DESIGN AND INTEGRATION OF AGENT-BASED PARTIAL BRAIN MODELS FOR ROBOTIC SYSTEMS BY MEANS OF HIERARCHICAL COOPERATIVE COEVOLUTION

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A thesis submitted in partial fulfillment
of the requirements for the degree of
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Doctoral Committee

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I would like to finish with a couple of lyrics that have been very influential to me during all these years, and I think they sufficiently describe my point of view on the present work (I have to translate them in English):

“ ... its not an issue to be me above you or you above me,
what really the issue is for us, is to be above ourselves”

They are coming from a poem of Giannis Ritsos, being orchestrated by Christos Leontis, at 1975. The same year, Nikos Xilouris sang the respective song, included in his album Kapnismeno Tsoukali.

Abstract

The current work addresses the development of cognitive abilities in artificial organisms, a topic that has attracted many research efforts recently. We introduce a novel computational framework for modelling partial brain areas, following a co-evolutionary agent-based approach. Specifically, self-organized agent structures are employed to represent distinct brain areas. In order to facilitate the design of agents, we introduce a Hierarchical Collaborative CoEvolutionary (HCCE) approach that specifies the structural details of autonomous, but cooperating system components. By utilizing a distributed model and a distributed design methodology, we are able to explicitly address the special characteristics of substructures representing brain areas, and additionally integrate them effectively formulating composite systems.

Overall, the proposed computational framework facilitates the design of brain-inspired cognitive systems because it:

- assigns distinct roles to the agents representing brain-areas,
- supports computational modelling of biological lesion findings, addressing explicitly the pre- and post- lesion performance of the model,
- alleviates the integration of partial models developing gradually more complex ones,
- re-designs (if necessary) existing substructures in order to support forthcoming modelling efforts.

The effectiveness of the proposed computational framework is demonstrated on a number of different experiments. The implemented models are successfully embedded in a simulated robotic platform, developing artificial organisms with advanced behavioral and cognitive abilities.

Chapter 1

Introduction

This thesis addresses the development of a consistent methodology to support the design of artificial cognitive systems, which are inspired by the mammalian central nervous system. In this introductory chapter, we define the problem, indicate its scientific and practical significance and outline the thesis structure.

1.1 Problem Statement

The wide progress of technology during recent years, allowed man to develop many products that would seem infeasible only a few decades ago. At the same time, advances in many scientific domains gave rise to research achievements that in some cases reproduce or even by-pass nature. Thus, many challenging long-term goals are currently worked out (e.g. cloning, Mars colonization).

In the field of computer technology, the goal of developing artificial systems with human competitive cognitive abilities, belongs to the most widely discussed issues. Many different approaches (Mathematical Logic, Artificial Intelligence, Cybernetics, etc.) pledged to turn the vision into reality. The common characteristic of these conventional approaches is that the implemented system usually is based on human specified, build-in knowledge. Specifically, well known rules of human-like activities are interpreted computationally to solve effectively predefined problems. As a result, existing systems employ man-manufactured intelligent mechanisms in order to accomplish their goals.

Until recently, the need for intelligent computational systems seemed to have been successfully met by these methods. This is because intelligence needed to be exhibited only internally in the system. The majority of computer applications performed on their own synthetic world, which has been manufactured and properly constrained by the human factor. For example, in the field of computer networks or information systems technology, daily data are filtered by human engineers in order to meet the needs of the system, and additionally they are structured in the proper form to be ready for future "intelligent" usage. Thus, the artificial system does not actually come in contact with the real world, since men always mediated, to transform a snapshot of the real environment to a snapshot of the synthetic environment.

Contrary to the above, the rapid development of robotics over the last years, forced artificial systems to come in contact with the real unstructured world. The new kind of problems that artificial systems need to address, is neither constrained nor well structured. Furthermore, it is impossible for the human factor to transform every snapshot of the environment in a synthetic image to be handled efficiently by the artificial system, and additionally it is impossible to predict all environmental circumstances when the robot operates in the dynamic human world.

A large number of experiments investigating robot performance in everyday human environments revealed the limits of existing approaches. It has been shown that traditional computational approaches are often faced with limitations when approaching real life problems. As a point of reference, robot performance is often compared to the respective abilities of biological organisms, which operate autonomously in the well known daily environments. This comparison helped researchers realize that, despite the increased efforts to furnish machines with intelligent competencies, robotic cognitive abilities are very primitive, at least compared to the corresponding capabilities of mammals. This is because the human designed intelligent systems, are based on different principles than those offered by nature to biological organisms.

The substantial introduction of robots in everyday human environments increased the demands for systems with effective cognitive abilities, that are able to coexist and cooperate seamlessly with people. The advent of robotics in recent years made the old *dream* of artificial systems with cognitive skills a *need* in recent days. In the new formulation of artificial intelligence problems, robots have to develop cognitive abilities related to the continuously coming unstructured data of the real world, and exhibit intelligent performance similar to man or other mammals by handling efficiently a variety of unknown and unpredicted circumstances.

In order to approach this new type of problems, nature is utilized as a source of inspiration providing alternative approaches to develop intelligent artificial systems. Along this line, a large field of robotic research has recently shifted emphasis on the investigation of biological cognitive mechanisms as a means to develop robots with advanced cognitive skills. Specifically, the mechanisms that guide the development of cognitive competencies of biological organisms are interpreted computationally in order to advance the mental abilities of artifacts. Following this approach, biological organisms are utilized as prototype structures, providing inspiration for the development of robots with advanced cognitive skills.

Even if the biological prototype should not be considered as a panacea to approach robotic problems, it is clearly one of the most advanced information processing systems existing today. Consequently, there is much to gain from understanding its functioning, and extracting principles for the development of robots. Since mammals constitute the category of biological organisms that exhibit the highest level of intelligence, they could be used as an excellent prototype for the development of machines with advanced cognitive and behavioral abilities.

In order to have a better understanding of the behavior of animals it is necessary to appreciate how their Central Nervous System (CNS) is functionally and anatomically organized. One of the cornerstones in brain research area, is that the mammalian central nervous system consists of several interconnected modules (brain-areas) with different functionalities. A lot of research is recently oriented in determining how the information flows within modules, what kind of information is processed in each area of the CNS, and how these parts cooperate in order to accomplish real world tasks. These efforts are often supported by computational models which test existing hypotheses regarding brain functionality. In this endeavor, real-time environmental interaction is of utmost importance, because it is difficult to investigate the mammalian brain without embedding the models into a body to interact with its environment. Therefore, robotics and brain science can support each other in the development of successful artificial brain models.

Over the last decades, a wide variety of computational models have been implemented, mimicking successfully certain aspects of brain operation. However, during the implementation of the models, partial structures of the mammalian CNS are often considered as isolated modules whose properties are investigated from a limited and local point of view. As a result, each approach follows a different level of description and explanation, based on different working assumptions. Unfortunately, existing models seem to form a heterogeneous collection, where computational differences among them constitute their integration very difficult.

In order to develop large scale models of biological cognitive mechanisms, new research efforts should be directed in investigating the connectivity of brain substructures. This is because the consideration of information exchange among brain substructures shapes a solid research base that will enforce the consideration of partial models under a common and unified research framework. As a result, strong simplifications and harmful assumptions will be avoided during the design of the system components. Furthermore, a new computational methodology should be formulated that will highlight the *process* of developing the global model, rather than the intermediate partial results. The components of the overall system should be tested on complex operating scenarios, considering an extended set of the interactions among partial areas.

Evidently, the successful development of brain-like computational models is of great importance for the advancement of robotic research because it will alleviate furnishing robots with intelligent competencies similar to those of mammals. This thesis introduces a computational framework to support these modelling efforts. Instead of emphasizing on the computational details of the result, the present study aims at formulating a new methodology which supports the design procedure by means of iterative systematic steps. Specifically, the proposed approach shifts emphasis from the *"final model"*, to the *"process to the model"* by means of two main guidelines. First, it follows a distributed modelling approach in order to facilitate replication of the prototype modular CNS architecture. Second, it introduces a distributed optimization method, which is able to design effectively the components of the composite artificial system. Overall, the proposed methodology facilitates both the independence and the co-operability of partial system components addressing the biologically inspired characteristics of the solution in both a partial and a global system level.

1.2 Scientific Interest

The adoption of biological inspiration is currently one of the most widely accepted approaches in modern robotics. However, this approach can not guarantee to provide solutions to the difficult and long lasting problems of the area. As a result, a consistent computational framework is necessary to study brain-inspired artificial cognitive mechanisms, and the extent that biological principles are necessary to design robots with intelligent competencies. In other words, systematic efforts of the bio-inspired research agenda should be directed in investigating what kind of problems are more easily solved by adopting this approach, and which of them are made more difficult. As a result, a consistent methodology to replicate computationally specific aspects of brain performance, will be very important for an advanced and successful new generation of robots.

A consistent methodology to investigate the development of brain-like computational cognitive mechanisms may also support research efforts in the field of psychology and neuroscience. The implemented models could be utilized to make predictions regarding the activation of the central nervous system of animals. Moreover, the embodiment of the computational model could reveal important aspects of brain functionality. This is because it is difficult to investigate the mammalian brain without embedding the models into a body to interact with its environment. Consequently, robots could be useful in exploring several hypotheses regarding the behavior of animals which is considered to be the result of environment-body-brain interaction.

Additionally, biologically inspired robotic cognitive systems can serve as a means for the evaluation of existing brain function theories, regarding their sufficiency to explain real-life data. Specifically, during the process of modelling biological mechanisms, connections and gaps among existing theories may be revealed, that otherwise would have been overlooked. The adoption of a common solid base to investigate partial brain modules, may provide a global viewpoint in theoretical and computational studies, which will facilitate the integration of existing theories in new ones, with advanced features in terms of completeness and reliability.

The exchange of information among different scientific areas may develop new ideas that will trigger their successive advancement over time. For example, by adopting a methodology to develop brain-like artificial systems it will be possible to implement computational models of the central nervous system of different mammalian species highlighting their distinct functional and anatomical characteristics. The implemented models can be further employed to study phylogenetic evolution of species and the distinct specialization of the brain among them. Additionally, they can be utilized to formulate new experiments revealing the particular behavioral characteristics of each species. Then, the new findings will provide feedback to robotic researchers that will gain a clear understanding of the mechanisms they should provide to artifacts in order to meet particular objectives on their performance.

1.3 Practical Interest

Today, it can be claimed that robotics has reached a point that the basic task of controlling successfully partial robot elements and performing simple basic tasks has been almost achieved. Existing robotic competencies have been employed successfully in industry to improve the quality and quantity of production. The next step for robotics is to overcome the limitations of industrial applications which lack self-motivated performance, and start operating autonomously in human environments, faced with real world problems. The challenge for future applications concerns the development of artificial systems whose cognitive abilities will match the respective abilities of mammals. Thus, the implementation of methodologies that support the design of biologically inspired artificial brains will have a significant impact to attain this challenge.

The effective investigation and systematic mimicking of biological cognitive mechanisms will enable the enrichment of artificial creatures with novel features, such as consciousness or emotions, which are currently found only in biological organisms. These features will significantly facilitate human interaction with artifacts. For example, intelligent homes or cars could be implemented that mature accordingly in order to meet the needs of their owners. By bringing the operation of artificial creatures closer to that of biological organisms, well known natural rules can be directly utilized to alleviate their coexistence and cooperation. As a result, new and complex products can be seamlessly integrated in the human everyday life.

Moreover, the replication of biological brain functionality in a certain approximation level, could by used to investigate new techniques to approach specific aspects of the life of biological organisms (e.g. new training approaches can be designed to facilitate the educational process). The same computational models can also be employed to explore various aspects of human life in order to design changes on social structure that will improve daily-round quality. For example, massive behaviors of human communities could be reliably simulated in order to support the decisions of civic authorities or even governments.

Additionally, the methodology to replicate successfully brain performance could be employed to renew and potentially advance the experimental processes followed in brain sciences. Specifically, the modelling process can be adjusted in different ways each time, highlighting the details which are of greater interest to a particular brain investigation study. Then experiments can be performed on the model, to test certain hypotheses regarding brain functioning. For example, it will be possible to simulate drug or lesion effects in the brain, eliminating the need to perform experiments with animals or humans. Finally, in the long term, when sufficiently detailed and reliable models will have been implemented, biological brain areas with improper performance may even be substituted by artificial modules which will perform in a desirable, normal way.

1.4 Proposed Approach

The present thesis introduces a *methodology* to design brain-inspired artificial cognitive mechanisms. Specifically, the methodology addresses the architecture of the prototype biological central nervous system, that consists of many partial areas with distinct functionalities. Along this line, a distributed modelling framework is proposed, that is able to highlight both the independent and cooperative characteristics of brain areas.

The proposed methodology employs a distributed computational structure to develop the artificial cognitive system. Similar to partial brain areas, each module of the system is represented by an agent structure, that emphasizes its autonomy and special features. Hence, the composite model consists of a collection of primitive components, each one assigned the functionality of a mammalian brain area. Following the argument that mammalian cognition is epigenetically specified by subjective experience, agents are properly designed to develop the desired functionality after a certain amount of environmental interaction.

An automated design mechanism is employed to specify the structure of agents, enforcing the similarity of the model with the biological prototype. The mechanism is similar to the phylogenetic evolution of biological organisms. In particular, the structure of agents is specified by a computational evolutionary process. Instead of using a unimodal evolutionary approach, we employ a cooperative coevolutionary method which offers enhanced search abilities of partial modules. This is because the coevolutionary mechanism also follows a distributed architecture that matches the distributed computational model. In the present study, we introduce a novel Hierarchical Cooperative CoEvolutionary (HCCE) scheme which supports the coevolution of a large number of system components, each one guided by separate design criteria. Thus, both the individual and combined characteristics of the agents formulating the cognitive system can be adequately addressed.

Following the proposed computational framework, the implementation of the brain-like cognitive system is considerably simplified. This is because the distributed computational structure facilitates the decomposition of the modelling process to small tractable tasks. At the same time, the distributed coevolutionary design mechanism is able to solve efficiently partial tasks and it is further able to integrate system components in order to formulate complex computational structures.

The proposed computational framework is able to enforce the brain-like characteristics of the artificial cognitive system. This is because the coevolutionary mechanism provides a systematic way to furnish model components with the desired characteristics. Furthermore, the autonomy of partial system components facilitates their partial elimination simulating the conditions of biological lesion experiments. As a result, the pre- and post- lesion performance of the model can be considered by the HCCE design procedure. Following this approach, brain lesion results can be adequately replicated enforcing the functional similarity of the model to the biological prototype. By employing computational models with brain-like characteristics, we aim at the construction of artificial systems able to develop mammal-like cognitive skills.

1.4.1 Contributions

The present study investigates issues pertaining to different research areas ranging from robotics to computational cognitive neuroscience and also from agent technology to coevolutionary methods, contributing novel ideas to approach and integrate them in a common computational framework. Specifically, the present work introduces:

- the agent-based modelling of brain-inspired artificial cognitive systems,

- a cooperative coevolutionary method to design simple agent structures emphasizing their integration in composite systems,
- a novel Hierarchical Cooperative CoEvolutionary (HCCE) scheme which supports the agent based modelling of biologically inspired artificial cognitive systems.
- the consideration of phylogenetic - epigenetic interaction, as a means to investigate and design brain-like computational systems,
- a systematic methodology to replicate computationally biological findings in order to furnish artifacts with enhanced mammal-like cognitive and behavioral capabilities.

1.4.2 Publications

Parts of the work presented in this thesis have been already submitted for publication or published in international scientific journals and conference proceedings as follows:

Journals

- M. Maniadakis, P. E. Trahanias, *Hierarchical CoEvolution of Cooperating Agents Acting in the Brain-Arena*, submitted to Adaptive Behavior journal, MIT Press.
- M. Maniadakis, P. E. Trahanias, *Agent-based Brain Modelling for Artificial Organisms by means of Hierarchical Collaborative CoEvolution*, submitted to Artificial Life journal, MIT Press.
- M. Maniadakis, P. E. Trahanias, *Modelling brain emergent behaviours through coevolution of neural agents*, accepted for publication, Neural Networks journal, in print.

Conferences

- M. Maniadakis, P. E. Trahanias, *Hierarchical Cooperative CoEvolution Facilitates the Redesign of Agent-based Systems*, to appear in the 9th International Conference on the Simulation of Adaptive Behavior (SAB'06).

- M. Maniadakis, P. E. Trahanias, *Design and Integration of Partial Brain Models Using Hierarchical Cooperative CoEvolution*, in Proc. International Conference on Cognitive Modelling (ICCM-2006), pp. 196-201, 2006.

- M. Maniadakis, P. E. Trahanias, *Modelling Robotic Cognitive Mechanisms by Hierarchical Cooperative CoEvolution*, in Proc. 4th Hellenic Conference on Artificial Intelligence, (SETN-2006), pp. 224-234, 2006.

- M. Maniadakis, P. E. Trahanias, *Distributed Brain Modelling by means of Hierarchical Collaborative CoEvolution*, in Proc. IEEE Congress on Evolutionary Computation, (CEC-2005), pp. 2699-2706, 2005.

- M. Maniadakis, P. E. Trahanias, *CoEvolutionary Incremental Modelling of Robotic Cognitive Mechanisms*, in Proc. VIIIth European Conference on Artificial Life, (ECAL-2005), pp. 200-209, 2005.

- M. Maniadakis, P. E. Trahanias, *A Hierarchical Coevolutionary Method to Support Brain-Lesion Modelling*, in Proc. International Joint Conference on Neural Networks, (IJCNN-2005), pp. 434-439, 2005.

- M. Maniadakis, P. E. Trahanias, *Evolution Tunes Coevolution: Modelling Robot Cognition Mechanisms*, in Proc. Genetic and Evolut. Comput. Conference, (GECCO-2004) pp. 640-641, 2004.

- M. Maniadakis, P. E. Trahanias, *A Computational Model of Neocortical-Hippocampal Cooperation and Its Application to Self-Localization*, in Proc. VI-Ith European Conference on Artificial Life, (ECAL-2003), pp. 183-190, 2003.

1.5 Thesis Structure

This thesis is organized into seven chapters, which are structured as follows:

Chapter 1: Introduction. The present chapter has attempted to give an outline of the problem approached by the present study, and the basic features of the methodology followed to solve it.

Chapter 2: Literature Review. The next chapter reviews the literature of the main scientific fields related to the present study, namely robotics, computational neuroscience, agent technology, and optimization methods.

Chapter 3: Overview of the Computational Framework. This chapter combines the scientific fields discussed in chapter 2, in order to shape the proposed new methodology for the design of biologically inspired artificial brains. The presentation highlights the emergence of the approach from the integration of diverse scientific areas, and the contributions it offers to them.

Chapter 4: Computational Model. This chapter presents the primitive computational structures employed as building blocks by the present study, in order to facilitate the design of composite models with cognitive abilities.

Chapter 5: Hierarchical Cooperative CoEvolution. This chapter presents a novel coevolutionary scheme which is utilized in the present study as the main mechanism to support the design and integration of partial computational models.

Chapter 6: Results. This chapter presents a series of results which aim at illustrating the effectiveness of the proposed methodology in the design of brain-inspired artificial cognitive mechanisms.

Chapter 7: Conclusions. The last chapter summarizes the basic features of the proposed computational framework, and indicates directions for future work.

Chapter 2

Literature Background

The present work investigates the development of brain-inspired artificial structures as a means to enrich robots with advanced cognitive abilities. A novel computational framework is proposed to facilitate cognitive system design. This is based on an agent modelling approach, and a coevolutionary design tool. Thus, the present work addresses issues from diverse scientific fields. Specifically, we investigate aspects from the fields of robotics, computational cognitive neuroscience, agent technology, and evolutionary computing (Fig 2.1).

In this chapter we review relevant parts of the literature of the above scientific areas, referring mostly to the issues related to the present study.

2.1 Robotics

Robotics is a field where many ideas from different scientific areas have been mixed and applied over the years. As a result, it is usually hard to define the borders among different methods. In the following, we will attempt to present an overview of the major existing approaches. Research literature in the area of robotics is broadly classified in conventional robotics, encompassing the majority of algorithmic approaches, and bio-inspired robotics borrowing ideas from biology in order to facilitate the design

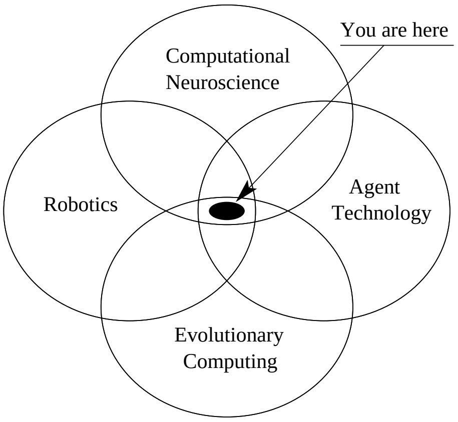

Figure 2.1: A graphical representation indicating the context of the present study.

of advanced robotic systems.

2.1.1 Conventional Robotics

Traditionally, roboticists have tried to tackle the problem of robot development in a top down fashion [43]. That is, human designers first analyze/specify what is the desirable performance for the robot, and then they develop methodologies to specify the computational details of this performance, following an algorithmic approach.

The earliest attempts utilized well known results of control theory to build automated systems able to perform very accurately specific tasks [250, 81, 281]. Following this approach, the efficiency of robot performance was considered synonymous with the speed and accuracy of the motion. The successful results of these methods had a considerable acceptance in the industry, facilitating the automation of production.

The necessity to apply robotics in gradually more sophisticated applications, revealed the need of artificial systems to perform complex movement sequences. One important aspect of robot operation is the ability to plan tasks, actions and motions without human intervention. As a result, the emphasis of robotic research shifted to complex forms of behavior. At that time, the advancement of artificial intelligence

(AI) brought new notions in the field, such as knowledge representation, reasoning, and planning [318, 262]. Hence an AI approach was followed in the field of robotics, utilizing computational structures that perform computations on abstract symbolic representations of the world [148]. These computations were governed by a stored program, which contains an explicit list of human designed instructions and rules [83].

Having gained experience with the AI methodology, roboticists realized that it is not possible to describe all aspects of the real world in a storage device to be utilized by the robot. On the contrary, robots should be enriched with decision making and learning capabilities to acquire knowledge on their own, in order to accomplish their goals. As a result, a large variety of statistical methods were utilized to support the extraction of knowledge from the world [19, 292, 288, 257, 255] and the decision making process [102, 141, 271, 218]. Still, the long term goal of developing artifacts with autonomous cognitive skills was not reached. This is because the mediation of the human factor remained significant, specifying both the learning mechanism and which were the aspects of the real world that a robot should learn, according to the human experience on the problem.

At the same time, soft-computing methodologies (artificial neural networks, fuzzy systems, genetic algorithms, [284, 165, 279, 248, 299]) became very popular, mainly due to their success in learning problems. Following that trend, the soft-computing methodologies were transferred in the field of robotics, aiming at solving efficiently the problem of learning [188, 101, 64, 150, 161, 186]. However, these methods did not change the general approach since the human mediator specified both the goal and the details of the learning procedure. Consequently, humans constrained the plasticity offered by these methods to design artificial cognitive mechanisms.

Nevertheless, experimentation with soft-computing methods made researchers realize that some desirable features are able to appear in the system, even if humans do not specify the details of their machinery [201]. These features are specified by the special characteristics of the environment, the body of the robot and its previous experience. As a result, new key aspects came into play, namely situatedness (the robot is coupled with and influenced by the environment), embodiment (the robot has a body which modifies its interaction with the environment and specifies its experiences) , and emergence of intelligence (the observed intelligent performance of the robot comes from the situation in the world, the body-brain coupling, and past experiences) [43, 261].

Following these principles, a new methodology to robot design was formulated, named behavior-based. This approach gets its name from behaviors, which are patterns of activity emerging from interactions between the robot and its environment. Such systems are constructed starting with a set of primitive/survival behaviors. Next, gradually more complex behaviors are added, in order to enrich the robot with more advanced capabilities, formulating a distributed decision mechanism [44, 254, 10, 184, 182, 319]. Thus, intelligence is considered as the result of collective phenomena emerging from the cooperation of partial behaviors [182].

The social extension of behavior-based robotics is usually referred to as multi-agent system technology which studies the emergence of new behaviors by means of the interaction of complex organisms, not just single behaviors. Thus, multi agent systems study the interaction among organisms (represented by groups of behaviors) which might have conflicting goals, and how the dynamics of this interaction shape the overall performance of the community. The benefits of the multi-agent approach have been described in many studies [277, 63, 315, 152], including from a programmer's perspective, easier, modular implementation, and for the performance of the overall system, scalability, robustness, parallel problem solving, and adaptivity in changing environmental conditions. However, the controllability of the overall system is reduced due to the potential emergence of new unexplored behaviors.

A new popular methodology in the design of robots is the bio-inspired approach.

This is based on the fact that for the time being, robotic abilities are very primitive, at least compared to the corresponding capabilities of many biological organisms. Thus, instead of trying to design intelligent robots from scratch, we can mimic nature, making copies of biological mechanisms in order to achieve the long term goal of designing robots with advanced competencies [26]. Since this is the approach followed in the present study, the main research directions in the area are discussed in the following section.

2.1.2 Bio-Inspired Robotics

The wide application of robots in real life has increased the demands for novel, advanced design methodologies which will support the construction of better, that is, more autonomous, and more adaptable robotic systems. The observation of every day action of biological organisms, revealed that biological cognitive mechanisms do not necessarily match to an algorithmic process that can be universally applied to any kind of artifacts. Each organism perceives the world from its own perspective, which means that it assigns meaning to surrounding objects and acts in the environment according to its own needs. These observations offered new, biologically-inspired ideas in approaching the problems related to the development of machines that operate in the real world [26, 10, 219, 104].

Following this currently very active research direction referred to with the general term of bio-inspired robotics, substantial efforts are devoted in mimicking the features of biological organisms. Along this line, explicit references are made to the known natural mechanisms involved in the cognitive process and the expression of behavior. The basic argument of the approach is that mind has emerged as a complex form of life, and thus it is not possible to achieve intelligence without life-like characteristics [117]. Previous studies have roughly classified bio-inspired robotics in three main categories, namely bio-mimetic [216], cognitivist [252], and emergent [252]. The first emphasizes more on robot motion kinematics, while the following two address mainly robot intelligent competencies.

Biomimetic Robotics. Research efforts in the area of biomimetic robotics, aim at extracting principles from biology and apply them to man-made devices. Even if biomimetic approaches do not exclude studies which aim at mimicking advanced aspects of biological behavior, currently most research endeavors emphasize on reproducing the mechanics and dynamics of animal bodies [216, 163]. Usually, artificial creatures borrow their structure and senses from simple biological organisms like insects, worms, lampreys, salamanders, rats, or even humans [293, 24, 304, 135, 96, 185, 191]. Biomimetic studies address biological questions by building physical models of animals, and strive to advance engineering by integrating aspects of animal sensory systems, biomechanics and motor control into the construction of robotic systems [164]. Following this approach, engineers are able to blend expertise from the fields of biology and computer science, taking advantage of new developments in materials, fabrication technologies, sensors and actuators. Consequently, robotic systems that exhibit increased robustness when they perform in unstructured environments can be developed.

Cognitivist Robotics[1]. This research direction has been formulated by incorporating ideas from the field of cognitive neuroscience into robotics. Following the terminology utilized often by neuroscientists, psychologists, cognitive scientists, certain aspect of the real world are “represented” in the brain of biological organisms (e.g. [76, 234, 305]). Along this line, a representational or symbolic approach is often followed by cognitive researchers to model mental processes. This paradigm, which is usually refereed to as the pure cognitivist approach [252], utilizes the metaphor

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[1] **Here, we use the term ”Cognitivist” in the same sense that it is used in [252].**

of the mind as a digital computer, according to which the body is the output device that merely executes commands generated by a rule-based manipulator of the symbols associated with the internal representation of the world [8, 301, 297]. Computational approaches following these ideas are often based on unified computational frameworks such as SOAR, EPIC, or ACT-R, modelling theories of cognitive processes based on psychological experimentation. These working frameworks have been also utilized to implement computational models supporting robotic cognitive tasks [210, 27, 54, 298, 203].

Additionally, we encompass in the category of pure cognitivist approaches those research efforts which embed models of cortical and subcortical brain areas in robotic platforms [159, 111, 127, 146, 95, 233, 48]. The focus of these efforts is on the reproduction of human understanding regarding brain performance, rather than the development of artifacts with efficient functionality [158, 155]. The implemented models are usually designed without taking into account the specialized characteristics of the robot that they will be embodied. This pure brain-copy based research direction is in contrast to the emergent approach (discussed below).

In the early 1990s a new way to investigate cognition redirected the focus of scientists. This new approach considered cognition as a temporal phenomenon which could be better understood by means of dynamical terms [286, 23, 297, 42]. Following that way of thinking, new issues came into the field of cognitive mechanisms investigation, such as environmental interaction and the personal experience of the organism. The new approach to cognition, termed "Dynamic Hypothesis" recognizes that the organism-plus-environment creates a unified, living system, that has to be considered as a whole, in order to investigate the emergence of intelligence [276]. Sensing and acting in the world are considered necessary and sufficient for intelligence [261]. Such a view follows a less human-centered approach to cognition, because it takes into account that different organisms perceive the world from different viewpoints which are probably different than the human one. Living organisms need to act in order to develop their own view on the world, based on their own needs and experiences. These ideas were also transferred in the field of robotics by means of situatedness, embodiment, and emergence of intelligence. Robotic cognitive systems are significantly advanced by obtaining the necessary power to model social and other experience based phenomena, facilitating the development of cognitive artifacts [59, 13].

Emergent Robotics. Research efforts in this area start from the dynamic hypothesis of cognitive science, and goes further by adopting approaches that do not explicitly aim to replicate or reproduce the brain. They rather try to get inspiration by the internal brain processes in order to develop intelligent artificial systems [164, 252]. The basic argument of emergent robotics is that the body, the brain and the environment are reciprocally coupled and strongly affect one another. Consequently they can not be studied separately. The cognitive processes arise from having an organism with specific perceptual and motor capabilities specified by its body, interacting with and moving in the world [285]. Passing this argument to the field of robotics, the intelligent competencies of artificial organisms should be developed with minimal human intervention, and they should be the emergent result of the interactions mentioned above.

The performance of the artificial brain is subject to a never-ending adaptation process which binds it with the body and the environment. This is often simulated by means of neural network structures with self-organized synaptic plasticity [101, 133, 137, 30, 320, 33]. The artificial mind is a continuously changing system whose performance is affected by several epigenetic factors existing internally and externally to the organism, and ranging from neuromodulatory value systems [272, 157] to social behaviors [65, 41, 32, 78, 84].

The organism should be able to develop a subjective view of its environment which will not necessarily be in accordance to the well known human understanding. In order to achieve cognition, the computational structure representing the brain should pass through a maturation process which specifies the way that early experiences modulate subjective perception of the world and future behavior. This is often simulated by developmental computational structures which aim at mimicking biological developmental processes [150, 13, 245, 306, 164, 252]. Even if the developmental process of these structures is often inspired by the mechanisms presented in nature, they usually result in computational systems with efficient performance but without any organizational or functional similarity to biological brains [39, 29, 235, 87]. Other models employ more traditional computational structures to model the developmental process such as expanding trees [307].

Furthermore, the claim that embodiment is an integral part of intelligence, has recently enforced investigating the shape of the body of artificial organisms. Many studies are recently oriented in discovering which are the desirable shapes of robot bodies that exhibit tractable passive dynamics. Such bodies will facilitate the efficiency of robot performance, constraining at the same time the set of possible configurations of the cognitive mechanism, in order to alleviate its design. These approaches are referred with the general term of computational morphogenesis [86, 130, 38, 274, 28, 153]. The most recent research direction in this field emphasizes the co-design of robot bodies and brains [180, 39, 222, 252] to achieve a perfect match.

Cognitivist vs Emergent Robotics. The diverse features of the two approaches are best revealed by considering the most extreme cases of each side. According to *my own* point of view, they can be summarized in the following three points:

- The cognitivist approach assumes that embodiment and environmental interaction are not always necessary to achieve cognition (e.g. the interaction with the pen does not guide the thoughts written in the paper), while the emergent approach considers embodiment as the crucial point to cognition (e.g. it is necessary to feel the particular properties of your body and also to sense the glass in order to decide what is the appropriate way and force to grasp it).

- The cognitivist approach argues that it is possible to design a general purpose computational brain which can be embedded in many different types of artifacts, with minor changes. In contrast, the emergent approach believes that each brain matches a specific body type and vice versa, and consequently both should be developed in parallel.
- In order to develop artifacts with advanced mental abilities, the cognitivist approach argues that we need to copy biological brains (at least in some level of detail). The artificial brain should be understandable by the designer, and reflect our current knowledge on the performance of biological brains. The emergent approach argues that robots constitute a new, independent type of organism, and consequently the architecture of their bodies and brains could follow an architecture which can be independent of the biological prototype. What we should get from nature are the mechanisms which formulate the result (e.g. developmental process), but it is not necessary to consider the brain as the target structure.

Previous studies addressed cognitivist and emergent robotics as being antagonistic design methodologies [252]. However, we believe that the two robot design methodologies share many common ideas. A similar argument is also stated in [261].

2.2 Computational Neuroscience

The task of computational neuroscience is to reverse-engineer the central nervous system: to dissect its architecture into functionally isolable information-processing units, and to reproduce computationally the operation of these units at a physical level. These models play a significant role in the formation of recent theories regarding CNS functionality, and they are often utilized to test the reliability/completeness of a specific assumption regarding brain activity, or make predictions for further investigation.

Unfortunately, at the present time there are not appropriate computational systems to approximate brain organization and performance. The reason is that there are many unknown and unexplored parameters of CNS functionality, while, at the same time, the technological advancement is still lacking to implement an artificial system with that level of complexity.

2.2.1 Neuroscience - Brain Science

Neuroscience is currently one of the most rapidly growing areas of science, examining the biological basis of consciousness and the mental processes by which we perceive, act, learn, and remember. The current section aims at highlighting those aspects of neuroscience which are mostly relevant to the present thesis. For further details, the interested reader is referred to several recent textbooks which deal with the most well known aspects of brain performance (e.g. [144, 321]).

Roughly speaking, neuroscience follows diverse directions to achieve a deeper understanding of the brain, examining different disciplines regarding its structure and functioning. In summary, modern neuroscience emphasizes on (1) the brain areas and functions which support higher mental processes such as perception, attention, memory, learning, thinking, (2) the structure and functional properties of the neurons, glia, and synapses that are the building blocks of the nervous system, (3) the developmental process clarifying how neural cells are generated and acquire their identity, and how patterns of neuronal connections are established, (4) the genetic determinants of the CNS in order to understand the mechanisms that genes and proteins modulate the formulation of neural circuits.

A wide range of brain investigation techniques are available today, serving the goals of neuroscience. These techniques emphasize on different aspects of brain performance including single-unit recordings, focal lesion of brain areas, cortex manipulation methods (TMS), temporal data acquisition techniques (EEG, ERP, MEG), brain imaging methods (PET, fMRI). Each one of those methods measures different characteristics of brain performance and thus they differ in spatial and temporal resolution, as well as in the area coverage. Consequently, following each one of them, only a part of the complete picture of brain functionality is available every time. Modern approaches aim at applying data fusion techniques to combine data collected from different techniques, in order to provide a more complete understanding of brain performance [132].

The brains of diverse biological organisms share common characteristics which become gradually more complex as we are examining more advanced animals. Consequently, neuroscientists often investigate the functional and anatomical organization of the CNS of simple organisms in order to formulate hypotheses which are also tested on more complex organisms. Specifically, mammals are considered as a group of species with common characteristics in their central and peripheral nervous system. Thus, in order to achieve a deeper understanding of the brain of the higher biological organism (human), a great part of neuroscience community concentrates their research efforts on the CNS of lower or other mammals. Then, their results are properly scaled up to higher species. For example, all mammal species share similar sensory and motor systems to receive information from the environment and act on it, similar regulatory systems to balance their-self needs ensuring that they obtain the resources needed to survive, and similar structures to perform mental functions

[144].

One of the cornerstones of modern brain science is that the central nervous system consists of specialized subregions. These regions are organized in both a hierarchical and parallel way with an interactive but largely independent performance. The central nervous system of mammals consists of six main parts, namely spinal cord, medulla, pons, mindbrain, diencephalon, and cerebral hemispheres, each one assigned a different set of functions [144]. Each of those six main parts of the CNS is further divided in smaller building units, related to specific aspects of brain performance [112].

The complex and diverse functions of the mature CNS (e.g. perception, motor coordination, motivation, memory) depend on the precise interconnections formed by many thousands of neural cells. The establishment of the mature pattern of neuronal connections is shaped by an interaction of genetic and environmental factors [144, 112, 321].

The biological system of the central nervous system runs in massively parallel, low speed computation, within an essentially fixed topology network with bounded depth. Thus the secrets of its flexible and efficient operation are appropriately encoded in this bounded network, and we have to decode it. Some of the questions asked by researchers working on this issue are: how does the brain develop? how do nerve cells in the brain communicate with each other? how do different patterns of interconnections give rise to different perceptual and motor acts? how is neural communication modified by experience?.

2.2.2 Modelling

The construction of computational models is a standard practice in the field of brain sciences, facilitating the endeavor to explain observed phenomena. Distinct models aim at replicating diverse phenomena observed in neuroscientific studies in order to accomplish a deeper understanding of their dynamics. There are many design issues that distinguish the approaches followed for the implementation of CNS models. In the present study, we follow two different categorizations, in order to review the main directions of brain modelling efforts.

Neural Models. The most widely used paradigm addresses the employment of neuron-like elements that are linked into circuits to model elementary or larger portions of the CNS [258]. To a very coarse approximation, one can distinguish three classes of models in common use, namely compartmental, leaky integrator, and firing-rate models [9, 66].

Compartmental models, are biophysical plausible structures which place their emphasis on the morphology and other detailed characteristics of a neuron in order to investigate the way that a single or just a few neurons compute, with a high degree of detail. Such models divide the neuron in compartments containing resistances, capacitances and batteries, representing the interaction of its components. They are based on the classic work by Hodgkin and Huxley in 1952 [129], derived from cable theory, incorporating equations to describe ionic and synaptic channels. Compartmental models are ideal for explaining phenomena related to the generation of spikes, precise effects of synaptic input, spike adaptation, bursting, etc. [267, 74, 237, 66, 22]. However, multi-compartmental neurons tend to be too complex to incorporate into models of animal behavior [74, 66, 80]. This is because the large number of variables that need to be computed, makes them very demanding in terms of computational resources. Additionally, it is hard to study the dynamics of complex networks consisting of compartmental neurons in order to formulate conclusions on their overall performance.

A much simpler modelling approach leads to the class of leaky integrate and fire neurons providing a simple mechanism of spike generation and dentritic integration, based primarily on the loading time of the cell [58]. It is a continuous-time model in which the internal state of the neuron is described by a single variable, the membrane potential [9]. The potential of a neuron is given by a differential equation which integrates the inputs utilizing also a leakage term which tries to return the neuron at an equilibrium state. The leaky integrator model can simulate either the emission of spikes, or firing rates by means of a sigmoid function of the membrane potential [9]. However, in the literature these models are considered as the simplest form of neuron that still outputs spikes. Leaky integrator models are good for simulating large, recurrently connected, networks of neurons. Many mathematical issues about networks, such as the synchronization and de-synchronization of spiking across the whole population, the effects of different sources of noise, and phenomena such as synaptic plasticity, which depend on precise time differences between pre-synaptic and post-synaptic activity have been explored through using them [66].

The more abstract level of approximating neural functioning are firing-rate models. They usually involve a non-linearity, turning an internal continuous variable like current into a firing rate. Networks of firing-rate models can be constructed, in which the influence of one cell on another is given by the product of the pre-synaptic cell's firing rate and the synaptic strength of the connection. The main advantages of these models are their simplicity and analytical tractability. Networks of firing-rate neurons can be treated as coupled non-linear differential equations that can be shown to exhibit many desired dynamical behaviors. Due to their computational tractability, these models have been used widely in the past in the development of functional still abstract models regarding the performance of either biological or artificial organisms. They usually emphasize more on the performance of the model than its biophysical reliability [244, 32, 7].

Synaptic plasticity is appealing for computational modelling, since it offers an obvious way for large networks of simple processing units to perform computationally sophisticated tasks. Different learning rules are utilized to guide the adjustment of synaptic weights according to the objective of the neural structure. Although it is possible to study the effects of synaptic plasticity in the context of compartmental or leaky integrate and fire models, by far the bulk of work on computational analysis has been performed using firing-rate models. There are three main classes of learning approaches, namely unsupervised, reinforcement, and supervised learning, which have been mostly studied under the framework of firing rate neurons [20, 217, 213]. However, learning schemes have been also implemented concerning the utilization of properly formulated learning rules for leaky integrator [268, 79, 113, 1] and compartmental models [167, 300, 267, 237].

Modelling Methodologies. A different classification of existing modelling efforts is also possible, emphasizing on the design methodology rather than the biophysical reliability of the computational structure. For example, a modular design approach has been proposed, representing brain areas by re-usable building blocks [242]. One well known example is the synthetic neural modelling approach to develop the so called brain-based devices, embedding computational structures in robots [158, 159]. Other studies in this context are [107, 16, 94]. A similar modular methodology is also followed by the K-set modelling approach [106, 155] which aims to model brain phenomena by means of re-usable chaotic computational modules representing brain areas.

Other studies following a dynamical systems modelling approach also exist in the literature [264, 194, 126, 162, 283, 191]. These efforts usually work at the brain area representation level. Following the systemic approach these studies embed existing knowledge regarding CNS activity in systems specified by a set of dynamical equations in order to explore the phenomena occurring by their interaction.

The main difference within the systemic and neural modelling methodologies is considered to be that systemic approaches do not usually address learning phenomena, while the neural approaches are not able to describe efficiently and in an understandable form the temporal structure of phenomena and the pattern of interactions among partial elements of the system [227, 266].

Other studies aim at incorporating existing knowledge regarding brain performance in large scale computational models. For example [210, 118, 301, 36] illustrate the development of causal models of primate neocortex following a symbolic approach, where partial brain areas are represented by a set of logical inference rules. Following a less hardwired approach [68] utilizes thousands of cellular automata -based modules to simulate large scale brain activity.

Additionally, there is an emerging research area, where modelling efforts emphasize on the developmental process of the brain. They employ Gene Regulatory Networks (GRN) to simulate the specification of brain development by genes, and the adjustment of this process by epigenetic factors [86, 160, 249, 115, 125, 145]. These structures are usually referred as developmental or computational neurogenetic models. Even if these studies aim at modelling biological processes such as growth and morphogenesis, the resulted structures are rarely parallelized to specific brain areas. However, computational studies on the developmental process, emphasizing on the structure of the biological prototype, have been also proposed [142, 73].

Recently, genetic algorithms have been also employed in computational neuroscience, as an optimization methodology to facilitate the modelling process [92, 246]. Along this line, [67] utilizes an evolutionary design methodology to create large scale structures which aim at mimicking brain operation, paying however more attention on the computational power of the processing units.

Overview. It is clear from the above, that many diverse approaches are followed to model different aspects of animal's CNS functionality. Usually, computational models emphasize either on a specific attribute of brain performance (e.g. consciousness, perceptual abilities, learning, memory, motor/movement coordination, motivation/emotions), or on a specific feature of brain machinery architecture (e.g. neurogenesis [86, 145], neural-death [228], neuromodulation [240, 272], lesions-effect [118, 220, 4, 264, 193]). As a result, the majority of computational systems do not integrate many different characteristics of the biological prototype. Additionally, researchers usually model only a part of the CNS, making strong assumptions regarding the performance of the surrounding areas which are not modelled. Thus, the specific operating conditions required by the model to be functional, inhibit its further integration with models of other brain areas, reducing our potential ability to design a valid large scale brain model.

In support of these efforts, robots can be employed as research tools for the investigation of embodied models of cognition [24, 14, 303, 123, 253, 21]. Specifically, neuroscientists and psychologists are trying to gain insights from embedding their models into an artificial organism, and let it interact with the environment to observe its performance, and compare it with the performance of animals [304, 296, 48, 219]. As a result, following an embodied modelling approach, existing hypotheses regarding brain functioning (e.g. [62, 114, 37]) can be accurately tested, and systematically improved.

2.3 Agent Software Technology

The term agent has been used widely in diverse areas of Computer Science. For example, in the field of Artificial Intelligence (AI), the term agent is used to represent the process of situating various AI techniques in an environment. Conversely, on the Internet, agents are considered to be software that can be sent out for a mission, usually to find some information and report back. Thus, the agent-technology is really an umbrella which covers a wide and heterogeneous body of research and development [317].

An attempt to summarize and clarify the various aspects of agent definitions as they are applied in diverse areas is given in [60]. Four main categories are identified. The first concerns the employment of the term agent in the context of artificial intelligence to represent an intelligent autonomous entity that is located in some environment [103, 319]. The second, approaches agents from a social viewpoint, investigating the structures and processes underlying social interaction among autonomous entities [314]. The third category examines agent technology from a distributed systems perspective, emphasizing on software systems that are distributed over multiple processors [2]. Finally, mobile agents are identified as a software abstraction that can migrate across a network (possibly the internet), representing users in various tasks [189, 205].

Evidently, different disciplines have different needs, use different terminology, and may have different notions of what exactly they mean by an agent. In the following we will identify the key concepts of agent-based computing that are relative to the present work. In accordance to the classification of agent systems introduced in [60], we exclude from our research filed the last two categories, which emphasize on programming tips and www applications. The agent concept that the present study is interested in, encompasses characteristics of the artificial intelligence and social agency approach, which share many common properties of what an agent is [291]. Hence, in the following we concentrate on describing these properties further.

An agent is considered as an encapsulated computer system situated in some environment. This artificial entity is capable of flexible, autonomous action in that environment, with the intention to meet its design objectives [166, 313]. We identify the following properties of the agent entities relevant to the present study [138]:

- they are identifiable problem-solving entities with well defined boundaries and interfaces,

- they are situated (embedded) in a particular environment over which they have partial control and observability,
- they receive inputs related to the state of the environment, and they are able to act on it in order to change its state,
- they are autonomous, able to control both their internal state and their own behavior,
- they are designed to fulfill a specific role with particular objectives to be achieved,
- they are both reactive (able to respond in a timely fashion to changes that occur in their environment) and proactive (able to opportunistically adopt goals and take the initiative).

The agent based approach is often followed in the design of very complex structures which can not be easily studied analytically. In order to accomplish the individual and collective objectives of subsystems the active and autonomous components need to interact. However the inherent complexity of many systems makes impossible to know a priori all potential interactions that will occur at random times, for unpredictable reasons. Thus, it is futile to try to analyze all possibilities at design time. A better approach is to endow the components with the ability to make decisions about the nature and scope of their interactions at runtime. In that way, partial agents may explore and manage the inter-dependencies that arise from being situated in a common environment, adjusting their performance to serve both their own and the composite structure's objectives [138, 152].

An agent-oriented view is adopted in many problems, because they are able to represent the decentralized characteristics of many real-life problems, the multiple loci of control, and the multiple perspectives of the problem with respect to partial structures [139]. Moreover, agent-oriented systems have the concomitant computational mechanism for flexibly forming, maintaining and disbanding organizational assemblies of partial components [291, 316, 317]. Furthermore, individual agents or organizational groupings can be developed in relative isolation and then added into the system in an incremental manner. Thus, agent's technology enables whole subsystems and flexible interactions among partial entities to be re-used [138]. This, in turn, ensures a smooth growth in modelling and behavioral functionality of artificial systems.

Having highlighted the potential benefits of agent-based computing we turn now to its main drawbacks, in order to identify those aspects of complex systems design that are made more difficult by adopting this approach. There are two major drawbacks associated with agent based computing [138]. First, the patterns and outcomes of the interactions among partial agents are inherently unpredictable. Second, it is extremely difficult to predict the behavior of the overall system based on its constituent components because of the strong possibility of emergent behavior. That is, the whole is often greater than the sum of the parts. Thus, a question now arises: is agent technology a drawback or an advantage for the design of systems ?

It is clear that the particular power offered by the agent-based technology is at the same time its main weakness. This is because the emergence of new collective behaviors and the potential ability for dynamic adaptation in new unexplored circumstances, which is a desirable feature in modern systems design, comes with the cost of reduced controllability from a designer's perspective [317], which could potentially lead to system failure. As a result, a method to balance within the properties of system predictability, and the emergence of new behaviors, is necessary, since these two desired properties contradict each other.

2.4 Optimization Methods

This section explores optimization methods in order to present their basic features. Literature suggests a number of different techniques for solving optimization problems (reviewed in [187]). According to the no-free-lunch principle, no single method can outperform all the other methods on all problems. Thus, different methods are required to solve different classes of problems. The importance of studying optimization problems has enforced the development of many different efficient techniques. Optimization techniques can be classified into two broad categories: algorithmic and evolutionary [204].

2.4.1 Algorithmic approaches

Most traditional algorithms use a point-by-point deterministic procedure for approaching the optimum solution. Such algorithms start from a random guess solution. Thereafter, based on a pre-specified transition rule, the algorithm suggests a search direction, which is often arrived at, by considering local information. A uni-directional search is then performed along the search direction to find the best solution. This best solution becomes the new solution, and the above procedure is performed for a number of times. Algorithms vary mostly in the way the search directions are defined at each intermediate solution, and the size of update steps performed [75].

Traditional optimization methods can be classified into two distinct groups: direct methods, and gradient methods [98]. In direct search methods only the objective functions and the constraints can be evaluated in order to guide the search strategy. Some examples of these methods are the simplex search method [270], Hooke-Jeeves pattern search method [131], and Powell's conjugate direction method [232]. On the other hand, the gradient-based methods use the first and/or second order derivatives of the objective functions and/or constraints, to guide the search process. Some well known examples of these methods are Cauchy's steepest descent method [119], Marquardt's method [181] and conjugate gradient method [99].

Since derivative information is not used, the direct search methods are usually slow, requiring many function evaluations for convergence. For the same reason, they can also be applied to many problems without a major change in the algorithm. On the other hand, gradient-based methods quickly converge near an optimal solution, but are not efficient in non-differentiable or discontinuous problems. In addition, there are some common difficulties with the majority of direct and gradient-based techniques, as mentioned below [75]:

- They are ineffective for optimizing black-box structures because they demand a detailed mathematical description of the problem.
- Algorithms are not efficient in handling problems having a discrete or an unordered search space.
- The convergence to an optimal solution depends on the chosen initial solution.
- Most algorithms tend to get trapped to a sub-optimal solution

The above mentioned drawbacks of classical optimization techniques have led to the growth of stochastic search methods, which are able to solve difficult real world problems providing nearly global optimal solutions. One of the most widely utilized stochastic search approach is evolutionary computing, discussed in the following section.

2.4.2 Evolutionary Computing

Evolutionary Computing (EC) methodology is inspired by the Darwinian theory of evolution, exploiting the power of natural selection to turn computers into efficient optimization tools. There are a variety of evolutionary models that have been proposed in the literature under the term of evolutionary computing, and they have been reviewed in several documents [269, 17, 90, 204, 147]. They share a common conceptual base of maintaining a population of structures that evolve according to rules of selection and other operators, such as recombination and mutation.

The origins of EC can be tracked back to 1950s [40, 105]. Since then, several evolutionary algorithms have been proposed, which are usually classified [17, 90, 204, 299] to Genetic Algorithms (GA), Evolutionary Strategies (ES), Evolutionary Programming (EP), and Genetic Programming (GP).

The terms used in EC are analogous to the terms used to explain the biological evolutionary process:
gene - a basic unit, which defines a certain characteristic (property) of an individual;
chromosome - a string of genes; it is used to specify a set of characteristics of an individual;
individual - a candidate solution to a problem in the domain of solutions (practically, it is often utilized as synonym of chromosome);
population - a collection of individuals;
crossover - a mating operator which specifies the generation of new chromosomes by substrings of other existing chromosomes;
mutation - an operator which specifies random change of gene values in a chromosome;
fitness function - a measure that evaluates the success of each individual;
selection - a procedure of choosing part of the population to be employed for reproduction of new individuals, while the rest part ‘dies‘.
generations - the number of evolutionary steps performed to formulate iteratively new populations by applying the selection-recombination process.

```
Generation $g = 1$
Initialize Randomly Population $P(g)$
While (not termination criterion) do
    Evaluate individuals of $P(g)$ according to fitness function
    Select $k\%$ best individuals of $P(g)$: $P_1(g) = S(P(g), k)$
    Reproduce P(g) using crossover: $P_2(g) = C(P_1(g), P(g))$
    Apply Mutation: $P_3(g) = M(P_2(g))$
    Go to the next generation: $P(g) = P_3(g)$, and $g = g + 1$
end while
```

Picture 1.1: Algorithmic description of a standard evolutionary process.

Evolutionary methods start with a random or semi-random collection of candidate solutions for the problem at hand, which are evaluated by an experimental objective function. Then the population is evolved iteratively applying stochastic operators crossover and mutation. A typical evolutionary process is described in picture 1.1.

Given sufficient processing time, the evolutionary process tends to fit the population on the specific problem characteristics, finding nearly optimal solutions. The EC techniques can handle most of the drawbacks of conventional algorithms, because they offer exceptional adaptive capabilities to handle non-linear, highly dimensional and complex problems. Additionally, they are more robust against noise and multimodality in the search space, than conventional methods. Furthermore, they do not require explicit knowledge of the problem structure or differentiability, and thus they are able to provide multiple near-optimal solutions to even ill-defined or black box problems. However, all these advantages of EC techniques come at the cost of their high computational expense, which makes them un-suitable for applications that require real-time optimization.

Their robustness and near global search abilities has encouraged the wide usage of evolutionary techniques in many difficult problems where the processing time is not a critical factor. EC techniques have been successfully applied in many areas including: manufacturing systems [204, 116], process control [294], medical-diagnosis [248], simulation and approximation systems [279, 56] robotics [150, 101], computational neuroscience [92, 246], and others.

2.4.3 Distributed Evolutionary Computing

The extensive research in evolutionary computing techniques facilitated the emergence of two new modern areas of distributed processing, namely parallel evolution, and coevolution [147]. Both of them involve the evolution of many partial populations. The main difference among the two approaches emerges from the objective criteria employed to guide the partial evolutionary processes.

Parallel evolutionary schemes [6, 85, 49, 50] evolve many different populations with the same fitness objectives, each one consisting of complete problem solutions that can be tested independently. However, each population is initialized separately in order to facilitate a better exploration of the global search space. During the evolutionary process, partial populations are communicating by means of individual exchange in order to keep diversity within populations. Thus, the composite process addresses successfully the practical problems related to the exploration-exploitation dilemma. By utilizing multiple search processes to investigate the space of solutions, parallel evolutionary schemes enforce the robustness and efficiency of the composite process while at the same time they increase the speed of convergence of the optimization procedure.

In contrast, coevolution is formulated for problems where explicit notions of modularity are present. Specifically, coevolution occurs when two or more populations encoding different but interacting physical structures evolve simultaneously. The fitness function driving the evolutionary processes is not static, but depends on the interactions of individuals among coevolving populations [310, 247]. As a result, coevolutionary techniques [229, 46, 209] generally utilize distinct fitness functions for the evolution of each partial population, specified by the interactive coevolutionary dynamics. Compared to unimodal evolution, coevolutionary schemes exhibit increased search abilities facilitating the exploration of partial components of the solution, and thus they have been proved experimentally more effective than traditional schemes [212, 31, 308]. Coevolutionary processes constitute one of the main research areas of the present study, and thus they will be discussed in more detail in chapter 5.

2.5 Thesis Coordinates

In the current chapter the broader literature of the main scientific areas involved in our study have been reviewed briefly. As already pointed out, the present thesis addresses the problem of developing cognitive computational structures which are embedded in robotic platforms, in order to facilitate the mental abilities of artifacts. Due to certain design considerations that will become clear in the following chapters, our research work is more relevant to a subset of the topics outlined above. In particular, our work relates clearly to bio-inspired robotics, computational neuroscience, agent-based systems, and coevolutionary methods.

In the following chapters, the details of the proposed computational framework will be presented and the considerations of our work in the mentioned sections will be revealed.

Chapter 3

Overview of the Computational Framework

The previous chapter presented the main existing approaches towards the development of artificial cognition and the large number of computational models that have been proposed to support this task. Even if this issue has been studied extensively during the last decades, the progress observed is rather low. It seems that the main problem that prevents progress towards the long-term goal is not the formulation of the correct computational structure (there are thousands of them), but rather the overall computational framework that has been followed. In particular, most of the existing approaches emphasize the solution of limited problems rather than the formulation of extensible, scalable modelling methodologies.

The current study aims to shift the emphasis from the development of one more "promising" computational structure, to the methodology that should be followed in order to achieve the long term goal. In the present chapter we discuss some of the basic issues that should be considered during the formation of the new methodology. These thoughts are then combined to shape a novel computational framework for the development of artificial brain-like cognitive mechanisms, which is the core proposition of this thesis.

3.1 Cognitivist - Emergent Approach

In the previous chapter, we discussed the main approaches of robotic research, with the bio-inspired being the most modern and promising one, towards the design of artifacts with advanced cognitive skills. Biologically inspired approaches are broadly categorized in to cognitivist methods which exploit brain replication models embedding computational structures in robotic platforms, and the emergent methods which emphasize the coupling of the artificial organism with the environment and how this interaction shapes the artificial brain. Even if other researchers consider these methods as antagonists (e.g. [252]), we discussed in the previous chapter that they share many common characteristics. A possible way in the quest for artificial cognition could be to merge these two approaches, supplying each other with new creative ideas.

It is well known that many animals exhibit advanced cognitive competencies compared to the corresponding abilities of robots. The brain of biological organisms is the only functional structure existing today, which integrates efficiently subsystems of conscious, cognitive, behavioral, motivational (emotional), perceptual and motor responsibilities. This is because nature has enriched it with some very good characteristics. The advancement of the biological system is easily observed when we compare the performance of artifacts with mammals. Hence, robot designers can use some of the well known principles exhibited by the central nervous system of animals (e.g. distributed architecture with hierarchical and parallel organization), to develop efficient cognitive mechanisms for artificial organisms.

Furthermore, even if the mammalian brain is embodied in very different species, its architecture follows mainly the same organizational and functional principles. Specifically, there are hundreds of mammalian species with different body structures. Still, their brains consist mainly of the same subsystems, sharing a large number of common characteristics in terms of their architecture and operation. As a result, the biological central nervous systems seem to be enriched with a common set of basic features that facilitate the ability of animals to perform both simple behavioral tasks, and intellectual mental processes. These features should not be re-discovered in our attempt to furnish artifacts with similar capabilities. Nature has already done all the work for us. Hence, we have much to gain from studying biological mechanisms in order to extract design principles for our models.

Along this line, the implementation of a successful cognitive mechanism operating in a mammal-like way (the approach proposed by cognitivists), can be facilitated by following the design principles proposed by the emergent approach. This is because environmental interaction is of utmost importance in the endeavor of developing an efficient artificial brain. The detailed investigation of the principles that offer the mammalian central nervous system its efficiency, makes the embedding of computational structure into a body to interact with its environment, necessary. This is where the brain-body-environment interaction (emphasized by the emergent approach) comes in play when the cognitivist methodology is followed. The particular features of both the body, and the environment, should enforce the specification of brain areas in order to successfully serve the life goals of the artifact.

An additional way to combine the two approaches is by utilizing models of the emergent design, to implement partial components of the cognitive system. Specifically, computational structures with self-organized or developmental dynamics can be utilized to represent cognitive modules with distinct roles, similar to partial brain areas. This new modelling approach, which inherently furnishes modules with their own adaptation dynamics, will also provide increased flexibility in terms of integrating subsystems, in order to construct complex artificial cognitive mechanisms.

We have just argued that the characteristics of the emergent approach are able to facilitate the approach followed by the cognitivist methodology, in order to design computational cognitive systems which share common characteristics with the biological brain prototype. The reverse interaction is also true. We just need to state the same goal the opposite way: how can we design emergent computational structures that will be enriched with the desired competencies of biological brains (conscious, cognitive, emotional capabilities, etc.). Specifically, it will be hard to develop from scratch a very complex structure that self-adapts in the desired direction, exhibiting all the above competencies. To achieve the desired goal, it could be more effective to specify milestones that should be accomplished before developing the final composite system.

The partial milestones should be related to the desired characteristics of the artificial organism and can be specified taking inspiration by the specialized modules and mechanisms of the brain. For example, will the cognitive system be able to learn, to make plans, to be sensitive, etc., or not? And even more, how all these characteristics will be incorporated successfully in the same model? Answers to these questions could be provided by means of the cognitivist methodology. Specifically, the computational structures representing subsystems of the overall artificial cognitive system can be combined in a single functional model, according to the architecture of the biological prototype. Thus, the cognitivist methodology could provide inspiration to the emergent modelling processes, facilitating their long-term success.

3.2 Design Methodology

Having accepted the biological brain as a prototype structure, the design of the artificial system should ideally be based on the natural principles that guide the specification of biological CNS. Recently there is a debate among genetics and neurobiology to what extent the brain organization and the associated cognitive functions are genetically predetermined (by means of the phylogenetic process), or emerge through patterns of developmental experience, following an epigenetic specification process (for a recent review, see [112]). One proposition claims that brain structure has been formulated by the evolution of species over time [82]. Other approaches emphasize the importance of environmental interaction during the developmental process, highlighting at the same time, the subjective understanding of each independent organism about the world [62, 285].

Based on the above, it seems that both genetically encoded features and subjective experience have a significant role in the successful schematization of the biological brain and in turn the expression of the desired behavior by the animal [199]. Specifically, it seems reasonable to assume that phylogenesis determines the internal dynamics of the brain that allow the epigenetic (fine-)specification of the structure (after a certain amount of interaction with the environment), and the emergence of valuable behaviors. Besides the modulation of epigenetic process by phylogenesis, the reverse interaction is also true. The well known, since 1896, Baldwin effect, discusses the outcome of epigenetic learning on evolution, with the organisms that are most able to learn having larger numbers of offsprings [265].

Thus, a computational method able to design an efficient artificial cognitive mechanism could be based on both phylogenetic and epigenetic processes, or, in other words, the interaction of evolutionary and self-organization dynamics [260]. Such a method will take advantage of the way phylogenetic and epigenetic processes can affect one another in order to achieve successful convergence for both.

3.3 Simulating Epigenesis

There are two main approaches to represent epigenesis computationally. The first accounts for utilizing developmental neural structures which expand gradually based on simulating cell reproduction processes [39, 235, 87, 145], and the second accounts for utilizing neural structures with internal dynamics which self-organize during real-time operation [133, 101, 30, 320].

In the present study, we chose to follow the latter approach to simulate epigenesis mainly for the following reasons. First, regarding developmental structures, existing approaches emphasize only on the process of expanding the computational model. However, it is known that most brain neurons are generated before birth or during the early neonatal period and then persist during many decades of the life span [211]. Furthermore, biological studies shown that brain maturation mostly involves the reduction of the overall number of cells and synapse over time [55, 53]. This is in contrast to what is often assumed by developmental approaches, and can not be modelled sufficiently by a pure cell reproduction process. As a result, there is currently a lot of work to be done in modelling computationally the developmental process of biological organisms, at an adequately realistic level.

Additionally, existing computational developmental processes result in a single, compact structure and it is not yet possible to define partial modules with their own identity, similar to biological brain areas. In contrast, regarding the employment of non-expanding, still self-organized structures, their employment makes clear the definition of the intermediate borders among partial system modules. In turn, this fact makes possible the endowment of various brain-area characteristics of the biological prototype, in the computational model (e.g. assignment of different role, testing their performance in lesion conditions). Unfortunately, the investigation of brain characteristics in a brain area-level is not yet possible with the existing developmental approaches.

Furthermore, self-organized structures can be utilized as flexible building blocks for the construction of enhanced composite structures. In particular, self-organized components are able to adjust in cooperation with surrounding structures in order to accomplish a certain task, while at the same time preserving their autonomy which is mainly specified by their internal adaptation dynamics. As a result, autonomous components with their own identity can be utilized to simulate the activity of the biological prototype, in a brain area level. These components could have the form of self-organized agents as it is described below.

3.3.1 Agent-Based Modelling

The brain of mammals consists of several interconnected modules with different functionalities [144, 273]. Assuming that the architecture of the biological brain is optimized by evolution, and also that we have to formulate an artificial cognitive mechanism with similar organization, a distributed artificial system has to be designed. Along this line, the modern software engineering approach for the design of complex distributed systems, namely agent technology, can be employed to support the design procedure. This is because the agent technology matches the distributed nature of the biological prototype. Specifically, each brain area can be represented by a separate agent, having a distinct role in the performance of the composite cognitive system.

In contrast to the majority of existing approaches where many agents interact by means of the external environment, in the current approach, this interaction occurs internally in the cognitive system. Only the composite computational structure comes in contact with the external environment, mediated by the body of the artificial organism. In other words, the brain of the robot defines the operating environment of agents. Thus, a "brain-arena" is virtually specified, where many active agents coexist, each one cooperating with, and modulating the performance of, the others. The successful coupling of agent structures and their effective cooperation, is expressed by means of the artificial organism's performance.

According to the agent-based modelling methodology, each partial module is designed in principle plastic, ready to cooperate with the remaining structures specifying its functional environment. Thus, the components of the overall system are inherently able to interact and adjust their performance according to the goal of the composite cognitive structure, preserving at the same time their own internal dynamics and partial objectives, exhibiting a brain area-like independence. Consequently, the composite intelligent performance of the artificial organism will be the result of collective phenomena emerging from the cooperation of agent substructures.

Additionally, following an agent-based framework for the design of artificial cognitive mechanisms, the composite problem can be split into small tractable and progressively solved tasks. The results of partial tasks (implementing subsystems of the artificial brain) can be further combined, formulating a gradually more complex system. Fortunately, the inherent plasticity of agent structures will facilitate the integration process. This is because when a new component (agent) is added in a pre-existing distributed structure, then an additional information amount (originated by the activation of the new component) will be projected on pre-existing agents. As a result, the latter need to self-organize themselves accordingly taking into account the additional information amount, in order the overall system to reach a new equilibrium point of successful cooperative performance. Following the agent-based modelling approach this is possible to happen because partial elements will exploit their internal dynamics to adapt successfully to the new operating conditions [195]. As a result, an incremental process can be followed to design a properly complex artificial brain with a gradually enriched behavioral repertoire.

Moreover, the deactivation of a subset of agent substructures will not cause the complete crash of the composite computational model as it is often the case with compact, hardwired approaches [93, 239, 241]. This is because in the case of deactivation of some components, the remaining agents will again self-adapt in the new operating conditions which will result in the elimination of only a subset of the composite behavioral repertory. Thus, the agent-based approach supports the robustness of the overall system which will be less fragile, similar to the biological prototype.

By studying the interactive dynamics among agents and their simultaneous adaptation, it is furthermore possible to consider external factors affecting biological brain performance. These factors are specified by the coupling of the cognitive mechanism with the body of the organism, and also the coupling of the organism with environment and the surrounding physical objects available for interaction. Along this line, the composite artificial brain is considered to be a higher level plastic agent which regulates according to the constraints imposed by its functional environment and the specific life-goals of the robot. Then, turning back to the distributed architecture of the composite cognitive system, these global objectives and patterns of interaction are distributed to the agent modules which adjust accordingly, considering the particular characteristics of both the body and the environment.

Finally, we need to note that the employment of an agent-based approach for the design of artificial cognitive mechanisms is in accordance with both the cognitivist and the emergent methodologies of robot systems design. From the cognitivist side, following a distributed computational model, biologically inspired artificial brains can be designed, with distinct agents assigned the roles of biological brain areas. Additionally, from the side of the emergent approach, the inherent plasticity of agent structures is able to highlight the brain-body-environment coupling and how it affects the shaping of cognition.

3.4 Simulating Phylogenesis

The field of phylogenesis studies how genomes function and how they evolve through centuries, producing a wide diversity of animal species. The phylogenetic process has been a subject of computational modelling, aiming at achieving a deeper understanding of evolutionary relationships among animals, and the way environmental conditions guide the evolutionary process [280, 154, 12]. Usually, computational studies specify parameterized models of the evolutionary step, and then they try to identify the parameter values that best explain a set of biological data, in order to formulate conclusions regarding the natural evolutionary processes [154, 35, 140].

In contrast to the above, the subject of the present study does not concentrate on modelling the natural dynamics which guide phylogenesis, and the explanation of related phenomena. We take inspiration from the phylogenetic process, in order to obtain a tool that is able to evolve computational systems. Specifically, we employ the simplified counterpart of phylogenesis, namely the evolutionary computing methodology, as an optimization mechanism that is able to design effectively complex computational structures [245, 279, 248]. In the following, we concentrate on the suitability of evolutionary techniques to support the configuration of brain-inspired artificial cognitive systems.

In order to design an artificial system which is able to mimic the brain at a certain level of detail, a very complex computational structure has to be designed, with a large number of parameters to be tuned. Thus, it will be very difficult to follow a manual trial and error process, to specify the parameters of the composite model. In support of this endeavor, the evolutionary computing methods could facilitate the estimation of parameter values, accomplishing a near globally optimal configuration to this highly non-linear system.

Evolutionary methods are particularly able to address problems that can not be described by a detailed mathematical formula, as it is often the case with the computational models which aim at replicating certain aspects of brain operation. Specifically, what designers usually have at hand, is a large number of multi-modal biological data such as those obtained by EEG, fMRI, lesion studies, each one highlighting different aspects of brain functionality. The evolutionary approach is able to exploit effectively multi-modal data in order to support the design of artificial systems [259]. Thus, evolutionary methods can systematically facilitate mimicking of the brain, enforcing the reproduction of existing data by the computational model. As a result, considerable progress in brain modelling studies could arise, by adopting the evolutionary design approach. Fortunately, evolutionary processes are able to work with all kinds of computational structures.

Finally, we have already claimed that an incremental approach could be very promising towards the successful development of artificial cognitive mechanisms. Following such an approach, there will be cases that partial components need to be re-designed as gradually more substructures are integrated in the model. Evolutionary computing techniques are particularly appropriate to support this process, because they are easily adapted in changing operating conditions [72]. Thus, in each re-design step, they are able to avoid the previously identified local optima estimating a new efficient solution which meets the enhanced set of objectives.

3.4.1 Cooperative Coevolution

Evolutionary psychologists proposed the coevolution of partial brain areas over time [149, 309]. The computational analog of this hypothesis is that the evolutionary approach can be further extended to a cooperative coevolutionary one. Fortunately, by adopting this approach, the structure of partial system components could be more easily specified, because exploration is confined to a much smaller and easily searchable domain. Furthermore, the coevolutionary approach can be properly formulated to allow separate fitness functions to be employed during the design procedure, for each component of the cognitive mechanism. This is in contrast to a unimodal evolutionary process that calls for a single fitness function, preventing the consideration of each agent's own performance. As a result, different roles can be assigned to partial cognitive entities in order, for example, to simulate the performance of distinct biological brain areas. In other words, coevolution provides advanced design facilities of distributed systems because it is able to emphasize explicitly on the independent characteristics of substructures enforcing at the same time their coupling in a single, unified system.

Specifically, the coevolutionary approach exhibits the following properties [229], which are of significant importance for the design of brain-inspired artificial cognitive mechanisms:

- it facilitates the design of distributed systems approaching the problem in the level of the partial structures utilized as building blocks,
- it is able to highlight the distinct roles of partial structures in the composite model,
- it is able to enforce the cooperation among system components,
- it is independent of the computational structures employed to develop each subsystem of the cognitive mechanism,
- it facilitates the simultaneous evolution of different computational structures, each one exhibiting desired characteristics to represent a particular subsystem of the artificial brain.

Overall, due to its distributed nature, the coevolutionary design approach, seems particularly appropriate to meet the challenge of designing effectively distributed brain-like cognitive systems.

3.4.2 Hierarchical Cooperative Coevolution

Even if the coevolutionary methodology seems appropriate to address the problem investigated in the present study, existing approaches are not able to coevolve a large number of cooperating components as is the case with brain-inspired systems. This problem can be alleviated by classifying partial components in groups with common objectives, which are coevolved towards the same direction. These groups can be further combined, representing gradually more complex structure of the artificial system. The combination of groups can be also evolved by a higher level process. Following this approach, the cooperative coevolutionary methodology can be organized in a hierarchical mode, to facilitate the solution of complex design problems.

Specifically, in the present study, we introduce a Hierarchical Cooperative CoEvolutionary (HCCE) scheme that is able to coevolve simultaneously a large number of partial components. This scheme facilitates further the design of biologically inspired artificial brains, because:

- it is able to co-design a large number of partial components, drawing in a single step a large number of autonomous, but cooperating agents,
- it enforces mimicking of the biological prototype in a brain-area level, by facilitating distinct role assignment to different agents,
- it is able to consider the performance of the model in diverse operating conditions (e.g. simulated lesions),
- it can provide the human designer a systematic methodology to proceed with

the integration of partial models facilitating the re-usability of partial results, in order to formulate gradually more complex cognitive mechanisms,

- it can additionally provide a systematic methodology to revise the configuration of existing partial models, and if necessary, re-design them, according to an improved set of design objectives.

Additionally, we need to note that the hierarchical coevolutionary design mechanism will potentially provide a systematic method to approach the main problems of the agent technology, namely the specification of the interactive dynamics among agents, and the predictability of the overall system's performance [138]. Particularly, by utilizing the hierarchical coevolutionary scheme, the interactive dynamics among agents, can be efficiently investigated. This is due to the inherent ability of hierarchical coevolution to work explicitly with the components of the complex system. Furthermore, the assignment of distinct roles to agent structures and the possibility to investigate system's performance in diverse operating conditions (e.g. partial failure) will provide additional insight of the processes taking place internally to the system. In other words, the hierarchical coevolutionary approach is anticipated to shed light at the dynamics of both the autonomous agents and also their coupled interactions that shape the operation of the composite structure. As a result, the hierarchical coevolutionary approach offers a mechanism to exploit the effectiveness of agent technology, balancing adequately among predictable but constrained performance, and emergent but uncontrollable performance.

3.5 Summary

The present work addresses the problem of developing computational structures which are embedded in robots in order to furnish them with cognitive abilities. Due to the advanced cognitive competencies of mammals, the biological central nervous system is considered as a prototype, with the artificial system trying to mimic its functionality, at a certain level of detail. In the present thesis, we study a computational framework that facilitates mimicking the biological prototype, by computational structures. Thus, we shift the emphasis, from the final model, to the process of designing the model.

Specifically, similar to the brain prototype, the computational system has a distributed architecture. As a result, a scalable process can be followed to design the composite model. Along this line, autonomous agent structures are utilized to represent the components of the artificial system, representing brain areas. This approach offers enhanced flexibility in terms of modelling complex distributed systems, because it supports both the independent roles of substructures, and their cooperative performance in a composite model. Additionally, the inherent plasticity of agent structures highlight the importance of brain-body-environment interaction in shaping the overall performance of the organism.

The internal dynamics of each agent are specified by an evolutionary process. The latter aims at enforcing the emergence of the desired functionality in each agent structure, after a certain amount of environmental interaction. Instead of using a unimodal evolutionary process, we propose the employment of a cooperative coevolutionary methodology which offers enhanced abilities to specify the computational details of agent structures. The coevolutionary approach facilitates the autonomy of agents and the assignment of distinct roles in partial components. At the same time, it provides a systematic method to integrate agent structures in order to formulate a composite system with enhanced cognitive abilities.

Particularly, in the present study, we propose a novel Hierarchically Cooperative CoEvolutionary (HCCE) scheme which supports the development of brain-like cognitive structures by enforcing the enrichment of the computational system with bio-inspired characteristics. The proposed scheme is furnished with specific properties which address a scalable design procedure. Specifically, HCCE provides a systematic methodology to integrate and re-design (if necessary) partial structures, facilitating the implementation of gradually more complex cognitive systems.

Overall, the proposed computational framework incorporates in a single design methodology the properties of partial autonomy and cooperative performance of substructures. Both of them are particularly appropriate for the successful design of brain-like artificial cognitive mechanisms. In the proposed approach they are provided as a direct consequence of combining the distributed modelling (specifically, agent-based modelling) with the distributed design mechanism (specifically, the HCCE scheme).

3.6 Discussion

The proposed computational framework that employs evolutionary techniques as a design mechanism of biologically inspired artificial brains, can be parallelized with the well known "function approximation" approaches, a field where evolutionary algorithms have many successful applications (e.g. [279, 248, 259]). By adopting a similar way of thinking, one can state that the proposed computational framework follows a "brain approximation" approach, in the sense that biological brains provide a prototype performance, that the computational model needs to approximate. Along this line, the employment of evolutionary methodologies to approach the design of brain-like systems seems to be a reasonable and very promising choice.

Particularly, the proposed approach aims at exploiting the existing qualitative and quantitative information regarding the functionality of partial brain areas. This information is supplied to the fitness functions that guide the coevolutionary design process. Furthermore, the "co-"evolutionary methodology exhibits many desirable features to replicate biological findings addressing the components of the model. Combining this argument with the huge number of existing biological data (from fMRI, PET, EEG, lesion studies, etc.), the proposed design methodology can be a useful tool towards the design of advanced brain-like cognitive systems. Specifically, the more biological findings the model is able to reproduce, the closer it will be to the biological prototype.

Chapter 4

Computational Model

In the following, we present in detail the computational framework proposed by the present thesis, in order to approach the design of biologically-inspired artificial cognitive systems.

Specifically, the mammalian brain serves as the prototype structure that guides our efforts towards implementing artificial cognitive systems. In the present chapter we discuss its basic organizational principles, and how they modulate our modelling endeavors. According to the distributed nature of the brain, partial computational entities should be employed to facilitate mimicking of the biological prototype in terms of the connectivity of partial areas and the type of information they convey to each other. Then, we discuss the computational characteristics that should be provided to the partial entities in order to support the scalability of the modelling process. These characteristics are considered in order to specify the details of the proposed computational model. Specifically, two primitive computational entities are formulated. The first is employed to represent partial brain areas, while the second is employed to facilitate their linking, according to the connectivity pattern of brain areas. The primitive computational entities follow a flexible parameterized formulation, being able to model diverse substructures of the biological prototype. As a result, they can be employed as building blocks in order to design effective brain-inspired robotic cognitive systems.

4.1 Design of Distributed Brain-Inspired Models

The brain is described as a group of cooperating specialists (the brain areas) that achieves the overall cognitive functionality by splitting the task into smaller parts [242]. In order to develop a composite and successful brain performance, each area processes a specific subset of currently acquired environmental stimuli and existing knowledge, extracting further information elements which are properly structured and passed to other areas. The information flows according to the well known by neuroscience connectivity pattern of mammalian brain areas [144]. As a result, partial brain modules operate in a coupled and interactive mode, while cognition is considered as the result of collective phenomena emerging by the cooperation of brain substructures.

A brain-like artificial system should follow a similar distributed architecture. Along this line, the implementation of the overall computational system is related to the design of autonomous, still cooperating entities, each one associated with a limited set of responsibilities. These entities have to communicate and take advantage of one another in order to perform effectively, being able to accomplish both their partial goals and the composite goal of the overall system. Due to the distributed organization of the biological prototype, an agent-based approach seems suitable to support the design of brain-inspired cognitive structures [273].

Agents are deemed as a new tool for flexible modelling of complex systems which are described as a collection of partial components [139, 152]. This is achieved by addressing partial flexibility, autonomy, subjectivity, and situatedness of substructures in the environment formulated by their interaction [103]. From a human designer's point of view, agent technology supports problem decomposition, abstraction of partial models, and scalability of global problem solution [138]. As a result, it matches the problem of designing brain-inspired computational models.

Existing knowledge regarding the functional organization of the biological prototype, can be thoroughly exploited to guide the implementation of the artificial cognitive system. Specifically, the components of the composite system have to replicate the role that a brain area is known to play in the central nervous system of animals, the biological connectivity pattern that facilitates the flow of information, and the modifications that the projection of diverse stimuli impacts on the recipient brain area.

Along this line, separate agents can be utilized to represent computationally brain areas and their connectivity. The agent based modelling enriches the proposed approach for the design of brain inspired cognitive mechanisms with two basic features. First, it facilitates the decomposition of the composite task in smaller problems that can be more easily solved, addressing at the same time the integration of partial results. Second, it is able to consider the large number of biological findings referred to a brain-area level in order to facilitate the "brain-inspired" characteristics of the computational cognitive system.

In the present study, each agent is implemented by a neural network structure enriched with self-organization dynamics. Self-organized plasticity is one important feature that the employed computational structure encompasses, because it assists the scalable modelling of the overall system [195]. This is achieved due to the following reasons. First, plasticity facilitates the individuality of substructures. Specifically, diverse self-organization dynamics of partial components enforce them to develop distinct roles, affecting the functionality of the composite system in diverse ways. Second, plasticity facilitates the integration of partial components in a unified system. Particularly, the internal plasticity of agents enforces their adaptation on one another, formulating seamlessly a complex system consisting of autonomous partial components. At the same time, all agents adjust according to the characteristics of the external environment, which for the case of the cognitive system is specified by the body of the artificial organism and the surrounding physical objects.

4.2 Computational Model

The computational structures that are utilized to represent brain areas and the connections among them, specify the computational details of how information processing is performed, how communication among agents is implemented, how the roles of partial structures are assigned etc. The design of agent structures should ideally be based on the natural principles of the central nervous system of biological organisms. Along this line, we implement two different neural network based agents, to provide a general computational structure for the design of brain-inspired artificial systems [172, 173]. These agents are utilized as primitive building blocks for the design of the composite cognitive system. Specifically, we introduce: (i) a computational cortical agent to represent brain areas, and (ii) a link agent to support information flow across cortical modules.

It should be noted that the above computational structures are by no means restrictive for the composite computational framework proposed in the present study. They mainly serve as a guide on how coevolutionary approaches can be employed to support the design of brain-inspired computational systems. Currently, the employed agent components have been formulated as simple configurations that are suitable for the tasks studied in the present thesis. Additional constraints can be integrated to increase their effectiveness or biological reliability. Moreover, completely different computational structures exhibiting certain desirable features can be utilized to serve the needs of future studies.

4.2.1 Link Agent

The structure of the link agent is appropriately designed to support connectivity among cortical modules. Using the link agent any two cortical modules can be connected. Thus, proper connectivity among cortical agents can be defined, to simulate the connectivity of brain areas.

Each link agent is specified by the projecting axons between two cortical agents (Fig 4.1(a)). Its formation is based on the representation of cortical agents by planes with excitatory and inhibitory neurons (see below). Only excitatory neurons are used as outputs of the efferent cortical agent. The axons of projecting neurons are defined by their (x, y) coordinates in the receiving plane. Thus, a link agent consists of the set of axons, each one terminating at any desired position of the receiving cortical agent. In order to specify the link agent which facilitates the projection of cortical activity of an agent A with N_e excitatory neurons, on the plane of a cortical agent B, N_e pairs of coordinates need to be specified (i.e. $(x_1, y_1)(x_2, y_2)...(x_{N_e}, y_{N_e})$).

Cortical planes have a predefined dimension, and thus, projecting axons are deactivated if they exceed the borders of the plane. Consequently, not all excitatory neurons project their outputs on the receiving plane. This is illustrated graphically in Fig 4.1(a), where active projections are represented by an × on their termination. Projections outside the cortical plane are illustrated without a terminal point, and thus they are deemed deactivated.

When the locations of axons on the cortical plane are defined, synapses between axon terminals and the excitatory or inhibitory neurons of the receiving plane can be defined. The details of synapse definition are based on the post-synaptic neuron as it is proposed in [246], and explained below.

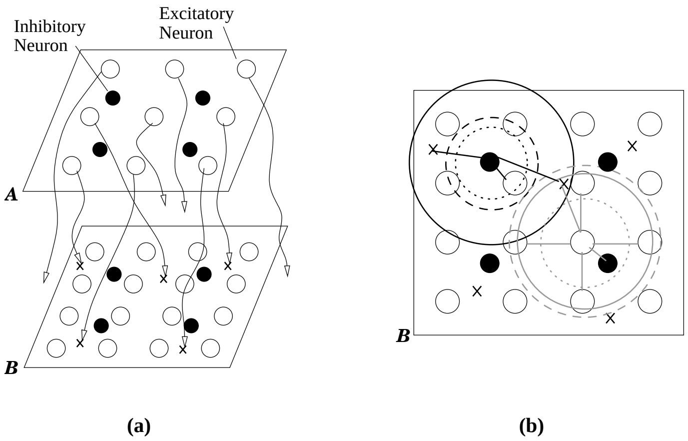

Figure 4.1: Schematic representation of a computational model with cortical and link agents. Part (a) illustrates a link agent which supports information flow from cortical agent A to B. Part (b) illustrates synapse definition in cortical agent B. Neighborhood radii for (i) afferent axons are illustrated by solid lines, ii) for neighboring excitatory neurons by dashed lines, and iii) for neighboring inhibitory neurons by dotted lines. Sample neighborhoods for excitatory neurons are illustrated with grey, while neighborhoods for inhibitory neurons are illustrated with black.

4.2.2 Cortical Agent

Each cortical agent is represented by a rectangular plane. A cortical agent consists of a predefined population of excitatory and inhibitory neurons. Both sets of neurons are uniformly distributed. Thus, an excitatory and inhibitory grid are defined on the cortical plane. On the plane of cortical agent, the axon terminals from the projected cortical agents are also located (Fig 4.1(b)).

Both types of neurons follow the Wilson-Cowan model with sigmoid activation, similar to [289]. Let x represent the firing rate of a neuron. It is updated based on the incoming signals, following the equation:

$$\mu \Delta x = -x + S(W_A A + W_E E - W_I I) \tag{4.2.1}$$

where μ presents the membrane time constant, W_A are the weights of the synapses with afferent axons, and W_E, W_I the synaptic weights of connections with neighboring excitatory and inhibitory neurons. $S(y) = 1/(1 + e^{-\alpha(y-\beta)})$, is the non-linear sigmoid function where β and α stand for the threshold and the slope, respectively. All excitatory neurons of a cortical plane share common parameters μ_e, α_e, β_e. The same is also true for inhibitory neurons using parameters μ_i, α_i, β_i.

Three synapse types specify the connectivity of each cortical neuron. All cortical neurons receive input information from (i) projecting axons, (ii) excitatory neighboring neurons, (iii) inhibitory neighboring neurons. Hence, the synapses of a cortical agent are classified in six sets, relevant to the three synapse types for excitatory neurons and three synapse types for inhibitory neurons.

The connectivity of neurons follows the general rule of locality [238], and thus synapse formation is based on circular neighborhood measures. A separate radius for each of the three synapse types, defines the connectivity of a neuron. This is illustrated graphically in Fig 4.1(b), which further explains the case shown in Fig 4.1(a). All excitatory neurons share common neighborhood measures, that is radii $n1_e, n2_e, n3_e$, relative to the three synapse types. The same is also true for all inhibitory neurons employing neighborhood measures $n1_i, n2_i, n3_i$.

The performance of cortical agents is greatly specified by the subjective experiences of the artificial organism, obtained through environmental interaction. This is similar to epigenetic[1] learning which has an important contribution to the performance of the mammalian brain [285]. To enforce experience based subjective learning of robots, each set of synapses is assigned a Hebbian-like biologically plausible learning rule, similar to [101]. We have implemented a pool of ten Hebbian-like rules that can be appropriately combined to produce a wide range of functionalities (see next section).

Each synapse is assigned a learning rule to adjust its synaptic weight during real-time performance. A separate rule is used for each of the three synapse types of

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[1] Epigenesis here, includes all learning processes during lifetime.

a neuron (either with a projecting axon, or with a neighboring excitatory neuron, or with a neighboring inhibitory neuron), defining learning dynamics of the cortical plane. All excitatory neurons share common learning rules $r1_e, r2_e, r3_e$. The same is also true for all inhibitory neurons employing rules $r1_i, r2_i, r3_i$. Consequently, in total, six rules are necessary to specify the dynamics of the learning process in each cortical agent.

4.2.3 Learning Rules

Epigenetic learning has an important contribution to the performance of the biological brain [285]. To enforce experience based subjective learning of robots, each set of synapses is assigned a Hebbian-like, biologically plausible learning rule, similar to [100]. We have implemented a pool of 10 Hebbian-like rules that can be appropriately combined to produce a wide range of functionalities. The learning rules employed in the present study have been selected based on their simplicity and their previous application in a variety of tasks [57, 100, 124, 151, 206, 213, 256]. Still, the architecture of agents is open and amenable to other learning rules with desirable characteristics in terms of either model performance or biological plausibility. Each learning rule is specified by a unique identification number. Assuming that there is a synapse with strength w_{ab} from neuron a with activation x_a to neuron b with activation x_b, then employed learning rules are formally described bellow:

1. *Differential Decorrelation* [57]: $\Delta w_{ab} = -\dot{x}_a \dot{x}_b$, where $\dot{x}$ is approximated by its discrete time counterpart $\dot{x}(t) = x(t) - x(t-1)$.

2. *Differential Correlation* [57]: $\Delta w_{ab} = \dot{x}_a \dot{x}_b$, where $\dot{x}$ is similar as above.

3. *PostSynaptic* [100]: $\Delta w_{ab} = w_{ab}(x_a - 1.0)x_b + (1.0 - w_{ab})x_a x_b$.

4. *PreSynaptic* [100]: $\Delta w_{ab} = w_{ab}(x_b - 1.0)x_a + (1.0 - w_{ab})x_a x_b$.

5. *Covariance* [100]: $\Delta w_{ab} = \begin{cases} (1 - w_{ab})t & , \text{ if } t > 0 \\ w_{ab}t & , \text{ otherwise} \end{cases}$
   where $t = tanh(2 - 4|x_a - x_b|)$

6. *Connectedness* [124]: $\Delta w_{ab} = 1 - w_{ab}$.

7. *Kohonen* [151]: $\Delta w_{ab} = x_a - w_{ab}$.

8. *PCA* [206]: $\Delta w_{ab} = x_b(x_a - x_b w_{ab})$.

9. *AntiHebbian I* [213]: $\Delta w_{ab} = k - x_a x_b$, $k > 0$ a small forgetting factor, to avoid vanishing.

10. *AntiHebbian II* [256]: $\Delta w_{ab} = k + \frac{-2x_a x_b}{{x_b}^2+1}$, where k is similar as above.

Each one of the totaly six synapse sets of a cortical agent is assigned a rule, specifying the dynamics of the agent during the epigenetic learning process. The assignment of the appropriate learning rule to each synapse set allows the emergence of the desired performance in each component of the composite computational model, after a certain amount of robot-environment interaction. Thus, adequate flexibility is offered to agent structures to develop a desired performance mimicking the role of biological brain areas.

The plasticity of agent structures, which stems from the assignment of learning rules, allows synaptic adjustments at run-time. Consequently, a large number of synapses (in the order of thousands in our case) can be self-organized based on internal agent dynamics and environmental experience. The most common, but harder to evolve, alternative of genetically-encoded synaptic strengths, results in a rather unmanageable problem complexity, and at the same time prevents experience based learning.

4.2.4 Reinforcement Learning

Reinforcement learning models (particularly those based on temporal difference learning) are very popular in robotic applications in recent years [315]. Despite of the effectiveness of reinforcement learning approaches, the biological reliability of this learning scheme has been criticized. Other researchers suggested that Hebbian learning mechanisms are able to facilitate training processes based on reinforcement signals [217]. As a result, the Hebbian self-organized dynamics of cortical agents can be exploited to guide the learning process of the artificial organism.

The idea is based on treating the reward as an ordinary signal which can be properly given as input in a pre- and a post- synaptic neuron to coordinate their activations [169]. The self-organized learning rule which adjusts the weight of the synapse connecting the neurons, is then responsible to either strengthen or weaken their connection. As a result, the external reinforcement signal is able to take advantage of the internal plasticity dynamics of the agent, in order to modulate its performance accordingly. Similar computational models exhibiting reinforcement learning characteristics have been also utilized by others (e.g. [34]).

4.3 Agent Plasticity

In the first section of the present chapter we discussed that self-organized dynamics facilitate the assignment of distinct roles to substructures and additionally facilitate their integration in a composite system.

However, there are many different ways to provide a model with self-organized plasticity. In the proposed computational model, internal plasticity dynamics is determined by the assignment of learning rules to the synapses of cortical agents. In contrast, the connectivity induced by link agents, remains static during real-time performance of the artifact. Following a different approach, we have also tested the employment of a different model which aimed particularly at offering the flexibility of self-organization dynamics to link agents [170, 171, 174]. Still, that model exhibited reduced flexibility in terms of projecting axon position. Specifically, the coordinates of the efferent neuron of the sending cortical plane were also utilized as the projection coordinates of the respective axon on the receiving cortical plane.

In summary, the one model provides flexibility of axon projection coordinates, but no real-time adjustment of axon weights, while the other assigns learning rules to axons providing them with the ability to learn, but keeps predefined and constant their projection coordinates. Practically, utilizing the first scheme, diverse information projections on a common cortical plane, are all treated and processed in the same way, even if separate link agents are employed to perform each projection. This is because the dynamics of information processing (guided mainly by the learning process) are defined only on the receiving agent. By utilizing the second scheme, diverse information amounts can be manipulated in a separate way (because each link agent is furnished with its own learning facilities), but now axons follow a predefined and non-evolvable projection pattern, that prevents flexible mixing of incoming information. The formulation of a computational structure which facilitates both issues (axon plasticity and projection flexibility) is not convenient, because the complexity of the problem concerning the parametrical specification of that structure increases dramatically.

Several experimental tests have revealed that the flexibility of projecting axons coordinates is more important than the self-organization dynamics of link agents, in terms of implementing gradually more complex computational models. As a result, the first model is employed in the present study, keeping also the complexity of the computational structure at easily manageable levels.

Since the goal of our work is not concentrated on the design of a specific computational model with special characteristics, but rather concentrates on the methodology which facilitates the design of scalable cognitive structures, we do not concentrate further on the properties of the computational model. Having formulated a robust design methodology, a new computational model exhibiting enhanced characteristics can be utilized in the future.

4.4 Discussion

In the present chapter we have presented the computational structures that are utilized as elementary building blocks for the design of complex brain-inspired computational systems. Specifically, neural network -based agents are utilized to represent computationally distinct brain areas of the biological prototype. Agents are enriched with internal plasticity dynamics which facilitate the adjustment of the model in real-time. This is similar to the modification of brain activity by epigenetic, experience-based factors.

Compared to the utilization of static building blocks, the internal plasticity of the employed components offers the composite cognitive system increased robustness. This is because the system is able to self-organize in order to be functional in diverse operating conditions that might result from changes in the external physical environment. Furthermore, the system is more robust against modifications occurred to its own structure. Particularly, when some components are deactivated, the remaining structures will self-adapt, avoiding the complete crash of the system. In a similar way, when a new component is integrated on the system, pre-existing substructures will self-adapt properly, in order to handle effectively the new information amount projected on them.

The agent structures employed in the present study are formulated in a flexible and abstract form, being able to serve as diverse computational structures. In other words, different instantiations of the agents are able to model efficiently different components of the composite structure. Along this line, the specification of agent parameter values, is able to configure a wide range of different functionalities, supporting the representation of the separate roles of brain areas.

As a result, the next issue that needs to be investigated, addresses how the identity of agent structures can be successfully drawn by means of parameter specification. Particularly, in order to formulate a complete and applicable computational framework that employs the agent structures as primitive building blocks, we are interested in addressing a consistent mechanism to support application-dependent design of agents. The present study argues that this problem can be approached effectively by means of cooperative coevolution. This is the subject of the following chapter.

Chapter 5

Hierarchical Cooperative CoEvolution

The previous chapter presented the computational building blocks employed to construct distributed biologically-inspired cognitive models. In order to develop complex computational structures exhibiting advanced cognitive skills, a systematic design mechanism is necessary. Due to the distributed nature of the computational model, a mechanism that also follows a distributed architecture would be particularly appropriate to serve the design procedure. This is because the distributed design methodology is able to consider explicitly the specialties of partial components, and at the same time address their coupled performance as a unified structure.

Along this line, the modern engineering approach for optimizing distributed systems, namely cooperative coevolution, can be employed to support the development of complex computational structures. Specifically, cooperative coevolution can be utilized as a tool to design brain-inspired computational systems, enriching systematically the model with biologically inspired characteristics.

In the present chapter, we first review the coevolutionary literature, and we discuss the suitability of cooperative coevolutionary methods to serve the design of bio-inspired cognitive systems. Then, we highlight the main limitations of existing coevolutionary methods, and we introduce a novel Hierarchical Cooperative CoEvolutionary (HCCE) scheme, to address them. Additionally, we discuss the particular features of the HCCE design methodology that facilitate the process of developing distributed models with biologically inspired characteristics.

Overall, the computational model presented in the previous chapter and the HCCE-based design methodology discussed here, provide a consistent framework to formulate complex brain-inspired artificial cognitive systems.

5.1 Coevolution

The extensive research into evolutionary computing techniques and their application to large scale problems enforced the emergence of coevolutionary approaches which involve two or more concurrently performed evolutionary processes with interactive performance. Initial ideas of modelling coevolutionary processes were formulated by [183, 15], and further extended in [128, 214]. Even if some researchers include single population models in coevolutionary approaches (e.g. [192]), in the present study we concentrate only on those schemes employing two or more distinct populations, because this approach is followed by the majority of recent studies [147, 198].

In the majority of real-life applications, partial entities can be identified, which together compose the overall picture of the problem. However, by utilizing an ordinary evolutionary scheme which employs a single, compound representation to map problem solution to genotype, the structural nature of the problem is usually underestimated, or overlooked. Additionally, the operators of the evolutionary process typically have a uniform range of application, without considering the characteristics of the problem's structure. In combination, the use of compound representations and uniform operators of variation, make it unlikely that partial solutions will persist since no mechanism for protecting them is present, and also make it unlikely that different combinations of partial solutions will be explored [287, 69]. Partial specifications of the genotype representing the components of the solution should be considered explicitly by the evolutionary process to facilitate the effective exploration.

This is particularly the case with coevolutionary algorithms which utilize separate populations to evolve each component of the problem. Each population is able to use its own evolutionary parameters (e.g. encoding, genetic operators). Accordingly, increased search competencies are inherently available in coevolutionary algorithms, while the special characteristics of partial solutions are also preserved [52, 69].

Furthermore, the design of the appropriate fitness function of an ordinary evolutionary process is a very crucial factor towards successful convergence. The formulation of the fitness function is usually a difficult task, which requires that the designer should have a deep knowledge of the application domain, and additionally should follow a time consuming trial and error procedure in order to combine properly all the details of the problem, in a single measure. An alternative approach to reveal information regarding the quality of individuals could be to test their performance in different operating conditions, and use these results in order to formulate an estimate of their fitness.

Coevolution differs from ordinary unimodal evolutionary algorithms in terms of fitness function usage, because the evaluation process is based on interactions between individuals. Each individual represents a distinct component of the problem which has to collaborate with the others in order to construct an effective composite solution. In other words, the fitness function is non-stationary, but it is also based on the quality of co-existing individuals representing different problem components [71]. Since the fitness measure is specified relatively to other individuals, the improvement of the quality of a partial population, is triggering further improvements in other populations. As a result, the coevolutionarry process is guided by continually changing goals, created by the coevolutionary adaptation itself, rather than being fully specified by the human designer, who might have misunderstood some important aspects of the problem [222]. Additionally, the plasticity of the fitness measure also enforces the advantageous side-effect concerning the effortless maintenance of diversity in partial populations.

Thus, it is not surprising that several studies report that coevolution outperforms unimodal evolution [212, 31, 308]. These results can be explained by the inherent ability of coevolutionary processes to decompose the overall problem domain in small searchable areas, and by the utilization of relative fitness functions among components, facilitating both the exploration of partial components and their integration in a composite solution.

Even if the field of coevolutionary algorithms is relatively new, it has gained the interest of many researchers over the last years. Some of these studies have been recently reviewed in [226]. The significant research attention on coevolutionary algorithms has been expressed by extended theoretical studies (e.g. [230, 310]). However, many theoretical issues are under investigation, including the identification of the decomposable structure of problems [69, 243], the design of consistent estimates measuring the progress of coevolution [108, 275, 18], and the investigation of the internal dynamics governing coevolutionary processes [302, 224, 225]. Other more practical research directions related to the computational details of the coevolutionary schemes include their enrichment with pareto optimality characteristics [97, 69, 70, 110, 136], the estimation and assignment of appropriate fitness values to individuals representing subcomponents [311, 3, 110] and the selection of the proper cooperating individuals [45, 209, 311, 46, 312, 310, 52].

Coevolutionary approaches are distinguished in competitive and cooperative. The main differences among the two categories are discussed below.

5.1.1 Competitive Coevolution

Competitive coevolutionary models are especially suitable for problem domains, where the problem can be stated in the form of two or more opponent entities [147]. Thus, each opponent can be utilized by the others as a test case in order to estimate their fitness. In other words, the competitive approach exploits the idea of co-evolving solutions and test cases, in coupled populations. Competition takes place between partial evolutionary processes, i.e. the success of the one implies the failure of the other [128, 263, 247, 215, 221, 64, 209]. The fitness of a candidate solution is proportional to the number of test cases it solves, while the fitness of a test case is proportional to the candidate solutions which fail to solve it [209]. As a result, it is expected that each opponent will become increasingly efficient by exploiting the weakness of the other, and also eliminating its own weak points. Competitive coevolution has been proved very efficient for those problems which are difficult to explicitly formulate an objective fitness function, but they can be described by an antagonistic scenario, because they facilitate the process of fitness assignment.

5.1.2 Cooperative Coevolution

The motivation for this approach comes from problem domains where explicit notions of modularity have to be introduced [230]. The cooperative scheme provides an appropriate framework for evolving solutions in the form of co-adapted subcomponents, and hence is of crucial importance for many difficult problems [229]. Usually, complex engineering design problems are decomposed into simpler tasks which are solved independently and then they are re-combined. This is effective for problem domains that can be linearly decomposed. That is no longer the case, however, for complex problems where non-linear interactions take place among the components, making partial structures dependent on one another. For these domains, cooperative coevolution is more suitable, because it allows an explicit co-adaptation of subcomponents [147, 198].

The standard approach of applying cooperative coevolution is to identify a natural decomposition of the problem into its partial components [231, 222, 311, 52, 198, 156, 310]. The structure of each component is assigned to a different subpopulation. Each component is evolved simultaneously, but in isolation from one another. Then, in order to evaluate the fitness of an individual from a given partial population, collaborators are selected from the other subpopulations, and the combined chromosome is decoded to form a complete solution of the problem which is further tested and evaluated [311]. Thus, partial populations need to adapt on one another in order to achieve their own successful performance and by this way formulate successful composite solutions.

5.1.3 Designing Brain-Inspired Artificial Systems

The coevolutionary scheme matches the design of brain-inspired artificial cognitive mechanisms, due to the distributed nature of both the biological prototype and the computational model. Specifically, the artificial system should consist of partial components representing brain areas. Thus, separate cooperatively coevolved populations can be utilized to perform design decisions for the components of the composite solution. Following this distributed design approach, it is able to consider the distinct roles of partial areas of the biological prototype and assign them adequately to the components of the artificial structure. Additionally, the cooperative coevolutionary scheme enforces the integration of subcomponents in a composite system, simulating the performance of the brain.

As a result, the cooperative coevolutionary scheme is utilized as a relational mechanism which binds the responsibilities of the modules of the biological prototype to the responsibilities of the modules of the computational system. According to the overall argument of the present thesis, this is able to happen due to the agent-based modelling of the artificial system, which implies that increased flexibility and autonomy is offered to the components of the model. At the same time, coevolution offers many advantages in terms of design effectively autonomous partial solutions, and facilitate their integration, because it is originally designed to work with substructures instead of the composite solution. Thus, the coevolutionary design mechanism and the agent-based representation fit one another. The first is able to assign distinct roles, while the second is able to accept them, facilitating the design of a complex distributed system.

Since the design of biologically inspired artificial brains aims at the cooperative performance of partial structures, in the following we only consider cooperative coevolution. Additionally, we note that in the coevolutionary literature, distinct populations are usually referred as species, and thus henceforth, these two terms will be employed interchangeably.

5.2 Hierarchical Cooperative CoEvolution (HCCE)

Despite the increased scientific interest in cooperative coevolutionary algorithms, the majority of existing applications are concentrated on problems consisting of a small number of components. This is a weak point for the wide acceptance of coevolutionary schemes, because in order to approach effectively large scale, complex problems, they should be capable of designing systems consisting of many substructures.

This level of effectiveness is difficult to be accomplished with existing cooperative coevolutionary schemes because they usually overlook the significance of choosing the appropriate collaborators within populations [311, 312]. For the majority of existing applications, all individuals of a species (population) are only able to cooperate with the best individual from the other species (e.g. [156, 229]). Following this heuristic, evolution is driven to a direction of reduced diversity, since all individuals of one subpopulation have to cooperate with the same (best) partial solution suggested by the remaining population. Even the additional random selection of more collaborators, followed by some approaches [52, 121] is not always able to improve the performance. Especially in the case of many coevolved species, the random selection of collaborators would demand unreasonably more computational resources. Additionally, depending on the fitness assignment method (e.g. average) it could destabilize the estimation of the appropriate fitness value, harming the convergence of the composite procedure.

Thus, it is necessary to formulate a purposeful approach to select the best collaborating individuals among species. Evidently, the coevolutionary process could be supported by the maintenance of successful cooperator assemblies as it is proposed in [192, 69, 243]. Additionally, the efficient selection of cooperators could be facilitated by a properly formulated optimization process performed in a higher level, which searches within species to identify the best cooperator assemblies. This higher level search can be implemented by means of one more evolutionary process. Thus, exploration is performed simultaneously in two different spaces. On one side, the evolution of partial processes searches for the appropriate structure of subcomponents, while on the other side, the evolution of assemblies searches to identify the component structures which are most able to cooperate. As a result, the composite coevolutionary procedure can tune partial evolutionary processes in order to converge successfully.

Furthermore, this process of simultaneous evolution of partial components and assemblies of components, can be organized hierarchically formulating a multiple level structure consisting of gradually more complex assemblies. The hierarchical scheme can facilitate the solution of problems described by multiple levels of modularity, where simple components are parts of other more complex ones.

In the present work we introduce a multiple level coevolutionary scheme which addresses the above mentioned issues [169, 168, 175]. The proposed approach follows a Hierarchical Cooperative CoEvolutionary (HCCE) architecture in order to develop a powerful cooperative coevolutionary scheme able to design complex systems consisting of a large number of components. Besides the evolution of species corresponding to partial components, the proposed HCCE scheme employs additional higher level evolutionary processes, to select the proper individuals from each species that cooperatively are able to construct effective component assemblies. These configurations can be used as a basis to guide the composite coevolutionary process since individuals are more likely to be members of effective cooperator assemblies. Thus, the multiple level process successfully formulates gradually more complex assemblies developing the composite solution of the problem.

Following the proposed approach, the coevolutionary schemes are enriched with hierarchical characteristics of non-coevolutionary schemes (in the sense that there are not distinct species for each component) described in [69]. To the best of our knowledge, there is only one work presenting a hierarchical cooperative coevolutionary method in the literature [77]. In contrast to [77], our approach is properly formulated to coevolve larger assemblies of cooperating species, and at the same time, emphasizes the independence of substructures utilizing multiple and potentially separate criteria to guide partial evolutionary processes.

5.2.1 Hierarchical Design of Brain-Inspired Artificial Systems

In section 5.1.3 we discussed the suitability of cooperative coevolutionary schemes for the design of brain-inspired artificial mechanisms. This issue is further facilitated by utilizing a hierarchical scheme.

First, we need to address that regarding the commencement of the coevolutionary process, the design of the fitness functions which describe the functionality of biological brain areas is not straight forward. This is because, at least at the present time, many details of the roles of brain areas are unknown. Thus, no consistent mathematical description of the design problem can be formulated. An alternative approach could be based on modelling extensive portions of the brain, emphasizing the cooperation of substructures. This is available by means of the HCCE because the hierarchical scheme facilitates the study of systems consisting of many partial components. Following this approach, the coevolutionary process can take advantage of simple partial fitness functions which only give an abstract description of the role of brain areas. The coevolutionary dynamics among separate populations will reveal the hidden details of fitness functions. This is because the interactions of partial fitness functions will fulfil one another. Consequently, the interactive dynamics of semi-complete fitness functions will highlight the exact roles of brain areas, facilitating the design of the composite model.

Furthermore, the hierarchical scheme facilitates the investigation of the model's performance in diverse operating conditions. Specifically, the hierarchical scheme is able to consider the performance of the composite structure in different tasks, and evaluate each independent component according to its participation in their accomplishment. The evaluation measures should be formulated in accordance to the known participation of biological brain modules in these tasks. As a result, the roles of partial computational structures will be closer to the biological prototype, and the composite system will be potentially able to develop cognitive abilities similar to the brain.

The hierarchical scheme is also able to consider the functionality of the artificial system in cases that some partial components are deactivated. These operating conditions simulate lesion of the respective areas in the biological prototype. As a result, existing biological data referred to the performance of the brain in pre- and post-lesion conditions can be exploited in order to specify the way the artificial system should perform in the respective conditions, with the intention of simulating even more efficiently the roles of biological brain areas in the composite structure.

Finally, due to the coevolutionary architecture, the hierarchical scheme is inherently able to combine efficiently partial components [172, 176]. This advantageous feature can be exploited to combine groups of components, formulating incrementally larger structures. This can be achieved by gradually adding more levels in the coevolutionary hierarchy, simulating the performance of new brain areas. As a result, the reusability of existing models is supported, facilitating also the design of complex structures with a progressively more advanced set of competencies. Furthermore, the HCCE scheme can be utilized to redesign, if necessary, pre-existing substructures according to the enhanced set of objectives, resulted by the integration of new components. The combined ability of HCCE to support these three steps - design, reusability, redesign - seems particularly appropriate for the development of effective artificial cognitive mechanisms.

In the following we present the proposed Hierarchical Cooperative CoEvolutionary (HCCE) architecture, emphasizing its employment in the design of brain-inspired artificial cognitive mechanisms, by utilizing the agents described in chapter 4 as building blocks.

5.2.2 Hierarchical Organization

The HCCE scheme is properly formulated to facilitate the design of systems consisting of partial components, organized in groups with complexity that gradually varies from simple to more complex ones. Specifically, two different kinds of species encoding the

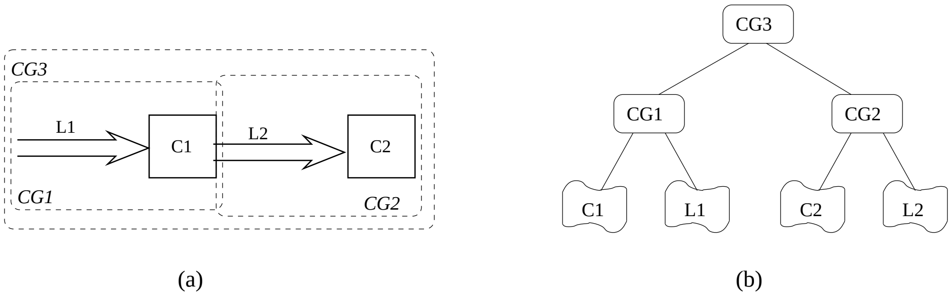

Figure 5.1: The design of agents by cooperative coevolution. Part (a) represents a hypothetical connectivity of agents. Cortical agents are illustrated with blocks, while link agents are illustrated with double arrows. Part (b) represents the hierarchical coevolutionary scheme used to evolve partial structures. CGs are illustrated with rounded boxes, while PSs are represented by free shapes.

configurations of either a Primitive agent Structure (PS) or a Coevolved agent Group (CG) are employed [168]. PS species specify partial elements, encoding the exact structure of either cortical or link agents, presented in the previous chapter. A CG consists of a group of cooperating PSs with common objectives. Thus, CGs specify configurations of partial solutions by encoding individual assemblies of cortical and link agents. Additionally, a CG can also be a member of another CG. Thus, several CGs are organized hierarchically in a tree-like architecture, with the higher levels enforcing the cooperation of the lower ones (Fig 5.1). However, different CGs can have different objectives, and consequently their evolution can be driven in different directions.

The details of the HCCE can be made clear by means of a specific example. Let us assume the existence of two cortical agents and two link agents representing their afferent projections (Fig 5.1(a)). We assume that agents $L1$,$C1$, have to support the fulfillment of task $T1$, while agents $L2$,$C2$, have to support the fulfillment of task $T2$. Thus, coevolutionary groups $CG1$ and $CG2$ are properly defined, each one classifying the structures supporting a respective task. At the same time, we assume that all structures have to cooperate to serve a third task $T3$. Thus, $CG3$ is also defined to enforce the cooperation among the groups $CG1$, $CG2$, aiming at the accomplishment of $T3$. This assumption is typical for the organization of the mammalian central nervous system (e.g. different brain areas serve visual or motor competencies, which further cooperate to form advanced real life behaviors). The corresponding HCCE process which aims at designing the structures of the current example, is illustrated in Fig 5.1(b). Four PS species are employed to evolve agent structures, while three CG species search for assemblies of cooperable individuals among PS species.

A snapshot of the HCCE process described above is illustrated in Fig 5.2. All individuals in all species are assigned an identification number which is preserved during the coevolutionary process. The identification number serves the definition of assemblies among different species. Each variable on the genome of a CG specifies the identification number of a partial solution at the lower level. The arrows connecting individuals among species illustrate how the HCCE builds the proposed compound solutions. For example individual with $id = 7$ of species $CG3$ specifies a solution consisting of partial assemblies with $id = 19$ at $CG1$ and $id = 3$ at $CG2$. Analyzing further the first assembly, it consists of the individual with $id = 14$ at $C1$ species, and individual with $id = 21$ at $L1$ species. In the same way, analyzing the assembly of $CG2$ it consists of the individual with $id = 4$ at species $C2$, and individual with $id = 5$ at species $L2$. It is clear that individuals at CG species might select some agents (or some assemblies of agent structures) multiple times. Following this mechanism, the cooperator selection process performed by the evolution of CG species, allows agents to participate in various assemblies aiming at the identification of a successful set of cooperators.

Following the HCCE approach, evolutionary exploration is performed concurrently in different spaces. The evolution of PS species facilitates search in the parameter space of sub-components. At the same time, the evolution of CG species searches within PS populations to identify suitable individuals in order to formulate successful assemblies of cooperators. Furthermore, CG species memorize good configurations of cooperating individuals across consecutive evolutionary generations. These configurations can be used as a basis to drive coevolution, since PS individuals are more likely to be members of good cooperating assemblies.

In order to test the performance of a complete problem solution, populations are sequentially accessed starting with the higher level. The genome values of CG individuals at various levels are used as guides to select cooperators among PS species. Then, PS individuals are decoded to specify the structure of cortical and link agents, and the performance of the proposed overall solution is tested on the desired task.

5.2.3 Lesion Simulation

Following recent trends aiming at the study of computational models in lesion conditions [4, 118, 220, 264, 193], we adapt our method to accomplish systematic modelling of biological lesion experiments [168, 174, 179]. This feature can be seamlessly supported by the overall proposed computational framework. Specifically, the proposed HCCE is able to consider the performance of the model under lesion conditions, by deactivating appropriate nodes in the tree hierarchy. Additionally, the distributed agent-based representation of brain areas facilitates lesion simulation by simply eliminating the appropriate agent structures. As a result, the performance of the model in pre- and post- lesion conditions can be easily tested by the proposed design methodology.

Similar lesion conditions are typical in biological experiments related to the performance of mammalian CNS. Lesion simulation is performed in the level of CGs, since all lower level species share common objectives, and thus they are deactivated as a group. This is not restrictive to our model, since the deactivation of a single PS can be simulated, if necessary, by defining a CG with only one lower level PS species.

As a result, the HCCE design process is able to consider the functionality of both the composite model, and any desired partial configuration, according to the needs of the prototype study of biological brain lesion.

Turning back to the example of Fig 5.1, a $CG3$ individual specifies the structure of the composite model which is tested on the accomplishment of task $T3$. Then, in order to simulate $C2$ lesion, the agents under $CG2$ are deactivated, and the remaining structures are tested on the accomplishment of task $T1$. Next, the respective agents from $CG2$ are isolated (lesion of $CG1$) and tested on the accomplishment of task $T2$. Fitness values are assigned to the respective individuals as it is described below.

5.2.4 Fitness Assignment

Even if the majority of existing cooperative coevolutionary methods assume that all species share a common fitness function [52, 156, 311], the proposed approach allows the employment of separate fitness functions for different species. This is in accordance to the coevolution of agent structures, because different objectives can be defined for each agent.

When an assembly of cooperators is tested, the cooperative performance of all agent structures is evaluated. The fitness function of each agent species evaluates subjectively the overall performance, that is it evaluates the performance according to the objectives it is designed for. Furthermore, the fitness function is formulated properly to evaluate the performance of the model in diverse operating conditions, which could correspond for example to the pre- and post- lesion state of the model.

For each species s, a fitness function f_s is designed to drive its evolution. Specifically, a partial fitness function $f_{s,t}$ evaluates the ability of the respective solution component to serve task t. Then, the values measuring for the accomplishment of each task are aggregated to estimate the global fitness value.

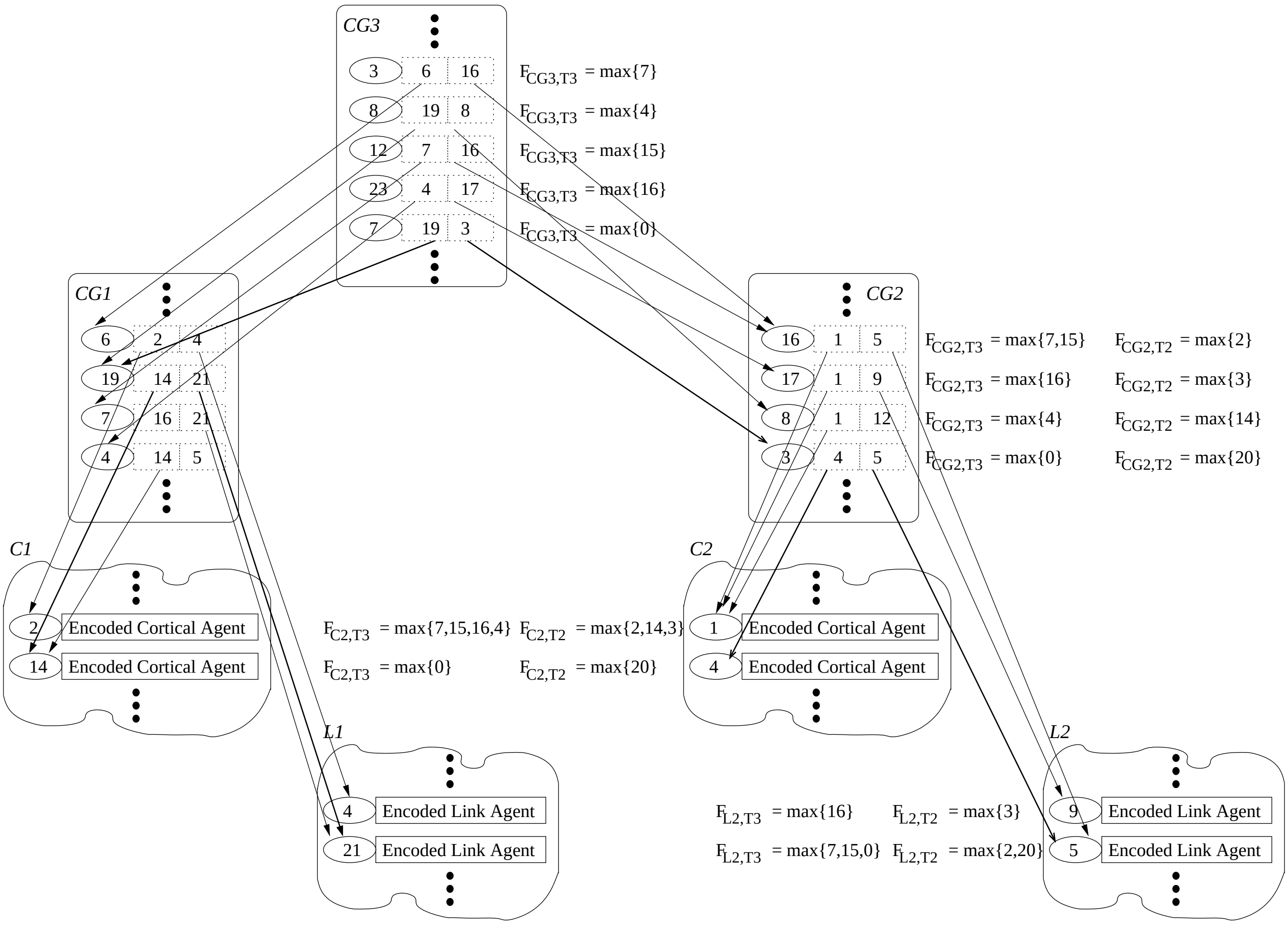

Figure 5.2: A snapshot example of the hierarchical coevolution of species. Identification numbers are represented by an oval. The arrows illustrate definition of individual assemblies. See text for details.

The most common operators for the aggregation of partial fitness values are sum and product. The main weakness of the sum operator is that in order to be effective, all partial fitness values should be normalized in a common scale. Unfortunately, this is difficult to happen in the context of cognitive mechanisms design, because the bounds of the fitness functions are generally unknown. As a result, in the present study, partial fitness values are aggregated in a productive manner. The product operator has also the advantage that the estimated global value is based on the percentage differences of partial measures (i.e. $f_{s,t1} \cdot (f_{s,t2} \cdot 80\%) = (f_{s,t1} \cdot 80\%) \cdot f_{s,t2}$) facilitating the convergence of the composite evolutionary process. Consequently, the composite fitness value is estimated by:

$$f_s = \prod_t f_{s,t} \tag{5.2.1}$$

For the agents which are not participating in the accomplishment of a task, the respective $f_{s,t}$ can be either omitted, or set equal to 1.

Since all PS species under a CG share common objectives, they also share the same fitness functions. For the example at hand the later means that the fitness function of species $L1$, $C1$ on a task t, is equal to the fitness function of $CG1$ (e.g. $f_{L1,t} = f_{C1,t} = f_{CG1,t}$). The same is also true for species $L2$, $C2$ and $CG2$ (e.g. $f_{L2,t} = f_{C2,t} = f_{CG2,t}$). However the fitness functions of $CG1$, $CG2$ and $CG3$, do not have to be related in general.

During the formulation of solutions for the composite problem, the cooperator selection process at the higher levels of hierarchical coevolution is able to select an individual to participate in many assemblies. Similarly to most existing approaches, individuals of the coevolved species are assigned for each task the maximum of the fitness values achieved by all the solutions formed with their membership. Thus, an individual of the s-th species is assigned for task t the value:

$$f_{s,t} = max_k\{f^k_{s,t}\} \tag{5.2.2}$$

where $f_{s,t}^{k}$ is the fitness value of the k-th solution formed with the membership of the individual under consideration. This result will be utilized by eq. (5.2.1) in order to estimate the composite fitness measure.

The fitness assignment process is further explained by means of the example illustrated in Fig 5.2. We remind the reader that according to the employed scenario, the composite model should accomplish task $T3$, the partial model of $C1$,$L1$ should accomplish task $T1$ (lesion of $CG2$), and the partial model of $C2$,$L2$ should accomplish task $T2$ (lesion of $CG1$). As a result, individuals of $CG3$ are evaluated for the accomplishment of task $T3$, individuals of $CG1$ and lower level PS species are evaluated for the accomplishment of both tasks $T3$ and $T1$, while individuals of $CG2$ and lower level PS species are evaluated for the accomplishment of both tasks $T3$ and $T2$. The assigned fitness values are illustrated in Fig 5.2, following the formulation introduced in eqs. (5.2.1) and (5.2.2). We present fitness assignment only on $CG2$ and its lower level species to avoid confusion. For the same reason we also assume that $F_{CG3,T3} = F_{CG2,T3}$, while in general they can be different.

The top level species $CG3$ is sequentially accessed and fitness values are estimated regarding the accomplishment of $T3$. Let us now examine the individual of $CG2$ with $id = 16$, which participates in two cooperator assemblies of $CG3$. Its ability to serve task $T3$ will be evaluated with the maximum of the respective fitness values. Additionally, $CG2$ individuals are assigned separate fitness values for the task $T2$ that they also serve. The same is also true for the individuals of lower level species $C2, L2$. For example, $C2$ individual with $id = 1$, has multiple participation in the accomplishment of tasks $T3$ and $T2$ and its evaluated properly.

We also note the fitness assignment of the individual with $id = 4$ of $C2$. Even if it receives a high score for its participation in task $T2$ it receives a zero for its participation in $T3$, and consequently its aggregative score according to eq. (5.2.1) will be also zero. There are also individuals which receive a high aggregative score, even if none of the assemblies they participate perform successfully in all tasks. This holds true, for individual 5 of species $L2$. One of its cooperating assemblies receives high score in $T1$ and low score in $T2$, while the other receives high score in $T2$ but low score in $T1$. However, the individual under consideration is finally assigned two high scores, because according to the partial performances, it is able to successfully serve both tasks. It seems that, at the moment, individual 5 of species $L2$ does not participate in good quality cooperative assemblies, but its high aggregative score indicates that it will probably participates in even better assemblies of cooperators in the next generation. Additionally, by means of genetic operators, parts of its genotype will be also transferred in the new populations with the hope to produce even better offsprings.

5.2.5 Encoding

A general purpose genotype is employed for both the evolution of PS species, and the cooperator selection process at CG species. The genotype is designed in an abstract form, able to handle a variety of computational structures (Fig 5.3). Thus, neural agents of any level of biological plausibility can be encoded and evolved.

Each individual is assigned an identification number and encodes two different kinds of variables. The first kind is allowed to get a value from a set of unordered numbers (e.g. {1,5,7,2}, with the ordering of the elements being of no use). These variables are called *SetVariables* and they are employed to store identification numbers, encoding the relationship between various elements of the model. The second kind of variables is allowed to get a value within a range of values (e.g. [0,1]); therefore, they are called *RangeVariables* and they are employed to search the domain of parameter values for each partial component of the solution. The values of SetVariables and RangeVariables are encoded in the genome by an integer and a real

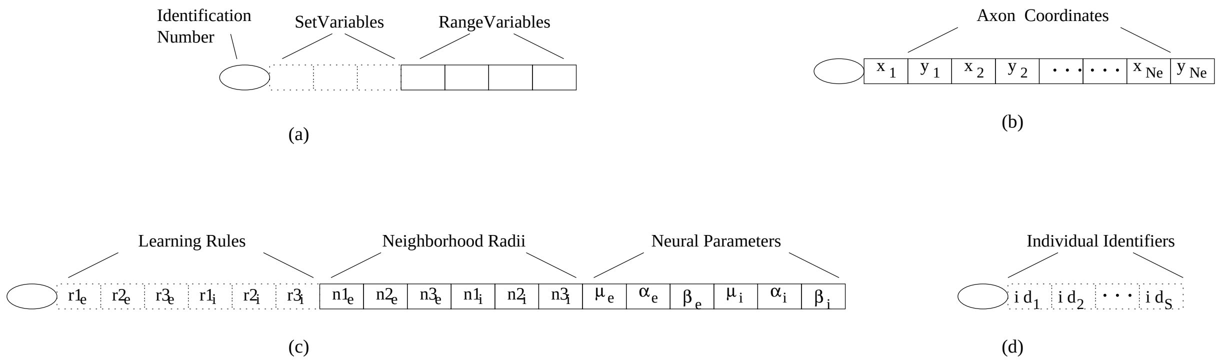

Figure 5.3: A schematic representation of (a) the general genome structure, (b) link agent's genome structure, (c) cortical agent's genome structure, (d) CG genome structure.

number, respectively, and they are graphically represented with dashed and solid boxes (Fig 5.3(a)).

Appropriately modified instances of the genotype are employed to encode the detailed structure of cortical and link agents. Following the description of link agents in section 4.2.1, their structure is specified by the (x, y) coordinates of axon projections. Thus, for a cortical structure with N_e excitatory neurons which employs a link agent to project on another cortical structure, $2N_e$ RangeVariables are necessary to encode the coordinates of link axons. The genotype used to encode link agent structure is illustrated in Fig 5.3(b).

In accordance with the description of cortical agents in section 4.2.2, their structure is completely specified by 6 SetVariables $(r1_e, r2_e, r3_e, r1_i, r2_i, r3_i)$ encoding the identifiers of the learning rules employed to adjust synapse weights, 6 RangeVariables $(n1_e, n2_e, n3_e, n1_i, n2_i, n3_i)$ to encode neighborhood radii employed for synapse definition, and 6 RangeVariables $(\mu_e, \alpha_e, \beta_e, \mu_i, \alpha_i, \beta_i)$ to encode neural parameters, separately for excitatory and inhibitory neurons. Thus, the genotype used to encode cortical agent structure is properly formulated as it is illustrated in Fig 5.3(c).

CG species encode assemblies of PSs (cortical or link agents) or other CGs (groups of cortical and link agents) located at the lower levels of the coevolutionary hierarchy. Thus, for the coevolution of S lower level species an equal number of SetVariables have to be utilized. Each SetVariable is joined with one lower level species, and its value can be any identification number id of the individuals from the species it is joined with. A graphical illustration of the genotype employed by CG's species is represented in Fig 5.3(d).

5.2.6 Genetic Operators

Because of the hierarchical and at the same time probabilistic nature of the process, some individuals of the species at the lower level could be multiply selected to participate in various assemblies. A large number of multiple cooperations is generally a drawback for the coevolutionary process. This is due to the fact that different cooperator assemblies would demand evolution of the same individual in different directions. This is a common problem for coevolutionary schemes which maintain and evolve cooperator assemblies [192, 110, 243].

However, at the same time, some individuals in the same species might exist, which are not offered any cooperation (termed *non-cooperative* henceforth). Unused individuals can be utilized to decrease the multiplicity of cooperations for those which are heavily reused. We introduce a new genetic operator to facilitate the hierarchical coevolutionary process addressing the issue of many multiple cooperations [178]. The operator is termed "Replication", and it is described bellow.

Replication. For each non-cooperative individual x of a species, replication identifies the fittest individual y with more than max_c cooperations. The genome of y is then copied to x, and x is assigned $max_c - 1$ cooperations of y, by updating the appropriate individuals of the CG population at the higher level. After replication, individuals x and y are allowed to evolve separately following independent evolutionary directions.

Replication is illustrated in Fig 5.4 for the case of one CG and one PS species. The same operator can be also applied for two CG species. The lower level individuals with ids $14, 7, 29, 9$ are offered $5, 2, 0, 3$ cooperations, respectively (Fig 5.4(a)). Assuming that $max_c = 3$, individual 14 is heavily reused. At the same time individual 29 is offered no cooperation at all. By applying replication, the genome of 14 is copied to 29 and two of the cooperations are appropriately redirected (Fig 5.4(b)). From now on, crossover and mutation operators can separately evolve individuals 14 and 29.

The value of the replication threshold max_c adjusts exploration - exploitation dynamics of the coevolutionary procedure. High max_c values imply that an assembly of cooperating individuals is able to participate in many composite solutions. Moreover, the application of the crossover operator on the higher level CG species, will enforce this assembly to participate in the construction of even more composite solutions, in order to identify the most promising set of cooperating individuals. This phenomenon implies that the successful assemblies are largely employed as test cases for the individuals of partial populations. Thus, by utilizing high replication threshold values, the dynamics of the coevolutionary procedure emphasize the “exploitation” of current results, in order to evaluate effectively partial components.

In contrast, low max_c values prevent individuals of partial species to participate in many cooperator assemblies. In that case, replication has an effect that is complementary to the one of applying crossover on the higher level CG. This is because the latter multiplies the participation of a particular assembly in many composite solutions, while the former destroys them creating independent copies of the assembly at hand. In other words, replication enforces for each substructure the independent evolution of many successful copies towards many different directions. Thus, the dynamics of the coevolutionary procedure emphasize more on the “exploration” of the search space, as a means to identify successful assemblies of cooperators.

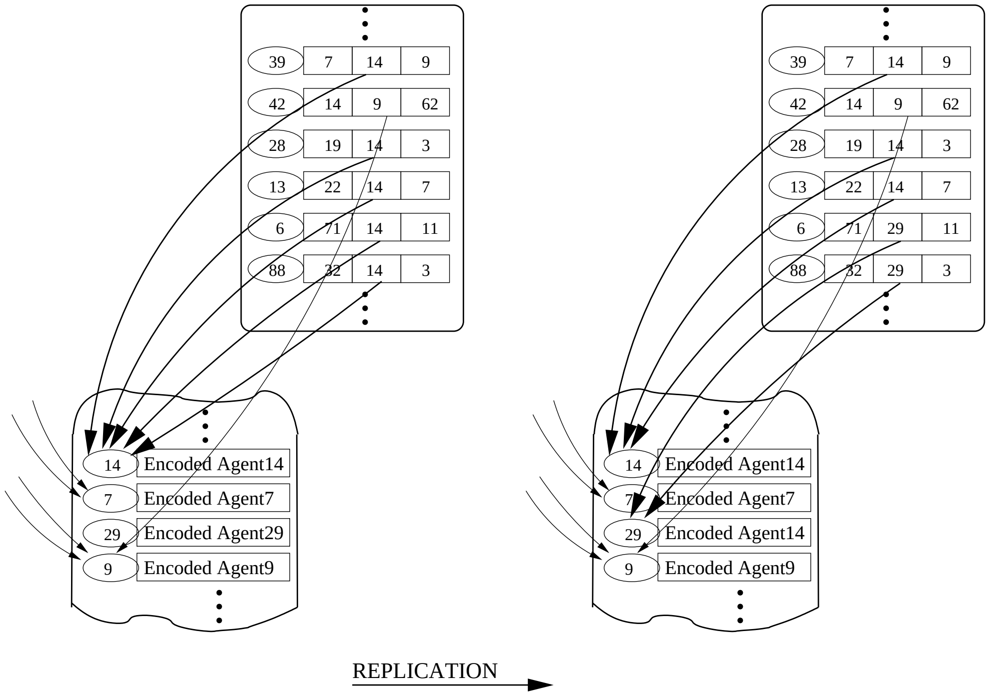

Figure 5.4: Schematic representation of the replication operator ($max_c = 3$). Collaborations of individuals considered by replication operator are illustrated by thick arrows, while additional connections which are not considered by replication are illustrated by thin arrows (see text for further explanations).

We need to note here that the proposed operator does not aim to be a computational representative of the biological DNA replication, even if they both share some common characteristics. The biological process is very complicated and can not be modelled easily because a number of different events may occur during its progression. Thus, the computational operator described above has been implemented independently, aiming to facilitate the effectiveness of the coevolutionary scheme.

Other Genetic Operators. Based on the genome structure, we have implemented crossover and mutation operators which perform separately on each kind of variables. During the mate process, the usual single-point crossover is applied separately for SetVariables and RangeVariables. Different mutation operators are implemented for each kind. In the case of RangeVariables mutation corresponds to additive noise.

Mutation of SetVariables is different for PS and CG individuals. As it has been described in section 5.2.5, in the case of PS, SetVariables encode learning rule identifiers. Thus, mutation corresponds to the random assignment of a new learning rule. In the case of CG, SetVariables encode identifiers of individuals at the lower species. Thus, mutation corresponds to probabilistic selection of a new individual, based on the accumulative probabilities at the lower level species. Following this approach, the best fitted individuals are most probably selected to participate in assemblies of cooperators.

In order to produce a new generation, each species is evolved independently. Initially, the individuals of a species are sorted according to their fitness values. Then, starting from the higher levels of the coevolutionary hierarchy, each species is sequentially applied all genetic operators, as described above. At first, replication reduces the very large number of cooperations for individuals. Then, a predefined percentage of individuals are probabilistically crossed over. Finally, mutation is applied in a small percentage of the resulted population to subserve diversity.

5.3 Discussion

The present chapter introduces a new Hierarchical Cooperative CoEvolutionary (HCCE) scheme that aims to facilitate the design of distributed, brain-inspired artificial cognitive mechanisms. Specifically, the proposed scheme can be utilized as a designing tool that systematically enforces mimicking of the prototype biological structure from the computational model. This is because the HCCE scheme provides the human designer the opportunity to replicate the performance of the biological system in many different tasks, and many different operating conditions, while at the same time, it also provides the designer the opportunity to assign separate roles to the components of the distributed artificial system which are similar to the roles of the components of the biological prototype.

Moreover, it is described the ability of HCCE scheme to replicate the results of biological lesion experiments, enforcing the similarity of the model with the biological prototype. The coevolutionary procedure is particularly appropriate to consider the performance of the model in pre- and post- lesion conditions, and additionally specify its functioning in both cases, according to biological findings.

The HCCE-based design methodology can be easily adjusted to address the results of biological studies which follow experimental processes different than lesion. This can be adopted in the future in order to enforce further the similarity of the model with the brain prototype. The HCCE -based design has been properly formulated to specify the performance of partial structures according to any kind of data. As a result, the HCCE scheme can be easily modified to consider biological results, such as those obtained by fMRI or PET studies. The more biological data the model is able to reproduce, the closer the artificial structure will be to the brain prototype. Hence, a consistent methodology to develop brain-inspired systems can emerge, facilitating the long term goal of designing artificial systems with cognitive skills similar to those of mammals.

Additionally, we note that the HCCE scheme follows an abstract formulation, being able to handle a wide range of computational structures. For example, artificial components which do not exhibit self-organization dynamics (e.g. with static synaptic weight) can be utilized to represent the less-plastic subcortical structures of the mammalian brain. Furthermore, HCCE is able to coevolve simultaneously artificial modules which follow diverse computational implementations. In other words, different structures (e.g. based on a systemic or neural approach) can be utilized to model distinct components of the composite system. As a result, any other computational model can be utilized in conjunction with the agents presented in the previous chapter. Extending further the simple example mentioned above, plastic structures could be used to represent neocortical areas, while static structures will represent subcortical areas. The HCCE scheme is able to coevolve them simultaneously, enforcing their cooperative performance as a unified composite system.

Finally, we note that the proposed coevolutionary approach can also be utilized in contexts different than the design of biologically inspired artificial cognitive systems. Theoretically, it can be employed to approach any kind of problem described with explicit notions of modularity that decompose the overall solution into subcomponents. As a result, it can be employed to address difficult problems with non-linear dynamics among partial components, such as the design of cooperating robot teams, or the investigation of partial and composite social behaviors. Thus, HCCE can be potentially employed as a general purpose method to study complex distributed systems.

Chapter 6

Results

The current chapter aims at the assessment of the computational framework that has been introduced in the present thesis in order to facilitate the design of brain-inspired artificial cognitive structures for robotic applications. We start by discusing the employment of a simulated versus a real robot for the implementation and embodiment of the computational models. Then, the experimental results are described. They are separated in two main parts. The first emphasizes hierarchical cooperative coevolution, demonstrating its effectiveness to solve difficult optimization problems that follow a distributed formulation. The second part highlights the benefits provided by the hierarchical cooperative coevolutionary design mechanism and the agent-based representation of partial structures, in terms of developing distributed brain-inspired cognitive systems. Then, the issue of computational resources of the proposed methodology is addressed, and we conclude this chapter with a discussion of the results.

6.1 Robotic Platform

Real-time environmental interaction is of utmost importance for the design of brain-inspired computational models. This is because it is difficult to investigate the coupling of partial brain components without embedding the composite model into a body to interact with its environment. In the current study, a simulated mobile robot is utilized to support environmental interaction, while at the same time, the implemented cognitive models enrich the behavioral repertory of the robot. Specifically, we employ a two wheeled simulated robotic platform equipped with 8 uniformly distributed distance, light and food sensors. The employed simulator is based on the YAKS environment, which simulates motion dynamics of the Khepera robot [51, 295]. The simulator has been slightly modified to serve the needs of the present study.

Several previous studies discussed the employment of simulated versus real platforms on the design of robotic systems, by means of evolutionary approaches [200, 188, 299]. Specifically, the first approach provides increased speed up of the design process, while the latter provides increased robustness against environmental perturbations. In general, it is believed that the systems implemented and tested on simulated platforms can not be directly transferred on real robots.

However, recent studies reported that the difference between simulated and real systems can be considerably eliminated by evolving plastic learning mechanisms instead of static structures [89, 88]. Following this approach, it is possible to utilize a simulated platform in order to specify the internal dynamics of the system that facilitate its adaptation in a range of diverse operating conditions. Then, the computational structure can be easily transferred to the real robot, because the system has been enriched with the necessary plasticity to self-adapt in the real operating conditions. Thus, considerable elimination of behavioral differences among real and simulated robots is achieved.

We note that the computational structures studied in the present work, are properly furnished with the required internal plasticity to address this issue. Specifically, the agents utilized as building blocks of the composite model exhibit inherent self-organization dynamics that facilitate adaptation of the overall cognitive structure on both the body of the robot, and the operating environment. As a result, the computational models discussed in the following sections are enriched with the appropriate characteristics to be easily transferred from the simulated to the real robot.

In the present study, a simulated robot serves as the basic experimental platform, in order to evaluate the computational framework proposed for designing brain-inspired cognitive systems. This is because the target of our research does not concentrate on the efficiency of the implemented computational models, but rather on the validity of the design methodology. Towards this end, the simulated robotic platform provides significant benefits that facilitate our goal (easy setup of different experimental procedures, ability to modify the characteristics of sensors and effectors, significantly shorter evolutionary design procedures, ability to distribute the computational load over multiple workstations, etc.)

6.2 HCCE Effectiveness

The current section aims at investigating the effectiveness of Hierarchical Cooperative CoEvolution. In the evolutionary literature, mathematical functions are often employed as test-beds for the comparison of diverse evolutionary approaches [322, 25, 116]. Particularly for the case of coevolutionary algorithms, mathematical functions based on few independent variables are usually employed [311, 312, 225]. Thus, the investigated problem can be easily decomposed in few and very simple entities. However, this is in contrast to many practical circumstances where difficult problems have to be decomposed in complex components. Trying to obtain a better insight of the coevolutionary procedure, the HCCE scheme is tested on the design of cognitive systems consisting of many partial components.

In particular, in order to validate the speed and robustness of the proposed coevolutionary scheme, we perform a series of tests comparing HCCE with one of the most popular cooperative coevolutionary schemes, namely Enforced SubPopulations (ESP) [120, 121], and with a unimodal evolutionary scheme. We have designed to different sets of experiments, each one highlighting different characteristics of the HCCE scheme. Additionally, we evaluate the effect of the Replication operator that has been introduced in the present study to support the successful convergence of the coevolutionary procedure.

We need to note that despite the biological background of the models investigated here, any other problem involving the simultaneous evolution of complex components that have to be adapted on one another, could also be employed as a test case. In order to highlight this aspect of the comparative study, the set up of the current experiments are presented in an abstract form, shifting the emphasis on the qualitative characteristics of the HCCE scheme, rather than the brain-inspired characteristics of the models. The biological background of the problems investigated in the current set of experiments will be presented later on. Hence, the interesting reader is referred there for more information.

6.2.1 Two Level Coevolutionary Scheme

First, we investigate the effectiveness of HCCE compared to two other evolutionary schemes, namely Enforced SubPopulations, and ordinary unimodal evolution. The problem that we address aims at designing a model of motor brain areas. The biological background of the model is discussed in detail in section 6.3.1, and thus it is omitted here. The model consists of two cortical and three link agents, and it is

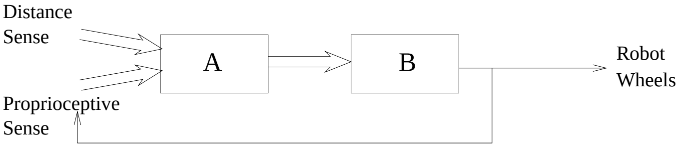

Figure 6.1: The computational model utilized as a test case for the evaluation of HCCE, ESP, unimodal evolutionary methods. Cortical agents are illustrated with blocks, while link agents are illustrated with a double arrow.

illustrated graphically in Fig 6.1. The structure of the composite model is specified by 92 parameters interacting with highly non-linear dynamics, and thus it is much more complex than a simple mathematical function.

The coevolutionary process has to design an assembly of cortical and link agents representing the respective components of the central nervous system. The components of the model have to cooperate successfully in order to accomplish task t, described by driving the robot in a wall avoidance mode. The level of accomplishment of t is evaluated by measure E. The detailed computational form of this measure is described by eqs. (6.3.1) in section 6.3.1. The fitness function that evaluates the quality of individuals driving the evolutionary process, is based on E values.

HCCE-based Design. Since all components need to facilitate the accomplishment of a common task, we utilize a two-level HCCE scheme to specify the structure of the overall model. This is demonstrated in Fig 6.2. Following the formulation introduced in eqs. (5.2.1), and (5.2.2), the fitness functions that drive the coevolutionary process are given by:

$$f_{CG1} = f_{CG1,t} \quad \text{with} \quad f^k_{CG1,t} = E \tag{6.2.1}$$

where k represents each membership of an individual in a composite solution. It is noted that all PS species are evolved by the same fitness function with their higher level CG.

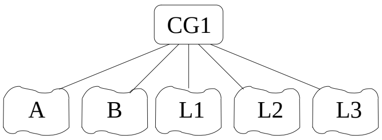

Figure 6.2: A graphical representation of the HCCE process employed to design the model. CG species is illustrated with an oval box, while PSs are represented by free shapes.

We have utilized populations of 200 individuals for all PS species, and 300 individuals for species $CG1$. Additionally, an elitist evolutionary strategy was followed with the 5 best individuals of each species, copied unchanged in the new generation. We have performed six independent runs of the coevolutionary design procedure. Each one of them, evolves the above described two-level HCCE scheme, for 170 epochs.

The obtained results are illustrated in Fig 6.3. We see that the first and the fifth run of the HCCE scheme were able to identify very good solutions to the problem. The second, third and sixth run converged to suboptimal solutions, which however were acceptable in terms of a qualitative evaluation of the results. The forth run gave the worst result, since it got stacked to a non-successful solution. Due to the probabilistic nature of the process, HCCE does not guarantee to always estimate the optimal solution to the problem. This is a common case for evolutionary processes. However, the obtained results shown both that HCCE is capable of solving the problem, and that in most cases it is able to produce a satisfactory result.

ESP-based Design. Additionally, we would like to investigate if a different coevolutionary scheme is capable to solve successfully the same problem, designing the model of motor brain areas. Specifically, we have approached the problem discussed above by utilizing the Enforced SubPopulations (ESP) coevolutionary scheme. In the current work, we have implemented the ESP algorithm described in [120], without however activating the stagnation check that practically re-initializes populations.

Five different populations have been employed to specify the structure of the five components of the model. Similar to HCCE, each population evolving the structure of a component consists of 200 individuals. Crossover and mutation probabilities on each sub-population are the same with the case of HCCE. The fitness function evaluating the success of individuals in each population is given by:

$$f = E \tag{6.2.2}$$

and thus ESP processes are directly comparable with HCCE processes. In each evolutionary epoch, a population of 2000 assemblies of components is randomly created. Thus, each individual representing the structure of a cortical or a link agent participates in an average of ten assemblies encoding complete problem solutions. The evolutionary process is driven by the average fitness of each individual.

We have performed six independent runs of the ESP-based coevolutionary design procedure. Each one of them, evolves for 170 epochs. The obtained results are illustrated in Fig 6.4. We see that there are not significant differences among the six runs. Unfortunately, non of them was able to solve the problem satisfactorily. The best results were given by the first and the third trial. However both of them are similar to the worst case of the HCCE processes. This might be because in each epoch, ESP employs random assemblies of the individuals encoding components structures. Thus, it is not able to enforce the cooperation among components and the successful co-adaptation on one another.

Unimodal Design. Finally, we have tried to approach the same problem by utilizing a unimodal evolutionary scheme. Specifically, a single, large chromosome is employed to encode the structure of all cortical and link agents of the model. The fitness function that drives the evolution of the complex chromosomes encoding the structure of the composite model, is given by:

$$f = E \tag{6.2.3}$$

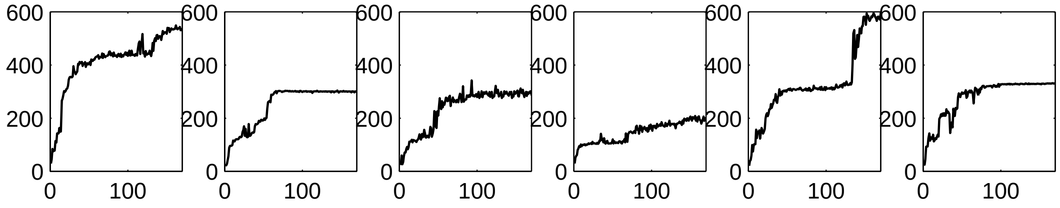

Figure 6.3: The results of six different HCCE-based design processes. Each plot demonstrates maximum fitness of individuals in a generation, against evolutionary epochs.

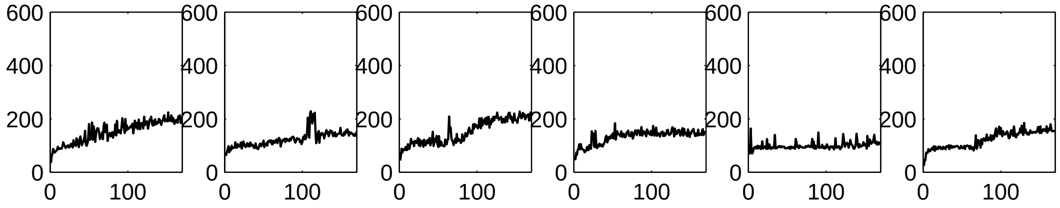

Figure 6.4: The results of six different ESP-based design processes. Each plot demonstrates maximum fitness of individuals in a generation, against evolutionary epochs.

and thus, the obtained results are directly comparable with the results obtained by the HCCE- and ESP- based processes.

In the current set of experiments a population of 400 individuals is evolved for 170 steps. The probability of applying crossover and mutation operators over the structure of a cortical or a link agent is the same as the previous experiments. We performed six independent runs of the unimodal evolutionary scheme.

The results of each run are illustrated in Fig 6.5. We see that most of the trials were not able to solve the problem successfully. The unimodal process is either highly unstable (runs 1,6), or it gets stacked to non-satisfactory sub-optimal solutions. The last run was able to identify occasionally sub-optimal solutions that solve the problem in a satisfactory level but due to the high non-linearity among problem parameters, the evolutionary process is too fragile, and they can not be exploited further. However, we note that these solutions are much worst than the optimal solutions identified by the HCCE processes.

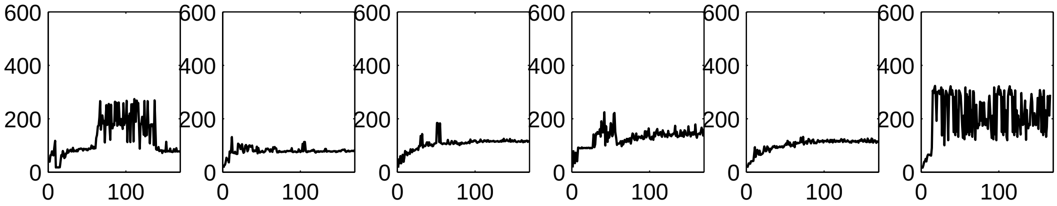

Figure 6.5: The results of six different unimodal evolutionary design processes. Each plot demonstrates maximum fitness of individuals in a generation, against evolutionary epochs.

Comments. In the present set of experiments we have utilize three different evolutionary methods namely HCCE, ESP, and ordinary unimodal evolution, to address the design of a brain-inspired computational model. The results obtained are illustrated in Figs 6.3, 6.4, and 6.5. By comparing these figures, we can easily observe the HCCE outperforms both ESP and unimodal processes. This is because HCCE has been properly designed to facilitate the evolution of large distributed systems consisting of complex components, enforcing their successful cooperation.

Additionally, it is worth emphasizing that the HCCE processes discussed above, are much faster than both the ESP and unimodal evolutionary processes. Each run needed approximately 150 minutes for the case of HCCE, 1050 minutes for the case of ESP, and 210 minutes for unimodal evolution. This is illustrated graphically in Fig 6.6. The experiments were performed on a PC with a Pentium 4, 3.00 GHz processor, and 512 MB RAM. The distribution of time is explained by the number of composite solution assemblies evaluated in each evolutionary epoch. Specifically, HCCE evaluates 300 assemblies of components, ESP evaluates 2000 assemblies, and unimodal evolution evaluates 400 assemblies. Thus, it is reasonable that ESP needs far most processing time, because it inherently performs more evaluations.

Overall, from the aforementioned set of experiments, we conclude that HCCE is more effective than both ESP and ordinary unimodal evolution for designing distributed computational structures consisting of complex components. Moreover, it has

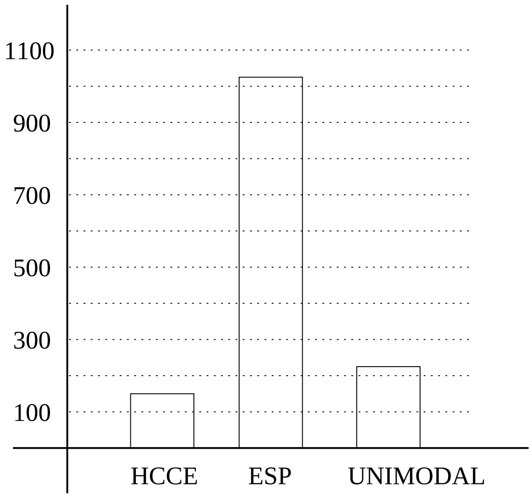

Figure 6.6: The processing time of a single run for each evolutionary design methodology. The y axes represents time minutes.

been illustrated that HCCE is also the fastest approach of the three tested.

We need to comment here, that ESP is comparable with two-level HCCE schemes because they both involve distinct populations to evolve the structure of system components, and additionally a population of assemblies of candidate substructures, trying to estimate the overall complex solution. The major difference among the two approaches is that in the case of HCCE, the population encoding assemblies has a relatively small size and it is computationally evolved, while in the case of the ESP, it has a rather large size and it is randomly created in each epoch. The experiments described above demonstrate that the evolution of assemblies is more important than the size of the population. Finally, we need to note that ESP does not support the formulation of hierarchies of coevolved populations, and thus it is not directly comparable with multi-level HCCE processes.

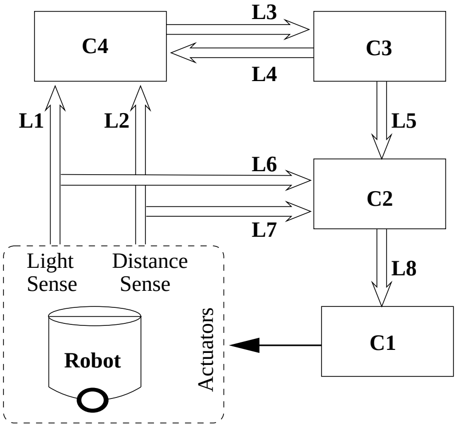

Figure 6.7: A schematic overview of the computational model. Cortical agents are illustrated with blocks, while link agents are illustrated with a double arrow.

6.2.2 Three Level Coevolutionary Scheme

The following set of experiments aims at evaluating the effectiveness of HCCE scheme on the design of a large computational model consisting of many components which have to cooperate in order to accomplish a set of tasks. Additionally, the operation of the model in conditions of partial failure (simulating brain area lesion) is investigated, highlighting the roles of substructures. The architecture of the model consisting of four cortical and eight link agents, is illustrated in Fig 6.7. The model is embedded in a robotic platform in order to evaluate its performance. The experimental process aims at reproducing computationally a biological lesion scenario of partial brain areas. The desired performance of the robot in the case of normal or lesion operating mode is as follows. Let us consider first the case of $C3$, $C4$ operation failure. In that case, $C1, C2$ perform in isolation, and they should be able to accomplish task A. Additionally, when failure in $C1$, $C2$ occurs, then only $C3$, $C4$ are operating and task B should be accomplished. When the composite model is active then all partial structures cooperate to develop a more complex functionality. Specifically, the activation of $C3$ is projected on $C2$ in order to accomplish task C. Three different

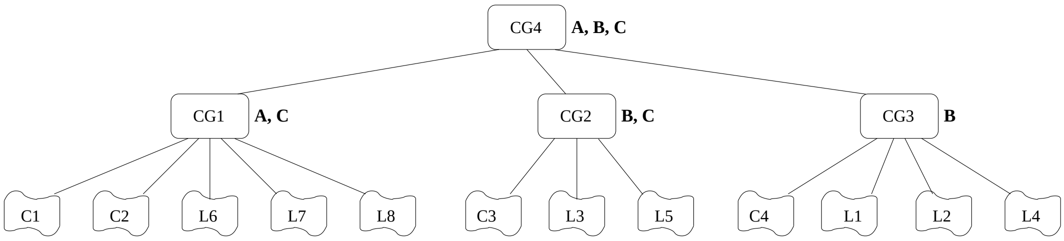

Figure 6.8: A graphical illustration of the coevolutionary process. CGs are illustrated with oval boxes, while PSs are represented by free shapes.

measures E_A, E_B, E_C are employed to evaluate the accomplishment of the respective tasks. The computational specification of these measures is presented in detail in section 6.3.3.

We need to note that the problem discussed above is much more difficult than the typical mathematical problems. Specifically, the composite structure consists of 12 complex components, each one assigned a certain role in the functionality of the system. Overall, the problem considered here involves the specification of totaly 264 variables, interacting in a highly non-linear way. Thus, it can be used as an advanced test case in order to investigate the dynamics of HCCE, and reveal its valuable characteristics.

HCCE-based Design. Since different groups of agents need to serve different tasks, we have employed a three-level HCCE scheme to facilitate the assignment of distinct roles to substructures. This is demonstrated in Fig 6.8. The tasks served by each group of agents are illustrated in the same figure, at the right side of each CG. Specifically, according to the problem description discussed above, the structures under $CG1$ serve tasks A, C. The structures under $CG2$ serve tasks B, C, while the structures under $CG3$ serve only task B. Finally, the top level CG4 is employed to enforce cooperation within partial configurations, facilitating the accomplishment of all three tasks.

The fitness functions which guide the evolution of partial species are designed accordingly, supporting the accomplishment of the respective tasks. It should be noted that all PSs share the same fitness functions with their higher level CG. Specifically, the fitness function employed for the evolution of $CG1$ and its lower level species is based on the measures evaluating the success of the respective tasks. Following the formulation introduced in eqs. (5.2.1), (5.2.2):

$$\begin{aligned} &f_{CG1} = f_{CG1,t1} \cdot f_{CG1,t2} \quad \text{with} \\ &f^k_{CG1,t1} = E_A, \quad f^k_{CG1,t2} = E_C \end{aligned} \tag{6.2.4}$$

where k represents each membership of an individual in a composite solution.

The fitness function which guides the evolution of $CG2$ is defined by means of the measures evaluating the success of tasks B,C:

$$\begin{aligned} &f_{CG2} = f_{CG2,t1} \cdot f_{CG2,t2} \quad \text{with,} \\ &f^k_{CG2,t1} = E_B, \quad f^k_{CG2,t2} = E_C \end{aligned} \tag{6.2.5}$$

where k is as above.

The third group $CG3$, serves only task C. Thus, the fitness function employed for the evolution of $CG3$ is defined by:

$$\begin{aligned} &f_{CG3} = f_{CG3,t1} \quad \text{with,} \\ &f^k_{CG3,t1} = \sqrt{E}_B \end{aligned} \tag{6.2.6}$$

where k is as above.

Additionally, the top level evolutionary process $CG4$, enforces the integration of partial configurations in a composite model, aiming at the successful accomplishment of all the three tasks. Thus, the fitness function employed for the evolution of $CG4$ is defined accordingly, following the formulation introduced in eqs. (5.2.1), (5.2.2):

$$\begin{aligned} &f_{CG4} = f_{CG4,t1} \cdot f_{CG4,t2} \cdot f_{CG4,t3} \quad \text{with,} \\ &f^k_{CG4,t1} = \sqrt{E}_A, \; f^k_{CG4,t2} = E_B, \; f^k_{CG4,t3} = E^2_C \end{aligned} \tag{6.2.7}$$

where k is as above.

The hierarchical coevolutionary scheme described above is evolved for 170 epochs. All runs employed populations of 200 individuals for all PS species, 300 individuals for $CG1$, $CG2$, $CG3$, and 400 individuals for $CG4$. Additionally, an elitist evolutionary strategy was followed in each evolutionary step with the 7 best individuals of each species, copied unchanged in the respective new generation, supporting the robustness of the evolutionary process.

We have performed six different runs of the HCCE scheme, each one evolving for 170 epochs. The obtained results are illustrated in Fig 6.9, where each column corresponds to a different run. In the first run, the progress of the HCCE scheme is initially slow, but after about 100 evolutionary epochs, the probabilistic search identifies a promising evolutionary direction which is efficiently exploited to identify a set of successful composite solutions. In the following two runs, we see that the coevolutionary process is rather unstable. Specifically, the evolution of species CG4 is not able to formulate successful assemblies of cooperators that will be preserved in the consecutive epochs. This fact additionally affects the progress of evolution in species CG2, CG3, which are trapped in suboptimal solutions. In the fourth run, the progress of the composite coevolutionary scheme develops slowly, and simultaneously for all species. The coevolutionary procedure is terminated without reaching the success rate of the first run. Still, we can easily observe that the progress of evolution is not stabilized, which implies that if the coevolutionary procedure could continue for more epochs, it should be able to estimate a sufficiently good result. The progress of the fifth run is similar to the first. The progress of the HCCE procedure is initially slow, until a promising assembly of cooperators is identified. After a small unstable period in the advancement of the coevolutionary procedure, an effective assembly is preserved, driving also the other individuals in an area of successful solutions. Finally, the progress of the last run is similar to the fourth. The evolution of each CG develops without rapid changes. However, in the current case, the advancement is a bit faster

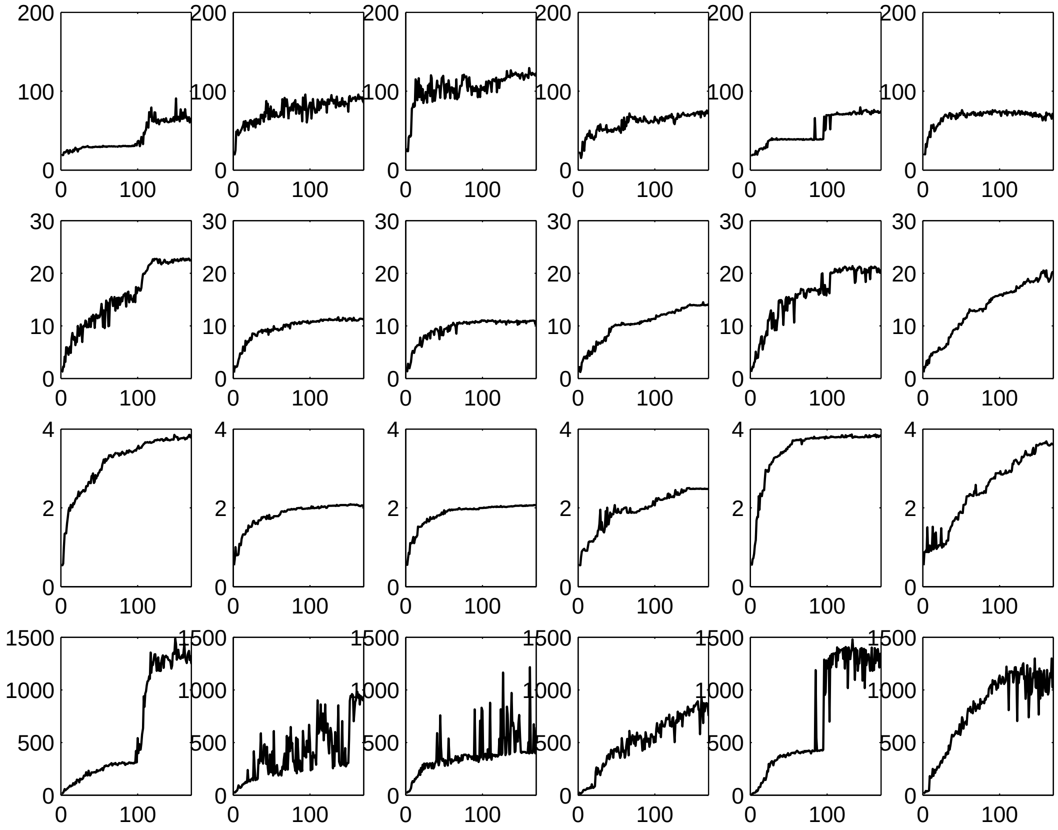

Figure 6.9: Graphical illustration of the progress of six different coevolutionary procedures. Each column is related to the results observed on the respective run. The lines 1-4 demonstrate the progress observed on the evolution of CG1, CG2, CG3, CG4, respectively. Each plot demonstrates maximum fitness of individuals in a generation, against evolutionary epochs.

than the fourth run, and thus the composite procedure is able to converge in a set of solutions with a nearly optimum fitness value.

In an attempt to formulate general comments on the progress of the HCCE scheme, we can state that the accomplishment of task B is critical for the success of the composite scheme. This is explained by the fact that task B is actually a subtask of task C. As a result, if task B is not sufficiently accomplished, it is not also possible to accomplish task C. We note that the evolution of CG3 aims only at the accomplishment of task B, see eq. (6.2.6). Thus, by observing the third line of Fig 6.9, we realize that whenever the solution of task B is stacked, then the composite coevolutionary procedure does not converge successfully.

Unimodal Evolutionary Design. In order to get a better idea of HCCE effectiveness compared to other coevolutionary schemes, it would be valuable to address the same problem by employing also different approaches. However, the majority of coevolutionary schemes proposed in the literature are not formulated in a hierarchical mode. Furthermore, the only hierarchical coevolutionary scheme that it is known to us [77], does not support the utilization of distinct fitness functions with multiple criteria for the evolution of partial species, and additionally, it is not formulated to evolve large assemblies of cooperators, as it is necessary in the current problem. Thus, any comparison with them, would be unfair.

In order to highlight the benefits provided by the HCCE scheme on approaching complex distributed optimization tasks we address the problem discussed above by using an ordinary evolutionary algorithm. This set of experiments aims mainly at stressing the limitations of the unimodal evolutionary approach, and the need for a specialized, advanced coevolutionary scheme, that facilitates the solution of problems with an inherent distributed structure.

Following the ordinary evolutionary approach, the structure of all cortical and link agents is encoded in a single chromosome. Hence, the parts of the genotype that correspond to system components participate in only one composite solution assembly. According to the unimodal approach, the autonomous role of substructures can not be indicated by partial fitness functions and thus, the evolution of partial groups of agents do not follow their own evolutionary directions. Still, their separate role can be revealed by testing the performance of candidate solutions in the accomplishment of the three different tasks.

The fitness function employed to guide the evolutionary process is defined according to the fitness function of the top-level CG of the coevolutionary scheme.

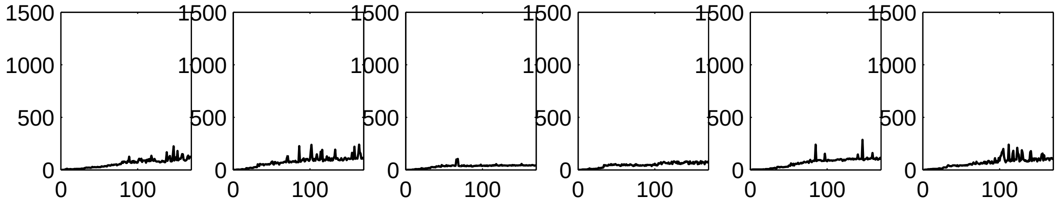

Figure 6.10: Graphical illustration of the progress of six different evolutionary procedures. Each plot demonstrates maximum fitness of individuals in a generation, against evolutionary epochs. Please compare with the last line of Fig 6.9.

Specifically, we consider the performance of partial structures in the accomplishment of the three tasks A,B,C. Similar to f_{CG4} (see eq. (6.2.7)), the fitness function is defined by:

$$f = \sqrt{E_A} \cdot E_B \cdot E_C^2 \tag{6.2.8}$$

which also implies that the progress of unimodal evolution is directly comparable with the progress of the HCCE scheme. In the current set of experiments a population of 400 individuals is evolved for 170 steps. The probability of applying crossover and mutation operators over the structure of a cortical or a link agent is the same with the respective probabilities of the coevolutionary scheme.

We have performed 6 independent runs of the unimodal evolutionary process. The results of the six process are illustrated in Fig 6.10. These results are directly comparable with the last line of Fig 6.9. Evidently, none of the ordinary evolutionary processes was successful. Additionally, even the best of them, was not as good as the worst case of the coevolutionary scheme. This is because ordinary evolution employs a single population consisting of individuals encoding the overall composite solution, and additionally employs a single fitness function which is not able to consider the partial objectives of substructures.

These results highlight the unsuitability of unimodal evolution to design distributed structures with distinct roles of partial components and, additionally, the need for a specialized scheme able to consider explicitly the individual characteristics of

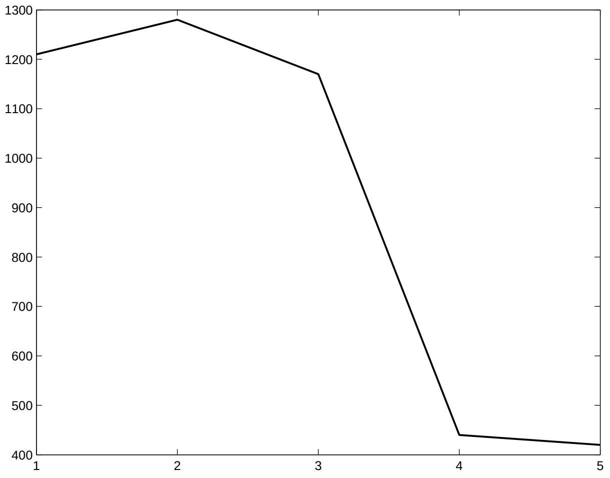

Figure 6.11: The average fitness of six runs of the HCCE procedure, utilizing different values of replication threshold max_c.

substructures. All these issues are sufficiently addressed by the HCCE scheme.

The Effect of the Replication Operator. Finally, we performed a set of experiments in order to investigate the effect of the "Replication" operator, on the progress of coevolution. Five different values of the replication threshold max_c are investigated. We note that the effect of the Replication operator is maximal when max_c values are low, and reduces gradually by increasing the value of this threshold. For example, in the case that very large max_c values are utilized, all species are evolved without the replication being actually ever applied. In contrast, by utilizing small max_c values, replication is applied very often, affecting the progress of coevolution.

Intuitively, max_c balances the exploration versus exploitation dynamics of the coevolutionary procedure. High values of the replication threshold indicate that the assemblies of individuals of partial species remain largely un-effected, in order to be employed as test cases for the individuals of the rest species. Thus, the dynamics of the coevolutionary procedure emphasize more on the "exploitation" of current results. In contrast, low values of replication threshold prevent individuals of partial species to participate in many cooperator assemblies, enforcing their independent evolution towards many different directions as it is indicated by mutation probability. Thus, in that case, the dynamics of the coevolutionary procedure emphasize more on the "exploration" of the search space.

For each value of max_c threshold ($\{1, 2, 3, 4, 5\}$), six runs are performed. The average of maximum fitness values of $CG4$ over the six runs is illustrated in Fig 6.11. According to the results, low values of replication threshold are preferable for the HCCE scheme at hand. In other words, the successful convergence of the coevolutionary process is facilitated more by the efficient exploration of the search space. This can be explained by the increased complexity of the problem and the high non-linear interaction among the partial elements of the solution.

Comments. The set of experiments described above aims at the assessment of the Hierarchical Cooperative CoEvolutionary scheme. The results obtained attest to its validity and effectiveness. Specifically, HCCE is capable of designing successfully a system consisting of a total of twelve complex partial components. Even if for the experiment with the much simpler model described in section 6.2.1 the two approaches gave comparable results, in the current set of experiments it is shown that HCCE significantly outperforms ordinary evolutionary processes, when addressing problems that the special characteristics of substructures have to be explored.

In the present set of experiments, both HCCE and unimodal evolution needed approximately 10 hours to process each run. This is because the embodiment of the cognitive system in the simulated robotic platform and the observation of robot performance for a large number of simulation steps has significantly increased the time of testing of each individual. However, long-lasting evolutionary design procedures are very common when behavioral tasks have to be solved. The experiments were performed on a PC with a Pentium 4, 3.00 GHz processor, and 512 MB RAM. Both approaches have similar time demands because in both cases 400 composite solution assemblies are evaluated in each epoch.

The partial roles of agents, and their relative contribution to the accomplishment of each task, are important factors for the successful convergence of coevolution. In the present work they are described by eqs (6.2.4) - (6.2.7). The cooperator selection process facilitates coordination of lower level processes enforcing the coupling of structures with completely different objectives (e.g. those under $CG1$ and those under $CG3$).

We note that the elitist strategy followed during the evolution of species has a positive effect on the progress of multi-level HCCE procedures. This is an empirical conclusion that is supported by all the evolutionary processes discussed in the present study. Particularly, for each species about 5-10 of the best individuals have to be copied unchanged in the new generation, facilitating the successful convergence of the composite process. Intuitively, the elitist strategy alleviates the robustness of the coevolutionary process, while the Replication operator supports sufficient exploration of the search space.

Finally, the results demonstrated that Replication operator facilitates significantly the successful convergence of the composite coevolutionary process. Specifically, Replication has been properly formulated to convey information from the higher to the lower levels of the hierarchy, in order to modulate and coordinate partial evolutionary processes. As a result, this particular operator can be applied in other coevolutionary schemes evolving assemblies of individuals [192, 110, 243], in order to facilitate integration of partial components.

6.3 Brain-Inspired Cognitive System Design

In the following, the HCCE scheme studied above is employed as a design mechanism, facilitating the development of brain-inspired cognitive systems. We note that the present series of experiments does not aim at implementing detailed and biologically reliable models of brain areas. The results demonstrated here, are indicative for the proposed agent based coevolutionary framework, aiming at highlighting its main characteristics. Specifically, the experiments presented bellow serve as a means to demonstrate the ability of the proposed framework to design, integrate and redesign computational structures, facilitating the development of complex biologically inspired systems.

6.3.1 Modelling Simple Modular Structures

First, we consider the functionality of the lower levels of the central nervous system motor hierarchy, which serve primitive motion behaviors[1]. The ability of biological organisms to reason and make plans of future action is mainly supported by the higher level prefrontal cortex, and is considered in the following experiments.

The connectivity of partial components is illustrated in Fig 6.12. The proposed model discusses the projection of sensory information in Primary Motor Cortex (M1) which formulates simple motion commands encoded in a population of active neurons [144]. These commands are then passed to the Spinal Cord which decodes them to specific motor actions. Spinal cord is simulated only by its descending pathway and a cortical agent is employed to represent it. We assume the existence of an agonist and antagonist muscle in each side of a robot wheel. One motor neuron of the spinal cord activates each of these muscles. Wheel speed is defined by the activation difference between the muscles. Thus, four motor neurons are necessary to define muscle's activation, and consequently the speed of the robot. Proprioceptive information of muscles activation is fed back to the motor cortex, via a link agent.

The whole computational model consists of 5 subcomponents (2 cortical and 3 link

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[1] Slightly modified versions of this experiment have been presented in [171, 178].

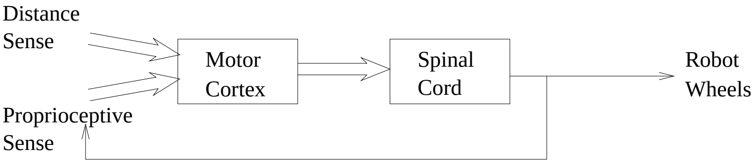

Figure 6.12: A schematic overview of the Primary Motor Cortex model.

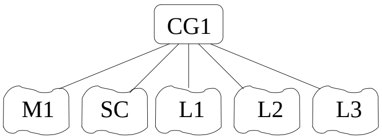

Figure 6.13: A graphical representation of the coevolutionary process employed to design M1-SC model.

agents) which have to cooperate to accomplish the desired performance. Specifically, the composite model aims at developing wall avoidance navigation behavior, after a certain amount of interaction with the environment. Computational models of the same brain areas have been also proposed in the literature, eg. [5, 290], which, however, do not emphasize on the self-organized robot understanding of environmental characteristics.

The HCCE scheme employed to design the computational model is demonstrated in Fig 6.13. The evolution of the five components is tuned by a single CG species, since they all have to support the accomplishment of the same task. Populations of 200 individuals evolve the structure of cortical and link agents, while a population of 300 individuals evolves the higher level cooperator selection process. Each individual is assigned a fitness value according to the evaluation measure:

$$E_{wa} = \left(\sum_{M} (sl + sr - 1) \cdot (1.0 - p^2) \right) \cdot \left(1 - \frac{2}{M} \left| \sum_{M} \frac{sl - sr}{sl \cdot sr} \right| \right)^3 \cdot \left(1 - \frac{2B}{M} \right)^3 \quad (6.3.1)$$

where we assume that robot performance is observed for M steps, sl, sr are the instant speeds of the left and right wheel, p is the maximum instant activation of distance sensors, and B is the total number of robot bumps. The first term of eq.

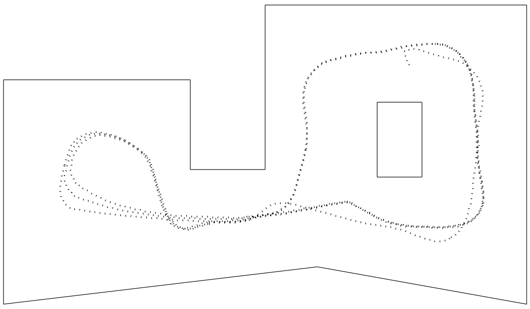

Figure 6.14: A sample result of robot wall avoidance navigation.

(6.3.1) seeks for forward movement far from the walls, the second supports straight movement without unreasonable spinning, and the last term minimizes the number of robot bumps on the walls.

The fitness function employed for the evolution of $CG1$ and its lower level species is based on the measures evaluating the success of the wall avoidance task. Following the formulation introduced in eqs. (5.2.1), (5.2.2):

$$f_{CG1} = f_{CG1,t1} \text{ with, } f^{k}_{CG1,t1} = E_{wa} \tag{6.3.2}$$

where k represents each membership of an individual in a proposed solution. Evolution was performed in synchronous steps for all populations. After 70 epochs we got many computational structures able to drive the robot without bumping on the walls. A sample result is illustrated in Fig 6.14.

6.3.2 Modelling Complex Distributed Structures

The hippocampus is one of the most studied areas of the mammalian cortex because of its prominent role in the memorization of spatial information. Different groups of cells, namely place cells, have been detected in the mammalian's hippocampus, which preferably fire when the animal is in a particular portion of its environment. Additionally these cells are largely independent of the orientation of the animal and its actual view [207]. The hippocampus consists of partial areas which cooperate to develop place cells. Following recent trends in the area, we focus our study on the investigation of the entorinal cortex (EC) from parahippocampal region and dentate gyrus (DG), and Amon's horn structures CA3, CA1 from hippocampal formation. Recently, place cells have been detected in all these structures. Since the exact role of hippocampal areas has not been specified yet in the literature, the design of the computational model will be based on existing knowledge, that is the development of place cells in hippocampal substructures[2].

A number of hippocampal computational models have been proposed in the literature, which are able to develop place cells based on allocentric sensory stimuli. Some approaches consist of an arrangement of appropriately connected neurons on a planar map [11, 124]. Other hippocampal models are based on the recurrent connectivity of CA3 neurons [143]. A combination of planar map with recurrent connections is presented in [251]. Moreover, according to [208, 91], the existence of a topographical relation between environmental location and hippocampal cells seems not valid. This is taken into account in [278] where attractor networks are employed to perform feature encoding. The majority of existing models employ simplified structures which omit the projection from CA1 to EC. This is a very critical design decision, since a recurrent cellular structure is computationally represented by a feed forward one. A computational model with re-entrant projections from CA1 to EC is presented in [202], but it is not tested for the development of place cells.

In the present experiment, we present a detailed hippocampal model with separate neural agents representing each hippocampal area (EC, DG, CA3, CA1). Thus, all interactions among these areas can be simulated. Similar to the majority of the models, we follow an approach based on environmental features for the development of place cells, but in contrast to them we do not assume global view of the environment.

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[2] A modified version of this experiment has been presented in [178].

Appropriate fitness functions drive the coevolutionary process (as explained below), aiming at the development of place cells.

It has been experimentally shown that the hippocampal system processes allocentric (orientation invariant) information [47]. This is a common hypothesis for all computational models discussed above. We have implemented a simple computational formula to perform this transformation, given the current orientation ϕ of the animal [170]. For the sake of simplicity we assume that the number of head-direction (HD) neurons is equal to the number of light or distance sensors; let this number be M. Each HD neuron has a preferred direction θ of maximal activation and follows the gaussian model, similar to real HD cells [282]. Let us assume that the information of the $i-th$ egocentric sensor is given by h_i. The allocentric measure is estimated by the following summation over all HD neurons.

$$g_i = \frac{\sum_{j=0 \ldots M-1} e^{-(\phi - \theta_{(M-j) mod M})^2} h_{(i+j) mod M}}{\sum_{j=0 \ldots M-1} e^{-(\phi - \theta_{(M-j) mod M})^2}} \tag{6.3.3}$$

where g_i is the new orientation invariant measure. This formula has a slight smoothing effect on sensory stimuli, which is due to the averaging performed. Intuitively, it considers stimuli from all sensors, rotated by certain angles, and weighted each time by a factor that is proportional to the matching of rotation and head direction. It is interesting to observe that this formula can be directly used to combine our approach with other computational models that develop HD cells (e.g. [238]).

The hippocampal model is fed with allocentric measures. Distance and light sensory stimuli are projected to EC and then they travel along partial hippocampal structures as it is illustrated in Fig 6.15. The composite computational model consists of 12 subcomponents (4 cortical and 8 link agents) which have to cooperate to accomplish place cell development.

In order to test the development of place cells, we define P ($P = 13$ in this experiment) areas in the environment (see Fig 6.16), where the activation of hippocampal

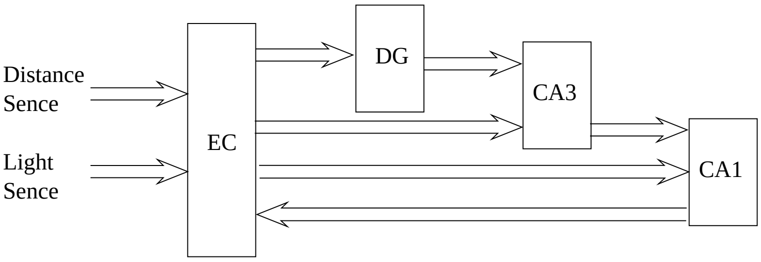

Figure 6.15: A schematic overview of the hippocampal model.

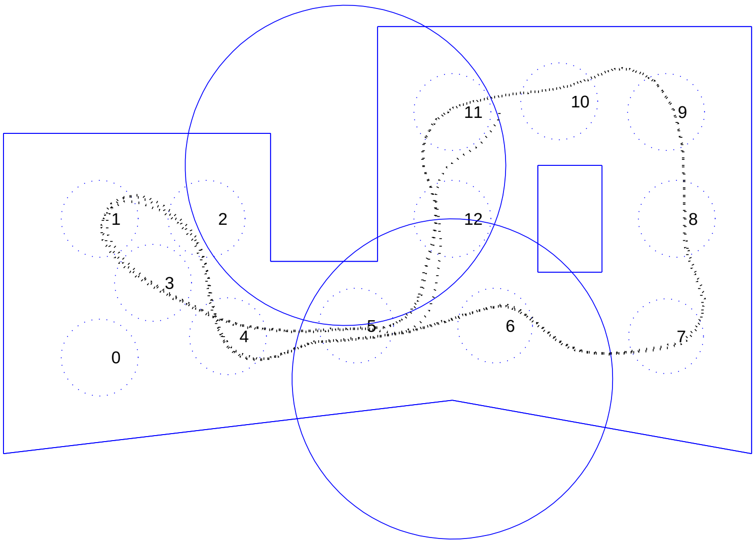

Figure 6.16: Experimental setup of the hippocampal model testing. Environmental areas ($P = 13$) are illustrated with dashed circles. Solid circles illustrate the existence of two light sources.

excitatory neurons is observed. The activation of inhibitory neurons is not examined, since only excitatory neurons encode efferent information. For each cortical agent $i \in \{EC, DG, CA3, CA1\}$, and each location $p \in \{1...P\}$, separate activation - averages over time, a_j^{ip}, are computed, with j identifying excitatory neurons.

Place cell development implies that when the robot is positioned in two different areas, the rate rd of differences within activation-averages, divided by the total activation, should be close to one. For two locations p, q, with $q \neq p$, this measure is expressed mathematically by:

$$rd^i(p,q) = \frac{\sum_j \left|a_j^{i,p} - a_j^{i,q}\right|}{\sum_j \left(a_j^{i,p} + a_j^{i,q}\right)} \tag{6.3.4}$$

A successful development of place cells in cortical agent i implies that the average activations at any two locations p,q give high values of relative difference rd. Following a worst case scenario, a separability measure of place cells RD^i can be defined based on the most similar locations:

$$RD^i = min_{p,q}\{rd^i(p,q)\} \tag{6.3.5}$$

One more measure is also defined to support the stability of cortical agents performance. It estimates the consistency of activations for the case that the robot is located in area p more than once. This can be done using the contrast of activation-average values at p. We use the variance $v^{i,p}$ as a contrast measure:

$$v^{i,p} = \frac{1}{N_e}\sum_j \left|m - a_j^{i,p}\right|, \quad with \quad m = \frac{1}{N_e}\sum_j a_j^{i,p} \tag{6.3.6}$$

for a cortical agent i, with N_e excitatory neurons. If the same neurons are activated every time the robot is located in p, contrast measure $v^{i,p}$ will have a high value, while if different neurons are activated every time the robot is located at the same p, then $v^{i,p}$ will have a small value. The average of variances at all locations is employed as a consistency measure of cortical agent $i \in \{EC, DG, CA3, CA1\}$:

$$V^i = \frac{1}{P}\sum_p v^{i,p} \tag{6.3.7}$$

Since CA1 is the major efferent structure of hippocampus, we assume that the excitatory activation in CA1 agent should be able to infer the location of the robot. This is done at every simulation step by estimating the distance of current activation x_j^{CA1} with the activation-averages of CA1, at every location p:

$$d^p = \sum_j \left|x_j^{CA1} - a_j^{CA1,p}\right| \tag{6.3.8}$$

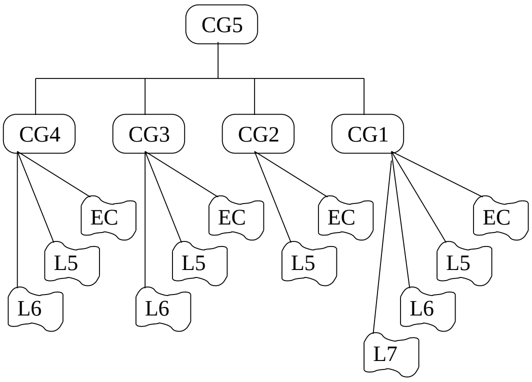

Figure 6.17: Graphical representation of the HCCE process utilized to design the Hippocampal model. CG1 is not evolved in the current coevolutionary process.

A simple process infers robot location p as the one with the minimum distance d^p. By utilizing this localization process, a success rate $S = s/t$ is defined for the total hippocampal model. It is based on the number of simulation steps s that the inference process is able to successfully identify the robot location, relative to the total number of simulation steps t that the robot is located in known positions.

The fitness measure which evaluates the successful development of place cells in each partial hippocampal structure, is based on the equations described above. Particularly, the operation of the i-th cortical agent, $i \in \{EC, DG, CA3, CA1\}$, is evaluated by:

$$E^i_{pc} = RD^i \sqrt{V^i} S \tag{6.3.9}$$

(e.g. $E^{EC}_{pc} = RD^{EC}\sqrt{V^{EC}}S$, for the EC cortical agent). The first term seeks for increased separability of place cells in the respective partial hippocampal area, the second term supports the consistency of place cell firing, and the third maximizes the success rate of the overall hippocampal model.

The hierarchical coevolutionary scheme utilized to design the model is illustrated in Fig 6.17. Following the formulation introduced in eqs. (5.2.1),(5.2.2), the fitness functions which guide the hierarchical coevolutionary process are:

$$\begin{aligned}
&f_{CG1} = f_{CG1,t1} \text{ with } f^{k}_{CG1,t1} = E^{EC}_{pc}, \\
&f_{CG2} = f_{CG2,t1} \text{ with } f^{k}_{CG2,t1} = E^{DG}_{pc}, \\
&f_{CG3} = f_{CG3,t1} \text{ with } f^{k}_{CG3,t1} = E^{CA3}_{pc}, \\
&f_{CG4} = f_{CG4,t1} \text{ with } f^{k}_{CG4,t1} = E^{CA1}_{pc}, \\
&f_{CG5} = f_{CG5,t1} \text{ with } f^{k}_{CG5,t1} = E^{EC}_{pc} \cdot E^{DG}_{pc} \cdot E^{CA3}_{pc} \cdot E^{CA1}_{pc}
\end{aligned} \tag{6.3.10}$$

where k represents each membership of an individual in a proposed solution.

Evolutionary learning is performed following a two phase incremental procedure. In the first phase (epochs 1-20) the robot is randomly moved to one of the P areas every k simulation steps ($k = 25$ for the results illustrated here). Hippocampal processing is then performed with a standing robot. This phase enforces the fast consideration of environmental differences at various locations, by the first generations of hippocampal substructures. In the second phase (all following epochs) the random movement of the robot is stopped, and coevolutionary testing is performed with a freely moving robot, by employing the navigation behavior described in section 6.3.1. This phase additionally enforces the synchronization of the robot's wheel speed, with the change rate of activations at hippocampal neurons.

The results of place cell development at CA1 for the robot path of Fig 6.16 are illustrated in Fig 6.18. Similar to biological place cells, neural activation is able to specify environmental areas. We can easily observe that there is no spatial relationship within the developed place cells, as it is suggested by biological studies [208, 91]. Finally, it should be mentioned that place cells are also developed in the rest hippocampal structures.

6.3.3 Modelling Lesion Effects

After the first two experiments, it is experimentally assessed that the proposed coevolutionary agent based approach is able to design distributed structures, emphasizing

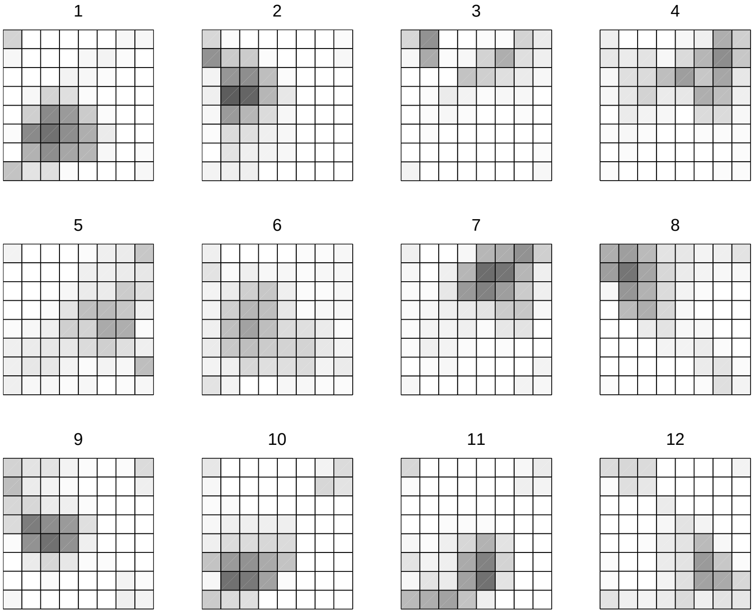

Figure 6.18: Development of place cells at the CA1 agent for the environment areas of Fig 6.16. Activation of cells is illustrated with levels of grey.

both the independent characteristics of partial components and their integrated operation in the composite model. These features are particularly useful for the design of complex, distributed systems, which aim at mimicking the operation of the brain.

In the current section, we investigate the ability of the proposed computational framework to simulate the effects of lesioning partial brain structures[3]. Specifically, the present experiment aims at modelling posterior parietal cortex (PPC) - prefrontal cortex (PFC) - primary motor cortex (M1) - spinal cord (SC) interactions (Fig 6.19), emphasizing on working memory (WM) usage. We note that the proposed model does not aim to be a detailed replica of the biological prototype (e.g. premotor areas are not represented).

Our study focuses on the distinct role of each partial area in the mammalian brain. Several years of experimentation with biological organisms in delayed response (DR)

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[3] The current work has been presented in [173].

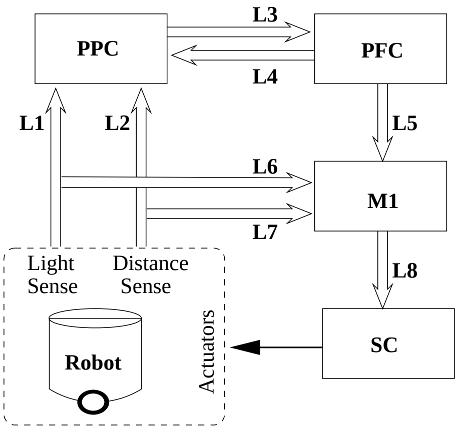

Figure 6.19: A schematic overview of the working memory computational model.

tasks, has shed light on their behavioral organization [109]. M1 encodes primitive motor commands which are expressed to actions by means of SC. PPC-PFC reciprocal interaction operates in a higher level encoding WM [61], in order to develop plans regarding future actions. PFC activation is then passed to M1 which modulates its performance according to the higher level orders. As a result, all the above mentioned structures cooperate for the accomplishment of a DR task by the organism. Several experiments have also highlighted the performance of these structures in lesion conditions. Specifically, PFC lesion affects planning ability of the organism, resulting in reduced ability to move by purpose [236], while M1 lesion eliminates motion ability of the organism [144].

Computational models regarding the structures under discussion have also been presented in the literature. For example computational models of M1 have been developed in [5, 290], which however, do not emphasize the self-organized understanding of environmental characteristics by the robot. Existing PFC computational models emphasize WM activity by means of recurrent circuits [61, 134]. However, these models are not operative, in the sense that they are not linked to other structures to affect their performance. A computational model aiming at the accomplishment of memory guided tasks has been proposed in [190, 320], which however employs a compact artificial neural network structure, without specific assumptions for the performance of partial brain areas.

The present work employs the hierarchical cooperative coevolutionary approach to model the areas under discussion. The experimental process aims at reproducing a lesion scenario which is in agreement to the biological data presented above. The composite computational model aims at the accomplishment of a DR task, developing a behavior similar to the one described in pre-lesion performance of animals [109]. This is further supported by two partial behaviors. The first accounts for the development of WM-like activation in PPC-PFC which are the brain structures most closely linked to WM [61]. The second accounts for purposeless motion by M1 when lesion occurs on the higher level structures [236]. Both partial and composite models are embedded in the robotic platform to furnish it with cognitive abilities and prove the validity of results. The employed scenario is properly adjusted to the needs of robotic applications. Three tasks are designed to demonstrate the effectiveness of the computational procedure and also highlight the role of each agent in the model.

Wall Avoidance. The first task accounts for primitive motion abilities without purposeful planning. For mobile robots, a task with the above characteristics is wall avoidance navigation. Thus, for the needs of the present study, M1-SC structures aim at wall avoidance navigation. Similar to eq. (6.3.1), the successful accomplishment of the task is evaluated by the function:

$$E_{wa}=\left(\sum_{M}(sl+sr-1)\cdot(1.0-p^{2})\right)\cdot\left(1-\frac{2}{M}\left|\sum_{M}\frac{sl-sr}{sl\cdot sr}\right|\right)^{3}\cdot\left(1-2\sqrt{\frac{B}{M}}\right)^{3} \qquad (6.3.11)$$

The robot is tested for M steps, sl, sr are the instant speeds of the left and right wheel, p is the maximum instant activation of distance sensors, and B is the total number of robot bumps. The first term seeks for forward movement far from the walls, the second supports straight movement without unreasonable spinning, and the last term minimizes the number of robot bumps on the walls.

Working Memory. The development of working memory like performance specifies the second task. Working memory (WM) is the ability to store goal-related information to guide forthcoming actions. In the present experiment, a light cue is presented in the left or right side of the robot. WM performance aims at persistent PFC activity, related each time to the respective side of light cue presentation.

Two different states l, r are defined associated to the left or right side of light source appearance. For each state, separate activation-averages over the time of M simulation steps, a_j, are computed, with j identifying excitatory neurons of PFC agent. The formation of WM related to the side of light cues is evaluated by measuring the persistency of activation in PFC:

$$E_{wm} = \frac{1}{2}\left(\frac{v_l}{m_l} + \frac{v_r}{m_r}\right) \cdot \min\left\{ \sum_{j, a_j^l > a_j^r} \left(a_j^l - a_j^r\right), \sum_{j, a_j^r > a_j^l} \left(a_j^r - a_j^l\right) \right\} \tag{6.3.12}$$

where m_l, v_l, m_r, v_r are the means and variances of average activation at the respective states. The first term seeks for consistent PFC activation, and the second supports the development of a distinct set of active neurons for each state.

Same-Side Response. Finally, the third task aims to combine the above behaviors formulating a complex model. The successful interaction of all partial structures is demonstrated by means of a DR task that in the present study will be named Same-Side (SS) response task. Specifically, a light cue is presented on the left or right side of the robot. The robot has to move at the end of a corridor memorizing the side of sample cue appearance, and then make a choice related to 90^o turn left or right, depending on the side of light cue presence. Robot response is considered correct if it turns to the side that the light source appeared.

A target location is defined on each side of the corridor depending on the position of the initial light cue. The robot has to approximate the target location without

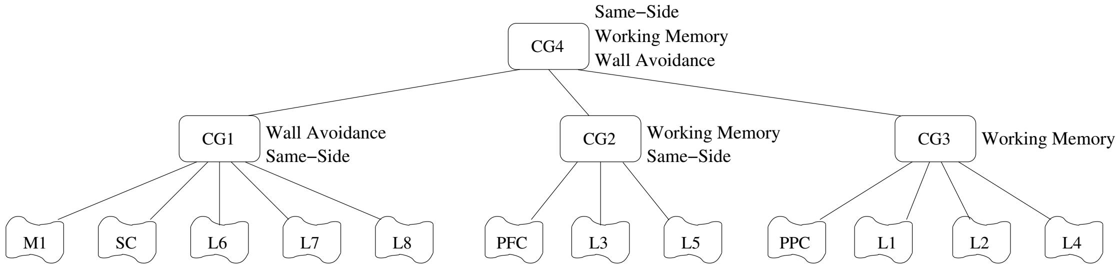

Figure 6.20: A graphical illustration of the coevolutionary process employed to design the working memory model.

crashing on the walls. The successful approximation to the target location is estimated by:

$$G = \left(1 + 3.0 * \cdot \left(1 - \frac{d}{D}\right)\right)^3 \cdot \left(1 - 2\sqrt{\frac{B}{M}}\right)^2 \tag{6.3.13}$$

where d is the minimum Euclidian distance between the target and the robot, D is the Euclidian distance between the target and the starting location of the robot, and B is the total number of robot bumps. The accomplishment of the SS response task is evaluated by means of two subtasks testing separately the right or left turn of the robot for the respective positions of the light cue, employing each time the appropriate target location:

$$E_{ss} = G^l \cdot G^r \tag{6.3.14}$$

We turn now to the design of the model by means of the HCCE process. In accordance to the lesion experiment followed in the present study, each agent needs to serve more than one task. This guides the classification of the respective PS species into CG species, Fig 6.20. The tasks served by each group of agents are illustrated in the same figure, at the right side of each CG. Specifically, the structures under $CG1$ are related to M1-SC interactions, and they need to serve both the wall avoidance and the SS response task. The structures under $CG2$ are related to PFC and its afferent and efferent projections, which need to serve working memory persistent activation, and the same-side response task. The structures under $CG3$ are related to PPC and its afferent projections which have to support working memory activation only ($CG2$ structures are responsible for the proper formulation on working memory and its projection to M1). Finally, a top level CG is employed to enforce cooperation within partial configurations aiming to support the accomplishment of all three tasks.

The testing phase for the individuals of the coevolutionary scheme proceeds as follows. The top-level species is sequentially accessed. Each individual of $CG4$, guides cooperator selection among its lower level CG and PS species. Individuals of PS species are decoded to detailed agent structures. The composite model is tested on the accomplishment of SS response task. Next, PPC-PFC interaction is isolated by deactivating the agents under $CG1$. The remaining structures are tested on working memory task. Finally, $CG1$ agents are activated back, and now $CG2$ structures are deactivated to simulate PFC lesion. The remaining agents are tested on the accomplishment of wall avoidance navigation.

The fitness functions which guide the evolution of species are designed accordingly to support the accomplishment of the respective tasks. Individuals are assigned a combination of evaluation indexes, for the accomplishment of tasks where the composite model is performing, and the accomplishment of tasks with performance of the eliminated model.

The agent structures grouped under $CG1$ serve the success of two tasks, namely wall avoidance and same-side response. Thus, the fitness function employed for the evolution of $CG1$ and its lower level species is based on the measures evaluating the success of the respective tasks. Following the formulation introduced in eqs. (5.2.1), (5.2.2):

$$\begin{array}{l} f_{CG1} = f_{CG1,t1} \cdot f_{CG1,t2} \quad \text{with} \\ f^k_{CG1,t1} = E_{wa}, \quad f^k_{CG1,t2} = \sqrt{E}_{ss} \end{array} \tag{6.3.15}$$

where k represents each membership of an individual in a proposed solution.

Similarly, $CG2$ design aims to support both the accomplishment of working memory and same-side response tasks. Thus, the fitness function which guides the evolutionary process is defined by means of the respective evaluation measures:

$$\begin{aligned} &f_{CG2} = f_{CG2,t1} \cdot f_{CG2,t2} \ \text{ with,} \\ &f^k_{CG2,t1} = {E_{wm}}^2, \ \ f^k_{CG2,t2} = \sqrt{E_{ss}} \end{aligned} \tag{6.3.16}$$

where k is as above.

The third group $CG3$, consists of PPC and all link agents projecting on it. These structures need to serve only the development of working memory activation in PFC. The fitness function employed for the evolution of $CG3$ is defined by:

$$\begin{aligned} &f_{CG3} = f_{CG3,t1} \ \text{ with,} \\ &f^k_{CG3,t1} = E_{wm} \end{aligned} \tag{6.3.17}$$

where k is as above.

Additionally, the top level evolutionary process $CG4$, enforces the integration of partial configurations in a composite model, aiming at the successful accomplishment of all the three tasks. Thus, the top level $CG4$ consists of all lower level CGs. The fitness function employed for the evolution of $CG4$ supports the concurrent success on wall avoidance task, working memory task, and same-side task. It is defined accordingly, following the formulation introduced in eqs. (5.2.1), (5.2.2), by:

$$\begin{aligned} &f_{CG4} = f_{CG4,t1} \cdot f_{CG4,t2} \cdot f_{CG4,t3} \ \text{ with,} \\ &f^k_{CG4,t1} = \sqrt{E}_{wa}, \ f^k_{CG4,t2} = {E_{wm}}^2, \ f^k_{CG4,t3} = E_{ss} \end{aligned} \tag{6.3.18}$$

where k is as above.

The exact formulation of the above fitness functions (eqs (6.3.15) - (6.3.18)) is a result of a trial and error procedure. Following this approach, different species enforce the accomplishment of each task with a different weight. For example, compared to $CG1$, the fitness function which guides $CG4$ evolution, enforces more the relative accomplishment of same-side response task than wall avoidance (see definitions of $f^k_{CG1,t1}$ - $f^k_{CG1,t2}$ and $f^k_{CG4,t1}$ - $f^k_{CG4,t3}$).

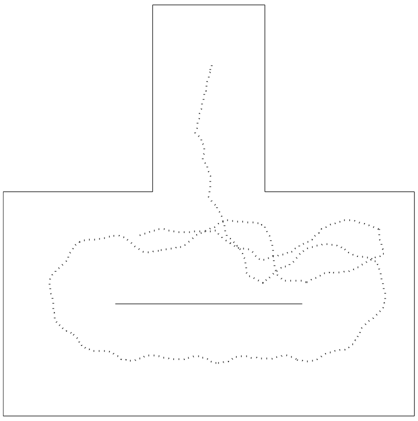

Figure 6.21: A sample result of robot performance, driven by M1-SC. The robot moves in a purposeless mode without bumping into the walls.

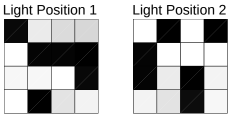

Figure 6.22: The average activation of 16 excitatory neurons at PFC, for each light position. Dark activation values indicate that the cell remain active during all the observed period, while light values indicate low activity in the same period. Evidently, each side of light cue presence is encoded by a different activation pattern.

The coevolutionary process described above employed populations of 200 individuals for all PS species, 300 individuals for $CG1$, $CG2$, $CG3$, and 400 individuals for $CG4$. Additionally, an elitist evolutionary strategy was followed in each evolutionary step with the 7 best individuals of each species, copied unchanged in the respective new generation, supporting the robustness of the evolutionary process. As a result, after 200 evolutionary epochs the process converged successfully and the coupling of agent structures with completely different objectives (e.g. those under $CG1$ and those under $CG3$) is achieved.

Sample results of robot performance on each task are illustrated in Figs 6.21, 6.22, 6.23. As indicated by the lesion scenario, M1-SC are able to drive the robot in a purposeless manner, following a wall avoidance policy (Fig 6.21). At the same

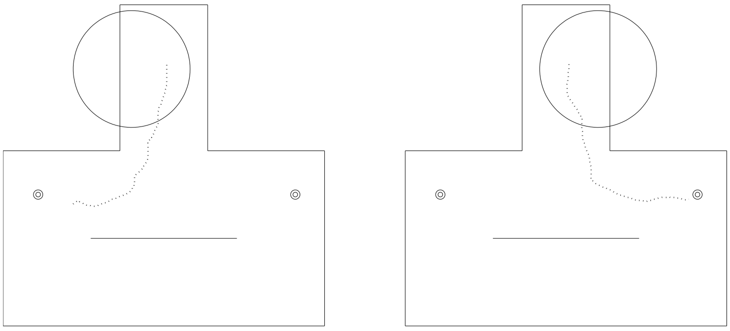
(a) (b)

Figure 6.23: A sample result of robot performance in the Same-Side delayed response task, for (a) the left and (b) the right side of light cue presence. Goal positions are illustrated with double circles.

time, PPC-PFC interactions are able to encode the side of light cue appearance and memorize it for a brief future period (Fig 6.22). Moreover, the composite model combines successfully the performance of partial structures to accomplish the delayed response task SS (Fig 6.23). Consequently, the results observed by biological lesion experiments related to the accomplishment of delayed response tasks, are successfully replicated by the model. This is achieved by means of the powerful HCCE process, which is able to consider and further specify the performance of the model in pre- and post- lesion conditions.

6.3.4 Incremental Modelling

Large scale modelling of brain functionality is hard to accomplish by developing from scratch a very complicated model. An alternative approach could be based on implementing separate models of partial brain areas which are properly integrated in gradually more complex ones. As a result, the ability to proceed by means of an incremental approach, is a desirable feature for a successful design methodology that aims at the development of brain-inspired artificial cognitive mechanisms.

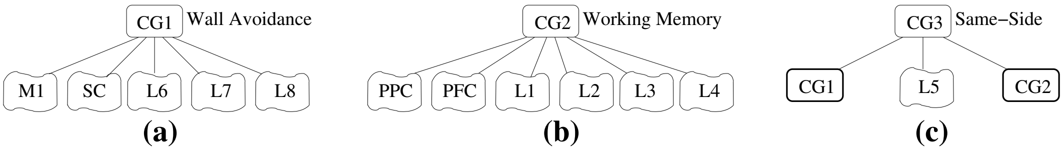

Figure 6.24: A schematic overview of the incremental coevolutionary design process. Part (a) illustrates the process employed to design the model of M1-SC interaction, part (b) illustrates the process designing the model of PPC-PFC interaction, and part (c) illustrates the coevolutionary process which serves their integration, with CG1 and CG2 not being evolved.

The computational framework proposed in the present study is formulated properly to support an incremental modelling process. Specifically, biological findings regarding lesion studies, facilitate the specification of partial incremental steps. At the same time, the agent-based representation of brain areas alleviates the decomposition of the problem to small tractable tasks. The HCCE scheme can be utilized to attain the design of partial brain models. Then, the results of partial processes should be further combined to develop a global solution. Fortunately, the HCCE can be utilized again to support the process of integration.

This incremental modelling approach is demonstrated by means of implementing a new computational model of the brain areas illustrated in Fig 6.19. Specifically, two hierarchical coevolutionary processes are performed independently, to design partial models of M1-SC, and PPC-PFC interaction[4]. Each process is responsible to design the structures involved in the respective partial models (Fig 6.24). When both processes are finished, a third coevolutionary scheme commences to design the intermediate link structure which integrates the performance of the two partial models in a composite one. In order to simplify the design procedure, the tasks and the fitness measures discussed in section 6.3.3 are also employed in the current experiment.

Step 1. The first coevolutionary process aims at the accomplishment of the wall

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[4] The current experiment has been presented in [172].

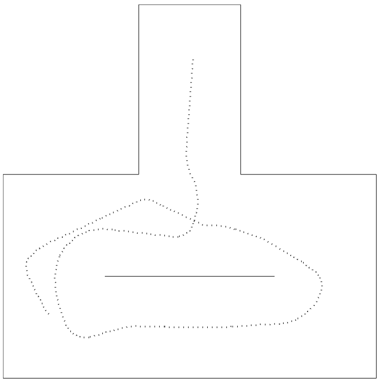

Figure 6.25: A sample result of robot wall avoidance navigation.

avoidance navigation task, by M1-SC interactions. The hierarchical scheme coevolves five lower level species (Fig 6.24(a)). Populations of 200 individuals evolve all subcomponent species, while a population of 300 individuals evolves the higher-level cooperator selection process. The fitness function that guides the coevolutionary process evaluates the success on wall avoidance navigation. Following the formulation introduced in eq. (5.2.1), (5.2.2), the fitness function is defined by:

$$f_{CG1} = f_{CG1,t1} \quad \text{with} \qquad f^{k}_{CG1,t1} = E_{wa} \tag{6.3.19}$$

where k represents each membership of an individual in a proposed solution, and E_{wa} is defined in eq. (6.3.11). After 70 epochs, the coevolutionary process converged successfully, and the robot could be driven without bumping on the walls. A sample result is illustrated in Fig 6.25.

Step 2. The second coevolutionary process aims at the accomplishment of working memory task by PPC-PFC interactions (Fig 6.24(b)). Populations of 200 individuals evolve all subcomponent species, while a population of 300 individuals evolves the higher-level cooperator selection process. The employed fitness function evaluates the success on $T2$ working memory task:

$$f_{CG2} = f_{CG2,t1} \quad \text{with} \qquad f^{k}_{CG2,t1} = E_{wm} \tag{6.3.20}$$

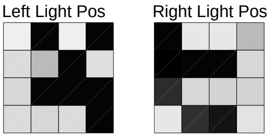

Figure 6.26: The average activation of 16 excitatory neurons at PFC. The dark activation values indicate that the cell remain active during all the observed period, while light values indicate low activity in the same period. It is clear that each side of light cue presence is encoded in a different activation pattern.

where k is as above, and E_{wm} is defined in eq. (6.3.12). After 80 evolutionary epochs we got many computational schemes able to simulate working memory performance. A sample result is illustrated in Fig 6.26.

Step 3. The third coevolutionary process aims at the accomplishment of delayed same-side (SS) response task by the composite model. The third hierarchical scheme performs on the results of the previous two processes evolving additionally the link agent $L5$ to support their connectivity (Fig 6.24(c)). The ten best individuals of $CG1$ and $CG2$ species are used as indicative partial models to form a basis for the construction of the global model. Thus, only two species need to be evolved. The first species, consisting of 200 individuals, is evolved at the lower level encoding the structure of $L5$ link agent. $CG3$ species is evolved at the higher level employing 300 individuals. The evolution of $CG3$ aims to choose one of the ten best individuals in $CG1$, $CG2$ which are appropriately connected by an $L5$ individual to accomplish the SS response task. The species of $CG1$ and $CG2$ are not evolved, and thus the ten best individuals of $CG1$ and $CG2$ remain unchanged. The coevolutionary process is driven by a fitness function equal to E_{ss}, evaluating the success on $T3$ delayed response task:

$$f_{CG3} = f_{CG3,t1} \quad \text{with} \qquad f^{k}_{CG3,t1} = E_{ss} \tag{6.3.21}$$

where k is as above, and E_{ss} is defined in eq. (6.3.14). After 40 evolutionary epochs we got many computational schemes able to simulate memory guided behavioral response

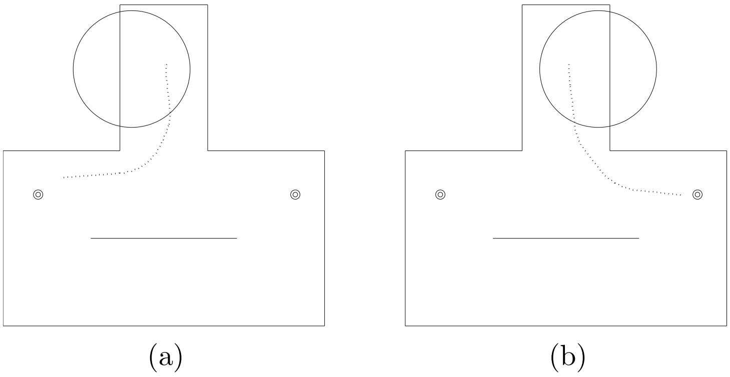
(a)
(b)

Figure 6.27: A sample result of robot performance in the delayed response task, for (a) the left and (b) the right side of light cue presence. PFC activation successfully modulates M1 performance to drive the robot to the desired goal.

accomplishing successfully the same-side response task. A sample result is illustrated in Fig 6.27.

At the end of the incremental design process, the model that simulates biological lesion results of memory-guided behavioral response, is complete. First, the composite model accomplishes the delayed response task SS. Second, working memory-like activation is observed in PFC, and third, deactivation of PFC eliminates purposeful motion, resulting to wall avoidance navigation.

6.3.5 Integrating Partial Models

The previous experiment demonstrated that the agent-based coevolutionary framework is able to design distributed partial structures following an incremental process. In the present experiment we investigate if it is possible to follow a similar procedure, integrating incrementally complex partial structures in order to formulate complex brain-like models[5]. Along this line, the current process aims at modelling Parietal - Prefrontal - Premotor - Primary Motor - Hippocampal interactions, emphasizing

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[5] The current experiment has been presented in [176].

on working memory (WM) usage. Particularly, we follow an incremental approach to combine the processes described in sections 6.3.1 and 6.3.2 in order to design a complex model of the above mentioned brain areas.

The model is illustrated in Fig 6.28. The connectivity of brain areas has been extracted from the detailed diagram presented in [62]. The organization of these areas is similar to the one described in previous sections. Hippocampus processes spatial information to identify the current location of the organism. On the other side, Primary Motor cortex (M1) encodes primitive motor commands which are expressed to actions by means of Spinal Cord (SC). Prefrontal cortex (PFC) is reciprocally connected to Posterior Parietal cortex (PPC) encoding working memory. Hippocampal activity is projected on prefrontal (PFC) and premotor (PM) structures which combine localization and working memory information formulating plans of purposeful motion. PM activation is then passed to M1 which modulates its performance accordingly in order to execute higher level orders.

The composite model is formulated following three design steps. The structures drawn in each step are demonstrated in Fig 6.28. The design procedure is similar to the one described in the previous sections.

Step 1. First, the design of M1-SC structures aim at efficient wall avoidance navigation, and they are modelled by means of a coevolutionary process illustrated in Fig 6.29. The success of wall avoidance task is evaluated by the fitness measure E_{wa} described in eq. (6.3.1). Following the formulation introduced in eqs.(5.2.1),(5.2.2), the fitness function which guides the coevolutionary process is:

$$f_{CG1} = f_{CG1,t1} \text{ with } \; f^{k}_{CG1,t1} = E_{wa} \tag{6.3.22}$$

where k represents each membership of an individual in a proposed solution. A sample result of robot wall avoidance motion is illustrated in Fig 6.30.

Step 2. In the next step, the hippocampal model is designed following the process

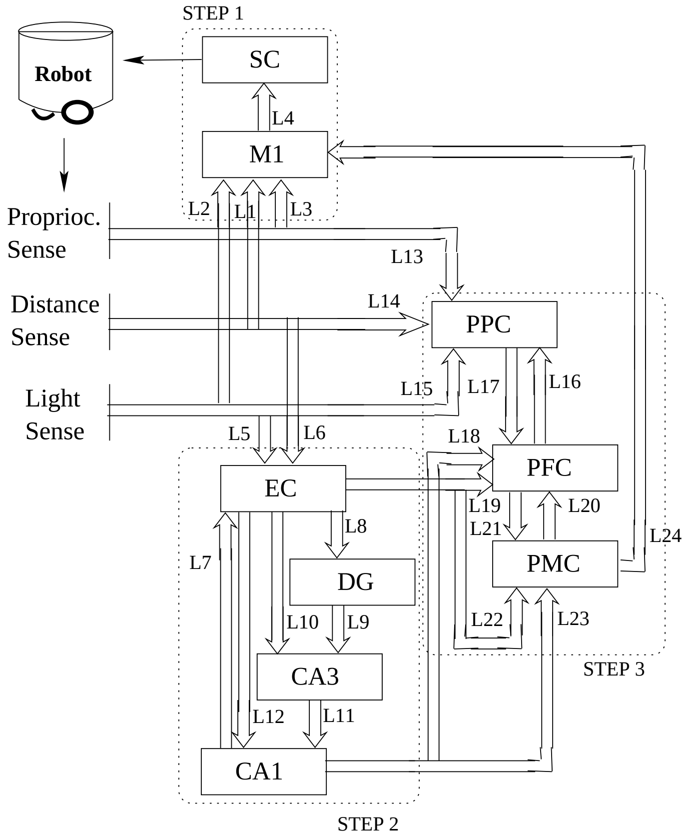

Figure 6.28: A schematic overview of the composite cognitive model employed to accomplish the delayed response task in the cross maze.

described in section 6.3.2. Our study on hippocampus is focused on the entorinal cortex (EC), dentate gyrus (DG), and Amon's horn structures CA3, CA1, aiming at simulating place-cell activity. The Hippocampal model is evolved by the hierarchical coevolutionary scheme illustrated in Fig 6.31. The process is joined with the ten best individuals of $CG1$ (which are not evolved in the present step), in order to enforce the synchronization of the robot's wheel speed with the change rate of hippocampal neurons.

The second task aims at successful localization by means of place cell development in hippocampal structures. In order to test the development of place cells, we define $P = 8$ areas in the environment (see Fig 6.30), where the activation of hippocampal

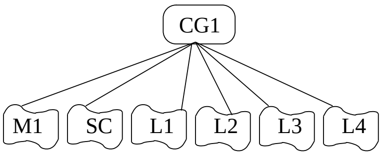

Figure 6.29: Graphical representation of the process used to design M1-SC model.

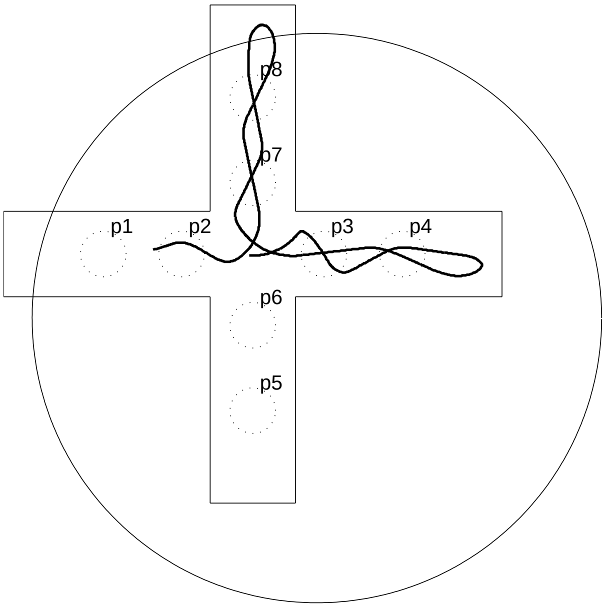

Figure 6.30: Solid line illustrates robot performance on wall avoidance navigation. The big circle illustrates the range of the light source, while the 8 doted circles illustrate the areas where place-cell development is considered.

excitatory neurons is observed. The successful development of place cell activity in cortical agents evolved by CG_i, $i \in \{2...6\}$ are evaluated by the measures E^j_{pc}, $j \in \{EC, DG, CA3, CA1\}$, described in eq. (6.3.9). Following the formulation introduced in eqs. (5.2.1),(5.2.2), the fitness functions which guide the hierarchical coevolutionary

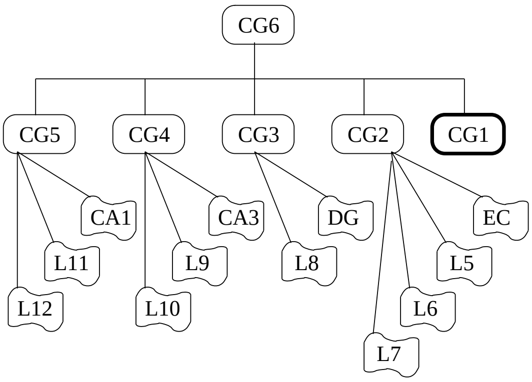

Figure 6.31: Graphical representation of the process used to design Hippocampal model. $CG1$ (see Fig 6.29), is not evolved in the present coevolutionary process.

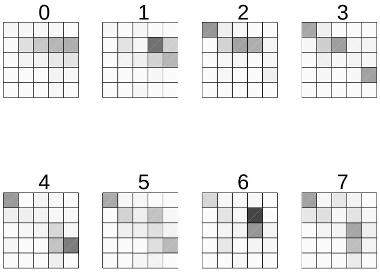

Figure 6.32: The development of place-cells in CA1 module, with respect to the locations defined in Fig 6.30.

process are:

$$\begin{aligned} f_{CG2} &= f_{CG2,t1} \text{ with } f^k_{CG2,t1} = E^{EC}_{pc}, \\ f_{CG3} &= f_{CG3,t1} \text{ with } f^k_{CG3,t1} = E^{DG}_{pc}, \\ f_{CG4} &= f_{CG4,t1} \text{ with } f^k_{CG4,t1} = E^{CA3}_{pc}, \\ f_{CG5} &= f_{CG5,t1} \text{ with } f^k_{CG5,t1} = E^{CA1}_{pc}, \\ f_{CG6} &= f_{CG6,t1} \text{ with } f^k_{CG6,t1} = E^{EC}_{pc} \cdot E^{DG}_{pc} \cdot E^{CA3}_{pc} \cdot E^{CA1}_{pc} \end{aligned} \tag{6.3.23}$$

where k is as above. The results of place cell development at CA1 are illustrated in Fig 6.32.

Step 3. When the design of the Primary Motor and Hippocampal model is completed, we turn to their integration. Specifically, a third coevolutionary scheme commences to design premotor, prefrontal and parietal structures integrating the performance of

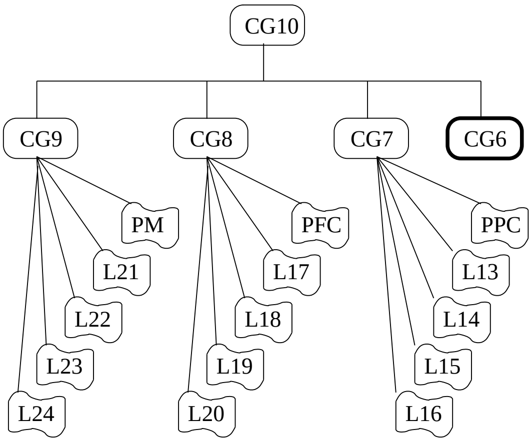

Figure 6.33: The coevolutionary process utilized to integrate partial models.

the two partial models in a composite one (Fig 6.33). The scheme under $CG6$, is not evolved. The ten best individuals of $CG6$ species are used as indicative hippocampal - primary motor pairs, to form a basis for the construction of the global model.

The successful interaction of substructures is demonstrated by means of a Delayed Matching to Sample (DMS) task. Similar to biological experiments with rats, we test the performance of the model in a cross (+) maze, highlighting the development and manipulation of working memory (WM), together with the utilization of a place consideration strategy to solve the task.

Specifically, during the sample phase the robot starts from position $s1$ facing the center of the maze. Then it drives along the corridor where it is appropriately driven to turn in the west or east side of maze, by utilizing a Γ-shaped wall (see cases 1,4 of Fig 6.34). Similar to the biological prototype, WM is encoded by the interactions of PPC, PFC which has to store what was the side of robot turning. Two different states w, e are defined associated with the two possible rotations. For each state, separate activation averages, a_l, are computed, with l identifying excitatory neurons. The formation of WM related to the side of sample turning is evaluated by considering activation in PFC, PPC structures:

$$E^{j}_{wm}=\left(\frac{v_w}{m_w}+\frac{v_e}{m_e}\right)\cdot\min\Big\{\sum_{a^w_l>a^e_l}^{l}(a^w_l-a^e_l)\,,\sum_{a^e_l>a^w_l}^{l}(a^e_l-a^w_l)\Big\} \tag{6.3.24}$$

where $j \in \{PPC, PFC\}$, and m_w, v_w, m_e, v_e are the mean and variance of average activation at states w, e. The first term enforces consistent activation, while the second supports the development of distinct activation patterns for each state w, e. Thus, E^{PPC}_{wm} and E^{PFC}_{wm} evaluate the development of distinct memories relative to the locations w and e, in PPC and PFC.

In contrast to the sample phase, during testing the robot is able to start either from $s1$ or $s2$. The cross maze is transformed in a T-maze utilizing an extra wall (see cases 2,3,5,6 of Fig 6.34), and the robot is allowed to act freely performing a west or east turn. In order to have a correct response, the robot should turn to the same side with the sample turning. We note that in order to reach w, the robot has to turn right starting from point $s1$, while it has to turn left starting from $s2$. As a result, the successful accomplishment of the task demands the manipulation of both localization information developed in Hippocampus, and working memory stored in prefrontal-parietal structures.

The success on DMS task is evaluated by means of two subtasks related to the two starting positions $s1$, $s2$. Each subtask tests the responses of the robot related to two different sample phases, in order to evaluate proper target reaching of w or e. The first subtask concerns sample-test pairs 1-2 and 4-5 of Fig 6.34, while the second subtask concerns pairs 1-3 and 4-6 of the same figure. Two distinct evaluation measures are estimated E^{j}_{dms}, $j \in \{s1, s2\}$, one for each subtask:

$$E^{j}_{dms}=(1+2\,(1-D_w))^3\cdot(1+2\,(1-D_e))^3\cdot\left(1-4\frac{B}{M}\right)^2 \tag{6.3.25}$$

where $D_a, D_b \in [0,1]$ are the distances between targets w, e and the robot, and B is the total number of robot bumps. The first two terms enforce reaching of w, e, while

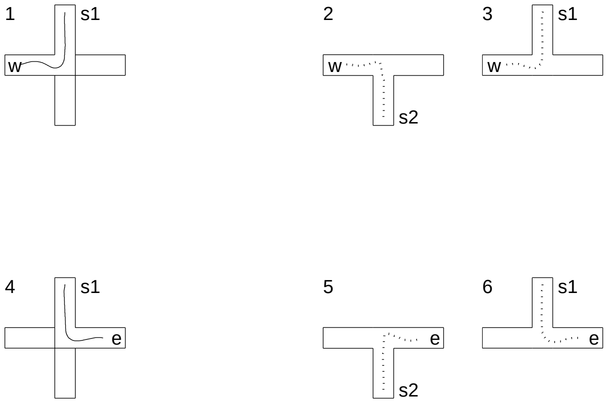

Figure 6.34: The performance of the robot during DMS task.

the last term facilitates goal approximation without crashing on the walls. Thus, E^{s1}_{dms} and E^{s2}_{dms} evaluate the success on DMS task when robot starts from $s1$ and $s2$ respectively.

Following eqs.(5.2.1),(5.2.2), the fitness functions which guide the hierarchical process illustrated in Fig 6.33, are:

$$\begin{aligned}
&f_{CG7} = f_{CG7,t1} \cdot f_{CG7,t2} \ \ \text{with,} \\
&\qquad f^{k}_{CG7,t1} = E^{PPC}_{wm} E^{s1}_{dms}, \ \ f^{k}_{CG7,t2} = E^{PPC}_{wm} E^{s2}_{dms} \\
&f_{CG8} = f_{CG8,t1} \cdot f_{CG8,t2} \ \ \text{with,} \\
&\qquad f^{k}_{CG8,t1} = E^{PFC}_{wm} E^{s1}_{dms}, \ \ f^{k}_{CG8,t2} = E^{PFC}_{wm} E^{s2}_{dms} \\
&f_{CG9} = f_{CG9,t1} \cdot f_{CG9,t2} \ \ \text{with,} \\
&\qquad f^{k}_{CG9,t1} = E^{s1}_{dms}, \ \ f^{k}_{CG9,t2} = E^{s2}_{dms} \\
&f_{CG10} = f_{CG9,t1} \cdot f_{CG10,t2} \ \ \text{with,} \\
&\qquad f^{k}_{CG10,t1} = E^{s1}_{dms}, \ \ f^{k}_{CG10,t2} = E^{s2}_{dms}
\end{aligned} \tag{6.3.26}$$

where k represents each membership of an individual in a proposed solution. Partial fitness functions of f_{CG7}, f_{CG8} aim at the development of working memory patterns (i.e. E^{PPC}_{wm}, E^{PFC}_{wm}) and the expression of the proper delayed responses from both starting positions (i.e. E^{s1}_{dms}, E^{s2}_{dms}). In contrast, partial fitness functions of f_{CG9}, f_{CG10} focus only on manipulating working memory in order to accomplish the DMS task (i.e. E^{s1}_{dms}, E^{s2}_{dms}).

A sample result of robot performance in the DMS task is illustrated in Fig 6.34. Solid lines (cases 1,4) illustrated sample robot motion, while the respective two dotted lines (cases 2,3 and 5,6) illustrate robot response from two different starting positions. It is obvious that localization and working memory information are successfully considered to solve the task. Therefore, in the third step, a new complex model is developed by combining existing substructures. Additionally, lower motor structures (M1, SC) adapt their performance according to the higher level orders, changing their functionality from wall avoidance, to goal reaching. As a result, the design of complex brain-inspired structures is considerably facilitated by re-utilizing simple structures in order to formulate gradually more complex ones.

Overall, the results presented in the last two sections illustrate the effectiveness of the proposed computational framework in both the design and the integration of brain inspired structures.

6.3.6 Design of Teachable Models

In the previous three sections, we demonstrated the development of computational models which are able to accomplish delayed response tasks. This particular ability of the models is provided built-in to the systems, by the hierarchical coevolutionary design methodology. In other words, the design procedure specifies self-organization dynamics with the built-in tendency to develop the desired behavior in real-time. After performing additional tests with the models discussed in the previous sections (not presented here), we found that the coevolutionary design mechanism could easily generate computational structures which perform successfully on the complementary versions of the respective delayed response tasks. However, in these unpublished cases, the models were again furnished with a built-in tendency to develop at run time a new response strategy.

The question that now arises, is if the proposed computational framework is able to design systems without a built-in tendency to develop a specific motion strategy, but with the ability to chose it during life-time. Along this line, we are interested in computational structures which are able to decide their motion strategy according to a set of external reward signals, as it is also the case with animals. Consequently, by following this approach, the human operator will be able to guide the mind of the artificial organism accordingly. In other words, a teachable artificial cognitive system will be designed.

The ability to simulate the training process of animals is very important for the development of brain-inspired artificial cognitive systems, because it allows the computational model to come one step closer to biological prototype. Specifically, similar to the process followed in biological experiments, artificial organisms will be trained to accomplish diverse tasks. Then simulated lesions will be performed in order to explore the performance of the organism in these new operating conditions. These tests can be combined with the ability of the agent-based coevolutionary framework to consider and further specify the functionality of the model in lesion conditions. Moreover, existing data of biological lesion experiments can be exploited by the HCCE design mechanism, in order to enforce the similarity of the computational model with the brain of biological organisms, in both the cases of pre- and post- lesion operation. Consequently, by following a modelling approach that addresses explicitly the training process, an enhanced version of biologically inspired models can potentially be developed.

In the current study, we make a first attempt towards a rigorous method to design teachable artificial cognitive systems which are trained to accomplish many different tasks[6]. The computational structure highlights the roles of the brain areas involved

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[6] The current experiment has been submitted for publication [169].

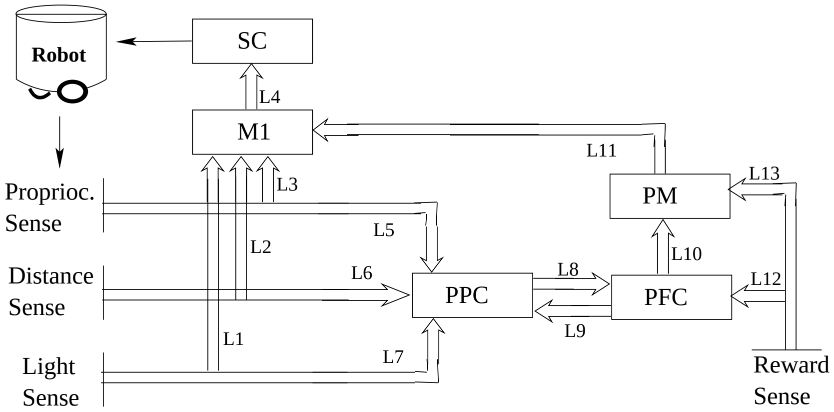

Figure 6.35: A schematic overview of the teachable cognitive model.

in the process of training animals by means of external reinforcement stimuli. Specifically we model the interactions of Primary Motor - Premotor - Prefrontal - Parietal Cortex, emphasizing on their training to accomplish two complementary WM-based tasks.

The connectivity of brain areas is illustrated in Fig 6.35. The performance of these areas is similar to the one described in previous sections. Primary Motor cortex (M1) encodes primitive motor commands which are expressed to actions by means of Spinal Cord (SC). Prefrontal cortex (PFC) is reciprocally connected to Posterior Parietal cortex (PPC) encoding working memory [61]. Prefrontal activity is projected on Premotor cortex (PM) to formulate the orders which modulate M1 performance according to the higher level plans, developing purposeful motion [109]. Additionally, in the present experiment, the training process by means of appropriate reward stimuli is considered. Prefrontal and Premotor areas receive information relevant to external environmental reinforcement, in order to modulate the plans of future motion in the desired way [197]. As a result, animals are able to develop very different strategies, e.g. Delayed Matching to Sample (DMS), or Delayed Non-Matching to Sample (DNMS), depending on the rewards provided.

Moreover, several experiments highlight the performance of these structures in lesion conditions. Specifically, lesioning at higher level structures affects learning of the organism [197], resulting in significantly reduced levels of purposeful motion and planning ability [122, 236].

The experimental process aims at reproducing a computational scenario replicating (i) the training process of animals for the accomplishment of delayed response tasks in a T-maze, and (ii) the biological findings related to the effects of lesion at higher level motor structures. Specifically, the composite computational model should be able to be trained by an external factor, adopting either a DMS or a DNMS strategy. This is similar to the pre-lesion performance of animals [236]. The accomplishment of these delayed response tasks is supported by the development of WM-like activation in PPC-PFC, which are the brain areas most closely linked to WM [61]. Furthermore, when lesion occurs on the higher level structures, then the robot is able to drive, but only in a purposeless mode, simulating reduced planing ability of animals [122, 223].

The employed scenario, is properly adjusted to the needs of robotic applications. Three tasks are designed to demonstrate the effectiveness of the computational procedure, highlighting the distinct role of each agent in the model, and their successful cooperation in the composite system.

The first two tasks are related with teaching the robot to perform the right delayed response, adopting either a DMS or a DNMS strategy. This process is standard in biological experiments [223]. Since the training process is very similar for both tasks, we will present in detail the experimental procedure followed for one of them, and then we will discuss only the differences for the other.

DMS Strategy. Let us consider first the process of training the robot to adopt the DMS response strategy. Overall, the process is separated to several trials. Each trial includes two sample-response pairs, testing the memorization of two different sample cues by the robot, and the selection of the appropriate delayed response. In the sample phase of the first pair the robot is driven to the left, while in the sample phase of the second, it is driven to the right. This is achieved by utilizing an extra wall properly placed, to force the robot to turn to a pre-specified direction (see partial drawings in the first columns of Figs 6.38, 6.39).

In order to make the right delayed response, the robot should first develop WM-like activity, encoding the side of turning during the sample phase. Similar to the biological prototype, working memory is encoded by PPC, PFC interactions. Two different states a, b are defined, associated with the two possible turning directions. For each state, separate activation averages, p_l, are computed, with l identifying excitatory neurons. The formation of WM related to the side of sample turning, is evaluated by considering activation in PFC, PPC structures:

$$E^{j}_{wm} = \left(\frac{v_a}{m_a} + \frac{v_b}{m_b}\right) \cdot \min\left\{ \sum^{l}_{p^a_l > p^b_l} \left(p^a_l - p^b_l\right), \sum^{l}_{p^b_l > p^a_l} \left(p^b_l - p^a_l\right) \right\} \tag{6.3.27}$$

where $j \in \{PPC, PFC\}$, and m_a, v_a, m_b, v_b are the means and variances of average activation at states a, b. The first term enforces consistent activation, while the second supports the development of separate activation patterns for each state a, b. Thus, E^{PPC}_{wm} and E^{PFC}_{wm} evaluate the development of distinct memories relative to the locations a and b, in PPC and PFC.

After encoding the distinct sample cues in WM, the robot should manipulate it properly in order to accomplish delayed response tasks. During the response phase an external human factor specifies a reward area in the left or right side of the T-maze, based on the sample cue. If the robot drives to this area, it receives a reinforcement signal, simulating the positive reward of animals with food or water. The presence or non-presence of the reinforcement signal should be considered by the robot in order to realize what is the correct strategy (either DMS or DNMS) it should adopt in the future trials.

During the response phase of the experimental process, the extra wall is removed, and the robot is transferred back to the starting position. Then it is allowed to act freely driving to the end of the corridor where it has to make either a left or a right turn choice. In the DMS training process, the response is considered correct if the robot turns to the same side with the sample turning. In the case of correct choice, the robot drives to the area of the reward stimulus, where it receives positive reinforcement.

The accomplishment of the DMS is tested for T trials. We remind that for each trial, two different responses are considered, each one related to either the left or the right sample cues. The success of the training process can be evaluated based on the total positive reinforcement that the robot has received. This is described computationally by:

$$E_{tr} = \left(\sum_{T,left}\sum_{M} r\right)\left(\sum_{T,right}\sum_{M} r\right)\left(1 - \sqrt{\frac{B}{2 \cdot T \cdot M}}\right)^3 \qquad (6.3.28)$$

where M are the number of simulation steps of the response phases for each one of the T trials, r is the maximum instant activation of the reward sensors, and B is the total number of robot bumps. The first term seeks for maximum reward stimuli when the correct response of the robot is considered the left side, while the second seeks for maximum reward when the correct response is the right side. The last term minimizes the number of robot bumps on the walls. The higher the reward the robot has received, the more successful was the reinforcement training process. In other words, high values of E_{tr} measure indicate successful cooperation among partial modules related to WM encoding, learning, and motion expression.

DNMS Strategy. Having described the criteria of successful adoption of the DMS strategy, we turn to the DNMS training. The computational structure is re-initialized, and we test if the same cognitive system is able to adopt successfully the strategy relative to the DNMS task, by means of a different set of reward stimuli.

During the DNMS tasks, the experimental process is again separated in T trials.

The process is very similar to the one described for DMS. Each trial includes again two sample-response pairs, but this time, the reward stimulus is located to the side that is different than the sample turning (i.e. if the extra wall forces the the robot to turn left, then, during the response phase the reward is located to the right, and vice versa). The robot should again encode the side of sample turning in different activation patterns of working memory, and then consider the location of the reinforcement signals in order to adopt the correct sample-response mapping. The measures evaluating the adoption of the DNMS strategy by the robot, are the same with those described in eqs. (6.3.27), (6.3.28).

Particularly, two sets of evaluation measures $\{E^j_{wm,dms}, E_{tr,dms}\}$ and $\{E^j_{wm,dnms}, E_{tr,dnms}\}$ are utilized, related to working memory encoding and correct delayed response, for either the DMS or the DNMS task. Similar to the training process of animals, the human designer enforces the robot to develop the correct strategy, by locating properly the reward signals. For both tasks, several trials (pairs of sample-response) are performed, and the robot should progressively realize what is the correct strategy. In the first trials the robot does not know if the testing procedure is related to one task or the other, and it performs a random turning response. In order to conclude what is the correct strategy that the robot should follow (either DMS, or DNMS), the composite cognitive system has to consider (i) what was the sample motion encoded in working memory, compared to the delayed response that it has chosen, and (ii) if it has received reward stimuli or not. After some explorative trials, the robot should be able to conclude what is the correct strategy it should adopt. Additionally, regarding the operation of partial structures, after some trails they will be able to coordinate their activities in order to drive the robot in the appropriate mode.

Lesion Effect - Wall Avoidance Strategy. The third task is relevant to the lesion of higher level motor structures, implying that the robot is not teachable any

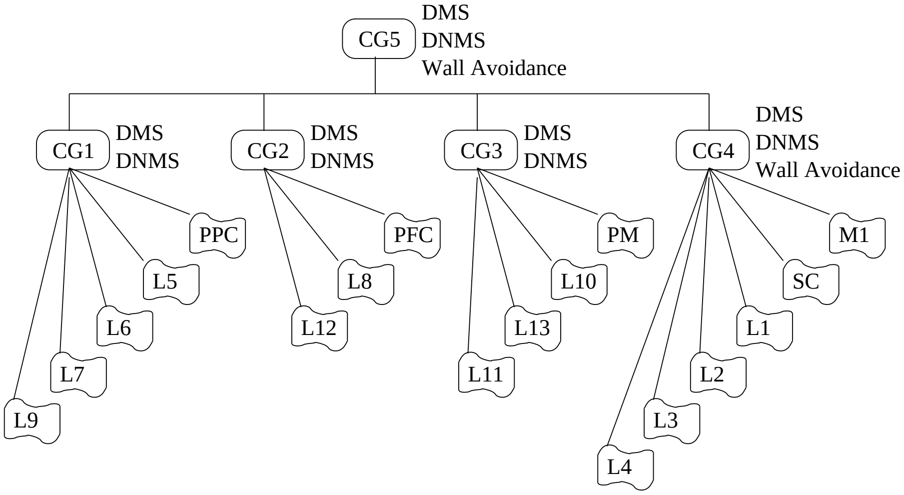

Figure 6.36: A schematic overview of the Hierarchical Cooperative CoEvolutionary process employed to design the teachable cognitive model.

more [197]. Thus, this task accounts for primitive motion abilities without purposeful planning. For mobile robots, a task with the above characteristics is wall avoidance navigation. The successful accomplishment of the task is evaluated by the function:

$$E_{wa} = \left(\sum_{M} (sl + sr - 1)(1.0 - p^2) \right) \left(1 - \frac{2}{M} \left| \sum_{M} \frac{sl - sr}{sl \cdot sr} \right| \right)^3 \left(1 - 2\sqrt{\frac{B}{M}} \right)^3 \qquad (6.3.29)$$

where we assume that the robot is tested for M steps, sl, sr are the instant speeds of the left and right wheel, p is the maximum instant activation of distance sensors, and B is the total number of robot bumps. The first term seeks for forward movement far from the walls, the second supports straight movement without unreasonable spinning, and the last term minimizes the number of robot bumps on the walls.

Coevolutionary Modelling. We turn now to the design of the model illustrated in Fig 6.35, by means of the proposed HCCE scheme. The hierarchical process which is employed to accomplish this task is shown in Fig 6.36. According to the experimental scenario followed in the present study, each agent needs to serve more than one task. The tasks served by each group of agents are illustrated in the same figure, at the right side of each CG. Specifically, the structures under $CG1, CG2, CG3$ are related to the delayed response training process for the accomplishment of either the DMS, or DNMS task. The structures under $CG4$ need also to serve these tasks, but additionally, in the case of lesion at higher level structures, they should be able to drive the robot in a wall avoidance mode. Finally, the top level $CG5$, enforces cooperation within partial configurations aiming to support the accomplishment of all the three tasks.

The testing phase for the individuals of the coevolutionary scheme proceeds as follows. The top-level species is sequentially accessed. Each individual of $CG5$, guides cooperator selection among its lower level CG and PS species. Individuals of PS species are decoded to detailed agent structures. First, we test the ability of the composite model to adopt the DMS strategy, and its components are evaluated with respect to their support for this task. Then, the model is re-initialized, and we test its ability to adopt the DNMS strategy. Next, a simulated lesion is performed, by deactivating the agents under $CG2$, $CG3$. The remaining structures are tested with respect to purposeless navigation of the robot, which is here represented by wall avoidance navigation.

The fitness functions which guide the evolution of species are designed accordingly, to support the accomplishment of the respective tasks. Individuals are assigned a combination of evaluation indexes for the accomplishment of tasks where the composite model is performing, and the accomplishment of tasks with performance of the eliminated model. It is reminded that all PSs share the same fitness functions with their higher level CG.

According to the employed scenario, the agent structures grouped under $CG1$ serve the success on the tasks DMS, DNMS. Thus, the fitness function employed for the evolution of $CG1$ and its lower level species, is based on measures evaluating the success of the respective tasks. Following the formulation introduced in eqs. (5.2.1), (5.2.2):

$$\begin{aligned} & f_{CG1} = f_{CG1,t1} \cdot f_{CG1,t2} \quad \text{with} \\ & f^k_{CG1,t1} = E^{PPC}_{wm,dms} \cdot (1 + E_{tr,dms}), \quad f^k_{CG1,t2} = E^{PPC}_{wm,dnms} \cdot (1 + E_{tr,dnms}) \end{aligned} \tag{6.3.30}$$

where k represents each membership of an individual in a proposed solution. We note that the evaluation measures employed for the evolution of CG1 are formulated in a subjective manner, examining those aspects of the tasks which are relevant to PPC. Particularly, partial fitness functions of f_{CG1} aim at the development of working memory patterns (i.e. $E^{PPC}_{wm,dms}$, $E^{PPC}_{wm,dnms}$) and their proper manipulation, expressing the right delayed response (i.e. $E_{tr,dms}$, $E_{tr,dnms}$).

The agent structures grouped under $CG2$ serve also the success on tasks DMS, DNMS. Thus, according to the formulation of eqs. (5.2.1), (5.2.2), the fitness function employed for the evolution of $CG2$ is:

$$\begin{aligned} & f_{CG2} = f_{CG2,t1} \cdot f_{CG2,t2} \quad \text{with} \\ & f^k_{CG2,t1} = E^{PFC}_{wm,dms} \cdot (1 + E_{tr,dms}), \quad f^k_{CG2,t2} = E^{PFC}_{wm,dnms} \cdot (1 + E_{tr,dnms}) \end{aligned} \tag{6.3.31}$$

where k represents each membership of an individual in a proposed solution. We note again the subjective evaluation of the tasks, which now aims at the development of working memory patterns at PFC (i.e. $E^{PFC}_{wm,dms}$, $E^{PFC}_{wm,dnms}$), and their successful manipulation (i.e. $E_{tr,dms}$, $E_{tr,dnms}$).

The agent structures grouped under $CG3$ serve also the success on DMS, DNMS tasks. However, this time, only the manipulation of working memory is considered, since Premotor area is not involved in WM development. Thus, the fitness function employed for the evolution of $CG3$ is:

$$\begin{aligned} & f_{CG3} = f_{CG3,t1} \cdot f_{CG3,t2} \quad \text{with} \\ & f^k_{CG3,t1} = E_{tr,dms}, \quad f^k_{CG3,t2} = E_{tr,dnms} \end{aligned} \tag{6.3.32}$$

where k represents each membership of an individual in a proposed solution.

Furthermore, according to the lesion scenario, the agent structures grouped under $CG4$ serve the success on the tasks DMS, DNMS, Wall Avoidance. Thus, the fitness function employed for the evolution of $CG4$ and its lower level species is based on the measures evaluating the success of the respective tasks. Following the formulation introduced in eqs. (5.2.1), (5.2.2):

$$\begin{aligned} &f_{CG4} = f_{CG4,t1} \cdot f_{CG4,t2} \cdot f_{CG4,t3} \;\; \text{with} \\ &f^k_{CG4,t1} = E_{tr,dms}, \;\; f^k_{CG4,t2} = E_{tr,dnms}, \;\; f^k_{CG4,t3} = E_{wa} \end{aligned} \tag{6.3.33}$$

where k is as above.

Finally, the top level CG enforces the integration of partial configurations in a composite model, aiming at the successful cooperation of substructures in order to facilitate the accomplishment of all three tasks. The fitness function employed for the evolution of $CG5$ supports successful DMS training, successful DNMS training, and wall avoidance. It is defined accordingly, following the formulation introduced in eqs. (5.2.1), (5.2.2), by:

$$\begin{aligned} &f_{CG5} = f_{CG5,t1} \cdot f_{CG5,t2} \cdot f_{CG5,t3} \;\; \text{with,} \\ &f^k_{CG5,t1} = E^{PPC}_{wm,dms} \cdot E^{PFC}_{wm,dms} \cdot (1 + E_{tr,dms}), \\ &f^k_{CG5,t2} = E^{PPC}_{wm,dnms} \cdot E^{PFC}_{wm,dnms} \cdot (1 + E_{tr,dnms}), \\ &f^k_{CG5,t3} = E_{wa} \end{aligned} \tag{6.3.34}$$

where k is as above.

The hierarchical coevolutionary process described above employed populations of 200 individuals for all PS species, 300 individuals for $CG1$, $CG2$, $CG3$, $CG4$, and 400 individuals for $CG5$. Additionally, an elitist evolutionary strategy was followed in each evolutionary step, with the 10 best individuals of each species copied unchanged in the respective new generation, supporting the robustness of the evolutionary process. As a result, after 200 evolutionary epochs the process converged successfully, and the cooperation of agent structures with different objectives (e.g. those under $CG1$ and those under $CG4$) is achieved.

Specifically, PPC-PFC interactions are able to encode the distinct sides of sample turning and memorize them for a brief future period, as it is illustrated in Fig 6.37.

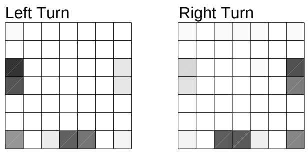

Figure 6.37: The average activation of excitatory neurons at PFC. The dark activation values indicate that the cell remains active during all the observed period, while light values indicate low activity in the same period. It is clear that different working memory patterns are formulated, encoding successfully each side of robot turning.

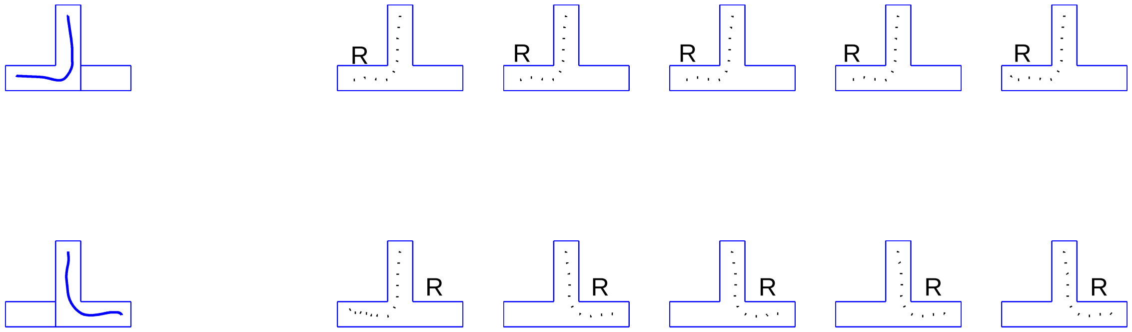

Figure 6.38: A sample result of robot performance in the DMS task. The first column illustrates sample cues. The rest columns (2-6) demonstrate the response of the robot in consecutive trials. Snapshots in the first line illustrate robot responses when sample cue is turn left, while the second line illustrates robot responses when sample cue is turn right.

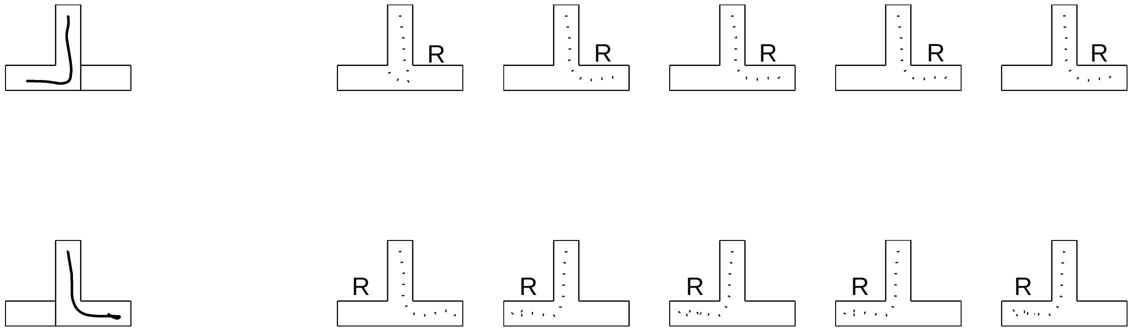

Figure 6.39: A sample result of robot performance in the DNMS task. The first column illustrates sample cues. The rest columns (2-6) demonstrate the response of the robot in consecutive trials. Snapshots in the first line illustrate robot responses when sample cue is turn left, while the second line illustrates robot responses when sample cue is turn right.

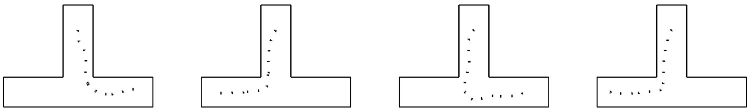

Figure 6.40: Sample results of robot performance driven by M1-SC. The robot moves in a wall avoidance mode, without following a purposeful motion strategy.

Sample results of robot performance during the two different training procedures on DMS and DNMS tasks are illustrated in Figs 6.38, 6.39. In both cases, the response of the robot in the first trial (column 2) is incorrect. However, in the second trial (column 3), the robot tries another strategy which is successful, and thus it is continued for the remaining trials. We note that in each trial, the robot is able to consider the presence or non/presence of the reward stimulus for about 30 simulation steps. Thus, it is able to adjust the synaptic weights of PFC and PM cortical agents, adopting the correct motion strategy.

In the case of lesion the components which are responsible for learning are deactivated, and thus the robot is not teachable any more. However the system does not completely collapse, but remains functional in a certain level of performance. As a result, the robot is still able to move, but making nearly random turn choices, guided by the wall avoidance strategy (Fig 6.40).

Consequently, the model replicates successfully the results observed by biological lesion experiments relative to the accomplishment of delayed response tasks. Particularly, the model is designed to accomplish three different tasks, exhibiting a biologically realistic performance in the case of pre- and post- lesion conditions. Partial structures exploit their self-organization dynamics to adapt on one another facilitating their cooperation, in order to formulate a composite, unified, distributed system. This is achieved by means of the powerful HCCE process which supports the design of biologically-inspired cognitive systems, considering both the individual and cooperative characteristics of substructures.

6.3.7 Partial Model Re-design

Having accomplished to develop reinforcement learning skills by utilizing computational structures with Hebbian self-organized dynamics, we would like to test if it is possible to enrich existing models with similar learning capabilities. The last experiment of the current study, investigates the possibility of partially re-designing existing computational structures in order to furnish them with the ability to learn a behavior, using external reward stimuli[7].

Specifically, we work on the model described in section 6.3.3, regarding the accomplishment of the Same-Side delayed response task. In short, in our previous experiment, a light cue is presented on the left or right side of the robot, which has to memorize the side of light cue appearance, in order to make the correct choice, related to 90^o turning, left or right. According to the Same-Side (SS) response strategy, the robot should turn left if the light cue appeared at its left side, and it should turn right if the light source appeared at its right side. The HCCE design process draws successfully cognitive computational structures with the inborn ability to develop the SS response strategy.

A different response strategy can also be defined named Opposite-Side (OS), which implies that the robot should turn left if the light cue appeared at its right side, and it should turn right if the light source appeared at its left side. We have performed experiments similar with those described in section 6.3.3, which shown that computational models with the inborn tendency to develop the OS strategy can also be designed. Thus, the question that now arises, is if we can design a single computational system that is able to adopt either the SS or the OS strategy during life-time, according to a set of environmental reward signals.

The present experiment aims at extending the results of section 6.3.3, in order to design a teachable model which is able to chose its response strategy at run time,

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[7] The current work has been presented in [177].

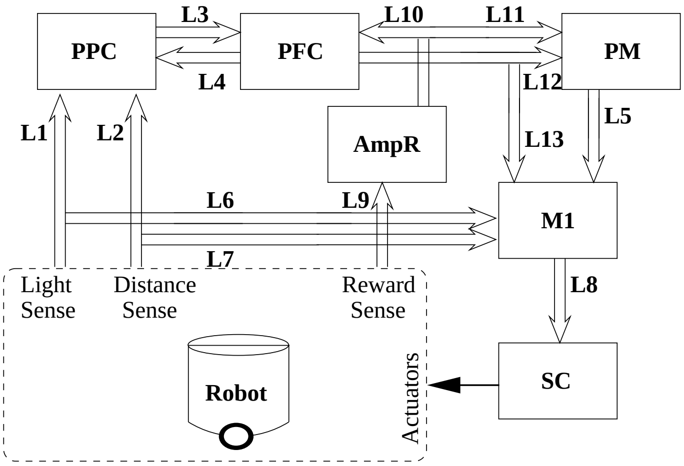

Figure 6.41: A schematic demonstration of the extended computational model (compare with Fig 6.19).

based on a reinforcement training process. The new, extended model is illustrated in Fig 6.41. In order to facilitate the design procedure, we avoid designing the composite model from scratch. Thus, we would like to re-utilize as much existing components as possible from the model of section 6.3.3. Particularly, the current experimental process aims at keeping in their original formulation those partial structures which are less involved in the learning procedure (namely, Posterior Parietal cortex (PPC), Primary Motor cortex (M1), and Spinal Cord (SC)). According to the discussion presented in the reinforcement learning experiment of the previous section, the biological structures mostly involved in the learning process are Prefrontal and Premotor cortices (PFC,PM). Since there was no PM module in the model of section 6.3.3 (see Fig 6.19), the computational structure is extended here, adding also a cortical agent representing Premotor cortex (PM). Both PFC and PM modules receive information related to the reward stimuli. An amplifier module (AmpR) is utilized to strengthen the reward information, in order to be more easily considered by PFC and PM structures (the exact role of the amplifier is discussed below).

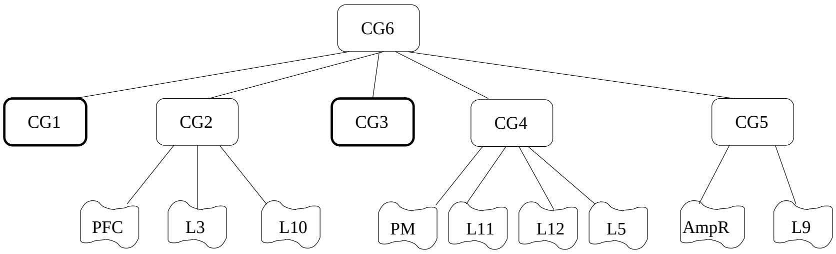

Figure 6.42: An overview of the extended Hierarchical Cooperative CoEvolutionary process employed to design the composite computational model.

The hierarchical coevolutionary process that re-designs and extends the computational model is illustrated in Fig 6.42, and it is also an extension of the process illustrated in Fig 6.20. The species below CG1 and CG3 are not depicted in this figure, in order to demonstrate that we keep their original structure formulated by the experiment described in section 6.3.3 and they are not evolved in the current coevolutionary design procedure.

Opposite-Side Strategy. Let us consider first the teaching ability of the robot to adopt the OS response strategy. The training process of the robot is separated to several trials. Each trial includes two sample-response pairs, testing the memorization of two different sample cues by the robot, and the selection of the appropriate delayed response in each case. Particularly, in the sample phase of the first pair, the light cue appears to the left side of the robot, while in the sample phase of the second pair, it appears to the right side. During the response phase, the robot is allowed to move freely, driving to the end of the corridor where it has to make a turn choice. An external human factor specifies a reward area in the left or right side of the maze, based to the side of the sample cue, and the strategy that the robot should develop. In the OS training process, the response is considered correct, if the robot turns to opposite side of light cue appearance. In the case that the robot makes the correct choice, it drives to the reward area receiving a reward that simulates the positive reinforcement of animals with food or water.

The accomplishment of the OS task is tested for T trials. It should be noted that for each trial, two different responses are considered, each one related to either the left or the right side of light cue appearance. The success of the training process is evaluated by the total positive reinforcement signal that the robot has received. This is similar to eq. (6.3.28), and it is described by:

$$E_{tr} = \left(\sum_{T,left}\sum_{M} r\right)\left(\sum_{T,right}\sum_{M} r\right)\left(1-\sqrt{\frac{B}{2\cdot T\cdot M}}\right)^{3} \qquad (6.3.35)$$

The first term seeks for maximum reward stimuli when the correct response of the robot is considered the left side, while the second seeks for maximum reward when the correct response is the right side. The higher the reward the robot has received, the more successful was the reinforcement training process. The last term minimizes the number of robot bumps on the walls.

In order to facilitate the convergence of the coevolutionary design procedure, we utilize additional criteria which highlight the role of PFC, PM and AmpR structures in the composite model. Particularly, one criterion highlights the development of WM-like activation patterns on PFC. Two different states a, b are defined, associated with the two possible sides of light source appearance. For each state, separate activation averages, p_l, are computed, with l identifying PFC excitatory neurons. The formation of WM patterns is evaluated by :

$$E_{wm}= \left(\frac{v_a}{m_a}+\frac{v_b}{m_b}\right)\cdot \min\left\{\sum_{p_l^a>p_l^b}^{l}\left(p_l^a-p_l^b\right), \sum_{p_l^b>p_l^a}^{l}\left(p_l^b-p_l^a\right)\right\} \qquad (6.3.36)$$

and m_a, v_a, m_b, v_b are the means and variances of average activation at states a, b. The first term enforces consistent activation, while the second supports the development of separate activation patterns for each state a, b.

Another criterion addresses the development of different activation patterns in PM structure. They are related to the different higher level motion commands that should be passed to M1. Two different states r, l are defined, associated with the commands of right or left turning. For each state, separate activation averages, p_k, are computed, with k identifying PM excitatory neurons. The successful development of distinct activation patterns for the right and left turning is measured by:

$$E_c = \left(\frac{v_r}{m_r} + \frac{v_l}{m_l}\right) \cdot \min\left\{\sum_{p_k^r > p_k^l}^{k} (p_k^r - p_k^l), \sum_{p_k^l > p_k^r}^{k} (p_k^l - p_k^r)\right\} \tag{6.3.37}$$

and m_r, v_r, m_l, v_l are the means and variances of average activation at states r, l. The formulation of the measure is similar to eq (6.3.36).

Finally, an additional criterion highlights the development of different patterns on the AmpR structure, related to the two possible types of the reward signal. Two different states x, y are defined, associated with the right or left reward location. For each state, separate activation averages, p_t, are computed, with t identifying AmpR excitatory neurons. This is described by:

$$E_r = \left(\frac{v_x}{m_x} + \frac{v_y}{m_y}\right) \cdot \min\left\{\sum_{p_t^x > p_t^y}^{t} (p_t^x - p_t^y), \sum_{p_t^y > p_t^x}^{t} (p_t^y - p_t^x)\right\} \tag{6.3.38}$$

and m_x, v_x, m_y, v_y are the means and variances of average activation at states x, y. Partial terms of the measure are similar to eq (6.3.36).

Same-Side Strategy. Just after testing the performance of the robot on learning the OS tasks, the computational structure is re-initialized, and we test if it is able to adopt the SS response strategy, by means of a different set of reward stimuli. The process is very similar to the one described for OS training, and it is again separated to T trials. Particularly, each trial includes two sample-response pairs, but this time, due to the SS strategy the reward stimulus is located to the same side that the light cue sample appeared. The robot should again manipulate the information encoded in working memory, and the location of reinforcement signals in order to adopt the correct sample-response mapping. The measure evaluating the adoption of the SS strategy by the robot is the same with the one described in eq. (6.3.35). Furthermore, additional evaluation measures similar to those described in eqs (6.3.36), (6.3.37), (6.3.38) highlight the roles of PFC, PM, AmpR structures in the composite model. Overall, we employ two different sets of measures, namely $E_{wm,os}$, $E_{c,os}$, $E_{r,os}$, $E_{tr,os}$ and $E_{wm,ss}$, $E_{c,ss}$, $E_{r,ss}$, $E_{tr,ss}$ evaluating the ability of the robot to adopt either the OS or the SS strategy during the reward-based training process, and the distinct role of substructures in the composite model.

Coevolutionary Modelling. We turn now to the design of the model by means of the proposed HCCE scheme. The hierarchical process which is employed to accomplish this task is shown in Fig 6.42. According to the experimental scenario followed in the present study, each agent needs to serve both the adoption of the OS and the SS response strategies during separate training processes. Specifically, the fitness function employed for the evolution of $CG2$ and its lower level species, is based on measures evaluating the success of OS and SS learning procedure, and the development of WM activity in PFC. Following the formulation introduced in eqs. (5.2.1), (5.2.2):

$$\begin{aligned} &f_{CG2} = f_{CG2,t1} \cdot f_{CG2,t2} \quad \text{with} \\ &f^k_{CG2,t1} = E_{wm,os} \cdot E_{tr,os}, \quad f^k_{CG2,t2} = E_{wm,ss} \cdot E_{tr,ss} \end{aligned} \tag{6.3.39}$$

where k represents each membership of an individual in a proposed solution.

The agent structures grouped under $CG4$ serve also the success on OS, SS learning procedures and the development of the appropriate higher level motion commands on PM. Thus, the fitness function employed for the evolution of $CG4$ is:

$$\begin{aligned} &f_{CG4} = f_{CG4,t1} \cdot f_{CG4,t2} \quad \text{with} \\ &f^k_{CG4,t1} = E_{c,os} \cdot E_{tr,os}, \quad f^k_{CG4,t2} = E_{c,ss} \cdot E_{tr,ss} \end{aligned} \tag{6.3.40}$$

where k is as above.

The agent structures grouped under $CG5$ support OS, SS learning and the development of different reward patterns on AmpR. Thus, the fitness function employed for the evolution of $CG5$ is:

$$\begin{aligned} &f_{CG5} = f_{CG5,t1} \cdot f_{CG5,t2} \ \text{ with} \\ &f^k_{CG5,t1} = E_{r,os} \cdot E_{tr,os}, \quad f^k_{CG5,t2} = E_{r,ss} \cdot E_{tr,ss} \end{aligned} \tag{6.3.41}$$

where k is as above.

Finally, the top level CG enforces the integration of partial configurations in a composite model, aiming at the successful cooperation of substructures in order to facilitate the accomplishment of both learning processes, and additionally highlighting the role of each cortical agent in the composite model. The fitness function employed for the evolution of $CG6$ is defined accordingly, following the formulation introduced in eqs. (5.2.1), (5.2.2), by:

$$\begin{aligned} &f_{CG6} = f_{CG6,t1} \cdot f_{CG6,t2} \ \text{ with} \\ &f^k_{CG6,t1} = E_{tr,os} \cdot \sqrt{E_{wm,os} \cdot E_{c,os} \cdot E_{r,os}}, \\ &f^k_{CG6,t2} = E_{tr,ss} \cdot \sqrt{E_{wm,ss} \cdot E_{c,ss} \cdot E_{r,ss}} \end{aligned} \tag{6.3.42}$$

where k is as above.

The hierarchical coevolutionary process described above employed populations of 200 individuals for all PS species, 300 individuals for $CG2$, $CG4$, $CG5$, and 400 individuals for $CG6$. Additionally, an elitist evolutionary strategy was followed in each evolutionary step, with the 7 best individuals of each species copied unchanged in the respective new generation, supporting the robustness of the evolutionary process. After 70 evolutionary epochs the process converged successfully.

Sample results of robot performance during the two different training procedures on adopting the OS and SS strategies are illustrated in Figs 6.43, 6.44. In both cases, the response of the robot in the first two trials (columns 2,3) are incorrect. However, in the third trial (column 4), the robot tries another strategy which is successful, and thus it is continued for all the remaining trials. As a result, the HCCE process is able to re-design partly the computational structure described in section 6.3.3, formulating

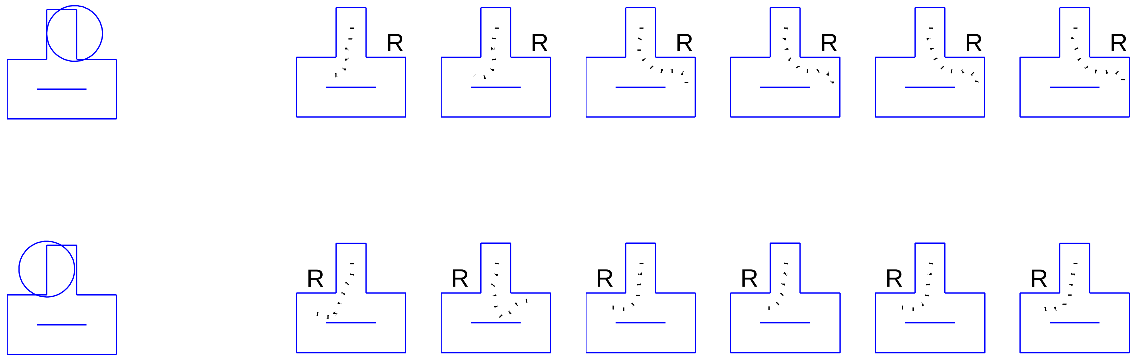

Figure 6.43: A sample result of robot performance in the Same-Side response task. The first column illustrates sample cues. The rest columns (2-7) demonstrate the response of the robot in consecutive trials. Snapshots in the first line illustrate robot responses when light sample cue appears to the right, while the second line illustrates robot responses when light sample appears to the left.

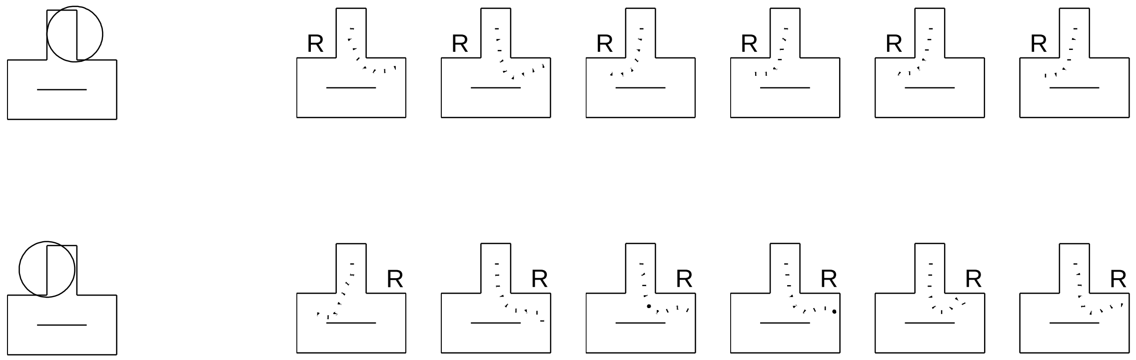

Figure 6.44: A sample result of robot performance in the Opposite-Side response task. The first column illustrates sample cues. The rest columns (2-7) demonstrate the response of the robot in consecutive trials. Snapshots in the first line illustrate robot responses when light sample cue appears to the right, while the second line illustrates robot responses when light sample appears to the left.

an enhanced model that is enriched with the ability to consider reinforcement signals in order to adopt different delayed response strategies.

Additionally, we remind that the effects of lesion described in section 6.3.3, with the robot being able to drive in a wall avoidance mode, remain also valid in the current case. This is because the computational structures representing the lower levels of the motor hierarchy, remain the same to the ones described in our previous experiment.

We have also performed experiments without the reward amplifier (AmpR), where the reward sensors projected environmental information directly on the prefrontal and premotor structures. These experiments were unable to make the robot learn the two different response strategies. This can be explained by the existence of only eight reward sensors, which implies that only eight axons with reward information is projected on PFC. Thus, the volume of the reward information on PFC is relatively small compared to the information projected by PPC. However, after utilizing the reward amplifier module, the volume of reward information is strengthened and can be more easily considered by the cortical agents involved in the learning process, in order to teach the robot effectively. Regarding its relevance to the brain prototype, this model could represent Ventral Tagmental Area (VTA) that guides learning in neocortex [144].

Overall, the present experimental procedure demonstrates the power of the HCCE-based design mechanism to redesign partly an existing computational structure in order to enhance its functionality. The same results demonstrate also that the distributed design mechanism is particularly appropriate to enforce the cooperation among new and preexisting components. As a result, HCCE can be consistently employed to facilitate the success of complex, long-term design procedures.

6.4 Computational Issues

Similar to the majority of evolutionary applications, all HCCE-based design procedures described in the present chapter are performed off-line. The coevolutionary processes described above are very demanding in terms of computational resources. This is because (i) the higher the number of the employed cortical and link agents in the computational model, the more the computational resources spent in a single simulation step, (ii) the individuals considered in each epoch are tested on the accomplishment of many different tasks, implying that many simulation steps have to be performed for their evaluation, and (iii) the interactions among different species, each one having different objectives, increases the number of evolutionary epochs that are necessary for the convergence of the complete coevolutionary scheme. Overall, the experimentation with complex hierarchical coevolutionary processes can be very time consuming even if they are performed on the simulator rather than the real robot.

In order to speed-up the experimental process, the Message Passing Interface (MPI) [196] programming environment is employed, distributing the inevitable computational burden in a set of different workstations. In the experiments discussed in section 6.3[8], a Master-Slave architecture is followed. Specifically, during each evolutionary epoch, the master workstation, submits individuals to slaves. Then, slaves decode individuals in order to evaluate their performance according to the set up of the investigated problem. The results of the evaluation are sent back to the master workstation, which then submits a new set of individuals to slaves. When all the individuals of the current population have been evaluated, an evolutionary step is performed on the master workstation, formulating the new generation of partial populations. Then, the same process is repeated again, with the master submitting a subset of the new individuals to slaves in order to evaluate their performance, and so

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[8] The experiments described in section 6.2 have been performed on a single, reserved workstation, in order to have a fair comparison among different evolutionary methods.

on.

On average, in the experiments described above, we have utilized four to six workstations (one serving as master). Still, due to the increased computational demands of the experiments, some of the HCCE processes described in the previous sections required more than 12 hours to converge.

6.5 Discussion

The results presented in the current chapter, aim at the assessment of the agent-based coevolutionary framework on the design of brain-inspired cognitive systems. First, the internal dynamics of the Hierarchical Cooperative CoEvolutionary (HCCE) scheme have been investigated. Specifically, we presented statistical data regarding the convergence of the optimization mechanism that is employed as an automated tool to facilitate the design of cognitive structures. It has been shown that HCCE outperforms other evolutionary methods, namely Enforced SubPopulations, and the ordinary unimodal evolution, when addressing difficult problems aiming to design complex systems consisting of many partial components. Furthermore, the Replication operator has been shown to be very effective, balancing adequately exploration/exploitation dynamics of complex coevolutionary schemes.

Then, we tested the proposed agent-based coevolutionary approach on the design of several biologically inspired cognitive systems. Instead of concentrating on the development of a particular partial model of brain areas, our study investigated the dynamics and design facilities of the proposed computational framework. Thus, the proposed computational framework is applied on a set of problems, each one highlighting different features of the design methodology.

According to the results demonstrated in the current chapter we can state that, the proposed computational framework can be employed as a consistent design methodology that supports the development of biologically inspired artificial cognitive mechanisms.

Specifically, it has been demonstrated that the agent-based coevolutionary framework is able to formulate partial models, integrate them in gradually larger structures, and partially re-design them in order to formulate computational systems with advanced cognitive abilities. Furthermore, the proposed framework facilitates the modelling of the training process of animals, and additionally the modelling of lesion effects observed on their performance. These particular features provide a consistent method to enforce the similarity of the implemented computational models with the biological prototype. Thus, we are able to proceed systematically towards the development of composite brain-like structures. This is because in each step of the modelling process, many biological findings are amenable to be reproduced computationally, validating the efficacy of the current result. Consequently, a solid base will be available for further extensions. Fortunately, the process of extending the model by integrating on it additional components, is also supported by the proposed computational framework.

Moreover, the results presented in the current chapter highlight the suitability of both the agent-based modelling, and the HCCE design mechanism, to serve the needs of designing brain-inspired computational systems. Particularly, the agent-based modelling supports the decomposition of the problem in smaller tasks, emphasizing on the autonomous role of partial structures. The inherent plasticity of agents facilitates the adaptivity of the model in different operating conditions. As a result, the model self-adapts in order to be functional when partial components are either added or deactivated. At the same time, the HCCE-based design mechanism is able to consider the performance of the model in diverse operating modes, to assign distinct roles to substructures, and additionally to enforce the cooperation among agents, facilitating the integration of partial models in a composite structure. Overall, the agent-based modelling and the HCCE design mechanisms match adequately to each other, mainly due to the distributed architecture they both follow.

Despite the successful accomplishment of the design problems discussed in the present chapter, we note that the current computational structures have been implemented in order to support robotic applications, and do not aim at the detailed modelling of mammalian brain areas. Additional constraints should be integrated in the models, in order to increase their biological reliability. This is in accordance to the HCCE -based design mechanism, because it is able to consider very easily many different design objectives, and additionally it is able to evolve any desirable computational model of partial structures. Consequently, the proposed design methodology can be potentially employed in the future, to design large-scale, detailed models of the mammalian brain.

Chapter 7

Conclusions

To conclude this thesis, we will review the work presented, we will highlight its main contributions, and we will point out possible directions for future research.

7.1 Summary

The present thesis addresses the problem of developing cognitive computational structures which are embedded in robotic platforms, in order to provide artifacts with cognitive abilities. The design of the cognitive computational system takes inspiration from the organization of the brain, aiming at the long term to achieve the cognitive abilities of animals. Even if the biological prototype is not a panacea in approaching robotic problems, it is clearly one of the most advanced functional systems existing today that integrates subsystems of cognitive, behavioral, motivational (emotional), perceptual and motor responsibilities. Consequently, there is much to gain from understanding its functioning, and extracting principles for the development of robots with cognitive capabilities.

The current work aims at formulating a computational framework which supports mimicking of the functional and organizational principles of the biological prototype by artificial systems. This is in contrast to the development of a unique computational structure with specific desirable properties. Thus, the present study shifts the emphasis from the final model, to the process of designing the model.

Specifically, the proposed computational framework is directed to the design of distributed computational structures, similar to the biological prototype. A novel agent-based coevolutionary methodology is introduced, that emphasizes on the cooperation of partial structures constituting the composite artificial cognitive system. By emphasizing on the integration of system components, the proposed methodology facilitates the scalability of the design procedure. Overall, the proposed computational framework incorporates in a single design methodology the properties of partial autonomy and cooperative performance, for the substructures of the composite system. Both of them are particularly appropriate for the successful design of biologically inspired artificial cognitive mechanisms.

Autonomous agent structures are utilized as primitive building blocks for the construction of the composite system, each one representing a brain area. The agent approach offers enhanced flexibility in terms of modelling the composite distributed system, because it emphasizes both the independent roles of substructures, and their coupled operation. Additionally, the plasticity of agent structures and consequently the inherent plasticity of the overall system, highlights the importance of brain-body-environment interaction in shaping the functionality of the artificial organism.

An evolutionary scheme is employed to support the design of agent structures. The evolutionary process aims at enforcing the similarity of agents with the respective brain areas, after a certain amount of environmental interaction. Instead of using a unimodal evolutionary process, we follow a cooperative coevolutionary approach which offers enhanced abilities of agent's design specification. This is because the coevolutionary approach is able to consider explicitly the structure and the role of each autonomous agent. At the same time, it also enforces the cooperation between agents, by means of evaluating their coupled functionality, facilitating their integration in a composite distributed structure.

Specifically, we introduce a Hierarchically Cooperative CoEvolutionary (HCCE) scheme which supports the development of brain-like cognitive mechanisms, enforcing mimicking of biological characteristics by the artificial system. This is achieved by assigning to agents the roles of distinct brain areas, and by enforcing the replication of biological experimental findings by the model. Additionally, HCCE provides a systematic methodology to design, integrate and re-design (if necessary) agent components, facilitating the development of large scale brain-inspired artificial cognitive systems. As a result, we argue that the proposed approach can be utilized as a consistent methodology to design artificial cognitive mechanisms, which mimic the biological prototype.

7.2 Contributions

The present work proposes a novel view on the design of brain-like computational systems, by addressing the systematic employment of evolutionary computing techniques to enforce mimicking of the biological prototype by artificial systems. This is a reliable, applicable, and very promising approach, because evolutionary computation is a well tested, robust methodology that has been employed in the past to solve many difficult problems. Particularly, it has been utilized widely to design systems that aimed to achieve a known, target-functionality. A similar view can be also adopted in the design of brain-like artificial systems. This is because there are plenty of data which describe the operation of the brain in many different operating conditions. Thus, a systematic methodology can be directed on exploiting existing data, in order to facilitate the design of brain-like computational structures. The evolutionary computing methodology seems particularly appropriate to facilitate the accomplishment of this task. Hence, the present work takes the paradigm of evolutionary computing utilization one step further, by addressing its systematic employment to design computational systems which reproduce certain aspects of brain functionality.

This view is also enriched with additional features specified by addressing the particular characteristics of the biological prototype. Specifically, we consider the distributed organization of the biological central nervous system with each partial area playing a distinct role in the composite structure. This fact implies that the artificial brain-like cognitive system should follow a distributed organization. In the present thesis we introduce a new computational framework to design brain-inspired cognitive systems, addressing explicitly the distributed nature of both the biological prototype, and the artificial structure.

Particularly, partial brain areas are considered as autonomous entities which coexist and interact in a common functional environment. Along this line, the modern software engineering approach that supports the design of complex distributed systems, namely the agent technology, is employed to facilitate the composite design problem. The employment of agent technology for the design of brain-inspired systems is another contribution of the current work. Specifically, neural network agents are employed to represent brain areas. Thus, the composite problem is split in small tractable tasks, that can be progressively solved. At the same time, the inherent adaptivity of agent structures facilitates their seamless integration in a composite, unified system. The interactive dynamics among the composite system, the body of the artifact, and the external physical environment, specify the “brain-arena”, where the agents need to interact, communicate, and cooperate with each other. Additionally, biologically inspired pathways facilitate the exchange of information among agents, and the coordination of their activities.

Moreover, a distributed evolutionary approach is employed to design the components of the cognitive system. Specifically, we introduce a Hierarchical Cooperative

CoEvolutionary (HCCE) scheme which is able to manipulate effectively the partial structures of the compound system. The coevolutionary scheme is able to highlight the autonomy of agent structures and their own special characteristics. This is achieved by utilizing separate subpopulations, each one responsible to design a component of the system, and additionally by using separate fitness functions for the evolution of these populations. As a result, the specialties of partial system components are explicitly addressed during the design procedure. This feature facilitates the assignment of distinct roles to agents, simulating the functionality of partial brain areas. Furthermore, the HCCE design mechanism facilitates the integration of autonomous agents, by means of evaluating their coupled operation. Finally, the hierarchical organization of the proposed scheme facilitates the simultaneous evolution of many partial populations, or in other words, the simultaneous design of many agent structures. Additionally, it provides a consistent mechanism to combine groups of system components. Thus, it supports the design of a progressively expanding distributed cognitive system with gradually enhanced mental abilities.

The combination of partial autonomy and cooperative performance in a single design methodology, seems particularly appropriate for the development of brain-inspired cognitive systems. Both of them are provided by the proposed computational framework, as a direct consequence of combining the distributed modelling (specifically, the agent-based modelling) with the distributed design methodology (specifically, the HCCE-based design mechanism). Thus, the novel computational framework proposed here, facilitates the design of distributed brain-inspired cognitive mechanisms, considering both the special characteristics of substructures and their integrated functionality.

The present thesis contributes significantly in the emerging research area of coevolutionary algorithms. Specifically, we combine the hierarchical evolutionary approach, with the maintenance of successful cooperator assemblies to develop a powerful coevolutionary scheme. The proposed Hierarchical Cooperative CoEvolutionary (HCCE) scheme is able to coevolve in parallel a large number of partial populations, facilitating the successful coupled operation of partial components. Furthermore, each partial population is driven by its own design objectives, considering the special characteristics of the respective component of the solution. The HCCE scheme is also able to consider the performance of the model in diverse operating conditions (different environments, different tasks, partial system failures) in order to facilitate the effectiveness and robustness of the result.

The present work contributes also in terms of agent design methodologies. This is because the HCCE scheme is inherently organized in a distributed manner which matches adequately to the distributed organization of agent-based systems. Thus, the proposed coevolutionary scheme can be employed to support the design of systems which follow this modelling approach. The HCCE approach can be employed in many difficult problems approached by the agent technology, in order to enforce the coordination, communication, and cooperation of partial agents. Additionally, the particular ability of HCCE to consider the performance of the model in diverse operating conditions (e.g. partial system failures) provides a consistent method to investigate the interactive dynamics among agents in order to facilitate/inhibit the emergence of desirable/harmful phenomena.

7.3 Future Work

Throughout this thesis we have studied a methodology that facilitates the design of brain-inspired artificial cognitive mechanisms. We strongly believe that this thesis has contributed to research efforts in the area. Additionally, the present work has highlighted new directions that need further research endeavors. These directions can be classified in three main areas, namely, brain-inspired computational systems, robotics, and coevolution. We conclude this thesis by pointing out the main research issues appearing to invite productive future work in each of these areas.

7.3.1 Brain-Inspired Computational Systems

The current work proposes a new approach for the design of biologically inspired artificial cognitive structures. The results presented in the previous chapter demonstrate its validity and effectiveness. Furthermore, the present study has also revealed directions that additional research efforts should be directed. Specifically, in the context of the proposed computational framework, the suitability of the agent-based representation of brain areas should be further investigated, in order to conclude on the proper agent structure that facilitates the development of brain-inspired artificial cognitive mechanisms. Furthermore, distinct, brain-area specific, computational structures should be utilized as parts of the same composite model, in order to highlight the anatomical characteristics of specific substructures of the biological prototype. Additionally, the HCCE design procedure should be also enriched with additional criteria (e.g. considering the temporal characteristics of the emergence of phenomena, or the formulation of reliable synaptic patterns among neurons) in order to enforce further the reliability of the result. All these criteria, and perhaps many others, are amenable to integration in the proposed design methodology.

The proposed HCCE design approach can be further utilized to facilitate the integration of diverse computational models, each one representing a different module of the biological prototype. For example, HCCE can be employed to combine computational approaches that are based on systemic models, developmental structures, and neural networks with increased biophysical reliability. As a result, a unified modelling test-bed can be developed where different approaches can be combined and evaluated, in order to formulate conclusions on their suitability to approach different aspects of the biological prototype.

The computational framework introduced in this thesis can be also employed in order to simulate and reproduce consistently more biological findings by computational structures. Along this line, the current methodology should be enriched further to facilitate the simulated reproduction of more biological data e.g. those obtained by fMRI, or PET studies. This approach seems to be very promising towards revealing the secrets of the brain. Particularly, the simultaneous reproduction of very different biological data, by the same model, will enforce its generalization ability, and additionally it will enforce partial structures to develop a role very similar to the respective structures of the brain. Thus, computational systems will come closer to the biological paradigm.

Having achieved the development of an abstract model of the central nervous system, it will be possible to enrich it gradually with more biologically reliable characteristics (e.g. by substituting partial structures with compartmental neural models, or by considering the particular roles of substructures located in the left or right hemisphere of the brain). This process can be also facilitated by the HCCE design mechanism exploiting its ability to integrate and re-design partial components.

7.3.2 Robotics

Further research should be also directed towards the design of robotic systems. The proposed methodology is enriched with many important characteristics that facilitate its utilization to approach significant problems in the area. First of all, the proposed methodology can be utilized to approach systematically the problem it is originally designed for, namely the design of brain-inspired cognitive mechanisms. Particularly, the experimental results presented in the current work can be extended further, integrating computational structures that represent more brain areas. As a result, it will be possible to combine diverse subsystems with sensory, motor, cognitive and emotional responsibilities, in a single robotic platform, following the architecture of the biological prototype. Additionally, the proposed methodology can also enforce the utilization of the implemented cognitive subsystems for the accomplishment of many different tasks, as it is also the case with the brain of animals. This particular feature will enforce the ability of partial systems to generalize, and be easily re-usable in the future for the accomplishment of new, currently unknown tasks.

Moreover, the computational framework proposed in the present study may contribute towards the unification of cognitive and emergent approaches in robotics. Particularly, the agent based representation of brain area can serve as a means to support this issue, since it emphasizes the characteristics inspired by the biological prototype, and additionally those imposed by robot-environment coupling. Thus, a new design methodology may emerge, that combines the benefits offered by cognitive and emergent approaches.

The HCCE-based design methodology may also facilitate the parallel design of robot brains and bodies, facilitating the perfect matching of them. This design approach may reveal completely new body and brain architectures, independent from the biological prototype. Thus, they will be particularly optimized to the tasks that they should aim to accomplish. The design procedure may also consider the operation of the organism in many different operating conditions in order to facilitate its effective performance.

Furthermore, the distributed design methodology can be employed to approach robot problems which are not referred to the design of cognitive mechanisms. Thus, it can be used to support the co-design of many partial robot modules which can be plugged in robotic platforms being ready for operation. The HCCE scheme can investigate the changes imposed by the integration or removal of a particular component in the composite system facilitating its successful operation in both conditions.

Finally, the same approach can be employed to investigate problems regarding social robots. This issue can be approached by designing robot teams that either compete or cooperate, facilitating their coordinated activity. Additionally, it can also facilitate research in the field of human-robot cooperation enforcing their communication, and the bidirectional transfer of knowledge.

7.3.3 Coevolutionary Scheme

One of the main contributions of the present work is the proposed Hierarchical Cooperative CoEvolutionary (HCCE) scheme, that is actually a general purpose optimization method, with a distributed organization. This particular feature makes it appropriate for the solution of many difficult engineering problems, because the distributed organization is met very often in a wide range of real-life systems. Examples in this context are related to the cooperation of brain areas, the formation of robot teams, the design of complex modular mechanical structures, and many others. All these systems share common problems which are mainly referred to the co-design of partial components that have to be adapted to each other. The coevolutionary scheme proposed in the present work can be utilized to approach effectively the design of such distributed systems, because it is able to consider both the special features of subcomponents, and their integration in a unified system.

However, further research should be directed in advancing the HCCE scheme. In order to proceed systematically towards that direction, we should first take a better insight in the internal dynamics that guide the HCCE procedure. This can be facilitated by formulating mechanisms that provide information regarding the progress of coevolution in partial populations, and how they affect each other. Then, we can formulate guidelines on the usability of HCCE, and the class of problems it is able to handle effectively. Additionally, this process will highlight directions for fruitful extension of the HCCE scheme, e.g. by means of new genetic operators, or new optimality characteristics such as pareto criteria.

Moreover, future versions of hierarchical coevolutionary processes should investigate the suitability of the hierarchical organization on competitive schemes. This is particularly applicable for problems consisting of more than two opponent entities. Another fruitful direction concerns the investigation of coevolutionary schemes with many co-existing entities that interact by formulating cooperative and competitive groups. This kind of problems needs a complex coevolutionary scheme with both cooperative and competitive dynamics among its partial populations. The extension of HCCE towards that direction could prove to be very useful, because it may facilitate studies on the dynamics that drive many social and economic phenomena.

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