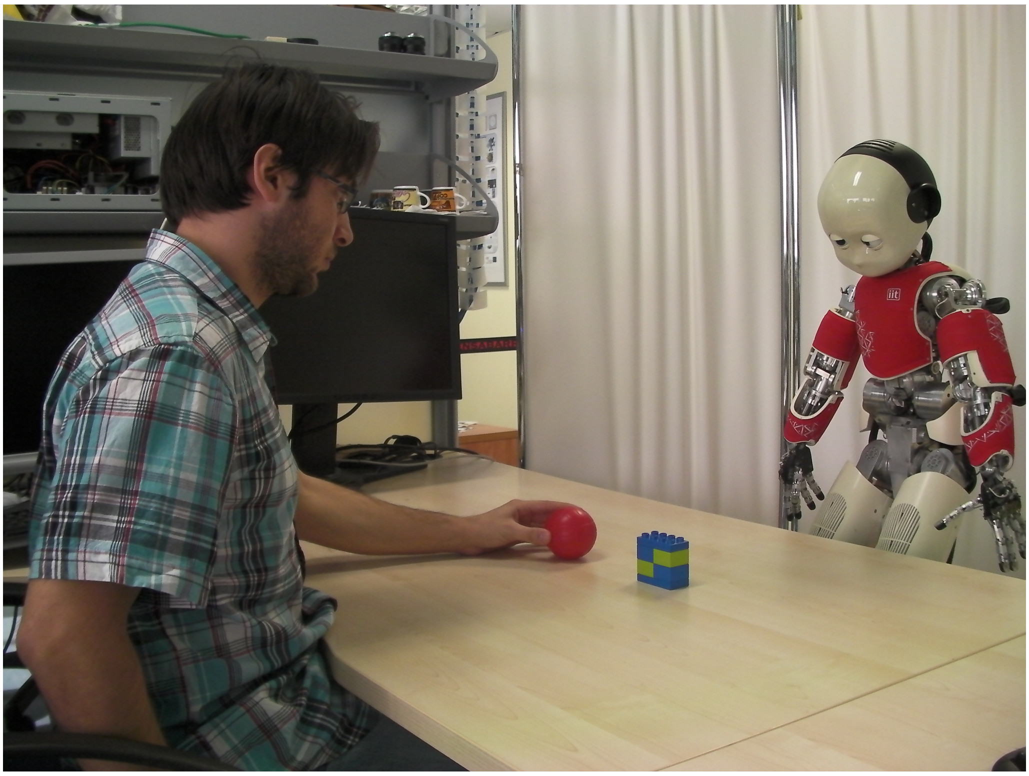
Code	Action	1	2	3	4	5	6	7	8	9
	Name	Res	Wait	Verg	smP	uSac	mSac	LSac	exSac	Pred
1	null	.	.	.	.	.	.	.	.	.
2	fixPred	.	.	.	.	.	.	.	.	.
3	mPred	.	.	.	.	.	.	.	.	.
4	LPred	.	.	.	.	.	.	.	.	.
5	motPred	.	.	.	.	.	.	.	.	.
6	antPred	.	.	.	.	.	.	.	.	.
7	stableOK	.	.	.	.	.	.	.	.	.
8	stableKO	.	.	.	.	.	.	.	.	.
9	smOK	.	.	.	.	.	.	.	.	.
10	smKO	.	.	.	.	.	.	.	.	.
11	antOK	.	.	.	.	.	.	.	.	.
12	antWait	.	.	.	.	.	.	.	.	.
13	verOK	.	.	.	.	.	.	.	.	.
14	verKO	.	.	.	.	.	.	.	.	.
15	fix	.	.	.	.	.	.	.	.	.

Table 7.4: Representation of the state-action combination in the normalized quality matrix



(a) View of the scene from behind the robot

(b) View of the scene from human partner‘s point of view



(c) Side view of the scene during learning

Figure 7.10: Learning of the situation where human partner interacts with the robot

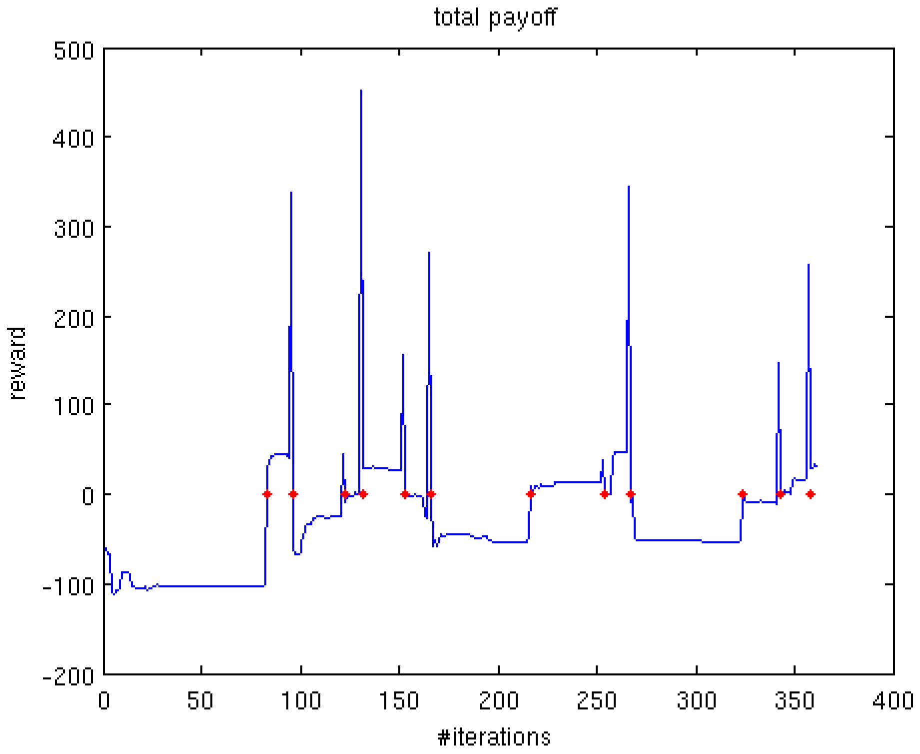


Figure 7.11: temporal representation of the total payoff

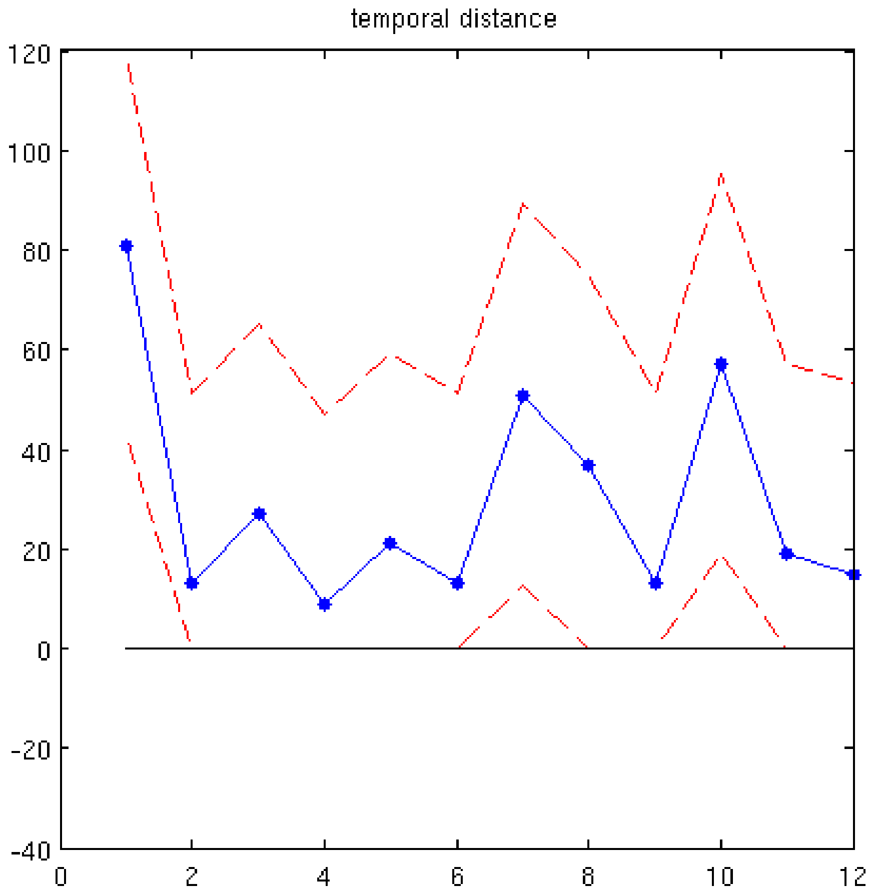


Figure 7.12: temporal decrement of the actions necessary to reach the goal state

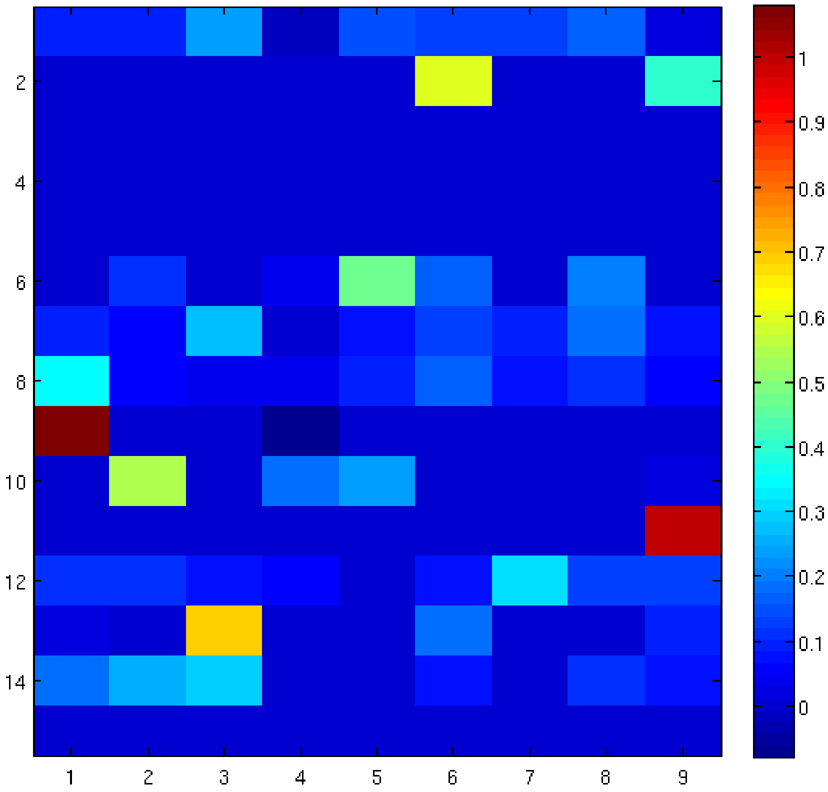


Figure 7.13: Value of the quality matrix that indicates the policy learned autonomously by the agent

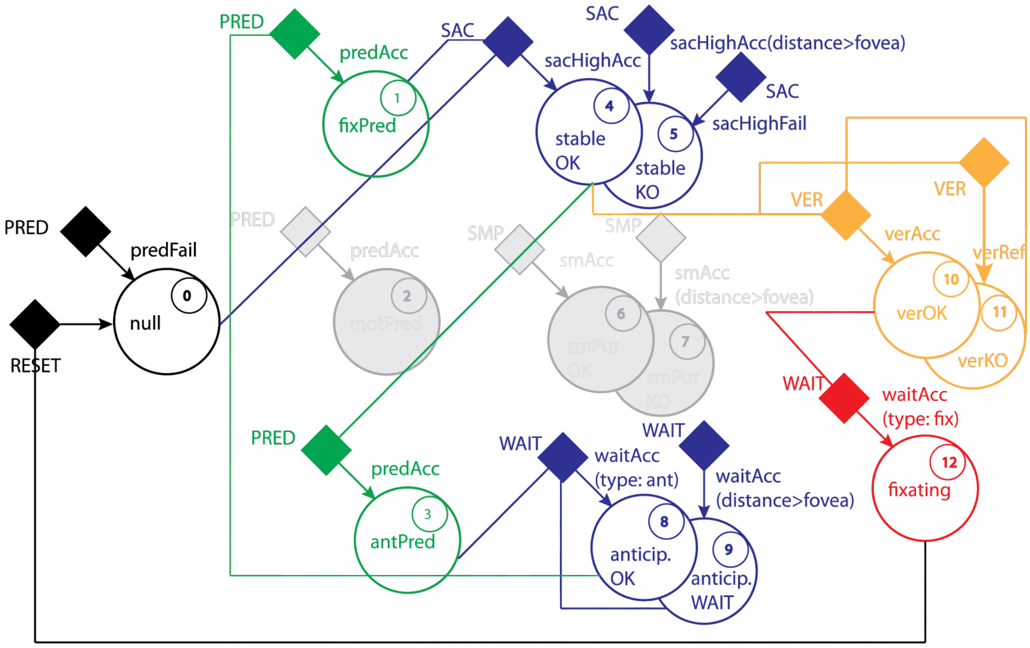


Figure 7.14: Representation of the quality matrix which gives insight on the policy learned by the system in Experiment B

CONCLUSIONS 8

He who is unable to live in society, or who has no need because he is sufficient for himself, must be either a beast or a god.
Socrates

Social evolution is a resultant of the interaction of two wholly distinct factors: the individual, deriving his peculiar gifts from the play of psychological and infra-social forces; and, second, the social environment, with its power of adopting or rejecting both him and his gifts.
William James

8.1 Introduction

In the challenging and inspiring quest presented, we propose an attempt of journey from the early stage of perception to theories that bring intelligence in the behavior of embodied agent. These concepts do not remain abstract but rather grounded on the humanoid robot iCub give concrete examples on how these become effective.

From the first perception stage that resembles the behavior of lateral geniculate nucleus to unsupervised learning mechanism, we opt to provide implementations inspired by biological models. From one hand we decide for an immediate implementation of models which are the result of years of evolution, understanding how those models work and why they represent actual stage in phylogenetic development. On the other hand, we concentrate on models of development that occur in relatively short period of life of a single individual.

In author‘s opinion, both approaches are equally promising and must coexist if we want one day to achieve the goal of creating a community of robots that really helps humans in their lives. It is not enough to merely move robots from laboratories to the human communities because it may result in situations where robots can only appear as superfluous treat to the community. We rather need to push for efficient collaboration between humans and robots which is, in author‘s opinion, unavoidable step in this endeavor. A collaboration where the human partner does not feel the load of the interaction with a undeveloped presence but rather perceives the collaboration as finalized to goal and facilitated by intelligent counterpart.

To obtain this the robotic partner must exhibit intelligence, which means a collection of skills harmoniously combined together to exhibit behaviors that look smart, and this intelligence commensurate to the human appearance. If we focus on the concept of intelligence within the task of human-robot collaboration we first need to analyze the structures involved in the interaction. The collaboration takes place at different domains. The first is the *environment* which is shared resource between the partners. For example objects in the environment are resources on which the intention becomes interaction. However the action on the common resources must appear intelligent and different actions give different feelings during the interaction. It is not enough to hard code instructions in the robot. This helps in accomplishing tasks but does not give feeling of smart partnership. The robotic arm that rotates the car chassis in conveyor-belt assembly lines and in factories can hardly be categorized as intelligence presence. On the contrary smart robots need to interpret, predict and react. These are cognitive mechanisms easily interpretable by human counterpart. That richness of smart behaviors might be achieved only if the robots share the similar development with humans. *Developement* domain is considered the second domain where interaction can be shaped. If two agents share the same development can easily mix actions to achieve common goal and further more one can interpret other‘s actions.

After we defined two domains where the interaction boost we would point out a third space that similarly brings success in the task. A further contribute to the interaction is given by the *empathic* domain where the human interprets the partner action by projecting feelings on it and where the robot improves the interaction outing its how internal condition by the mean of feelings and interpreting other‘s feelings.

Looking at these concepts together the goal is to define *social intelligence* that is one of the most crucial drive for absolute intelligence. Further more, from these perspectives, the author considers even more important the contribute that epigenetic robotics might give to the robotic panorama. The improving of the cognitive skills of the humanoid robot iCub can only step through epigenetic development.

8.2 Active Vision: from the Perception to Action

The models that contribute in the mastering active vision in the humanoid robot iCub are implemented keeping constantly in mind the recent discoveries in the field. In the last decade many researches provided evidences that probably the perception and action path in the cortex are not completely separated. On the contrary it seems that integration is distributed across different space maps.

We provide model at different complexity stages of perception and introduce different levels of integration between models. Further more we design models of oculomotor actions that interact with perception models at different stages. With an high degree of modularity, integrability we assure novel and proficuous interactions between components. We believe that this is the purest form of emulation of cognitive mechanisms of living beings.

We introduce visual information in the system through the mean of log-polar mapping which resembles the distribution of the photoreceptors in the retina. From there the information flows to the early stage of filtering. The stage comprises different filters that extract features from the scene. The extracted information reduced in dimensionality with respect to the original information is always enriched with meaning. By merging information from different filters we model further complex stages. The information after this stage gives topographic information on the location of relevant complex features (e.g: proto-objects). Any of these filtering stages present a well-defined model that we implement on the platform iCub which is inspired by real biological mechanism in living beings. This corresponds to introducing in the system model which are results of phylogenetic development or evolution.

The output of any stage of filtering is a topographic map which defines the position of the conspicuous stimuli in the field of view. The generated map competes in order to define a single saliency map. This mechanism occurs in the selective attention component of the system and it is inspired by the Itti & Koch model of *selective attention*. This is a biological plausible model of saliency-based of focal bottom-up attention. According to this model, the location where the focus of attention is deployed corresponds to the location that wins in the competition within the saliency map (winner-take-all). Further more, knowing that, we define an attention shift which is the novel deployment of the focus of attention somewhere else in the space. Most of the time, to an attention shift corresponds an eye movement, and this is a valid assumption for our framework too. We use the output of the attention system to control oculomotor action controller and redeploy the fixation point.

However we do not only limit the work done on the attentive system to the mere bottom-up component but we propose one possible technique that introduces top-down contribution in the system. We believe that pure bottom-up attention can hardly provide stable enough focus shifts that guarantee winning strategies in real world (usually cluttered environment where the goal of the task is provided by the human partner). The top-down contribution is based on valid although simple mechanism: the feedback. The top-down components knows the goal and then is aware of the

characteristic of the target. It refines the parameters of the bottom-up component in order to promote the response of the objects that match characteristic of the target.
We exploit the models of the premotor cortex that relate attentive system to the actions. In particular, we introduce biological plausible behaviors that emulate the ocular movements of major interest for the robotic community: saccades, vergence control, smooth pursuit. Concerning saccades we further enrich the collection with some specific actions: microsaccades, express saccades. For any of these models of control we take inspiration from the true model of eye movement in humans. That is, for example concerning accurate saccades we refine the model with dedicated post-saccadic corrections and for vergence we introduce vergence correction based on disparity measure. Additional actions such as prediction and wait action result important in the task presented in this thesis. In the next section, we stress the importance of these actions in the panorama of human-robot interaction.

Once we master these essential components, we obtain a dynamic system that perceives the resource in the environment (e.g.: target object) and correctly act on them. As reported in the related chapter we assume that the synthetic system owns enough capabilities in order to interact with the human counterpart. However another important aspect must intrigue in the analysis of the interaction between the human and robot. In many -although inspiring- works, usually presented as the state of the art in literature, prediction is not considered at all. In author‘s opinion, considering prediction as a tool of minor importance is a naive assumption. On the contrary we think that prediction is absolutely critical aspect that influences *human-robot interaction*.
In general, prediction guarantees decrement in the energy consumption in a typical task of human-robot collaboration. This is due to the fact that one can understand in advance the intention of the partner. If we project this concept to the situation where the human partner moves its hand toward an object, for example, it appears evident how the predict facilitates the mentioned task. The prediction guarantees an understanding of the relation cause-effect in act and this triggers positive anticipatory counter-actions. For instance, in the previous situation the robot agent can understand where the hand is going to end, relate the movement to its goal (which corresponds to defining the action), and act consequently. Usually the action is, in the simplest case, an anticipatory saccadic movement to the target but the potentialities of reading the target ”before hand” are vast. All these rich collections of reactions have all the benefit to improve the quality of the interaction.
We present a technique for prediction associated to some different typologies of movements: constant velocity, constant acceleration and minimum-jerk movement prediction. The prediction system is based on the concept of bank of predictors that analyzes concurrently the measurement of the first part of the movement. The predictors fairly compete in providing the most accurate prediction. The one that scores better in predicting the movement wins and defines in advance the target. The mechanism, as we proved, can be considered winning strategy when a saccade in the predicted location approximately locates the object of the movement in fovea. The *prediction* action is now listed in the collection of successful actions that the humanoid robot iCub can efficiently perform.

Other actions, such as *wait action*, were introduced in the system. In particular, the wait action is crucial task that synchronizes contribution in the environment between the robot agent and the human partner. The synchronization between actors of the interaction is one of the fundamental arguments that favorite the positive accomplishment of the collaboration.

These are all actions that allow the system to interact with the shared resources in the environment. This stage is crucial for the proficuous interaction between humans and robots. However it cannot be the absolute unique mechanism. We need to address other two domains where the interaction benefits: the development and empathy domain.

8.3 Human-Robot Interaction : Sharing Resources, Sharing Development and Sharing Feelings

Changes in the environment correspond to modifications to the shared resources between subjects that collaborate. Those changes are sensed by the mean of existing model of perception and attention. All the processes presented in the previous paragraphs interpret models that are result of evolution. As so, these models are components of phylogenesis that we introduce in the system. However to address completely new challenges in epigenetic robotics, the ontogenesis component must equally be part of the system. Reproducing biological models on the synthesized humanoid is time consuming task. The model has to be studied in human first and then correctly implemented on the robotics system. We aim at introducing development in the robot in order to save time necessary to create a new model. There are two considerations that we need to point out. First, if the ontogenetic development builds on top of biological model we can presumably assume that final result similarly respects biological rules. Second, we want the ontogenetic development to share similarities with the human development. In our opinion, this is crucial to favorite complete understanding of the action performed by the robot and viceversa.

In the next paragraph we further analyze the ontogenetic development within the concept of epigenetic robotics. Here we proceed with some consideration on the third domain of interaction: empathy domain. As in the previous domains we called for a proficuous sharing of resources and development here we point out that sharing feelings enhances the quality of the of the interaction. Empathy is defined as the ability of intelligent subjects of mirroring other‘s feeling and participate to the interaction with a similar set of feelings. In our experience this is a valid tool that enhances the quality of the interaction. Unfortunately at the current state of the art of the implementation on the humanoid robot iCub, there is no interpretation of the human‘s feeling. However the interpretation can take place in the opposite direction. We noticed that feelings transfer to the human partners when the robot reproduces basic facial expressions. The facial expression that we introduce are associated to the success of the reinforcement mechanism. These facial expressions give immediate indication of which state the system is in and at the same time are mapped into similar feelings in humans. We claim that when feelings of both the parts match, this absolutely and immediately enhances the quality of the interaction.

8.4 Epigenetic robotics toward Theory of Social Intelligence

Concerning the development in epigenetic robotics, we introduce semi-supervised learning in the system in the form that better reproduces biological mechanisms: *reinforcement learning*. In the task of reinforcement learning we create a mechanism where the robotic system decides which action to take in the world by looking at the generated expected reward. The expected reward for any action is a speculation on the world that the system builds through real-time ontogenetic process. The robotic agent exploits the world, first in a pure random way (*babbling*), later by using a policy autonomously mastered and frequently revisited. Finally it builds its own view of the dynamics of the world. Our approach is clearly defined up on the idea that robots must evolve following their own autonomous dynamics which are only initialized as biological models.

We demonstrated that the robot can choose the action that better fits the situation. This is the action that, at the same time, brings the maximum reward and corresponds to what a human agent selects in the same situation. The final result is a behavior which appears biologically correct which means that the human counterpart can easily and correctly interpret. We consider this the key aspect of the research. If the humanoid robot goes under the same developmental processes, it masters behaviors which are similar to human‘s behaviors and so they trigger the same neural response in the human. The same set of mirror neurons are proved to be active both when subject performs one action and when sees someone else to perform the same action. The activation of these areas helps in interpreting the action and therefore by reproducing the same actions the robot, although inanimate subject, can activate similar brain areas. The only constrain is that the robotic system has to perform actions that have identical features and this can only be achieved if those actions are the result of similar development.

The mechanism, that have already been proved to be winning strategy, can be further scaled up and adopted for other aspects of epigenetic development.

Looking at all the processes that we implemented on the robot and considering the effort in making them smoothly work together, we are convinced that this is the correct roadmap to obtain intelligent behaviors in synthesized collaborators. That is, intelligent behavior evolves tightly with social intelligence which makes machines able to interact in a social context. The social drive is profoundly embedded in the system and strongly influences the ontogenesis development. This is evident when prediction of the other partner influences the reinforcement learning procedure. In fact, it is proved that the absence of prediction can only reduce the performance of the system creating a different policy. We interpret the different policy as different action profile which is caused by the absence of correct prediction of the other‘s action. On the contrary the interpretation of other‘s intention is a powerful social drive that improves the learning process. The direct consequence of such improvement is evident in how the robot intends to act.

8.5 Conclusion

Epigenetic robots that learn by using social drive to improve their knowledge of the word is basically the direction that we intend to take in order to master effective active vision in human-robot collaboration. We present some models that follow this idea and we prove that the approach works in a clustered everyday environment for a complex humanoid robot. The humanoid robot iCub is dedicated platform for research but the concept that we present are fundamentally applicable for any synthesized machine. Therefore this confirms that epigenetic robotics can really promote the breakthrough that we need in order to free the robots from the laboratories and allow them in the community. It is the desire to socially interact that pushes the robot to rapidly learn and the evolution goes in the direction of immediate and tangible social valid results. The goal have direct validation in the social context and it directly enhances the counterpart‘s feeling of being understood. The feeling of being understood have a big impact in the quality of the collaboration.

Finally, from the point of view of the community, the effectiveness of the collaboration can encourage the diffusion of the robots in every place where humans need aid. This can absolutely introduce all of us in the era where humans really improves their lives by introducing robots in every day lives. The chimera of a robot companion is not longer a chimera but it is going to be socially acceptable.

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