On the Evolutionary Co-Adaptation of Morphology and Distributed Neural Controllers in Adaptive Agents

by

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- to my family

- to all my friends

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At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Graduate Committee. Relevant scientific seminars and conferences were regularly attended at which work was often presented; external institutions were visited for consultation purposes and several papers prepared for publication.

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Abstract

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On the Evolutionary Co-Adaptation of Morphology and Distributed Neural Controllers in Adaptive Agents

The attempt to evolve complete embodied and situated artificial creatures in which both morphological and control characteristics are adapted during the evolutionary process has been and still represents a long term goal key for the artificial life and the evolutionary robotics community.

Loosely inspired by ancient biological organisms which are not provided with a central nervous system and by simple organisms such as stick insects, this thesis proposes a new genotype encoding which allows development and evolution of morphology and neural controller in artificial agents provided with a distributed neural network.

In order to understand if this kind of network is appropriate for the evolution of non trivial behaviours in artificial agents, two experiments (description and results will be shown in chapter 3) in which evolution was applied only to the controller's parameters were performed.

The results obtained in the first experiment demonstrated how distributed neural networks can achieve a good level of organization by synchronizing the output of oscillatory elements exploiting acceleration/deceleration mechanisms based on local interactions.

In the second experiment few variants on the topology of neural architecture were introduced. Results showed how this new control system was able to coordinate the legs of a simulated hexapod robot on two different gaits on the basis of the external circumstances.

After this preliminary and successful investigation, a new genotype encoding able to develop and evolve artificial agents with no fixed morphology and with a distributed neural controller was proposed. A second set of experiments was thus performed and the results obtained confirmed both the effectiveness of genotype encoding and the ability of distributed neural network to perform the given task.

The results have also shown the strength of genotype both in generating a wide range of different morphological structures and in favouring a direct co-adaptation between neural controller and morphology during the evolutionary process.

Furthermore the simplicity of the proposed model has showed the effective role of specific elements in evolutionary experiments. In particular it has demonstrated the importance of the environment and its complexity in evolving non-trivial behaviours and also how adding an independent component to the fitness function could help the evolutionary process exploring a larger space solutions avoiding a premature convergence towards suboptimal solutions.

Contents

List of Figures

16

List of Tables

Chapter 1

Introduction

1.1 The Background

The original idea behind evolutionary robotics (Koza, 1992; Kodjabachian and Meyer, 1995; Harvey et al., 1997; Nolfi and Floreano, 2000), that is using evolutionary computation to develop controllers for autonomous robots, has been more and more influenced by the studies and the analysis on biological organisms.

The key concept that in particular has been investigated and analysed is related to the fact that biological organisms are not made of different units evolved separately, rather they are the results of interactions among their body, controller and the environment, that is they are the result of continuous successions of small mutual adaptations.

These interactions can act at two different levels:

- Phylogenetic level: variation that affects individuals from generation to generation. For instance, to consider humans it is the evolution that occurred from the ancestor *Homo erectus* (one million years ago) to the actual *Homo sapiens sapiens*.

- Ontogenetic level: variation that affects individuals during their life-time.

Continuing to consider humans it is the development process that starts with children, continue with teenagers and finishes with adults.

The low feasibility of building real robots able to modify their own morphology by themselves during their life-time (like human physical development) has moved evolutionary robotics towards two main directions:

- evolving neural controllers for robots with a fixed morphology, focusing the attention on interactions with the environment (in general in these cases morphological structures are designed by engineers inspired by complete adult biological organisms).

- evolving both the morphology and the neural controller simultaneously applying the variations only from generation to generation (not during the same lifetime).

The author of this thesis strongly believes that the limits arising from the human design of robot's morphologies are unlikely to be overcome only by evolving good controllers. The evolution of co-adaptation between morphologies and controllers might lead to a wide range of different solutions that could suggest new guidelines both in development of new kind of morphologies and also in giving the opportunity to better analyse the interactions arising from body and controller and from body, controller and environment.

In literature, most works addressing their investigations in this direction, focus their attention on genotype encoding and in particular on the way in which genotypes map into corresponding phenotypes (Sims, 1994b; Komosinski and Rotaru-Varga, 2001; Lipson and Pollack, 2000).

As known in nature, the anatomy and physiology of all organisms are the result of interpretation of DNA's instructions, where the number of genes (rules) is extremely small with respect to the number of possible phenotypes obtainable from them (Szathmáry et al., 2001; Pray, 2008) . This fact has led the author of this thesis,

together with many other researchers, to explore new kinds of indirect genotype encodings where the concept of gene reuse is a central point.

Furthermore, particular attention has been paid to the importance of neural controllers. The mechanisms used by morphology and neural controllers to co-adapt each other to any variations occurring during the evolutionary process play an important role and for this reason a preliminary investigation has been done in order to identify a controller that is more suitable to favour co-evolution.

1.2 Objectives

The main and general aim of this thesis is to propose a new bioinspired genotype encoding schema to create and evolve, from generation to generation, artificial agents with no fixed morphology in a physically simulated environment.

In contrast with most of the literature where the simulated agents' neural controllers are partially or fully centralized (Nolfi and Floreano, 2000; Floreano and Mattiussi, 2008), in this thesis the focus is on the definition of fully decentralized neural system with the main objective to reduce computational complexity and at the same time to understand if decentralized neural networks could evolve complex morphology and/or achieve non-trivial tasks.

Although decentralized systems have shown an interesting adaptiveness in artificial agents to solve a prefixed task (Wischmann et al., 2005), very few studies have tried to completely explore decentralized control systems. For this reason the first part of this thesis is dedicated to investigations of this kind of networks, with the main goal of understanding if they are really effective in evolving non-trivial behaviours, and if they are simple to modify in order to apply the evolutionary paradigm.

Inspired by gaseous neurostrasmitters, such as nitric oxide that are released by neurons and affect other neurons located nearby in a diffuse manner (Elphick et al., 1995, 1996; Husbands et al., 2001), the proposed distributed controller counts a

variable number of neural modules able to communicate with each other by exploiting signals. A direct connection among modules does not exist, but each of them can emit and/or detect signals on the basis of environmental conditions.

Each single neural module is coupled with a single motorized joint and vice versa, in the morphological structure, meaning that, all modules and joints have to be created and deleted at the same time.

This kind of distributed controller will be thoroughly described in chapter 3 and will be investigated with two different experiments, performed in order to confirm the validity of the proposed neural network.

The 1st Experiment was performed with the intention of understanding if the proposed simple modules could synchronize themselves exploiting their ability to emit and detect different signals. Obtained results were positive and for this reason a second experiment was performed in order to understand if the previous solution could be generalized to other problems or domains.

The 2nd Experiment was performed in order to evolve a neural controller with the objective of coordinating the legs of a hexapod robot in different environmental conditions. The results obtained have shown that this controller not only was able to perform the given task but it was also able to generalize its behaviour by varying both the number of modules (and as consequence the number of actuators and thus the morphology) and the environmental conditions.

Once the neural controller was defined a careful investigation was performed in order to identify the strengths and weaknesses arising from different existing genotype encodings.

At the end of this preliminary investigation phase, the author of this thesis decided to exploit an artificial ontogenetic process in which the genotype does not spec-

ify directly the characteristics of the creatures but rather the growing rules that determine how an initial artificial embryo will develop on a fully formed individual.

More specifically, the agents will be generated through a developmental process which occurs in time and space and which is realized through the progressive addition of both structural parts and regulatory substances, which affect the successive course of the morphogenetic process. A distributed control system composed of several independent neural modules embedded in different body parts was also added (one neural module for each actuator).

The last evolutionary experiment was performed with the objective of verifying the validity of the proposed genotype encoding joined with previously investigated distributed neural controllers. After a first phase in which the genotype was defined and the corresponding phenotype was created, individuals were evaluated in a physically simulated world according to their ability to move in any direction and as far as possible from the creation point.

The results obtained allowed the author to investigate several different aspects arising from the evolutionary process, both related to the expressiveness of the genotype encoding and related to the full analysis of evolved individuals.

1.3   Outline of the thesis

This thesis is organized in six chapters (including the current one) in which is presented an original research realized by the author with the suggestions of her supervisors and colleagues. The results obtained have also been presented in international conferences and published in the corresponding proceedings (articles will be reported at the end of this thesis).

Chapter 2   describes the field of evolutionary robotics focusing on the body-controller evolutionary co-adaptation area. Related works will be presented pointing out strong and weak features of the proposed solutions. An overview

on distributed neural networks is also shown together with the related works. The end of the chapter summarizes key points that will be exploited to define the proposed evolutionary model.

Chapter 3 describes the first preliminary experiments performed to test the validity and the effectiveness of the proposed distributed neural network.

In the first experiment results have demonstrated how this kind of controller can synchronize the output of oscillatory elements simply by acceleration/deceleration mechanisms based on local interactions (results have been presented at ALife X conference (Mazzapioda and Nolfi, 2006b)).

In the second experiment, results have showed how the distributed controller can coordinate the legs of hexapod simulated agents converging on a tripod or tetrapod gait on the basis of current circumstances (results have been presented at SAB 2006 conference (Mazzapioda and Nolfi, 2006a)).

Chapter 4 describe the new original proposed model including: genotype encoding, genotype to phenotype mapping and the evolutionary algorithm.

Chapter 5 describes the experiments performed in order to verify if the proposed model can generate and evolve artificial agents able to achieve given tasks. The results demonstrated, among other, the ability of this model to generate a wide range of different structures (expressiveness) and the ability to converge towards non-trivial solutions (evolvability).

The evolutionary process will be deeply analysed focusing on the importance and the specific role of each characteristic present in the model. Part of these results have been presented in IEEE Congress on Evolutionary Computation (Mazzapioda et al., 2009) ("Chairman's recognition of outstanding student paper").

Chapter 6 concludes this thesis with a discussion of all the results obtained and gives suggestions on of innovative directions in the studies of evolutionary robotics, in particular in evolutionary co-adaptation of morphology and neural controller area.

Chapter 2

Background

Artificial intelligence (AI) research officially started in 1956 during a meeting organized by John McCarthy at Dartmouth College with the main goal of understanding human intelligence and thus building intelligent machines (thought of as digital machines). For many years, until the 1980s, artificial intelligence was mainly focused on symbolic reasoning (Newell and Simon, 1972), representation (Marr, 1982) and language (Chomsky, 1957) addressing experiments in a well-defined task, typically the game of chess, that require sophisticated perceptual and cognitive abilities but not necessarily embodiment and behaviour.

One of the first works in which the importance of a body and of a purpose-driven behaviour were introduced is (Walter, 1950). His work was not supported at the beginning but it gave birth to two new sub-field of research: Artificial Life and subsequently Evolutionary Robotics, entirely based on the new concepts at the basis of modern approach to AI: behaviour, embodiment and situatedness (Pfeifer and Scheier, 1999).

Artificial Life, or ALife (Langton, 1995), is the research field that tries to recreate biological phenomena through simulations using computer models (soft approach), robotics (hard approach) and biochemistry (wet approach). In contrast to the traditional analytical research, where a complex problem is divided into elementary

components, artificial life research suggests a new methodology based on a constructionist approach (the natural world is simulated in a computer) where emergence and adaptation are the key concepts. Researchers try to re-build the main object of study starting from the basic elements that self-organize in their lifetime in order to obtain a complex behaviour.

Evolutionary robotics (Koza, 1992; Kodjabachian and Meyer, 1995; Nolfi and Floreano, 2000) is a more specific area of research with the objective of developing an automatic methods for the creation of intelligent autonomous robot controllers without a direct human programming. The clear advantage is that a deep knowledge neither about building nor programming robots is required.

Behaviour, embodiment and situatedness strongly affected research studies in evolutionary robotics and in next paragraphs will be described the evolution of this influence.

2.1 Evolutionary Robotics

Evolutionary Robotics (Koza, 1992; Cliff et al., 1993; Kodjabachian and Meyer, 1995; Nolfi and Floreano, 2000) is an automatic technique for generating solutions for a particular robotic task based on artificial evolution (Fogel et al., 1966; Holland, 1975; Schwefel, 1981; Goldberg, 1989). It is inspired by Darwin's theory of evolution (Darwin, 1859), which predicates the "survival of the fittest": the individual that best adapts to its environmnent has more chances to reproduce and to pass its genetic material to future generations.

The same idea is exploited in the artificial counterpart, in which a population of individuals is evolved for many generations. Each individual, called genotype, represents a solution for a given task. Its fitness, that is the quality of the solution to the task, is automatically evaluated in each generation. Individuals are allowed to "reproduce" by generating offspring similar to themselves but slightly different due

to some random variations. These variations are obtained by application of genetic operators, such as crossover (inspired by sexual reproduction) or mutation (inspired by asexual reproduction).

On average the majority of these variations lead to artificial agents with worse performances but some of them lead to agents with better performances than their fathers. Negative variations are discarded while the positive ones are retained by selection process and this cyclic repetition of the selection and reproduction process tends towards a population of robots able to accomplish the required task.

The main advantage of this methodology is that it does not require a deep human knowledge so it can be used to produce controllers or even whole robots able to function in environment where it is difficult to reproduce or that are not well known. Furthermore, the evolutionary process produces, generation over generation many good solutions. The best one, obtained at the last generation represent agents able to accomplish the task in an efficient way.

In Evolutionary Robotics, the behaviour of these agents becomes the object of post-evolution analysis with the objective of understanding: (a) different characteristics of different solutions, (b) common characteristics of different solutions, and (c) which are those mechanisms that lead to the emergence of adaptive solutions (Nolfi, 2005).

2.1.1 Behaviour, Embodiment and Situatedness

Behaviour can be defined as a sequence of interactions between an organism and its environment, where the actions of the organism affect its own perceptions and consequently its future actions and perceptions (Floreano and Mattiussi, 2008).

As corollary, a behavioural system can be defined as a body with:

(a)   sensors and motors that allow interactions with the environment;

(b)   a control system that maps sensory stimulation onto motor actions;

(c)   a sort of energy (or metabolism) to support its operations.

The importance of the body in studying and analysing artificial behaviour has been demonstrated by Grey Walter since 1950. His pioneering work (Walter, 1950, 1951) showed how complex and purpose-driven behaviour could emerge from a set of simple neuron-like devices embodied in a situated organism. Thirty years later (Braitenberg, 1984) proposed a new experiment in which simple imaginary vehicles displaying a range of complex behaviours were placed in an environment. He pointed out two main concepts:

1. complexity observed in behavioural systems comes from the interactions with the environment rather than from the complexity of the control system;

2. construction of embodied and behavioural circuits changes the "point of view" in analysing living brains reducing the complexity of the problem and potentially opening new research lines.

At the same time, a behavioural approach was also investigated by a group of cognitive science researchers. Instead of identifying the mechanisms and processes that occur between recording of sensory data and production of decisions and actions (Neisser, 1967), they started to consider the physical body and perception not only as passive recording of environmental stimulation but as a process of active exploration (Merleau-Ponty, 1962).

They gave the basis for the Ecological Approach (Gibson, 1979), that is the study and analysis of organisms, in particular how organisms interact with the environment and how organisms affect the stimulations that arrive to their sensing organs.

Artificial Intelligence and Robotics have been strongly influenced both by Braitenberg experiments and by the ecological approach suggested by Cognitive Science. The key role covered by behaviour leads researchers to deal with a completely new approach defined, few years later, by Rodney Brooks as *Behaviour-Based Robotics* (Brooks, 1986).

With respect to the first approach that prevailed among intelligent robotic researchers until mid-1980s (summarized in (Brooks, 1991)) and that divided the control system of a robot in a layered collection of functional modules, with the new behaviour-based approach (Brooks, 1999) introduces the concept of competence and completely changes the decomposition of problem.

The older functional division considered each module completely dependent on the previous one. As a consequence, any kind of problem emerging at any step of the sequence could compromise the functioning of the entire control system. Furthermore dividing the problem in functionally dependent levels requires a deep knowledge of the environment and a great computational power to cope with building the entire model and producing the corresponding plans.

Instead, decomposing the problem in competences (or task-achieving behaviours) makes them largely independent, that is each competence can have direct access to the sensors and actuators of the robot and can subsume or inhibit each other (Brooks, 1986). This means that decomposition can be done at different stages of knowledge, avoiding to have an initial full comprehension of the problem.

In general two kinds of behaviours are taken into account: *bottom behaviour* that is related with the basic survival competence of the robot (forage and escape), and *top behaviour* that is related to higher competences of the robot (communication and reasoning).

This kind of approach has several advantages, in particular:

- Robustness: Dividing in competences has let researchers to define multiple goals and find different solutions. Furthermore, if any component fails the artificial agent continues to have at least some competences.

- Fast Reaction: Behavioural modules can immediately map sensory information onto motor action.

- Low Complexity: Behavioural complexity does not derive from the control

system or from the world model complexity but from the interactions between several simple behavioural modules.

In spite of that, the core idea of Behaviour-Based Robotics is that the control system must be:

Situated - it must deal with the sensory and motor contingencies of the environment in which robots operate and not with an abstract description.

Embodied - it must experience the world directly through its sensors and physically act on the environment rather than operate in a simulated world.

Embodiment and situatedness are also the central aspects of all forms of life on this planet. Organisms exist in a physical form and live by acting in their environment. For this reason it should not surprise if biological inspiration almost completely affects researcher's choices in proposing and developing new artificial or real autonomous robots.

In Evolutionary Robotics the behaviour-based approach together with biological inspiration have been widely exploited in several lines of research. Here it will be considered the specific area that starting from evolving control systems for simple simulated agents in order to obtain nontrivial behaviours has led researchers to evolve both control systems and the bodies of simulated agents.

The objectives are different and range from investigating how changes in the morphology affect the behaviour of an agent to which kind of body could be better in order to reach a specific task.

2.2 From Control Systems Evolution
To Body-Controller Evolutionary Co-Adaptation

In these latest thirty years the application of the behaviour-based approach together with evolutionary robotics techniques gave birth to so many different sub-research

areas that is almost impossible to give an exhaustive description as well as a clear description of them.

After Braitenberg's experiments several researchers focused their attention mainly on the evolution of behaviour (that is evolution of system control) for artificial simulated agents (Harvey et al., 1997; Lund and Asada, 1998; Nolfi and Floreano, 2000; Floreano and Mondada, 1998; Miglino et al., 1995; Nolfi, 1998). In all these experiments morphology was defined by the corresponding authors (so by humans) and the objective was to understand how neural controllers evolved in order to accomplish given tasks.

This line of research completely focused the attention on the controller, trying to explain for each neural parameter, its specific role in global artificial behaviour. Despite these results, biological organisms teach us that not only the brain has an active role in individual behaviour, but the morphology is important too.

In particular developmental biology studies have shown that the body plans of all animals are controlled by Hox genes (Day, 1995) and that an axial Hox code determines the physical structure of vertebrates (Kessel and Gruss, 1990) and at the same time influences neural control development. This concept points out the importance of studying agents with their own structure situated in a physical environment and letting the control system and morphology evolve together.

Thus, new kinds of experiments have been performed in order to evolve also the morphological characteristics. Taking into account the real difficulty to perform experiments in which morphology heavily changes during evolution, in a first moment researchers focused their attention on the evolution of small physical variations (i.e. sensors position) on an artificial agent (Sims, 1994a,b; Balakrishnan and Honavar, 1996; Fend et al., 2003; Funes and Pollack, 1997; Pollack et al., 2001; Mautner and Belew, 2000). Furthermore, following this line of research, Cliff and Harvey (Cliff et al., 1993; Harvey et al., 1994) performed different experiments in which, together with the control system, they also evolve together the sensory morphology of robots,

in particular the number, the size and the position of sensors.

As results, they observed that co-evolution allowed to evolve robots relying on very simple strategies such as comparing the correlated activities of only two visual receptors located in strategic positions on the retinal surface.

A few years later, Lichtensteiger and Eggenberger(Lichtensteiger and Eggenberger, 1999) proposed a new experiment in which they evolved the morphology of a compound eye of a robot moving on a straight trajectory. They observed how evolved individuals displayed higher density of photoreceptors in the front demonstrating how those positions lead to more remarkable results.

In the same years, a further set of experiments were performed by Lund (Lund et al., 1997), focusing their attention on the evolution of some morphological characteristics of khepera-like robots. In these cases simulated robots were evolved for their ability to navigate in space avoiding obstacles, and evolution was applied both on neural controller and on some morphological features like: the diameter of body, the distance of the wheels and the wheel radius. Also from these experiments, the authors observed interesting correlations among morphological characteristics themselves, and with environmental properties.

Trying to summarize, all the results showed how the position, the dimension and the number of sensors played a key role both in the achievement and in the difficulty of achievement of given tasks. This fact further underlines the limitations of humans in designing fixed morphologies that are becoming a crucial aspect in reaching the final goal.

These observations together with the improvement of computer science technology has lead researchers to attempt new kinds of experiments in which morphology completely evolves with its own neural controller, reducing as much as possible the number of fixed parameters, i.e. human interventions.

2.3 Body-Controller Evolutionary Co-Adaptation

The scientific community seems to agree in establishing that Karl Sims's experiments (Sims, 1994a,b) are the origin and the most expressive works in the body-controller evolutionary co-adaptation research area. He proposed a new type of genetic encoding to create and evolve not only the neural controller of virtual creatures but also their morphological characteristics in order to let body and behaviour adapt to each other and evolve simultaneously during the evolution process. Furthermore, together with the positions of sensors and motors he also evolved the developmental process to map genotype into corresponding phenotype.

Sims (Sims, 1994a,b)developed a computer graphic simulator in which his artificial agents were subjected to certain physical rules (gravity, friction and collision) in order to obtain a physically plausible robot. His robots are composed of rectangular solids and several controlled joints that simultaneously were generated and evolved together with the corresponding controller using a methodology inspired by Lindenmayer's grammatical rewriting system (Lindenmayer, 1968). With this method, Sims evolved agents able to walk, swim, jump, but also to compete against a single opponent for the possession of a common resource.

Fig. 2.1 shows three hypothetical agents and their corresponding genome structures. This kind of genotypical representation completely satisfies two desirable properties in the artificial evolutionary process: (a) genetic compression; and (b) repeated phenotypic structures. Indeed, genomes are not simply strings of characters with a direct mapping (1-to-1) to phenotypes, rather they are composed of recursive structures able to reproduce more than one part of phenotype by simply calling the same part of genotype.

"Reuse of Genotype" or more in general "indirect encoding" has been supported also by other researchers (Dellaert and Beer, 1994b; Jakobi, 1995; Bentley and Kumar, 1999; Kitano, 1990), that analysed the importance and the potential of this kind of encoding respect to the direct encoding in creating and successively evolving more

Genotype: directed graph.   **Phenotype:** hierarchy of 3D parts.
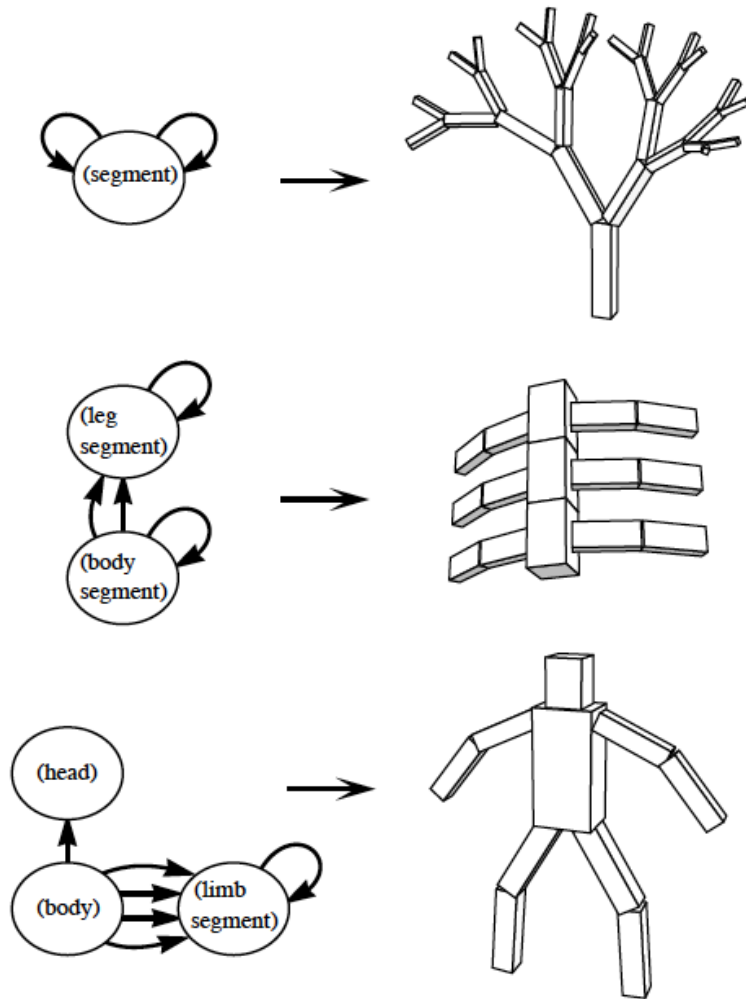
Figure 2.1: The genotype to phenotype mapping in Sims's work (permission to reproduce this picture from (Sims, 1994b) has been granted by Karl Sims).

complex phenotypes.

In literature we can find two main indirect encoding approaches[1] applied on body-controller evolutionary co-adaptation:

1. Formal Grammar Models,

2. Cell Chemistry Models.

Formal Grammar Models based on grammatical rewriting systems, was introduced by Lindenmayer (Lindenmayer, 1968) to model the biological development of multicellular organisms. After the success of Sims's experiments, other researchers proposed different genotype encodings in order to create and evolve new artificial agents (Sims, 1994b,a; Ventrella, 1994, 1998; Komosinski and Ulatowski, 1999; Komosinski and Rotaru-Varga, 2001; Adamatzky et al., 2000; Lipson and Pollack, 2000). They shared the same idea based on the fact that genotype to phenotype mapping starts from a simple phenotypic module (one or few ones) and subsequently develops applying to it a series of transformations that could be in parallel or sequential.

A further extension of this approach has been proposed by Hornby and Pollack (Kitano, 1990; Hornby et al., 2001; Hornby, 2003). They used formal grammar for high-level structures (Hornby and Pollack, 2001b, 2002) and afterwards proposed a classification of genotype representations depending on how the robot design was encoded, focusing in particular on the advantages (Hornby and Pollack, 2001a) of the generative representations: scalability and compactness (discussed also in (Cangelosi et al., 2003)).

Despite the success of these experiments, the fact that parallel rewriting systems were assumed (but not formally demonstrated) to be a good model of biological

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[1]This classification does not want to be exhaustive but only highlights on two different approaches to evolve a sophisticated behaviour in artificial agents created and evolved in a 3D virtual world.

development has motivated new researchers to suggest new methodology for identifying a more realistic biological developmental model.

Cell Chemistry Model was inspired by the early work of Turing (Turing, 1952) who proposed a mathematical model of diffusion and reaction within a physical substrate, attempting to imitate a how physical structure emerges in nature. This approach aims at simulating cell biology by modelling chemical reactions and gene regulatory networks.

Artificial life researchers extended this idea to simulate the low level interactions between cells during development and proposed a new genotype encoding composed of equations (or rules) that show how the concentrations of different substances change over time, according to diffusion or reactions with each other (Lewis, 1992; Eggenberger, 1997; Carrol, 2000; Bongard, 2002).

In order to maintain properties such as adaptability, robustness, flexibility and scalability, the first models were based on a direct genetic encoding without making use of evolutionary techniques. Only later Dellaert and Beer (Dellaert and Beer, 1994a; Dellaert, 1995) proposed an extensive model inspired from Genetic Regulatory Networks that use both an evolutionary approach and an indirect encoding, that is a particular encoding where the same genes are used multiple times in the process of building a phenotype (Stanley and Miikkulainen, 2003).

In Eggenberger (1997) proposed a new model with the objective of growing biologically realistic 3D structures. In his work, phenotypic modules closely resemble biological cells, each containing a complete copy of the genome. Genes contained in the genome diffuse their gene products both through the cells and into neighbours.

Bongard and Pfeifer expanded this line of research by evolving multicellular organisms where individual cells grow and differentiate according to the dynamics of gene regulatory networks (Bongard and Pfeifer, 2001). This new approach, named Artificial Ontogeny (Bongard and Pfeifer, 2003) exploits a developmental encoding
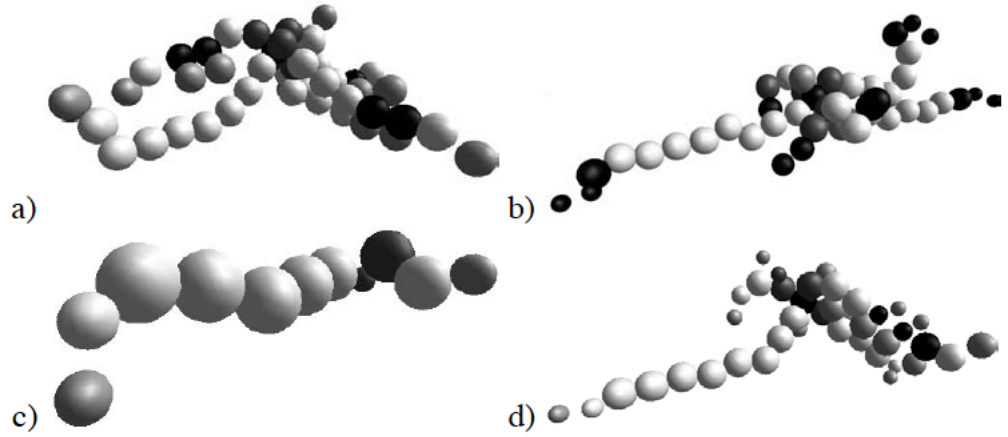
Figure 2.2: Four agents morphologies in Bongard work (permission to reproduce this picture from (Bongard and Pfeifer, 2001) has been granted by Josh Bongard).

scheme to translate a given genotype into a complete agent acting in a physically realistic virtual environment.

Genotypes are treated as genetic regulatory networks and their dynamics direct the growth of the agents leading to the construction of morphology that directly affects the phenotype and regulates the activation of other genes (with promotion or inhibition). These regulatory networks all together cause neural and morphological growth (figure 2.2).

However all these approaches exploit GRNs only during the developmental process and with strong constraints in model definition. With the objective to obtain a more biologically inspired models Quick (Quick et al., 2003) proposed GRNs defined as real time control systems for robotic and software-based embodied artificial organisms, whereas Knabe (Knabe et al., 2008) focusing on morphogenesis, proposed a model with continuous GRNs to growth and differentiate cells starting from a single one (differentiation is fully free and includes: target, volume, shape, orientation and diffusion).

2.3.1 Does a better approach really exist ?

Nevertheless several researchers have demonstrated with many experiments the validity of both Formal Grammar encodings and Cell Chemistry Models, which is the best genotype encoding, still remains an open question in evolutionary robotics.

The idea behind the cell chemistry model, later extended by Bongard and Pfeifer with the Artificial Ontogeny model (Bongard and Pfeifer, 2003), was to take inspiration from biological development. The goal was not to reproduce a detailed model of natural organisms rather to exploit the mechanisms of cellular development in order to obtain final phenotypes avoiding as much as possible human interaction.

On the other hand, in Formal Grammar models, despite phenotypes are built starting from a single initial component (inspired by biology) development is fully driven by mechanisms defined by humans. As a consequence, artificial ontogeny seems to be the better choice for biological modelling.

However, although interesting results have been obtained (Bongard and Pfeifer, 2001, 2003; Pfeifer et al., 2005; Devert et al., 2008) with this approach, a few years later Viswariathan and Pollack (Viswanathan and Pollack, 2005) demonstrated how this methodology could retard the entire evolution.

In particular, they showed that the conjunction of latent ontogenetic structures and the common practice of only evaluating the final phenotype obtained from development can have a net retarding effect on evolution. Using a formal model of development, they showed that this effect arises primarily due to the relation between the ontogenetic structures and the fitness function, which in turn impacts the properties being evaluated and selected during the evolution. To cope with this drawback new approaches have been proposed where GRNs exploit moment to moment interactions between artificial organism and the environment as a basis for producing current behaviour (Quick et al., 2003; Knabe et al., 2008). GRNs generates an active phenotype running through ontogenetic process.

From a different point of view, Stanley looking at natural DNA and its ability

to encode complexity on an enormous scale, proposed a new different form of indirect encoding named CPPNs (Compositional Pattern Producing Network) (Stanley, 2007). The objective still remains to achieve the same representational efficiency in computers by implementing a developmental encoding that maps genotype to phenotype through a process of growth from a small starting point to a mature form.

Trying to find the right level of abstraction CPPNs map the phenotype without local interaction, that is, each individual component of the phenotype is determined independently of every other component.

The main idea behind this new encoding is that it is possible to describe the structural relationships that result from a process of development without simulating the process itself. Description is encoded through a composition of functions, each of which, is based on observed gradient patterns in natural embryos. Results suggest that local interactions may not be essential to the desirable properties of natural encodings in the way that is usually assumed.

This new encoding has been exploited in producing neural network controls for legged robots (Clune et al., 2009a,b), and subsequently extended by Auerbach and Bongard (Auerbach and Bongard, 2010a,b) by allowing CPPNs to encode embedded neural network controllers as well as a variety of sensors modalities, and for evaluation of control as well as dynamic resolution. In a very recent work CPPNs have also been exploited to evolve 3D Objects with a generative encoding based on concepts from developmental biology (Auerbach and Bongard, 2010b).

This new line of research is much too recent to be considered the solution to the "genotype encoding problem", it needs to be further investigated. Finding a powerful, general and efficient genotype encoding still remain an open question in evolutionary robotics.

The author of this thesis proposes a different encoding, inspired by formal grammar to define developmental process rules, but also strongly inspired by gene regulatory networks in creating and using development rules. A full description of this method

will be given in chapter 4.

2.4   Neural Controllers:

From Centralized to Distributed Approach

In most of the experiments presented in the previous paragraphs, the neural controllers applied to artificial agents were always considered as a single unique connected neural network. This idea, directly inspired by the human brain, that is able to deal with each part of the corresponding physical body, has shown a great capability to replicate many specific no trivial behaviours.

However, focusing the attention on those experiments related to reproduction of locomotion in artificial agents, this kind of network has demonstrated its ability to replicate animal gait observable in nature, but only when artificial agents are simulated in simple environments such as flat surfaces. They are not able to generalize this ability on uneven terrains or on terrains with obstacles.

Furthermore, connected networks do not allow to obtain scalable controllers (one of the desirable properties mentioned in paragraph 2.1.1) with the clear disadvantages that they are not be able to achieve the desired task in case of complex physical structures. This instead is exactly what happens in natural organisms where complex animals show a clear ability to carry out lots of non-trivial behaviours.

A possible explanation may be that natural evolution gradually and simultaneously evolves:

(a)   animal body;

(b)   corresponding sensors and actuators;

(c)   corresponding nervous system;

(d)   interaction environment.

Unfortunately, in artificial evolution, mechanical and computational limitations in evolving all these characteristics, force us to abandon some of them.

In order to reduce computational complexity, new studies based on bio-inspired artificial robots loosely influenced by ancient biological organisms which are not endowed with a central control system, were proposed (Beer et al., 1992; Cruse et al., 1998; Reil and Massey, 2001; Buchli and Ijspeert, 2004; Fukuoka et al., 2003). In these experiments, where the morphological structure was kept fixed, a partial decentralization of control systems was adopted.

The main difference between centralized and partially centralized approaches concerns the processing of received information. In centralized systems all sensory data is received and processed by a unique controller that has to decide the next action for each actuator in the agent.

In partially decentralized systems, instead, each actuator has its own controller which receives two kinds of information: (i) local sensory data, (ii) other systems' states. These kinds of controllers have to decide only the actions of their own activator. In this way, each module is able to react to obstacles on the terrain by itself, by using sensorial information while it synchronizes its behaviour by using information from other modules.

Although decentralized systems have shown an interesting adaptiveness in artificial agents in order to solve a prefixed task, only in these latest years new studies have been performed to completely explore decentralized control systems (Wischmann et al., 2005; Mazzapioda and Nolfi, 2006b,a; Mazzapioda et al., 2009; Téllez et al., 2006; Téllez and Angulo, 2007). The objective was not to compare decentralized vs centralized neural controller in order to identify which of them is more powerful, rather try to understand if decentralized neural networks could evolve complex morphology and/or achieve non-trivial tasks.

Results obtained have shown how these kinds of networks display several advantages, in particular: fault tolerance, lower complexity and increased flexibility. Unfortu-

nately a valid criteria for evaluating these networks does not exist and too few studies have been done to generalize these characteristics for all kinds of problems. However these are the properties introduced by bio-inspired approaches and successfully used in finding new kinds of morphologies, perhaps they could be used to find efficient and powerful neural networks too.

2.5   Summary and Proposal

Embodiment and situatedness are central aspects of all forms of life on this planet. By observing natural organisms it is clear that not only the brain has an active role in individual behaviour, but the morphology and its environmental effects are important too. Organisms exist in a physical form and live by acting in their environment therefore we can define them as behavioural systems.

The definition of an artificial behavioural system that is equipped with appropriate embodiment and robust self-adaptation properties is still a major challenge in evolutionary robotics, because it requires choosing and balancing multiple components with high dynamical properties. More precisely, the main open questions are related to:

- the choice of genetic encoding and corresponding mapping

- the choice of fitness functions and methods for assessing behavioural systems

- the length of time required to obtain suitable solutions

The aim of this thesis is to answer these questions proposing a new bio-inspired genotype encoding with the objective of building and evolving in a virtual environment, physically simulated agents able to locomote. Creation and evolution of robots will include both morphological structure and corresponding neural controller.

Learning from the background, the author of this work wants to take advantages of aspects from both cell chemistry and grammar rules approaches:

- *protein concentration and propagation (inspired by cell chemistry)* - will be exploited during the initial phase in which the individual has been generated. The developmental process, that is the genotype encoding and genotype to phenotype mapping is inspired by the development and growing process of Drosophila melanogaster. In particular in reproducing the initial partition of the embryo in specialized areas depending on protein concentration produced by regulatory genes (Carrol et al., 2001).

- *high-level rules (inspired by formal grammar rules)* - will be exploited in the definition of genotype encoding. They will be not defined directly by humans but randomly generated and completely dependent on local environmental characteristics. In particular, starting from the initial embryo in which will be defined random proteins concentrations, high-level rules will let genotype to phenotype mapping add new morphological or neural components (see chapter 4.2 for a complete description).

As consequence, the main objective is to define a genotype encoding and genotype to phenotype mapping that satisfies all these features:

- **compactness** - strongly inspired by nature where DNA represents a clear form of indirect representation able to encode in a compact way an extremely wide set of different phenotypical characteristics.

- **expressivity** - the encoding should be able to generate a great variety of morphologies (from snake-like to hexapod structures, from asymmetrical to symmetrical shapes, from bodies composed of 2 or 3 components to bodies composed of 20 or 30 components... etc)

- **scalability** - computational complexity should be linear respect to the number of components.

- **evolvability** - the probability that genetic variations lead to improvements of creatures' adaptive skills should not be too low.

- **simplicity** - rules that determine the relationships between the genotype and phenotype should be as simple as possible in order to avoid the need, from the point of view of the experimenter, to deal with too many parameters that have to be chosen and optimized.

- **re-use of components** - key characteristic of indirect encodings exploited is to avoid that adaptive changing affecting a repeated component should be independently rediscovered each time by the genetic operators.

Furthermore particular attention has been paid in choosing :

- the **selection criterion** - with the objective of facilitating the evolution of required skills, the choice is to favour those fitness functions that will be neither too much was too little selective (see paragraph 4.5)

- the **neural controller** - Fault tolerance, lower complexity and flexibility are the keywords that guide us in choosing a valid controller for the proposed model. Respecting these properties and with the objective of defining a genotype encoding that is, as much as possible simple, compact and scalable, a fully distributed neural controller has been analysed and proposed (see paragraph 3.4.1).

Chapter 3

Distributed Neural Controllers: Model and Experiments

3.1   Introduction

Despite not many studies having been done to confirm their potential, the author of this thesis believes that a distributed neural controller could be a valid solution both for representation of the "brain" in simulated agents and for the implementation of features desired (2.5).

For these reasons, a system consisting of a collection of identical neural modules that: (a) have access to local sensory information only, (b) can communicate with others through signals and (c) regulate their own corresponding actuators, has been developed.

In order to understand if this kind of controller is robust enough to perform a non-trivial task, two different experiments, in which simulated agents have a fixed morphology (an hexapod with 12 degree of freedom) and evolution is applied only to the neural network, have been run.

In the first one (section 3.3) a preliminary controller was proposed and the robot has evolved on the basis of its ability to move as far as possible.
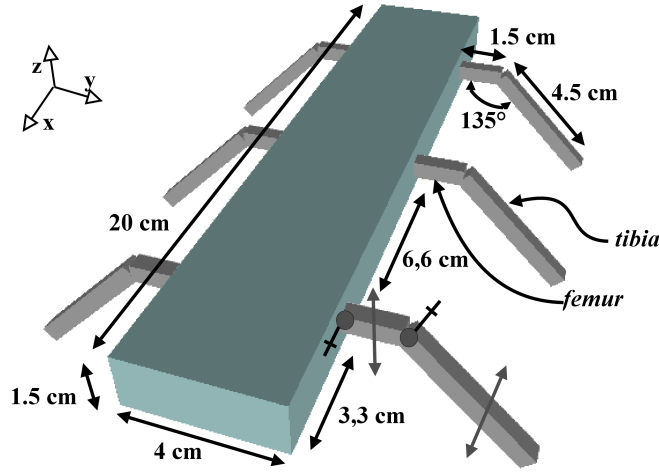
Figure 3.1: The simulated hexapod robot. The grey circles on the legs - on the bottom-right side of the picture - indicate the position of the joints, while the 2 grey arrows indicate their rotational axis.

In the second one (section 3.4) some adjustments were introduced in order to improve the power and robustness of the controller without increasing the complexity (the network continues to be decentralized).

3.2   The Hexapod Robot and The Physical Environment

The morphology of simulated hexapod robots and the physical environment are the same in both experiments and never change during all evolutionary processes.

The simulated robot (Fig. 3.1) consists of a main body (with a length of $20\,cm$, a width of $4\,cm$, and a height of $1.5\,cm$) and 6 legs. Each leg consists of two segments (a "femur" and a "tibia" with a length of $1.5\,cm$ and $4\,cm$ respectively) and has 2 motors controlling 2 corresponding joints (the body-femur and the femur-tibia joints).

The femur and the body-femur joint allow the robot to raise its central body from the ground and to move the tibia up and down. The body-femur joint is a motorized hinge joint with a rotational axis parallel to the x-axis that can rotate from $-\frac{\pi}{16}\,rad$

to $+\frac{\pi}{16}\,rad$. The femur-tibia joint allows to move the tibia forward or backward. It is a motorized hinge joint that rotates from $-\frac{\pi}{8}\,rad$ to $+\frac{\pi}{8}\,rad$ with respect to its own axis (i.e. an axis rotated of $\frac{\pi}{4}\,rad$ with respect to $yz-plane$).

The motors controlling the joints can apply a maximum torque of $0.03\,Nm$ at maximum speed of $3100\,rpm$ in both directions. For each leg, two simulated position sensors detect the current angular position of the corresponding joint.

The total weight of the simulated robot is $385\,g$. Gravity force is $-9.8\,m/sec^2$. The environment consists of a flat surface. The robot and the robot/environment interaction were simulated by using the VortexTM toolkit (Critical Mass Labs, Canada), that allows to realistically simulate the dynamics and collisions of rigid bodies in $3D$.

3.3   Synchronization Experiment

This first experiment (see also (Mazzapioda and Nolfi, 2006b)) was inspired by the synchronization phenomenon. Synchronization, that is coordination with respect to time, is studied in several disciplines ranging from astrophysics to laser physics, and from biology and neuroscience to communication (Strogatz, 2003). In most cases, synchronization can be characterized as a self-organizing process, that is as a property at the global level of the system that results from local interactions among lower-level components (Camazine et al., 2001; Strogatz, 2003).

In living beings, synchronization processes occur both at individual level (as a result of the interaction between elements that constitute the individual) and at group level (as a result of interaction between individuals). Examples of the former category include the synchronization between the pacemaker heart cells, and between the nerve cells generating locomotion (Glass, 2001). Examples of the latter category include synchronized flashing in fireflies and synchronized foraging activities in ants (Camazine et al., 2001).
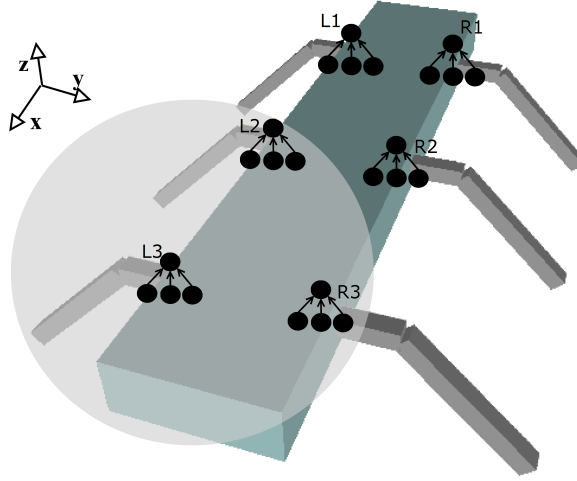
Figure 3.2: The robot and its control system consisting of 6 neural modules. $L1$, $L2$ and $L3$ indicate the front, middle, and rear legs located on the left side of the robot. $R1$, $R2$ and $R3$ indicate the front, middle, and rear legs located on the right side of the robot. The grey circle represents the range of diffusion of the signal produced by one neural module (that is the neural module controlling the $L3$ leg).

Inspired by these idea, understanding whether a hexapod robot (Fig. 3.1) composed of a set of identical elements might produce a coherent coordinated behaviour and identifying the possible roles played by diffusive communication systems and synchronization processes, have become the main goal of this experiment.

Furthermore, a deep investigation on how six homogeneous neural modules that control the six corresponding legs can coordinate in time in order to allow the robot to walk effectively was performed.

3.3.1 The Control System

The robot (figure 3.1) is controlled by a distributed control system consisting of six homogeneous neural modules, located at the junction between the main body and the legs, that control the six corresponding legs (figure 3.2).

The 6 neural modules are identical (have the same architecture and the same free parameters values) and have access to local sensory information only. More specifically, each neural module has access to the current angular position and controls the frequency of oscillation of the two joints of the corresponding leg. Neural modules
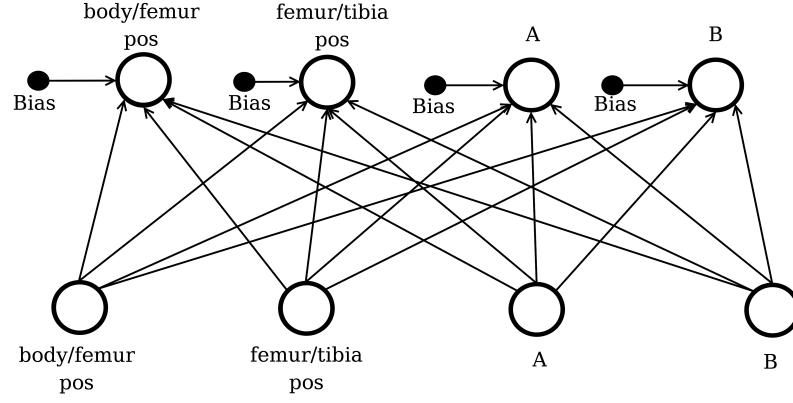
Figure 3.3: The topology of each neural module. The 4 input neurons indicated in the bottom part of the picture encode the current angular position of the two joints of a leg and signal A and B (see text). The 4 output neurons are indicated in the top part of the picture. The first two modulate the frequency of oscillation of the two corresponding motorized joints and the other two determine whether or not the signal A and B are produced (1 or 0 respectively).

communicate between themselves by producing signals and by detecting the signals produced by other neural controllers located within a given Euclidean distance.

Signals are inspired by gaseous neurotransmitters such as nitric oxide that are released by neurons and affect other neurons located nearby in a diffuse manner (Elphick et al., 1995, 1996; Husbands et al., 2001). In this experiment signal emission and expansion is instantaneous.

Each of the twelve motor neurons produces a sinusoidal oscillatory movement with a variable frequency of the corresponding joint, within the joint's limits. More specifically, the current desired position of a corresponding joint is computed according to the following equation:

$$pos(t) = sin(V(t) * t + \varphi) \tag{3.1}$$

where $pos(t)$ indicates the desired angular position of the joint at time t, $V(t)$ (that ranges between 7 and 14 Hz) indicates the current frequency of the oscillator, and φ indicates the starting position of the joint. The desired position is normalized within the range of movement of the corresponding joint.

Motors are activated to reach a speed proportional to the difference between the current and the desired position of the corresponding joint. Each neural module has 4 input neurons directly connected to 4 output neurons (Fig. 3.3).

The input neurons encode the current angular positions of the 2 joints of the corresponding leg (normalized in the range $[0.0, 1.0]$) and whether signals A and B, produced by other neural modules, are detected. Each neural module can locally produce two different signals (A and B) that can be detected up to a certain distance (D_a and D_b, in the case of signal A and B, respectively).

The intensity of the detected signal is linearly proportional to the number of neural modules that are currently producing the corresponding signal located within the corresponding maximum diffusion distance.

The activation of output neurons is computed by using a standard logistic function. The first 2 output neurons determine how the frequency of oscillation of the two corresponding joints varies. More specifically, at each time step (i.e. each $1.5\,ms$), the frequency of oscillation of a joint can vary by an amount whose range is $[-1.4Hz, +1.4Hz]$ according to the following equation:

$$V(0) = Val \qquad\qquad\qquad 7 \leq Val \leq 14$$

$$V(t) = V(t-1) + \begin{cases} (Out - 0.75) * 1.4 & Out \geq 0.75 \\ 0 & 0.25 < Out < 0.75 \\ (Out - 0.25) * 1.4 & Out \leq 0.25 \end{cases} \qquad (3.2)$$

where Val indicates the initial value of frequency of a joint that is randomly set within the range, Out indicates the output of the corresponding motor neuron, $V(t)$ indicates the current frequency and $V(t-1)$ indicates the frequency at the previous time step. Frequency is bounded in the range $[7\,Hz, 14\,Hz]$, that is variations that exceed the limits are discarded.

The other two output neurons determine whether or not signal A and B are produced (1 or 0 respectively). More precisely, signal A and B are produced when the output of the corresponding output neuron exceeds the corresponding threshold (T_a and T_b, in the case of signal A and B, respectively).

3.3.2 The evolutionary algorithm

The free parameters of the neural modules are evolved through an evolutionary algorithm. Robots were selected for the ability to walk as far as possible along any direction.

Each robot was allowed to "live" for 2 trials, each lasting $3000\,ms$ (that is 2000 time steps of $1.5\,ms$). The state of the sensor and motor neurons, the torque applied to the motors, and the dynamics of robot/environment interactions are updated at each time step (i.e. each $1.5\,ms$).

At the beginning of each trial the main body of the robot is placed at a height of $4.18\,cm$ with respect to the ground plane. The initial position of the twelve joints and the initial desired velocity of each corresponding motor is set randomly within the corresponding range.

The fitness of each robot is computed by measuring the Euclidean distance between the initial and final position of the centre of mass of the robot during each trial. The total fitness is computed by averaging the distance travelled during each trial.

The initial population consisted of 100 randomly generated genotypes that encoded: the connection weights and the biases of neural modules[1], the maximum distance of diffusion of the two signals (D_a and D_b), and the thresholds that determine when signals are produced (T_a and T_b). Each parameter is encoded as real number. Connection weights and biases, diffusion distances of signals, and thresholds that determine signal emission are normalized within the following ranges: $[-15.0, +15.0]$, $[0.0, 10.0]$, $[0.0, 1.0]$, respectively.

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[1] All modules have the same architecture and the same parameters values.
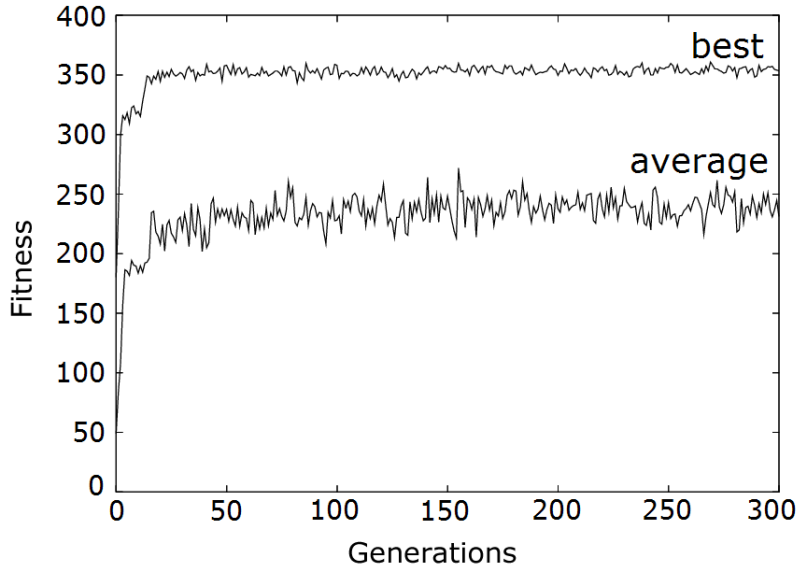
Figure 3.4: Fitness (that is average distance in cm travelled during 2 trials) of evolving individuals throughout generations in a typical replication of the experiment. The curves indicate the fitness of the best individual of each generation and the average performance of the population throughout generations.

Each genotype is translated into 6 identical neural modules that are embodied in the robot and evaluated as described above. The 20 best genotypes of each generation were allowed to reproduce by generating 5 copies each, with 3% of their genotype value replaced with a new randomly selected value (within the corresponding range). No crossover has been applied. Acting on a single genotype, mutation operator is more easy to analyze than crossover in particular when a lineage analysis is required (see section 5.4). Moreover it has been shown that crossover has no general advantages over mutation (Fogel and Atmar, 1990).

The evolutionary process lasted 300 generations (i.e. the process of testing, selecting and reproducing robots is iterated 300 times). The experiment was replicated 15 times starting from different, randomly generated, genotypes.

3.3.3 Results

By analysing the results of the evolutionary experiments it has been observed that evolved robots display an ability to walk effectively, in all replications of the exper-
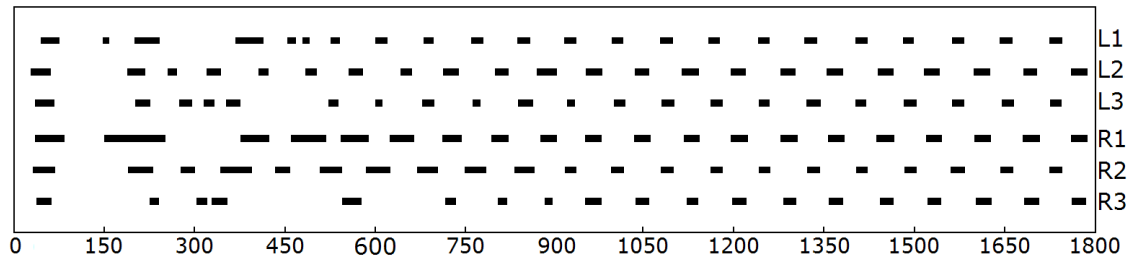
Figure 3.5: A typical behaviour exhibited by an evolved robot during a trial. At the beginning of the trial the position of the joints and frequency of oscillation are randomly initialised within limits. The black lines indicate the phases in which the tibia of the corresponding leg touch the ground. Legs are labelled with L for left and R for right and numbered from 1 to 3 starting from the front of the insect. The horizontal axis indicates time in milliseconds.

iment (figure 3.4 shows fitness throughout generations).

By visually inspecting the evolved walking strategy, it is possible to observe how, in all replications, evolved robots display an ability to quickly coordinate the phases and the frequencies of oscillation of their 12 motorized joints by converging toward a tripod gait, a type of gait used by all fast moving insects, independently from the initial position of the joints (see figures 3.5 and 3.6).

The analysis of the evolved robots indicates that after an initial coordination phase (that lasts about $1000\,ms$, on the average):

- the 12 joints converge on the same average frequency,

- the body-femur and femur-tibia joints of each leg coordinate so that the tibia touches the ground during retraction movements (in which the tibia moves toward the rear of the body) and do not touch the ground during protraction movements (in which the tibia moves towards the front of the body), see figure 3.5.

- the two groups of legs ($L1$, $L3$, $R2$) and ($L2$, $R1$, $R3$) are in phase within the group and in anti-phase between groups (see figures 3.5 and 3.6).

Once the 12 joints coordinate, they tend to keep the same frequency of oscillation (on the average, over a time span of $100\,ms$) but also slightly accelerate or decelerate,
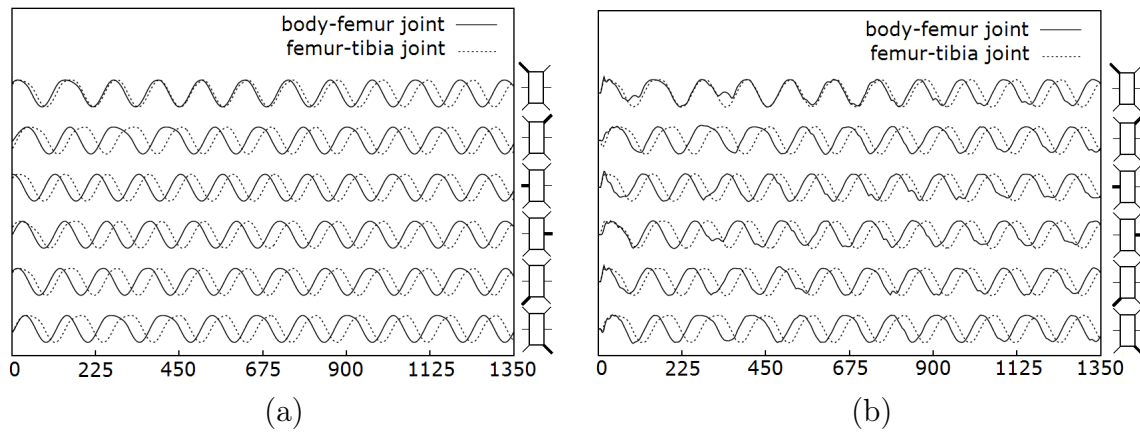
Figure 3.6: (a) Desired angular position (that is the output of neural network) and (b) Effective angular position (that is the real position of motorized joint) of the 12 joints during the same trial shown in figure3.5. Each line indicates the position of the joints of the leg indicated with a dark line in the right part of each figure. Full lines and dotted lines indicate the position of the body-femur and femur-tibia joints, respectively. High values indicate the positions in which the femur is elevated with respect to the main body and positions in which tibia is oriented toward the front of the robot.

with respect to each other, to compensate for misalignments arising during motion.

The dynamical behaviour produced by the walking robots does not only result from the interaction between the 6 neural modules that control the 6 corresponding legs but also from the dynamics originating from the interaction between the robot body and the environment. Indeed, the way in which the actual position of the joints varies in time (figure 3.6-B) is influenced not only from the variation of the desired joint position (figure 3.6-A) but also from the forces arising from the collision between the legs and the ground.

These forces are influenced by several factors such as the actual orientation of the robot with respect to the ground, the current velocity of the robot, the characteristics of the ground, etc. As shown in the figures, the effects of the robot/environment physical interaction are much more significant during the initial phase in which the legs are not yet coordinated.

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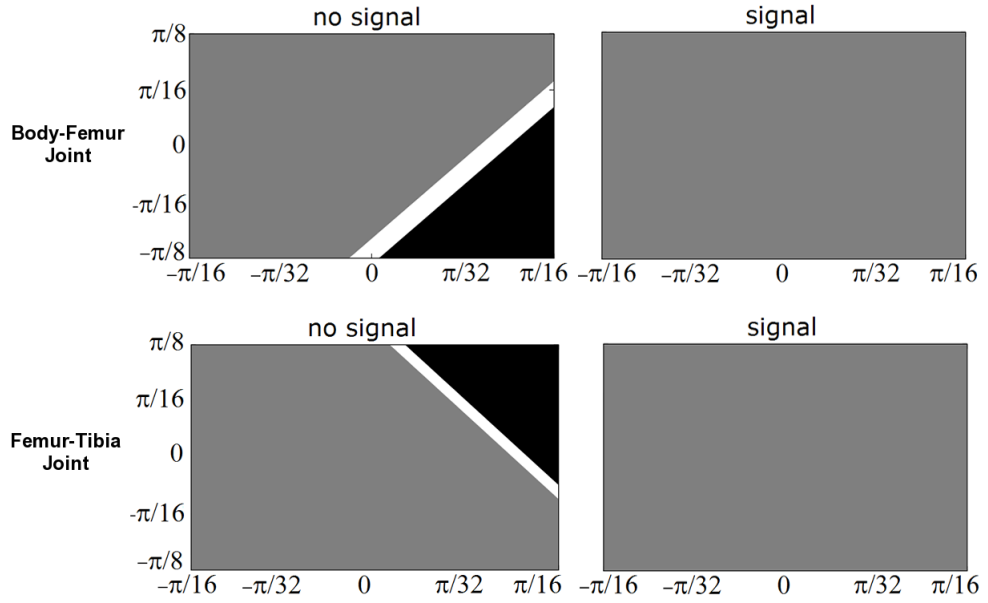
Figure 3.7: Condition in which joints accelerate (grey area), decelerate (black area) or maintain the same frequency (white area), as a function of current joint positions and of whether the neural module detects signals or not. The vertical and the horizontal axes indicate the femur-tibia and body-femur joints, respectively. Top: acceleration/deceleration effects on the body-femur joint. Bottom: acceleration/deceleration effects on the femur-tibia joint. Left: effects when signals are not detected. Right: effect when 1, 2 or 3 signals are detected.

Analysis of the mechanisms that lead to legs' coordination

To understand the mechanisms that lead to the synchronization of the 12 joints, a deep analysis of the interaction occurring within each neural module and between different neural modules (i.e. the conditions in which signals are produced and the effects of signals detected) has been done.

Here, it is reported the analysis conducted in the case of the evolved individuals already described in figures 3.5 and 3.6.

As be expected, the synchronization between the 2 joints of each leg is achieved within each single neural controller. More specifically: (*a*) the body-femur joint decelerates when it is elevated and the tibia is oriented toward the rear (figure 3.7, top-left picture), and (*b*) the femur-tibia joint decelerates when the body-femur joint is elevated and the tibia is oriented toward the front of the robot (figure 3.7, bottom-left picture).
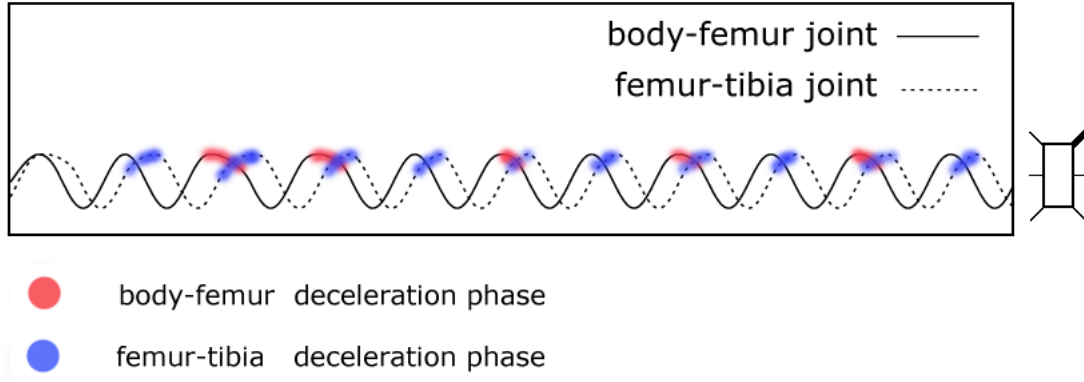
Figure 3.8: Desired angular position of the joints belonging to the right-front leg already displayed in figure 3.6 $(part\,a - 2^{nd}\,line)$. The *Red Area* identifies the deceleration phase of body-femur joint that occurs when the femur is moving upward and the tibia is moving backward and the *Blue Area* identifies the deceleration phase of the femur-tibia joint that occurs when the femur is moving upward and tibia is moving forward.

The combination of these 2 mechanisms leads to a stable state, that corresponds to the synchronized phase, in which the protraction movement of the tibia is performed when the body-femur joint is elevated while the retraction movement is performed when the body-femur joint is lowered.

This behaviour can be clearly observed also in figure 3.8 where in the desired angular position of the front-right leg (already displayed in fig. 3.6 - $part\,a - 2^{nd}\,line$) a deceleration phase of both body-femur and femur tibia joints has been highlighted. In particular:

Red Area   identifies the deceleration phase of the body-femur joint that occurs when the femur is moving upward and tibia is moving backward;

Blue Area identifies the deceleration phase of the femur-tibia joint that occurs when the femur is moving upward up and tibia is moving forward.

Furthermore, figure 3.8 shows how the deceleration mechanism is always exploited, both during the initial phase in which legs have to reach a coordinate state and during the stable state in which legs are completely coordinated. This behaviour

should not surprise because it is a direct consequence of the physical characteristics of simulated agents, in particular of their weight.

Indeed, as showed in the figure, the deceleration mechanism is only exploited during leg's protraction movement (femur moves upward and tibia moves forward) and this happens to compensate the retraction movement (femur moves downward and tibia moves backward) in which the weight of the agent directly affects leg's behaviour delaying their movements. This compensation, as explained later, lets the coordinated state stay stable.

Although neural modules can produce and detect up to 2 different signals (i.e. signal A and B), this individual only produces 1 of 2 signals: signal A. By analysing the signals used in the course of evolutionary process it has been observed that, in all replications of the experiment, evolving robots use both signals during the first evolutionary phases, and later, on average after 150 generations, robots use 1 signal only. A test experiment has thus been run in which neural controllers could exploit only 1 signal to communicate.

Results obtained have shown that in none of the 10 replications of the experiment evolved individuals have displayed an ability to walk effectively. This suggests that to achieve a given task at least 2 signals are necessary but to maintain the coordinated state among legs only 1 is sufficient. This results will be furthermore exploited during the 2nd experiment (sec. 3.4) in which the question will be: "what happens with a higher number of signals?".

Since the maximum distance of diffusion of signals A is $7.12\,cm$ (in the case of the individual shown in figures 3.5 and 3.6), the signal produced by each leg affects the contra-lateral leg of the opposite segment and the previous and succeeding leg of the same segment (when present). This means that the signal produced by a leg of one group ($[L1,\ L3,\ R2]$ or $[R1,\ R3,\ L2]$) affects only the legs of the other group that should be in anti-phase in a tripod gait. The legs that are affected by a signal are 2 out of 3 legs in the case of legs $[L1,\ L3,\ R1,\ R3]$ and 3 out of 3 legs in case of
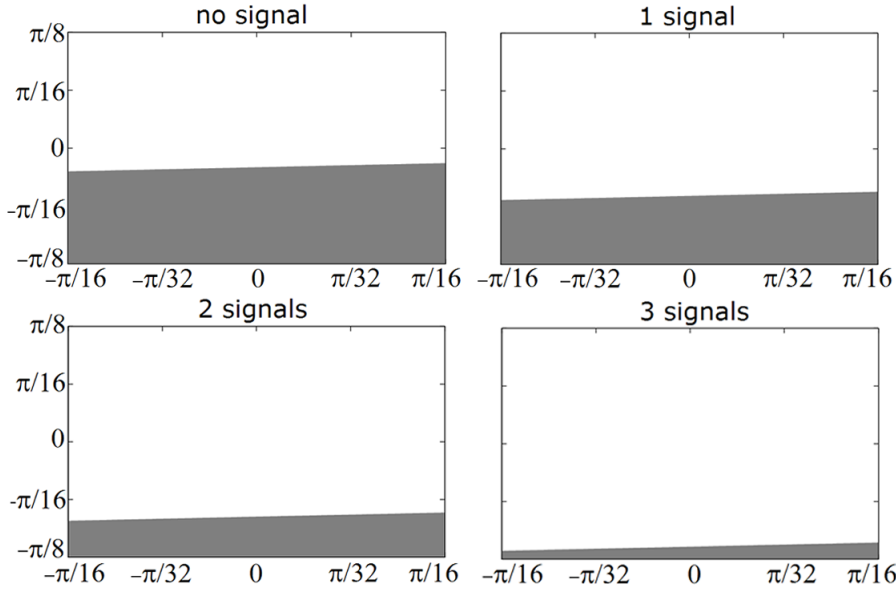
Figure 3.9: Conditions in which the signal A is produced (grey areas) as a function of the current joint position and of the number of detected signals. The vertical and horizontal axes indicate the femur-tibia and body-femur joint, respectively. The 4 pictures indicate whether the neural module detects 0, 1, 2 or 4 signals produced by other neural modules.

legs $[L2, R2]$.

To explain how the 6 legs coordinate it is necessary to explain why uncoordinated states are unstable and lead to coordinate phases (through relative acceleration/deceleration of the joints) and why coordinated states are stable.

The latter aspect can be explained by considering that, when the legs belonging to the 2 groups are in phase within the group and in anti-phase between groups, and the effect of the signals produced by the legs of the 2 groups does not produce a relative acceleration/deceleration of the legs of the 2 groups.

A leg produces a signal when its tibia is oriented toward the rear (figure 3.9). This implies that, when the legs of the 2 groups are in anti-phase, signals are produced in an alternate way from the 2 groups. This signal produced by the legs of the first group accelerates the joint of the legs of the second group (i.e. it prevents the deceleration that occurs when the signal is not detected - figure 3.7). However, the legs of the second group later produce a signal that accelerates the legs of the first group, so that the original relative frequency is restored.

To explain the former aspect (that is why uncoordinated phases are unstable) it is necessary to consider the case in which, when the legs of the first group completed their retraction movement, the legs of the second group did not complete their protraction movement yet.

Since signals are produced by the legs that have their tibia oriented toward the rear (see figure 3.9) and produce an acceleration only on legs that have their tibia oriented toward the front (see figure 3.7) the acceleration effect produced by the legs of the first group on the legs of the second group is lower than in synchronised conditions. This lack of deceleration of the legs of the second group increase their delay with respect to the legs of first group, implying that, the signals produced by the legs of the second group later on produce a larger lack of deceleration on the legs of the first group. This asymmetrical effect reduces the amount of desynchronization between the two groups, until a synchronized state is reached.

Finally, the instability of the cases in which, the legs of the two groups are erroneously in phase or almost in phase can be explained by considering the effect of the signal produced by one group of legs on the body-femur joints of the other group of legs (see figure 3.7).

The way in which the legs of one group tend to synchronize and phase within the group is an indirect effect of the processes that lead to synchronization and anti-phase between groups, described above.

For a better comprehension of coordination mechanisms, see the video available on dvd (enclosed with the hard copy of this thesis) or on the web page:

http://laral.istc.cnr.it/esm/phd_mazzapioda/1_exp.

Generalization

By testing the evolved neural controllers in new conditions it has been observed how they can generalize their ability to produce an effective walking behaviour in new environmental conditions and with new body characteristics.
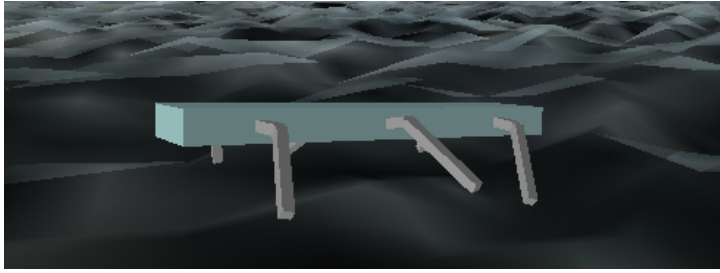
Figure 3.10: A robot evolved on a flat terrain and tested on a rough terrain (i.e. an uneven terrain with a variation in height up to $5\,cm$).
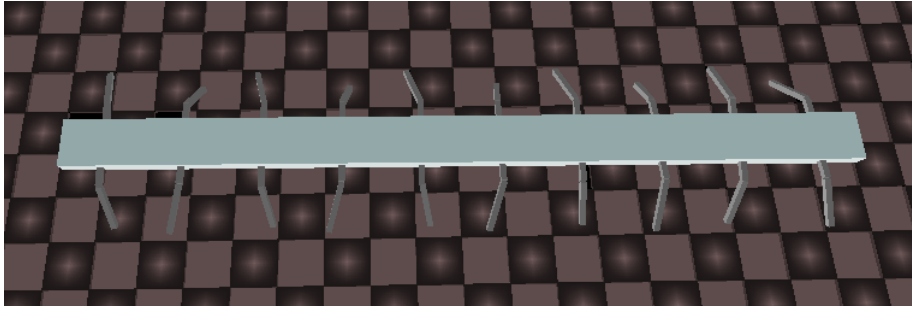
Figure 3.11: A robot with 20 legs and a body length of $67\,cm$ controlled by 20 neural modules previously evolved in robots with 6 legs.

Evolved robots display an ability to coordinate by exhibiting a tripod gait and to effectively walk also when tested on uneven terrains (see figure 3.10) or on inclined surfaces. The average speed of the robot after the initial coordination phase in these test conditions decreases of about 35% and 15%, in the case of a rough terrain and in the case of an inclined surface with a slope of $+15°$, and increases of about 15%, in the case of an inclined surface with a slope of $-15°$.

Evolving robots also show an ability to carry additional weights. Indeed, in test conditions in which the weight of the robot is doubled it is possible to observe that the robots are still able to coordinate and to walk. In these test conditions, speed decreases of about 25%, with respect to normal conditions.

Finally, by embedding the neural controllers evolved in robots with 6 legs in robots with a different number of legs (8, 12, 16 and 20), it is possible to observe that robots maintain an ability to coordinate on a tripod gait. Robots with a larger number of legs are able to walk at higher speed and to coordinate faster than hexapod robots. For example, a robot with 20 legs provided with 20 identical copies of the

neural modules described in the previous section (see figure 3.11) is able to walk with a speed that is about 10% higher and to coordinate in a time about 25% faster than hexapod robots.

3.3.4   Conclusions

Synchronization is a widespread phenomena in the universe and occurs in a large variety of animate and inanimate entities at different space and time scales. This generality can be explained by considering the inevitability of synchronization (Strogatz, 2003) providing that two simple conditions are met: spontaneously synchronizing element exhibit an oscillatory behaviour with a given intrinsic frequency, and each oscillatory element appropriately increases or decreases its frequency of oscillation on the basis of the output of the other elements (that provide an indication of their actual phase) and of its own phase.

When the differences between the intrinsic frequency of oscillation of the elements do not overcome a given threshold, synchronization will always occur, independently from the initial condition of the system and from the number of interacting elements (Strogatz, 2003).

With this experiment it has been demonstrated how an automatic process based on artificial evolution can develop the rules that determine: (a) the output of oscillatory elements, and (b) how frequency of oscillation of a given element is affected by the output of other elements.

Moreover, it has been demonstrated how, by leaving the system free to determine the range of interaction and whether the interaction is local or global, it converges towards a local interaction modality. This local interaction form combined with the fact that oscillatory elements are located in space with a given spatial configuration, allows the system to produce both a synchronization of the oscillatory elements and a differentiation of the phases of oscillation of the different elements.

This differentiation phase, in turn, allows the system to produce a tripod gait, i.e.

a coordinated movement in which contra-lateral legs of the same segment alternate in phase.

3.4   Synchronization and Adaptation Experiment

This second experiment (see also (Mazzapioda and Nolfi, 2006a)) was developed to understand whether the results previously obtained can be generalized to other problems and domains and whether distributed control systems consisting of collection of homogeneous elements located in space and interacting locally can produce complex coordinated behaviour in which single elements or groups of elements play different complementary roles.

It would be interesting to try to evolve robots varying environmental conditions to verify whether, by being selected for their ability to cope with environmental variations, they can develop even more effective strategies.

Starting from the same hexapod robot described in section 3.2, the author of this thesis proposes a new distributed control architecture consisting of 6 homogeneous neural modules controlling the 6 corresponding legs that only have access to local sensory information and that coordinate by exchanging signals that diffuse in space like gaseous neuro-trasmitters.

As seen in the previous experiment, when 2 different signals were exploited during the evolutionary process, the corresponding evolved individual was able to achieve a given task whilst this never happens when only 1 signal is used. This result seems to correlate the number of signals to neural module's communication power, and since in this new experiment the given task is more elaborated, each neural module can exchange (emit and/or detect) 4 different signals instead of 2. Results obtained will show the validity of this hypothesis: number of signals influence neural module's communication power.

Moreover, with the objective to add more computational power an indirect positional
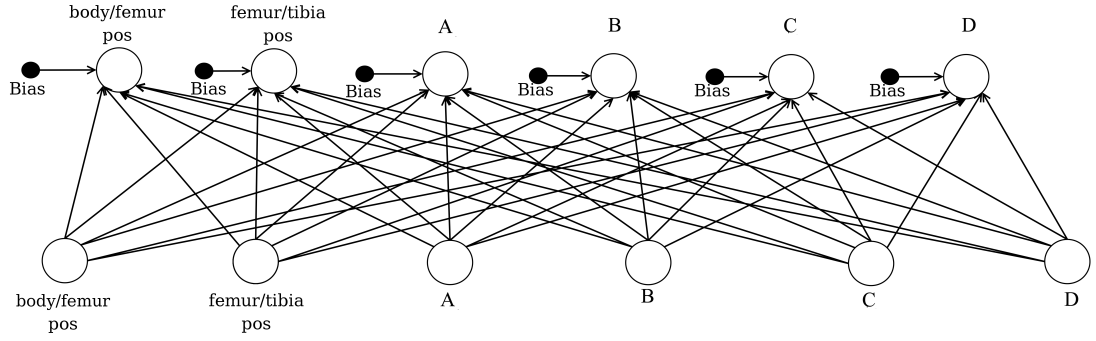
Figure 3.12: Neural module topology. The 6 input neurons indicated in the bottom part of the picture encode the current angular position of the 2 joints of a leg and the detection of 4 different signals A, B, C and D. The 6 output neurons are indicated in the top part of the picture. The first 2 modulate the frequency of oscillation of the 2 corresponding motorized joints and the other 4 determine whether or not the corresponding signal A, B, C and D are produced.

information (Wolpert, 1969) has been added: signal detection is linearly dependent from the distance of the emitting neural module varying in the interval [0.0, 1.0].

3.4.1 The Control System

In this experiment the hexapod robot (figure 3.1) is controlled by a distributed control system consisting of 6 homogeneous neural modules, located at the junction between the main body and the legs, that control the 6 corresponding legs (figure 3.2). The 6 neural modules are identical (that is have the same architecture and the same free parameters) and have access to local sensory information only. More specifically, each neural module has access to the current angular position and controls the frequency of oscillation of the 2 joints of the corresponding leg.

Neural modules communicate between themselves by producing signals and by detecting the signals produced by other neural controllers located within a given Euclidean distance. The new neural module architecture is showed in figure 3.12.

The input neurons encode the current angular positions of the 2 joints of the corresponding leg (normalized in the range [0.0, 1.0]) and whether signals, produced by other neural modules, are detected. Each neural module can produce 4 different

signals (A, B, C and D) that diffuse and can be detected up to a certain distance (D_a, D_b, D_c, and D_d in the case of signal A, B, C and D, respectively).

The intensity of the detected signal is not binary, like in previous experiment, but it is linearly dependent from the distance of the emitting neural module, and varies within 0.0 (when distance from emitting neuron is D) and 1.0 (when distance from emitting neuron is 0.0). Furthermore, the detected signal is linearly proportional to the number of neural modules that are currently producing the corresponding signal located within the corresponding maximum diffusion distance.

The activation of output neurons is computed by using a standard logistic function. The first two output neurons determine how the frequency of oscillation of the two corresponding joints varies (for details see section 3.3.1).

The other 4 output neurons determine whether or not signal A, B, C and D are produced. More specifically, signal A, B, C and D are produced when the output of the corresponding neuron exceeds the corresponding threshold (T_a, T_b, T_c and T_d in the case of signal A, B, C and D, respectively).

3.4.2   The evolutionary algorithm

The free parameters of the neural modules are evolved through an evolutionary algorithm. Robots were selected for the ability to walk as far as possible in any direction. Each robot was allowed to "live" for 5 trials, each lasting $3000\,ms$ (i.e. 2000 time steps of $1.5\,ms$). The state of the sensor and motor neurons, the torque applied to the motors, and the dynamics of robot/environment interaction are updated at each time step (i.e. each $1.5\,ms$).

At the beginning of each trial: the main body of the robot is placed at a height of $3.68\,cm$ with respect to the ground plane (i.e the whole robot floats in the air at $0.5\,cm$ from the ground). The initial position of the 12 joints and the initial desired velocity of each corresponding motor is set randomly within the corresponding range.

The fitness of each robot is computed by measuring the Euclidean distance between the initial and final position of the centre of mass of the robot during each trial. The total fitness is computed by averaging the distance travelled during each trial.

The initial population consisted of 100 randomly generated genotypes that encoded the connection weights and the biases of a neural module, the maximum distance of diffusion of the 4 signals (D_a, D_b, D_c and D_d) and the thresholds that determine when signals are produced (T_a, T_b, T_c and T_d). Each parameter is encoded as a real number.

Connection weights and biases, diffusion distances of signals, and thresholds that determine signal emission are normalized within the following ranges: $[-15.0, +15.0]$, $[0.0, 0.0]$, $[0.0, 1.0]$, respectively. Each genotype is translated into 6 identical neural modules that are embodied in the robot and evaluated as described above.

The 20 best genotypes of each generation were allowed to reproduce by generating five copies each, with 3% of their genotype value replaced with a new randomly selected value (within the corresponding range). No crossover has been applied (see section 3.3.2).

The evolutionary process lasted 300 generations (i.e. the process of testing, selecting and reproducing robots is iterated 300 times). The experiment was replicated 10 times starting from different, randomly generated, genotypes.

3.4.3   Results

By analysing the results of the evolutionary experiments it has been observed that evolved robots display an ability to walk effectively, in all replications of the experiment exactly like in first experiment (section 3.3). In particular, evolved robots display an ability to quickly coordinate the phases and the frequency of oscillation of their 12 motorized joints by converging toward a tripod gait independently from the initial position of the joints (see figure 3.13).
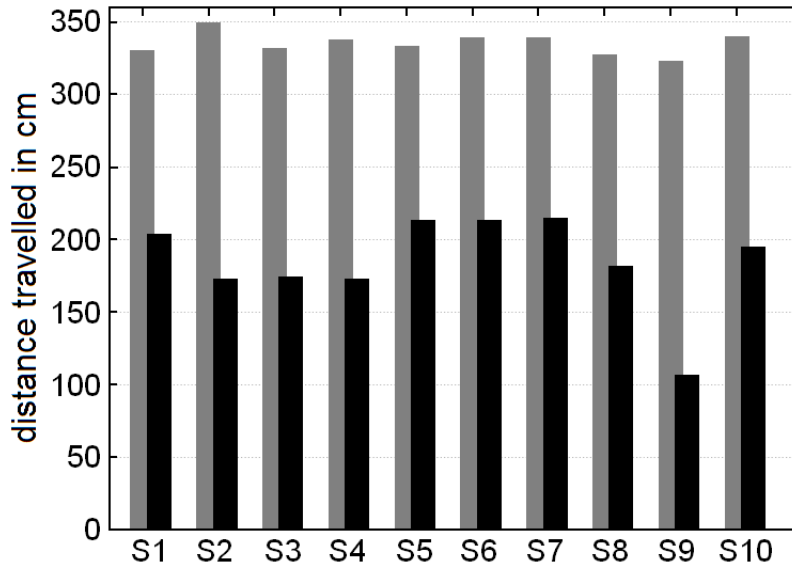
Figure 3.13: Average distance travelled by the best robot of each replication in a normal and in a test condition (grey and black histograms respectively) in which the robot is loaded with an additional weight corresponding to 1.5 times the robot's body weight. Average results for 100 trials each lasting $3\,sec$. The robots of all replications display a tripod gait when tested in a normal condition. In the test condition, the robots of replication $S1$, $S5$, $S6$, $S7$ and $S10$ display a tetrapod gait. The robots of the other replications, instead, by not being able to select an appropriate gait when loaded with additional weight, display lower performance in this condition.

To understand if the improvement of communication power has a real effect on hexapod behaviour, evolved individuals are tested in different conditions. It has been observed that evolved robots are able to generalize their ability to walk in situations in which they have to carry a weight equal to 1.5 of robots' body weight (see figure 3.13). More precisely, in some of the replications, evolved robots converge on a tripod gait (when they are not loaded with additional weight) and on tetrapod gait (when they are loaded with the additional weight, see figure 3.14). This implies that evolved robots are able, as real insects, to select a tripod gait in normal conditions and to select a tetrapod gait when they are loaded with additional weight.

The ability to converge on a tripod or a tetrapod gait in the two circumstances play a functional role since the tripod gait is faster when the weight of the robot is not too high but is ineffective when the robot is loaded with additional weight. Indeed as shown in figure 3.13, the robots that are not able to switch to a tetrapod gait when they are loaded with additional weight display significantly worse performance.

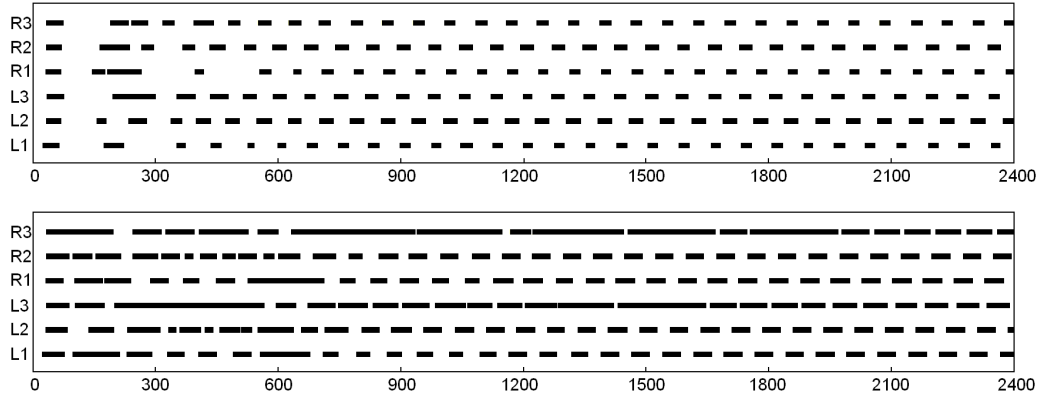Figure 3.14: A typical behaviour exhibited by an evolved robot of one of the best replications during 2 trials in which the robot is tested in a normal condition or in a test condition in which it is loaded with an additional weight (top and bottom figures, respectively). At the beginning of the trial the position of the joints and frequency of oscillation are randomly initialised within limits. The black lines indicate the phases in which the tibia of the corresponding leg touch the ground. Legs are labelled with L for left and R for right and numbered from 1 to 3 starting from the front of the insect. The horizontal axis indicates time in milliseconds. Gaits remain stable after $2400\,ms$. (Pictures do not indicate the trajectories of the robot in space but only the phase in time during which the legs touch the ground).

This can be explained by considering that in the tripod and in the tetrapod gait robots are supported by at least 3 or 4 legs, respectively. In the tetrapod gait therefore, the robot can exploit the power produced by 4 legs rather than 3 legs at the same time. In the tripod gait, in fact, the front and rear leg of one side and the middle leg of the other side perform their swing movement at the same time and the 3 other legs are in anti-phase. In the tetrapod gait, instead, a "wave" of swing movements passes along the body from rear to front.

The dynamical behaviour produced by the walking robots does not only result from the interaction between the 6 neural modules that control the 6 corresponding legs but also from the dynamics originating from the interaction between the robot body and the environment. Indeed, the way in which the actual position of the joints varies in time (figure 3.16) is influenced not only from the variation of the desired joint position (figure 3.15) but also from the forces arising from the collision between the legs and the ground. These forces are influenced by several factors such us the actual orientation of the robot with respect to the ground, the total weight of the

71

robot, the current velocity of the robot, the characteristics of the ground etc.

The results described above refer to robots that have been evolved in a normal condition (in which they were never loaded with additional weight) and have been tested in a normal and over-weight condition (in which in half of the trials they were loaded with additional weight and in half of the trials they were not).

By evolving and testing the robots in a normal and over-weighted condition it is possible to observe that evolved robots displayed lower performance on the average (with a loss of about 20% with respect to the results shown above). Moreover, in this new experiment evolved robots always displayed tetrapod gaits and were not able to adapt their gait on the fly so to select a tripod gait when tested in normal conditions.

This results can be explained by considering that in the latter experiment evolving robot converge on a local minima, that is a simple solution that allow them to reach good but sub-optimal performance on the basis of simple control mechanisms. This hypothesis is also supported by the analysis reported in the next sections that suggest how tetrapod gait tend to easily emerge as a result of the effects of the collisions with the ground without necessarily requiring control mechanisms that allow the legs to effectively coordinate and synchronize through signals.

In another replication of the experiment it has been verified that the role of space in modulating the effect of signals was really necessary to achieve effective results. More precisely, by running a replication of the experiment in which the signals produced by each module affect all other modules in the same way (independently from the distance between modules) it was possible to observe that evolved robots displayed significantly lower performance and were never able to converge on stable gaits.
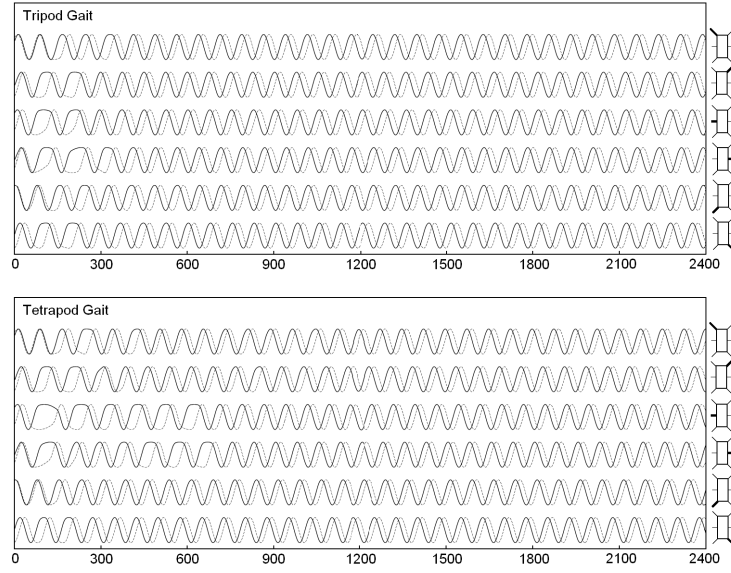
Figure 3.15: Desired angular position of the 12 joints during the same trials shown in figure 3.14 (top: data for the test in a normal condition, bottom: data for the test with additional weight). Each line indicates the desired angular position of the joints of the legs indicated with a dark line in the right part of the figure. Full lines and dotted lines indicate the position of the body-femur and femur-tibia joints, respectively. High values indicate positions in which the femur is elevated with respect to the main body and positions in which the tibia is oriented toward the front of the robot.
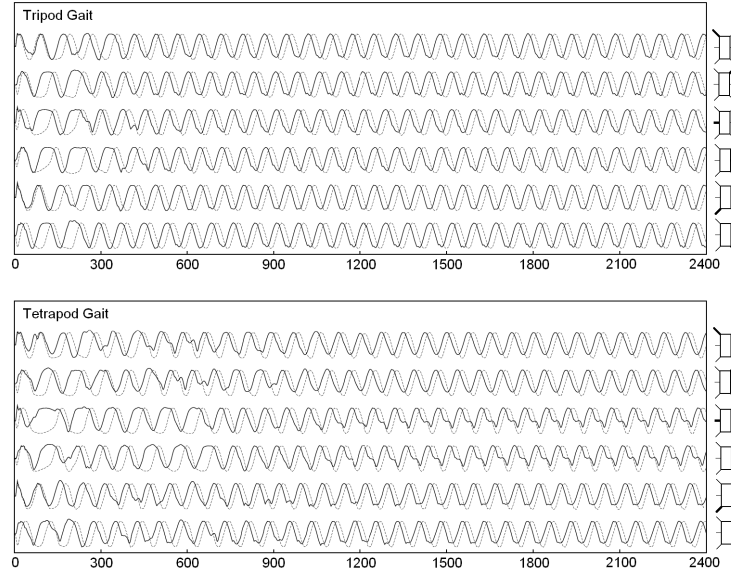
Figure 3.16: Actual angular position of the 12 joints during the same trials shown in figures 3.14 and 3.15 (top: data for the test in a normal condition, bottom: data for the test with additional weight). Each line indicates the desired angular position of the joints of the legs indicated with a dark line in the right part of the figure. Full lines and dotted lines indicate the position of the body-femur and femur-tibia joints, respectively. High values indicate positions in which the femur is elevated with respect to the main body and positions in which the tibia is oriented toward the front of the robot.

Analysis of the mechanisms that lead to leg coordination and gait selection

To understand the mechanisms that lead to the synchronization of the 12 joints, an analysis of the behaviour of each neural module and the interaction between different neural modules mediated by signals has been performed (that is the conditions in which signals are produced and the effects of signals detected).

In the following will be reported the analysis conducted in the case of the evolved individuals already described in figures 3.14, 3.15 and 3.16. The analysis conducted on individuals of other replications showed qualitatively similar strategies although in some case slightly more complex.

First will be described how the 6 legs converge toward a tripod gait in the normal condition and than how they converge on a tetrapod gait when the robot is loaded with additional weight.

As could be expected, the synchronization between the two joints of each leg is achieved within each single neural controller. More specifically: (a) the body-femur joint decelerates when it is elevated and the tibia is oriented toward the rear, and (b) the femur-tibia joint decelerates when the body-femur joint is lowered and the tibia is oriented toward the rear of the robot. Deceleration results both as the effect of output of the corresponding neural module and as a results of the effect of collisions.

The combination of these two mechanisms leads to a stable state, that correspond to stable phase observed after coordination, in which the protraction movement of the tibia is performed when the body-femur joint is elevated and the retraction movement is performed when the body-femur joint is lowered.

Analysis of the mechanisms that lead to a tripod gait

Although neural modules can produce and detect up to four different signals, the evolved individual shown in figures 3.14, 3.15 and 3.16 only produces one of the four

signals: signal B. In the other replications of the experiment, on average evolved robots use 1 or 2 signals.

Experiments in which neural modules were allowed to produce and detect only two signals have been performed but, interesting, significantly lower performance have been observed. This fact has suggested that the possibility of using many signals plays a crucial role during the first evolutionary phases despite only $1 - 2$ signals are exploited by evolved individuals.

This result confirm the preliminary hypothesis in which the number of signals was correlated to modules communication power. In particular, for this specific experiment results showed that 4 signals are necessary to let evolutionary process evolves neural modules able to achieve given task, but once obtained an optimized solution displaying an effective behaviour and coping with different environmental conditions, are sufficient 1 or 2 signals to maintain the correct behaviour. When a stable solution has been reached, managing 4 signals cause only noise in controlling communication among neural modules.

Since the maximum distance of signals diffusion is $7.8\,cm$, in the case of the robot shown in figures 3.14, 3.15 and 3.16, the signal produced by each leg affects the contra-lateral leg of the same segment, the previous and succeeding legs of the same segment, and the previous and succeeding legs of the contra-lateral segment (when present). Since the amount of the signal detected is proportional to the distance $(4.0\,cm$, $6.6\,cm$, and $7.7\,cm$ respectively) the impact of produced signal is larger on the contra-lateral leg of the same segment, smaller but still significant on the previous and succeeding legs of the same segment, and almost negligible on the previous and succeeding legs of the contra-lateral segment.

Ignoring the negligible effect on previous and succeeding legs of the contra-lateral segment, it is possible to consider the only fact that the signals produced by a leg of one group ($[L1, L3, R2]$ or $[R1, R3, L2]$) affects only the legs of the other group that should be in anti-phase in a tripod gait. The legs that are affected by a signal

are $2\,out\,of\,3$ legs in the case of legs $[L1, L3, R1, R3]$ and $3\,out\,of\,3$ legs in the case of legs $[L2, R2]$.

To explain how the 6 legs coordinate is necessary to explain why uncoordinated states are unstable and lead to coordinate phases (through relative acceleration/deceleration of the joints) and why coordinated states are stable.

The latter aspect can be explained by considering that, during coordinated phases, legs belonging to the two groups (A and B) are in phase within the group and in anti-phase between groups. Legs of group A produces a signal when their tibia are oriented toward the rear and their femurs are elevated (i.e. at the starting of the protraction phase) and they reduce their velocity only when their tibia are oriented toward the rear and they detect a signal produced by legs of group B.

Since the legs of the two groups are in anti-phase and the signals are produced in an alternate way by the legs of the two groups, in coordinated phases signals do not produce acceleration/deceleration effects.

To explain the former aspect (i.e. why uncoordinated phases are unstable) is necessary to consider the case in which the legs of group A and B, during a retraction phase, have both their tibia oriented toward the rear but the legs of group A are slightly advanced with respect to the legs of group B. Since the interval in which legs emit the signal is larger than the interval in which the legs decelerate when they detect a signal, the deceleration effect of the legs of the group A on the legs of the group B is longer than vice versa.

This implies that phase distance between the legs of the two groups tend to increase when they are in phase or almost in phase until the legs of the two groups reach the stable state described in the previous paragraph. To better observe this behaviour see the "tripod behaviour movies" available on dvd (enclosed with the hard copy of this thesis) or on the web page: http://laral.istc.cnr.it/esm/phd_mazzapioda/2_exp.

Analysis of the mechanisms that lead to a tetrapod gait

To understand the mechanisms that allow robots to switch from a tripod to a tetrapod gait when loaded with additional weight it is necessary to consider that the additional weight increases the intensity of friction in particular on the femur joints that are no longer able to reach their extreme posterior position (figure 3.16, bottom). Since legs emit the signal when the femur is elevated, this implies that the overall speed of the legs tend to decrease due to the fact that signals are produced for a longer time period.

Another factor to be considered is that when the body of the robot is not perfectly aligned with respect to the ground plane, different legs are subjected to stronger of weaker friction forces. For example, when the body of the robot is inclined toward the front, with respect to the rostro-caudal axis, the frontal legs are subjected to a stronger friction and, as a consequence, these legs produce signals for a longer time period.

The legs that are particularly stressed (due to current inclination of the body and to the fact that are performing a retraction movement) tend to slow down nearby legs that are also performing a retraction movement. This implies that legs that are under stress tend to recruit to their phase nearby legs. The final result is that the legs of the same side and of adjacent segments do not move in perfect anti-phase, as in the tripod gait, but with a partially overlapping phase. To better observe this behaviour see the "tripod behaviour movies" available on dvd (enclosed with the hard copy of this thesis) or on the web page: http://laral.istc.cnr.it/esm/phd_mazzapioda/2_exp.

3.4.4 Conclusions

In this second experiment a distributed control architecture was designed for a simulated hexapod robot with 12 degrees of freedom consisting of 6 homogeneous neural modules controlling the 6 corresponding legs that only have access to local sensory

information and that interact by producing and detecting signals that diffuse in space.

This controller allows the evolution of robots able to select solutions that exploit properties emerging from the interaction between the neural modules and between the robot and the environment. Indeed, the dynamical behaviour produced by the walking robots does not only result from the interaction between the 6 neural modules (variations of desired joint positions) but also from the dynamics originating from the interaction between the body of the robot and the environment. More precisely, the actual orientation of the robot with respect to the ground, the total weight of the robot, the current velocity of the robot, the characteristics of the ground, etc.

The analysis of the evolved neural controllers indicates that the 6 homogeneous neural controllers converge on an appropriate gait on the basis of extremely simple control mechanisms. In particular, in some replications, coordination and gait selection is achieved on the basis of one single signal. This implies that a single rule (that accelerates or decelerates the frequency of oscillation of nearby legs depending on the state of the leg that detects the signal) is sufficient to converge on a stable and effective gait.

Finally, it has been observed that evolved robots generalize their ability to produce an effective walking behaviour also when they are loaded with additional weight by displaying an ability to select a tripod or tetrapod gait both in normal and in test conditions in which they are loaded with an additional weights. Overall, the obtained results suggest that a hexapod robot can be controlled on the basis of fully homogeneous distributed control systems in which the interaction between the neural modules is only regulated by the distribution in space.

3.5 Summary

In this chapter the author of this thesis has presented two distributed control architectures (sections 3.3.1 and 3.4.1) for a simulated hexapod robot with 12 degrees of freedom consisting of 6 homogeneous neural modules controlling the 6 corresponding legs that only have access to local sensory information and that interact by producing and detecting signals that diffuse in space.

The free parameters of the homogeneous neural modules have been set through an evolutionary method that retains or discards their variations on the basis of the global behaviour exhibited by the robot in the environment. This method allows evolving robots to select solutions that exploit properties emerging from the interaction between the neural modules and between the robot and the environment.

The analysis of the evolved neural controllers indicates that in both versions the 6 homogeneous neural controllers converge on an appropriate gait on the basis of extremely simple control mechanisms. In particular, these experiments have shown how coordination and gait selection is achieved on the basis of one single signal, that is a single rule (that accelerates or decelerates the frequency of oscillation of nearby legs depending on the state of the leg that detects the signal) is sufficient to produce a stable and effective gait.

Furthermore, it is possible to observe how evolved robots can generalize their ability to produce an effective walking behaviour also when they are loaded with additional weight. In the first experiment just only by converging toward the same coordinated gait, whilst in the second experiment evolved agents display an ability to select an appropriate gait (tripod or tetrapod) on the basis of different environmental conditions (with or without additional weight). In both versions evolved agents can generalize their behaviour both on uneven terrain and with different numbers of modules without improving the complexity of controller.

The validity of these results (Mazzapioda and Nolfi, 2006b,a) has shown the computational power of this kind of controller, in particular those used in the Synchroniza-

tion and Adaptation experiment (section 3.4). For this reason, the neural controller described in section 3.4.1 will be used in a new model where the scientific focus will not be only in evolving a non-trivial behaviour but also in developing and evolving robot morphology and robot behaviour simultaneously.

Chapter 4

Body-Controller Evolutionary Co-Adaptation Model

4.1 Introduction

The model proposed in this chapter allows the evolutionary co-adaptation of the morphology and the control system of realistically simulated artificial creatures which are evolved for the ability to locomote on flat and irregular terrains.

The work is inspired by ancient biological organisms which are not provided with a central nervous system and by simple organisms, such as stick insects (Cruse et al., 1998) which display a high degree of decentralization (movements of individual legs are controlled by independent control systems).

The final goal of this model is not only to obtain evolved individuals but also to identify general mechanisms which can lead to the autonomous design of complete and evolvable artificial systems based on local distributed controllers.

The model is characterized by the following features:

1. An indirect encoding in which the genotype does not directly specify the characteristics of the phenotype but rather the way in which the embryo develops

into a full formed individual in a realistically simulated $3-Dimensional$ world in which physical objects cannot overlap (as in most of the models referenced in section 2.3).

2. The presence of regulatory processes which are realized through the synthesis in space of genetic products which later affect the morphogenetic process (as in (Bongard and Pfeifer, 2003; Quick et al., 2003; Knabe et al., 2008)).

3. The adoption of a highly distributed approach in which robots are composed of several independent neural controllers embedded in different body parts which only have access to local sensory information and which coordinate so as to exhibit a coherent and effective behaviour. More precisely, the different body parts coordinate through the effect of physical actions mediated by the external environment through the emission/detection of signals which are detectable locally in space (section 3.4.1).

4. Using signals instead of direct connection among neural modules has two main advantages:

   (a) adding or removing one single module does not strongly impact to the other ones. More precisely, it does not modify the architecture of connected modules by adding or removing connections);

   (b) the topology of communication networks between module can be dynamically modified in accordance with the behaviour of the agent, as each module can modify its relative position in the space while the agent move.

5. The adoption of a relatively simple formalism which attempts to maximize the need to keep the model as simple as possible and the number of parameters as small as possible.

6. The use of a selection criterion which favors the evolution of the required skills: coordination among motorized joints and ability to move. Fitness functions

will include two different components which reward the robots both for the ability to accomplish the desired task (locomote at the highest possible speed - in the case of the experiments performed) and for the ability to coordinate the movements of their parts.

4.2   Model Description

The developmental process that determines how creatures develop from a single elementary unit into complete creatures provided with an articulated body, sensors and actuators will be now described.

Each individual at the beginning of development is composed of an initial embryo and a set of growing rules. In next sections will be presented the properties inbred in the embryo, the rules applied and the distributed control system created and incorporated into morphology.

4.2.1   Genotype: Embryo

At the beginning of the developmental process, creatures consist of an initial *"embryo"*. Each embryo (figure 4.1-a) is composed of an elementary unit and 3 regulatory substances (α, β, and γ chosen from a set of 4 possible substance existing in simulated world: α, β, γ and δ).

The embryo is represented by a cupped cylinder with a length of $4\,cm$ and a diameter of $1.4\,cm$. Dimensions are fixed for all individuals and thus, they are not encoded in genotype.

Substances are represented by 3 distinct planes intersecting the embryo along the 3 main axes in 3 random positions and distributed inside and outside the elementary unit as showed in the figure 4.1-b.

The concentration of regulatory substance varies linearly, giving an indirect positional information (Wolpert, 1969), with respect to the distance from the plane of
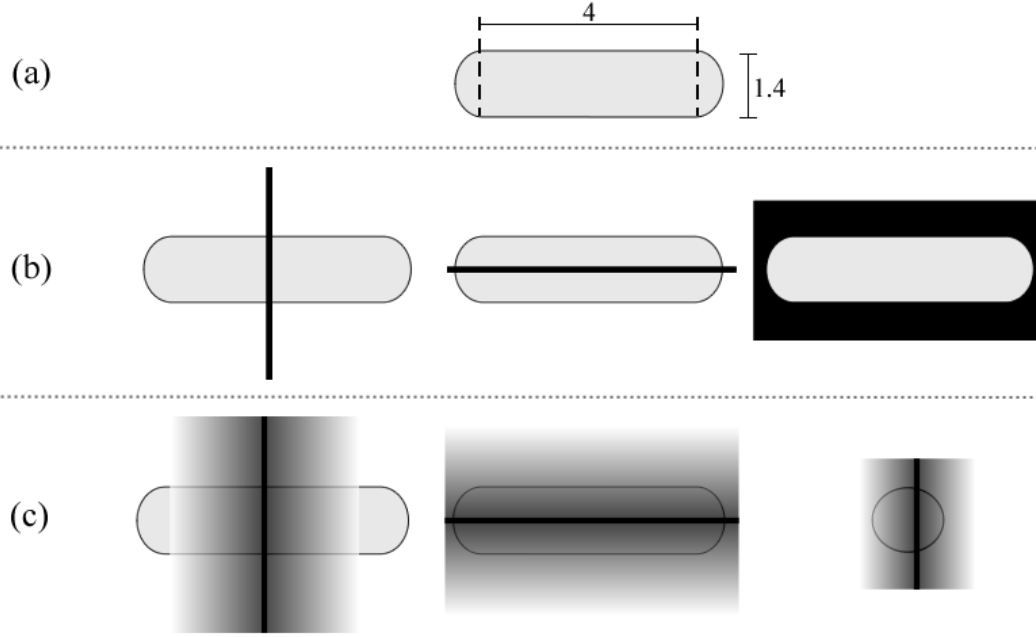
Figure 4.1: (a) an elementary unit; (b) the orthogonal planes representing the area of maximum concentration of the corresponding regulatory substances α, β, and γ; (c) concentration distribution of the three corresponding regulatory substances.

the maximum concentration, along the left-right, dorsal-ventral, and the rostral-caudal axis, respectively; with concentration of 1.0 on the corresponding plane that linearly decrease up to 0.0 for distances equal or greater than the maximum propagation range of the corresponding substance (D_α, D_β, and D_γ - figure 4.1- c).

Initial substances together with position and dimension of corresponding planes are randomly chosen at the beginning of individual creation. During evolutionary process these data could be change in according with their own mutation probability (see par. 4.4) and satisfying specific constrains. More precisely, in each time, initial substances have to be:

- Three,

- Different,

- Each one has to be placed in a different orthogonal plane.

Substance propagation is subjected to evolution too and its value can vary in the range [1 9], that is substances, starting from source, can reach at most two next

elements. Propagation is not a specific characteristic of initial embryo, it is a general property of regulatory substances. This means that the value is valid also for substances that will be added during phenotypic developmental.

Embryo: Summary

Cupped Cylinder			
Dimension	$(len \times rad)$	$5.4 \times 1.4\,cm$	fixed values
Substance Plane			
Substance name	$name$	$name \in \{\alpha,\, \beta,\, \gamma,\, \delta\}$	random values
Rotation	$(x,\, y,\, z)$	$x,\, y,\, z \in \{0°,\, 90°,\, 180°,\, 270°\}$	fixed values
Dimension	$(len \times len)$	$len \in [3,\, 8]\ cm$	random values
Position	pos	$pos \in \mathbb{R}$	random within cylinder dim.

Regulatory Substances: Summary

Substance Plane			
Substance name	$name$	$name \in \{\alpha,\, \beta,\, \gamma,\, \delta\}$	random values
Propagation	$prop$	$prop \in [1,\, 9]\ cm$	random values

4.2.2 Genotype: Growing Rules

For each individual 15 developmental rules and one vector of 15 indexes which indicates the order with which the developmental rules are executed has been encoded in genotype.

All rules comply with the same pattern that is formed by a condition part and an action part which is executed in the location/s of the current element (cupped cylinder) where the condition part holds.

The condition part encodes the regulatory substances (within the following possibilities $[\alpha,\, \beta,\, \gamma,\, \delta]$, encoded with an integer value) and the concentration of the

substances (within the range [1.0, 0.0]) which leads to the execution of the action part. At each given state of the developmental process, the condition part might be valid in more than one location.

During verification of condition part, sum of substances is not considered, this means that if exist different planes that produce the same substance, there will not be joined together but for each plane will be verified the condition and eventually applied the corresponding action.

Two different actions could be executed:

1. add-unit action;

2. add-regulatory-substance action.

The add-unit action adds from 0 to 6 elementary units (figure 4.1-a) in the location/s of the current embryo in which the condition part hold/s.
Two preliminary checks have to be execute before adding new elements:

(a)   the new element must not intersect any existing elements, in contrary case it will be discarded;

(b)   the total number of inserted cylinders, due to simulator limitations, can not be higher than 30.

Parameters related to this action include:

1. 6 binary values (insertion points) which specify the points for possible insertion of new elements.
   They encode whether or not (1 or 0 respectively) the elementary units are inserted along 6 possible orientations (0°, 60°, 120°, 180°, 240°, 300°) perpendicular with respect the longitudinal axis of the circular surface in which the condition holds (figure 4.2- a,b,c).
   There is an exception when the condition is satisfied at one of the end points of
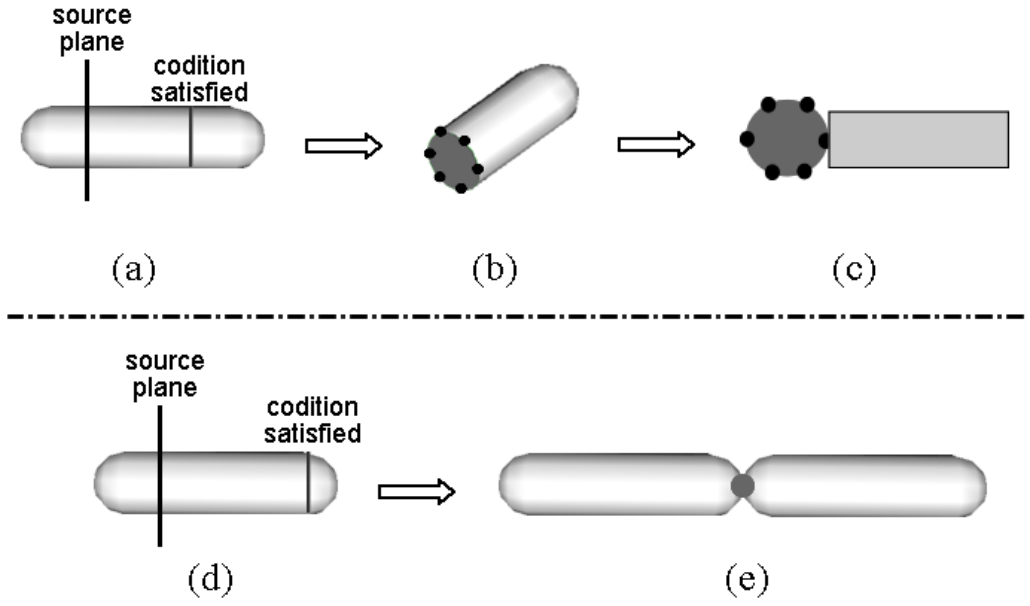
Figure 4.2: (a) an example of the plane in which the substance has the maximum distribution and of the circular surface in which the condition is satisfied. (b) An exemplification of the 6 points in which new elementary units can be attached. (c) An exemplification of a case in which the condition is satisfied at one of the ends of the elementary units. (e) An exemplification of the way in which the new element is attached in case (d).

the cylinder, in fact in this specific case, the new elementary units are added along with the same axis of the elementary unit in which the condition is satisfied (figure 4.2-d,e).

2. An integer value which determines whether the new elementary units are connected through a fixed joint or a motorized joint with one degree of freedom (DOF) within the following possible cases (x, y, or z) and within the following limits $[-30°, +30°]$.

0 indicates $fixed\,joint\,:\,fix$

1 indicates $motorixed\,joint - X - axis\,:\,mobX$

2 indicates $motorixed\,joint - Y - axis\,:\,mobY$

3 indicates $motorixed\,joint - Z - axis\,:\,mobZ$

The maximum force and the maximum velocity applied to the motorized joint correspond to $404\,Nm$ and $9.6\,rad/sec$ respectively.

3. A vector of values which encodes the connection weights and biases of the
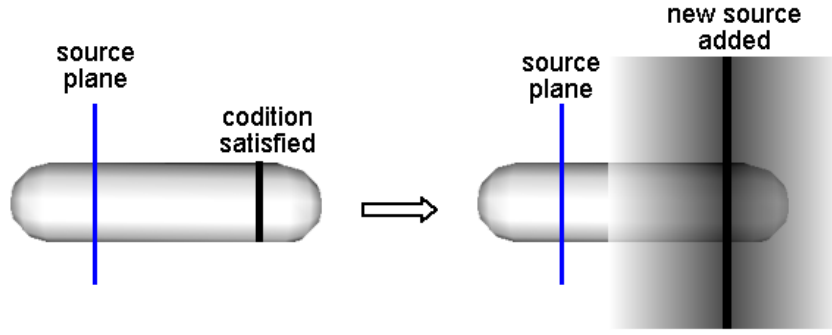
Figure 4.3: New source substances is added.

artificial neural network controlling the corresponding DOF (if any).

Each parameter is encoded with 8 bits and normalized in a floating point value in the range $[-15.0, +15.0]$. This implies that the neural network controllers which are generated through the same rule have the same characteristics whereas those that are generated by different rules might differ.

The add-regulatory substance action adds a new regulatory substance with a concentration which varies proportionally to the distance with respect to a new plane.

This new plane is created at the point in which the condition is satisfied with the same orientation of the regulatory substance which triggered the execution of the action (figure 4.3).

Parameters of the add-regulatory-substance actions include:

1. An integer value in the range $[0, 3]$ which encodes the type of regulatory substance added $[\alpha, \beta, \gamma, \delta]$.

2. A floating point value in the range $[3.0, 8.0]$ that encodes the size of the plane which determines the radius of influence of the regulatory substance.

Growing Rules: Summary

Condition Part	$? (substance = val)$	$sub \in \{\alpha,\, \beta,\, \gamma,\, \delta\}$
		$val \in [1.0,\, 0.0]$
Action Part: Add Unit		
joint type	jt	$jt \in \{fix,\, mobX,\, mobY,\, mobZ\}$
insertion points	$insVal\,[6]$	$insVal\,[i] \in [0,\, 1]$
network weights	$wMat\,[6 \times 5]$	$wMat\,[i,\, j] \in [-15.0,\, +15.0]$
Action Part: Add Substance		
substance name	$newSub$	$newSub \in \{\alpha,\, \beta,\, \gamma,\, \delta\}$
plane rotation	$planeRot\,[3]$	$planeRot\,[i] \in \{0°,\, 90°,\, 180°,\, 270°\}$
plane dimension	$planeDim$	$planeDim \in [1,\, 9]\ cm$

4.2.3   Genotype: Neural Controller

As introduced above, each elementary unit provided with a motorized joint includes a neural network controller acting at 2 different levels:

Locally   each neural controller has access to the current angular position and regulates the frequency of oscillation of the corresponding joint.

Globally   all neural controllers can communicate among themselves by producing up to 4 different signals and by detecting the signals produced by other neural modules located within a maximum Euclidean distance.

Each neural controller has a fixed architecture consisting of 5 sensory neurons directly connected to 5 output neurons (figure 4.4).

Sensory Neurons include:

- 1 neuron encoding the current angular position of the corresponding motorized joint (normalized in the range $[-1.0,\, 1.0]$).
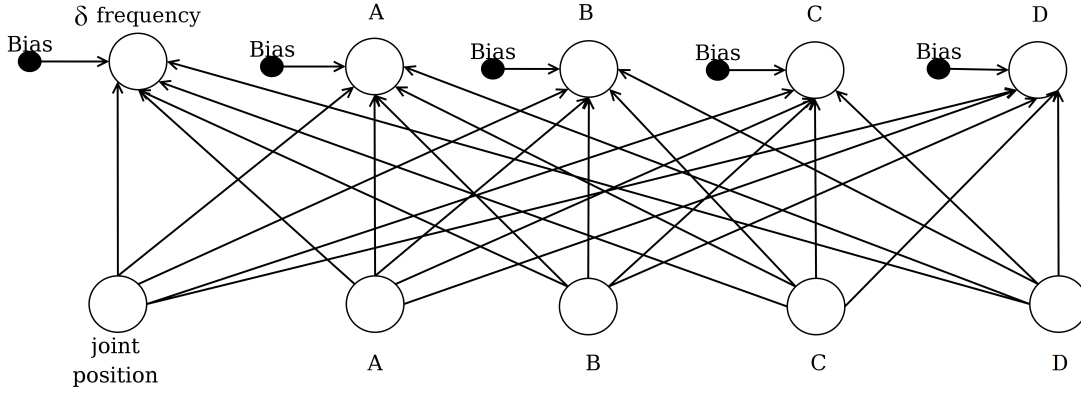
Figure 4.4: The architecture of single neural controller.

- 4 neurons encoding how many signals produced by other neural modules are detected.

  Each neural module can produce 4 different signals (A, B, C and D) that diffuse and can be detected up to a certain distance (D_A, D_B, D_c and D_D in the case of signals A, B, C and D respectively).

  Detection is a binary value, and the total sum of detected signals is normalized in the range [0.0, 1.0].

  Distance detection varying in the range [3.0, 10.0]. It does not start from *zero* mainly to avoid that elements created by the same rule (thus identical) and placed around the section of the same element (see figure 4.2 - b,c) could affect each other. Furthermore, the general idea was that signals should be used to coordinate elements situated in quite far different positions because, as demonstrated in experiments described in chapter 3, adjacent elements could coordinate themselves exploiting their physical characteristics.

Output Neurons include:

- 1 neuron encoding the acceleration or deceleration of corresponding motorized joint.

  The desired position of each joint is determined by a sinusoidal oscillator with a frequency that is initially assigned randomly in the range [7.0, 14.0] Hz and

that is later increased or decreased in each time step within the same range
on the basis of the current output of the corresponding neural controller ac-
cording to the following equation:

$$V(0) = Val \qquad\qquad 7.0 \leq Val \leq 14.0$$

$$V(t) = V(t-1) + \begin{cases} 2 \cdot (Out - 0.5) \cdot 1.4 & Out > 0.5 \\ 0 & -0.5 \leq Out \leq 0.5 \\ -(2 \cdot (-Out - 0.5) \cdot 1.4) & Out < -0.5 \end{cases} \quad (4.1)$$

Where Val indicates the initial value of frequency of a joint that is randomly
set within the range, Out indicates the output of the corresponding motor neu-
ron, $V(t)$ indicates the current frequency and $V(t-1)$ indicates the frequency
at the previous time step.

Frequency is bounded in the range $[7\,Hz,\ 14\,Hz]$, i.e. variations that exceed
the limits are discarded. In other words the frequency increases in the range
$[0,\ 1.4]\,Hz$ for outputs in the range $(0.5,\ 1.0]$, and decreases in the range
$[0.0,\ -1.4]\,Hz$, for outputs in the range $(-0.5,\ -1.0]$.

- 4 neurons are threshold units which determine whether the signals A, B, C
  and D are produced (value is 1) or not (value is 0).
  More specifically, signals are produced when the output of the corresponding
  output neuron exceeds the corresponding threshold.

4.3   From the embryo to finite individual:

A Practical Example

In order to better understand how genotype encoding create the corresponding
artificial agent, here will be reported an example obtained from the experiment

Exp_MI_half described in next sections.

More precisely it will be showed how the application of genotype rules, following the order defined by the index array, is able to modify the initial embryo by adding new elements and thus creating a finite creature.

Genotype of Best Individual at 500th generation Replication r4 (see section 5.2)

		Condition	Action	Joint Type	Insertion Points
Environmental Substances		$S0$ -> Green Plane $S2$ -> Pink Plane $S1$ -> Yellow Plane $S3$ -> Orange Plane			
Genotype Rules	0	$S1 = 0.169$	*Add Cyl*	*Fixed*	1 0 0 1 1 0
	1	$S2 = 0.304$	*Add Cyl*	*MobY*	0 0 0 0 0 0
	2	$S3 = 0.595$	*Add Cyl*	*Fixed*	0 1 0 0 0 1
	3	$S2 = 0.458$	*Add S2*	$--$	$--$
	4	$S3 = 0.617$	*Add Cyl*	*MobZ*	0 1 0 0 0 0
	5	$S1 = 0.401$	*Add S3*	$--$	$--$
	6	$S1 = 0.774$	*Add S2*	$--$	$--$
	7	$S1 = 0.316$	*Add Cyl*	*MobZ*	0 0 0 1 0 1
	8	$S2 = 0.5$	*Add S0*	$--$	$--$
	9	$S2 = 0.855$	*Add Cyl*	*Fixed*	0 1 1 0 0 0
	10	$S2 = 0.311$	*Add S1*	$--$	$--$
	11	$S0 = 0.167$	*Add Cyl*	*Fixed*	1 0 0 0 1 0
	12	$S3 = 0.66$	*Add S0*	$--$	$--$
	13	$S3 = 0.738$	*Add S2*	$--$	$--$
	14	$S0 = 0.149$	*Add S3*	$--$	$--$

Application	1°	*Rule N. 6*	6°	*Rule N. 8*	11°	*Rule N. 13*
Order	2°	*Rule N. 1*	7°	*Rule N. 2*	12°	*Rule N. 6*
	3°	*Rule N. 3*	8°	*Rule N. 13*	13°	*Rule N. 14*
	4°	*Rule N. 12*	9°	*Rule N. 0*	14°	*Rule N. 14*
	5°	*Rule N. 14*	10°	*Rule N. 14*	15°	*Rule N. 8*

Application of Genotype Rules to Initial Embryo

Initial Embryo, as described in subsection 4.2.1, is composed of a cupped cylinder (elementary unit) and 3 initial regulatory substances chosen from a set of 4 possibly environmental substances.
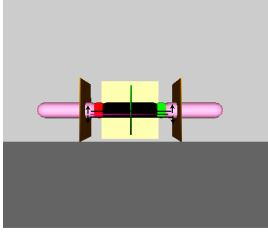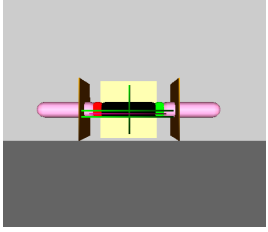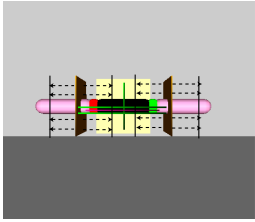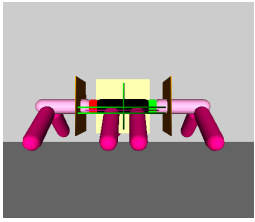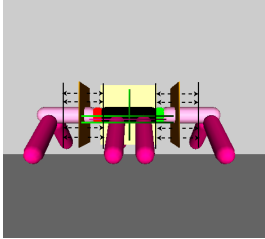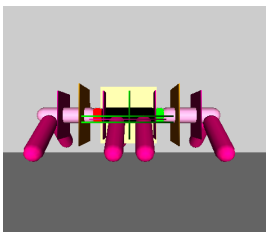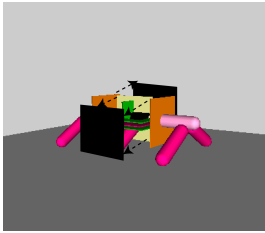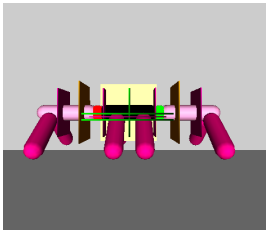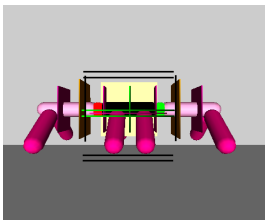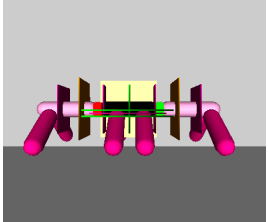
In simulated world this is represented as:
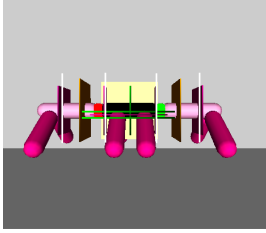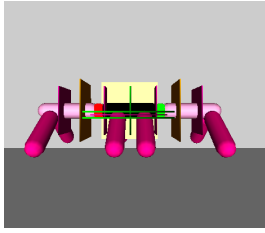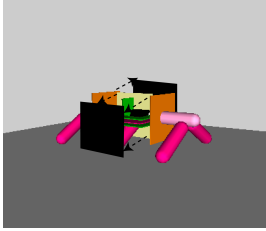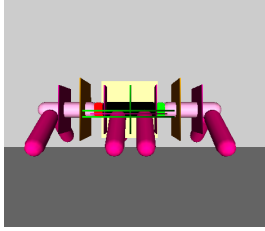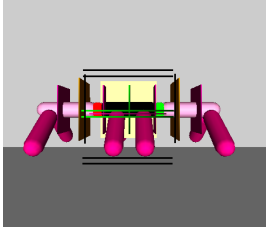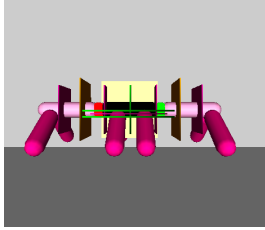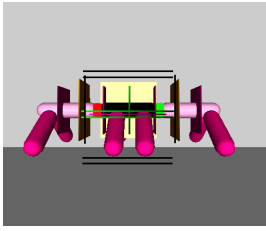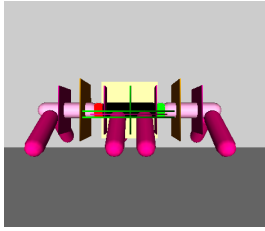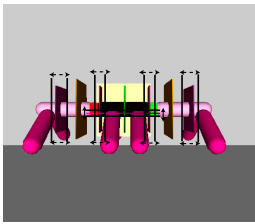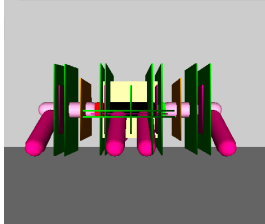
Initial Embryo	Environmental Substances	Propagation
	S0 -> Green Plane	4.68
	S1 -> Yellow Plane	7.02
	S2 -> Pink Plane	0.48
	S3 -> Orange Plane	7.05

Starting from the embryo, growing rules are applied following the order indicated by the vector belonging to genotype. In this way, as described in section 4.2 and how showed in next sequence, one rule could be applied more than one time, in different environmental situation, causing different morphological structures, like so, some rules could be never used.

Rules' Application

From	Step 1 - Rule 6	Not Applicable	Result
	Cond: $S1 = 0.77$ Action: Add $S2$	No intersection with existing elements	

From	Step 2 - Rule 1	Applicable	Result
	Cond: $S2 = 0.30$ Action: Add Cyl		

From	Step 3 - Rule 3	Not Applicable	Result
	Cond: $S2 = 0.458$ Action: Add $S2$	New planes overlap the existing ones	

From	Step 4 - Rule 12	Not Applicable	Result
	Cond: $S3 = 0.66$ Action: Add $S0$	Substance $S3$ does not exist	

From	Step 5 - Rule 14	Applicable	Result
	Cond: $S0 = 0.149$ Action: Add $S3$		

From	Step 6 - Rule 8	Applicable	Result
	Cond: $S2 = 0.5$ Action: Add $S0$		

From	Step 7 - Rule 2	Applicable	Result
	Cond: $S3 = 0.595$ Action: Add Cyl		

From	Step 8 - Rule 13	Applicable	Result
	Cond: $S3 = 0.738$ Action: Add $S2$		

From	Step 9 - Rule 0	Not Applicable	Result
	Cond: $S1 = 0.169$ Action: Add Cyl	No intersection with existing elements	

From	Step 10 - Rule 14	Not Applicable	Result
	Cond: $S0 = 0.149$ Action: Add $S3$	No intersection with existing elements	

From	Step 11 - Rule 13	Not Applicable	Result
	Cond: $S3 = 0.738$ Action: Add $S2$	Planes already inserted in the same position	

From	Step 12 - Rule 6	Not Applicable	Result
	Cond: $S1 = 0.774$ Action: Add $S2$	No intersection with existing elements	

From	Step 13 - Rule 14	Not Applicable	Result
	Cond: $S0 = 0.149$ Action: Add $S3$	No intersection with existing elements	

From	Step 14 - Rule 14	Not Applicable	Result
	Cond: $S0 = 0.149$ Action: Add $S3$	No intersection with existing elements	

From	Step 15 - Rule 8	Applicable	Result
	Cond: $S2 = 0.5$ Action: Add $S0$		

Complete individual (last picture) will be thus simulated and evaluated in physical simulated world, as described in next section.

4.4 The Evolutionary Process

The initial population consist of 100 genotypes. Each genotype includes a set of genes which encode the initial substances in the embryo, the developmental rules and the vector which determines the order with which rules are executed. Parameters are randomly generated within the corresponding intervals.

The 20 best genotypes of each generation are allowed to reproduce by generating 5 copies each (elitism is applied in firsts 5 genotypes only). The reproduction procedure recognizes two kind of genes: morphological and neural genes.

The first set contains genes that specify information related to robot physical structure whereas the second set contains genes that specify all information related to neural networks characteristics, that is the neural weights. For each genotype, reproduction is applied following this simple schema:

Probability	Morphological Genes	Neural Genes
50%	mutated	copied
50%	copied	mutated

This means that mutation operator is applied to morphological characteristics or to neural characteristics but never together. The basic idea is that morphology and controller have to co-adapt to each other, thus it has no much sense if they can mutate their values at the same time because in this case they can not adapt their values to others (test experiment have showed the validity of this hypothesis).

Keeping in mind that a too low mutation rate implies too little exploration of space of solutions and too high mutation rate could degenerate into random search, a preliminary tests have been executed to analyze the evolutionary process. As result, in this experiment each single gene is mutated with a probability of 3% with the only exception of vector elements which encodes the indexes and the order with which developmental rules are expressed. These elements can be moved at the end of the vector with a probability of 2%.
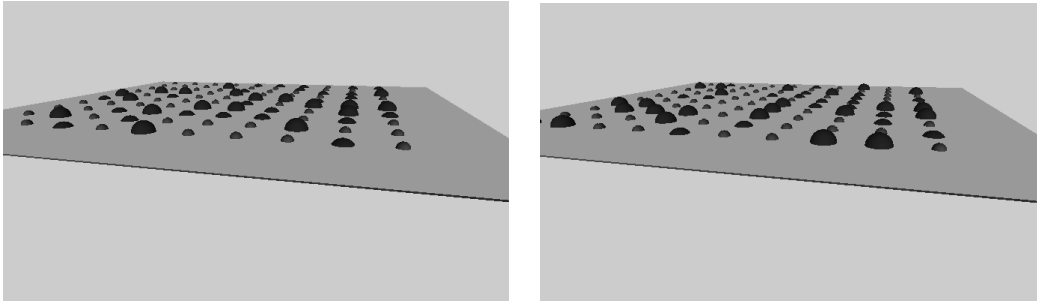
Figure 4.5: Two example of irregular terrains randomly created during evolutionary process

Furthermore, in order to increase the level of variability, the 10 worst-fitting individuals are replaced by new randomly generated ones every 50 generations. In this way genotype variability has been extended but without altering the evolutionary process. Preliminary results analysis indicated that variability is really increased only in firsts generations since on average around generation $n° 100$ the probability that a randomly generated individual will be selected became too much low and continue to decrease in successive generations (when evolved robots improved their ability to coordinate movements and to locomote).

No crossover has been applied. Acting on a single genotype, mutation operator is more easy to analyze than crossover in particular when a lineage analysis is effectuated (see section 5.4). Moreover it has been shown that crossover has no general advantages over mutation (Fogel and Atmar, 1990)

The evolutionary process lasts for 500 generations (that is the process of testing, selecting and reproducing robots is iterated 500 times). Each genotype is allowed to develop in a free space into the corresponding phenotype and is tested in the environment for 5 trials (2 trials on a flat terrain and 3 trials on an irregular terrain).

The irregular terrain in randomly generated each time and it is compost of a flat terrain with 400 spheres with a radius ranging in $[1.0, 3.0]\, cm$ and located in a squared area (see figure 4.5).

At the beginning of each trial the current phase and the current frequency of oscillation of each joint are set randomly within the corresponding range and the creature

is placed at a height of approximately $5.5\,cm$ from the ground. This implies that creatures fall on the ground and they have to learn:

- reach a stable posture/s;

- coordinate their movements;

- locomote.

Creatures are then allowed to move for 6000 time step lasting $1.5\,ms$ each.

For each time step the state of the sensors and of the motors of each neural controller, the torque exerted by the motorized joints, and the dynamics of the creature/environmental interactions are updated.

Creatures and creature/environmental interactions are simulated by using the ODE dynamical simulation engine (www.ode.org).

4.5 Fitness Function

The importance of choice of fitness function is a key-point well known in evolutionary robotics and genetic algorithms success. For this reason particular attention has been paid to decide for which specific ability evolved individuals should be rewarded.

As mentioned at the beginning of this thesis, one of the main general objective is to obtain evolved creatures able to move as far as possible from a starting point to any direction, thus certainly fitness function has to include a measurement of walked distance. However, as the other main interest is also understanding which mechanisms are used by individuals to coordinate their movements and furthermore which are and how much morphological characteristics affect the evolutionary process, particularly interesting are those evolved individuals with a *complex bodies* (i.e. a morphology composts of more than 5 cylinders with more than 4 motorized joints).

Attempting to maintain the general assumption that no direct environmental rules have to affect the dimension or shape of evolved individuals (neither in number of

cylinder nor in number of motorized joints) and observing that to walk effectively an evolved individual needs to produce coordinated movements, an indirect measurement of joint coordination has been introduced (Prokopenko et al., 2006a,b).

The proposed fitness formula includes two components which score individuals for the ability to move as fast as possible and for the ability to produce coordinate movements.

$$Fitness = Walked\,Distance + Joints\,Coordination \qquad (4.2)$$

The first component is calculated by measuring the Euclidean distance travelled by an individual during its lifetime starting from time step 1500 to time step 6000 (end of life). The first phase in which the creatures fall down and start coordinating is not considered and it has no effect on global fitness. In this way, individuals with no coordination but with huge body will not take advantage from falling and rolling along the ground.

The second component consists of the average mutual information (Shannon, 1948) calculated, following the equation 4.3, between the output of each couple of neural controllers (that is the current frequency of oscillation of each couple of joints) X and Y in the first half part of life of the individual, i.e starting from time step 0 to time step 3000.

$$I\left(X;Y\right) = \sum_x \sum_y P\left(x,\,y\right) \log_2 \frac{P\left(x,\,y\right)}{P\left(x\right)\cdot P\left(y\right)} \qquad (4.3)$$

Mutual Information quantifies the dependence between the joint distribution of X and Y and what the joint distribution would be if X and Y were independent. Mutual Information could be considered a measure of dependence in the following sense:

$$0 \leq I\left(X;Y\right) \leq H\left(X\right) \leq log_2 \mid X \mid$$

$I(X;Y) = 0$ when X and Y are independent random variables

$I(X;Y) = H(X) = \log_2 |X|$ when all values of X are equiprobable and X and Y are perfectly correlated int the sense that $X = Y$.

Mutual information component is calculated in fitness function only in the first part of individual life because the condition of maximum value. Indeed forcing motorized joints to explore all frequencies at the beginning of life gives the opportunity also to huge individuals coordinating their joints and producing an effective behaviour in order to locomote (high exploration of space of solutions). But, once coordination is reached (on average in the second part of life) it is no more necessary moving joints slow, especially because the first component of fitness required to go as far as possible, that is as fast as possible.

In fact equiprobability required to X variable (that is the output of neural controllers) means that all frequencies have to be exploited by motorized joints, from faster to slower. But this is in contrast with the other fitness component that requests to move as far as possible, that is as fast as possible once joint coordination has been reached.

However forcing motorized joints to exploit all frequency at the beginning of life, could help them to find a best coordination. Indeed exploiting slower velocity could help a huge morphology to reach a good coordination avoiding elimination in the first generations (results from test experiment where mutual information is calculated during all lifetime of individuals and test experiments where mutual information is not used will be shown in next chapter).

The total fitness is computed by normalizing, in the range [0.0, 1.5] the value of distance and coordination. More precisely *distance* has been normalized with respect to an estimation of the maximum distance which can be travelled by a creature whereas *coordination* has been normalized with respect to the theoretical maximum of the mutual information formula.

4.6 Summary

In this chapter the author of this thesis has presented a model which allows to evolutionarily co-adapt the morphology and the control system of realistically simulated robots (creatures). The method proposed is based on an artificial ontogenetic process in which the genotype does not directly specify the characteristics of the creatures but rather the growing rules that determine how an initial artificial embryo will develop into a fully formed individual.

Creatures are thus generated through a developmental process which occurs in time and space and which is realized through the progressive addition of both structural parts and regulatory substances which affect the successive course of the morphogenetic process.

Creatures are provided with a distributed control system composed of several independent neural controllers, one for each motorized joint embedded inside their body units. Each module has access to local sensory information only and can coordinate through the effects of physical actions mediated by the external environment through the emission/detection of signals which are detectable locally in space.

In the next chapter all the tests performed to validate the options described above and the results obtained from the evolutionary experiment will be shown.

Chapter 5

Body-Controller Evolutionary Co-Adaptation Results

5.1   Introduction

In order to understand whether proposed model can generate and evolve individuals able to perform the given task, 10 replications of the experiment (previously described in sections 4.4 and 4.5) have been run.

In the next sections obtained results will be shown and all analysis carried out to show how this genotype encoding is able to:

1. generate many different kind of morphologies,

2. provide an effective and robust neural controller able to coordinate individuals movements and let them achieve the task.

Furthermore, there will be shown results obtained from a set of control experiments in which some characteristics of original model have been varied. In particular, it will be underlined the importance of genotype expressiveness to generate more effective individuals, the importance and the role of the environment and the importance

of introduction of a task-independent component in fitness function (introduced to reward individuals for the ability to coordinate their movements).

Finally, the course of evolutionary process has been deep analyzed in order to identify all those mechanisms used to co-adapt morphological variation to neural controllers and vice versa.

5.2 Experimental Results

Analysis and observations presented in next sections are the result of the evolutionary experiment, named Exp_MI_half, described in 4.4 and 4.5.

5.2.1 Expressiveness of Genotype Encoding

A preliminary analysis has been performed to verify the expressiveness of proposed genotype encoding and its consequent ability to generate a large variety of different morphological structures.

This feature is important because, as much heterogeneous morphologies are part of evolutionary process, so much is the space of possible solutions investigated by the genetic algorithm and as consequence the final obtained results are more reliable and have a low probability to converge in good local solutions.

Thus, for each replication has been saved the best individual created at Generation 0 (see figure 5.1). By analysing all these morphologies it is possible to observe that very different structures can be generated by the proposed encoding both in number of elements and in regularity of shape.

It is possible to identify individuals with a chaotic shape ($r1$ and $r8$), individual with a small shape ($r0$, $r4$ and $r6$) and individuals with a well-ordered shape ($r2$, $r3$, $r5$, $r7$ and $r9$) both symmetric and non-symmetric.

On average all kind of morphologies show a good degree of symmetry. This characteristic is easily understandable by considering that in the proposed model the
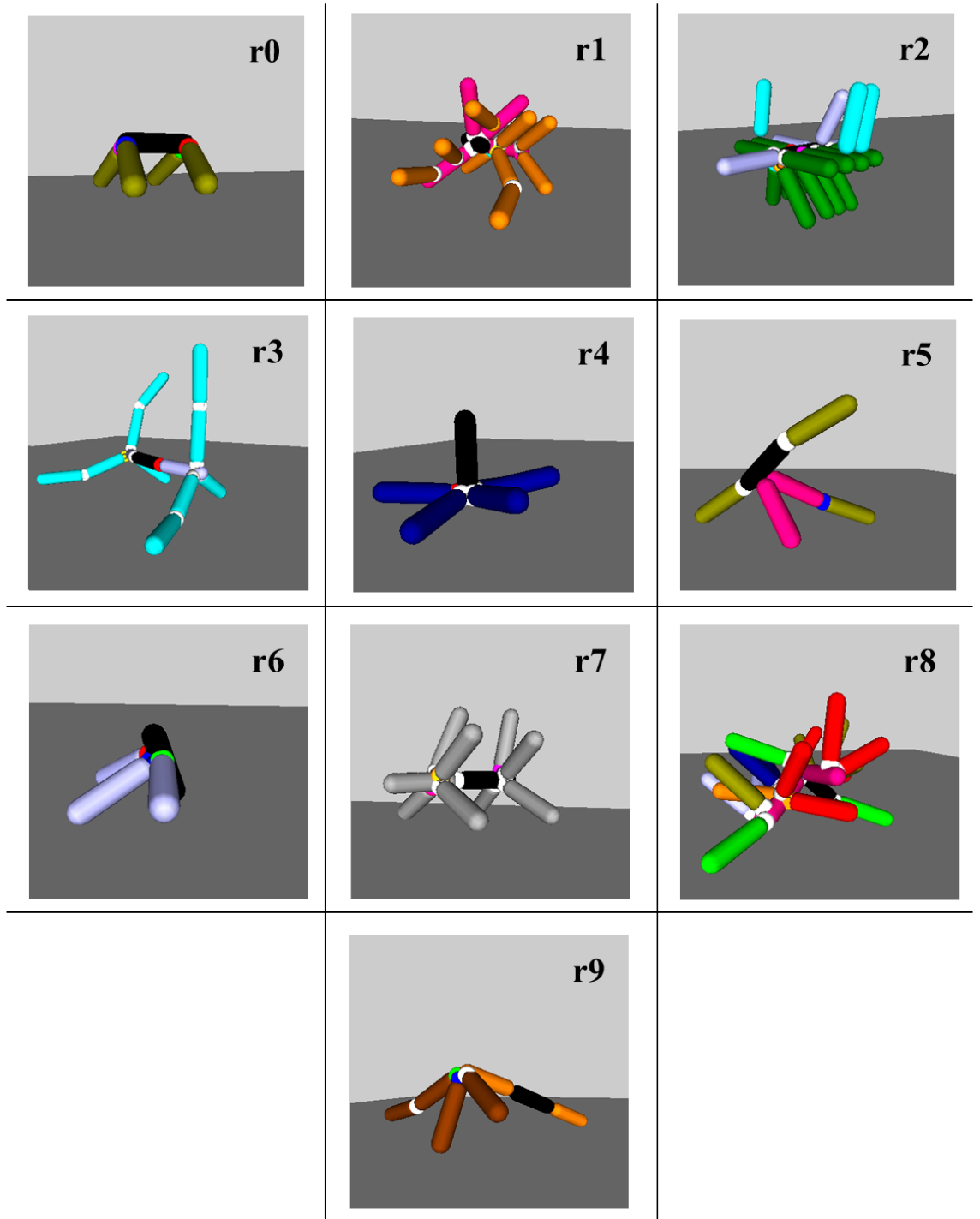
Figure 5.1: Morphology of the best individual at 1st generation of each replication of the experiment. Black segment is the embryo. Segments with the same colour are added by the same rule whereas joints with the same colour are provided with identical neural controllers.

developmental process occurs in the $3D$ space and it is governed by regulatory substances which have a symmetrical distribution with respect to the plane of maximum concentration.

5.2.2 Evolved individuals: Quantitative data

By analysing the final results obtained at generation 500, it has been observed that evolved robots display an ability to locomote effectively in all replications of the experiment.

A simple quantitative measurement of travelled distance is not sufficient to say whether and how well individuals are able to locomote. This is because morphology is not fixed and the ability to move is strongly influenced by the number of cylinders and by the number of motorized joints, allowing large individuals to merely fall and roll.

Indeed, a high number of motorized joints means high motor power but also more neural modules to synchronize, and furthermore, an higher number of cylinders means more stability in global body but also more weight to move.

Additional quantitative information, are thus necessary to better understand the obtained results (see table 5.1).

By analysing these data no general rule arises to correlate $Covered\,Distance$ with $N°of\,DOFs$ or with $N°of\,Cylinders$, however including in analysis also $Mutual\,Information$ it is possible to define some guidelines with which cluster evolved individuals on the basis of similar characteristics.

- $r3$ and $r8$ represent the simple case in which having lots of motorized joints produce high motor power. Indeed, the evolved individuals locomote for long distance and display low mutual information (that is joint movements converge in a stable pattern - see section 4.5);

	Covered Distance (cm)		Mutual Information		N° DOF	N° Cyl	Signals
	Flat Terrain	Irregular Terrain	Flat Terrain	Irregular Terrain			
$r0$	91.08	66.42	0.0201	0.0224	6	9	100%
$r1$	34.62	14.40	1.2149	1.2244	6	10	100%
$r2$	31.32	22.56	1.7068	1.7374	16	19	100%
$r3$	218.64	209.64	0.0822	0.0861	18	19	100%
$r4$	44.70	27.18	1.0646	0.9782	2	11	100%
$r5$	36.60	22.98	0.8417	0.8337	2	5	100%
$r6$	37.32	32.22	1.2789	1.3091	6	18	100%
$r7$	82.26	53.04	1.1792	1.1320	10	11	100%
$r8$	192.36	142.62	0.0089	0.0098	14	15	100%
$r9$	32.40	19.38	1.1204	1.0942	3	4	100%

Table 5.1: Performance and characteristics of the best individuals at the end of each replication: generation 500 (figure 5.2). Covered distances values indicate the average distance in cm covered by creatures during 4500 time steps (6.75 sec) after 1500 time steps from the beginning of each trial. During the test, creatures have been situated for 50 trials on a flat terrain and 50 trials on a irregular terrain. Mutual Information values indicate the average mutual information calculated on each couple of joints. $N°DOF$ and $N°Cyl$ indicate respectively the number of motorized joints and the number of cylinders possessed by the individual. *Signals* indicates the percentage of signals detection by the motorized joints (see text).

- $r2$ and $r7$ represent the case in which individuals have lots of cylinders but, in proportion, very few motorized joints. This means that low motor power have to carry a lot of weight reducing the robot's global velocity (mutual information tends to be higher);

- $r0$, $r5$ and $r9$ represent the case in which individuals have few motorized joints and few cylinders. In this specific case, individuals do not walk long distances but this can not be classified as a bad result, because they display a capability to locomote in effective way despite their morphologies are not particularly adapt to locomotion (highly unbalanced).

Observing the table 5.1, the ability to coordinate motorized joints for each individual, is also confirmed both by the column *Signals* and by comparing results obtained in flat and irregular terrain. In *Signals* column is indicated the percentage of joints exploiting signals: 100% in all replications, meaning that all motorized joints use

signals to coordinate themselves.

Whereas by comparing results in flat and irregular terrain it is possible to observe two main things:

(a)   as expected in irregular terrain individuals walk slower than flat terrain,

(b)   individuals never loose the ability to locomote in effective way.

Indeed $Mutual\ Information$ data show that there are not great differences between values calculated in flat and in irregular terrain and this means that individuals preserve their ability to coordinate their own motorized joints.

5.2.3   Evolved individuals: Qualitative observations

In order to obtain an analysis, as complete as possible, previous quantitative data are now compared and joined with qualitative analysis acquired by visually inspecting morphological characteristics (figure 5.2) and behaviour (appreciable with movies available on dvd enclosed with the hard copy of this thesis or on the web page: http://laral.istc.cnr.it/esm/phd_mazzapioda/3_exp) of the evolved individuals.

The first observation that is possible to do is that all evolved creatures are provided with morphologies which let them avoid falling on a side or tipping over and which allow them master obstacles of various sizes in irregular terrains.

By visually inspecting the behaviour of evolved creatures (see the movies available on dvd enclosed with the hard copy of this thesis or on the web page: http://laral.istc.cnr.it/esm/phd_mazzapioda/3_exp) three phases could be identified:

1. Initial - in which the creature falls down on the terrain and assume a certain posture;

2. Intermediate - in which the movements of the joints, which are initially not-coordinated, become coordinated;
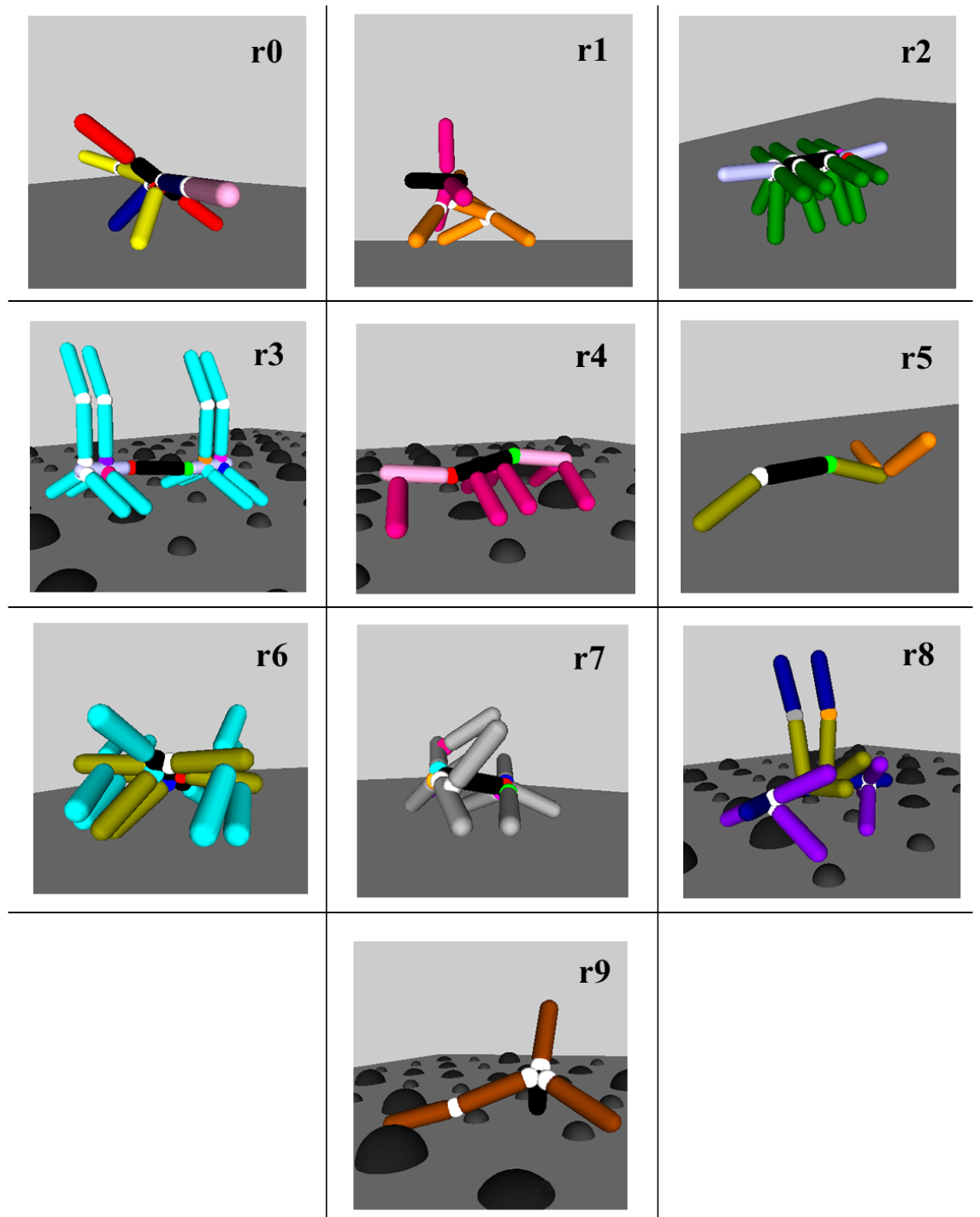
Figure 5.2: Morphology of the best evolved creatures of each replication of the experiment. Some creatures are shown on the flat and some creatures are shown on the irregular terrain. The colours of the segments and of the joints correspond to the ID of the developmental rules which generated them. Joints of the same colour are provided with identical neural controllers.

3. Final - in which the creature is coordinated, moves at its full speed, and compensates for the perturbations which occur during motion (which tend to reduce the level of coordination).

During the *initial phase* all the creatures (with the exception of replications $r1$ and $r7$, which will be illustrated later) show an ability to assume a precise posture, after falling down on the ground, from which they are able to coordinate and locomote.

This is accomplished thanks to the fact that the evolved morphologies are suitable both to stand in a preferred posture and to walk from that posture. Indeed, some of the evolved morphologies display segments which do not play a major role (or any role) for locomotion but which reduce the risk of tipping over (see for example $r2$, $r3$ and $r8$).

In some cases, creatures are able to assume more than a single posture from which they can locomote effectively. This is the case of creatures like $r6$ and $r9$ which could walk exploiting different sides of their body (very effective in rugged environments).

During the *intermediate phase* all creatures show an ability to coordinate on an effective gait taking advantages from different environmental characteristics. For example, looking at creatures $r3$, $r4$ and $r8$, it is possible to observe how they not only use signals to coordinate themselves but also how they exploit the effect of the forces applied to each joint.

More precisely, these forces, mediated by the collisions with the external environment, act on the posture assumed by the entire creature influencing the angular position of each joint. Indeed, in these particular cases the global posture is strongly influenced also by those cylinders that never touch the ground but, with their oscillations, modify the collisions and the movements of elements directly involved in locomotion.

All these physical interactions co-determine the current state of each joint which, in turn, affects the propriosensors of each corresponding neural controller and thus the output of the neural controller itself which determines the desired speed of oscillation of the corresponding joint. It is important to note that this ability to coordinate depends on two aspects:

1. the ability to modify the frequency of oscillation of each joint on the basis of the actual position of the same joint which is determined by its previous position, by the previous postures of the entire creature, and by the previous actions executed by each joint;

2. the morphology of the creature.

The rest of the creatures ($r0$, $r1$, $r2$, $r5$, $r4$, $r7$, $r9$) mainly exploit signals to coordinate. The analysis conducted indicates that coordination is achieved by producing signals which encode information about the current position of the joint emitting the signals. This information will be used by the neural controllers of the joints receiving signals in order to regulate their oscillation speed so to improve the coordination between the different part of the creature (see chapter 3).

During the final phase a further observation of creatures' behaviour indicate that they move at their full speed in a coordinated manner by compensating for relative misalignments between the joints which originate during motion especially in irregular terrains.

Evolved creatures significantly differ in the way in which they locomote (see movies available on dvd enclosed with the hard copy of this thesis or on the web page: http://laral.istc.cnr.it/esm/phd_mazzapioda/3_exp). In particular, it is possible to identify 3 family of locomotion styles:

1. Quadruped style (displayed by $r2$, $r3$, $r4$ and $r8$);

2. Jumping style (displayed by $r6$ and $r7$);

3. Dragging style (displayed by $r0$, $r1$, $r5$ and $r9$).

In Dragging style the effect of the friction between unactuated elements and the ground is minimized or maximized when the pulling legs are moving in the direction of motion or in the opposite direction. As can be observed by inspecting the morphology and the behaviour of these evolved creature, the control mechanisms and the developmental rules are tightly co-adapted.

5.3 Variations on Experimental Setup

In order to investigate how some of characteristics of the model described in section 4.2 influence the obtained results a series of experiments in which systematic variations were tested have been executed.

As consequence, variations have been retained or discarded on the basis of their effects in the observed results. In the most of test experiments, the variations considered did not produced significant effects.

In following section will be mainly presented those analysis to the variations that produced the most significant effect on the agent's morphology/behaviour and which highlights the crucial role of some of the model parameters or features.

5.3.1 The Role of the Environment

The first variation consisted in varying the type of environment (flat and/or irregular) in which the creatures are evolved.

The analysis of the results observed in a control experiment in which the creatures were evolved solely on flat terrain indicates that in this second case creatures tend to develop simpler morphologies which are less effective and which only work properly on flat terrains (see figure 5.3).
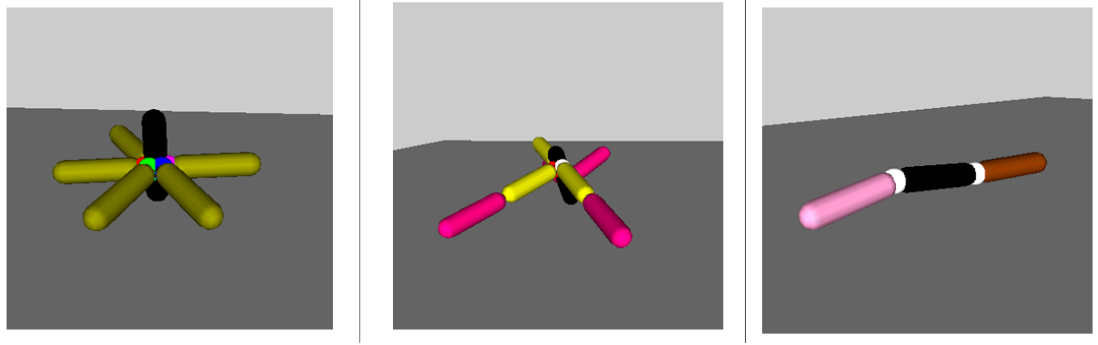
Figure 5.3: Examples of morphologies of the best evolved creatures obtained in test experiment in which solely flat terrain has been used. The colours of the segments and of the joints correspond to the ID of the developmental rules which generated them. Joints of the same colour are provided with identical neural controllers.

These data suggest that the environment plays an important role in the evolutionary process, especially when its characteristics are exploited by control system. In this specific case, one of the sensory inputs in the proposed neural network encodes the current angular position of the corresponding joint (see section 3.4.1).

There are two main reasons to explain these results: neural and morphological. The first one, is related to the fact that joint positions are more constant in a regular terrain than in a rugged one, implying that corresponding neural network will experience a smaller number of different input patterns. As consequence, neural networks in rugged terrain will be better evolved than networks evolved in regular terrain.

The second reason is strictly related to kind of evolved structures. As showed in figure 5.3, individuals converge on a very simple morphology that display on average two fixed behaviours: dragging and lateral rolling. In a rugged environment these individuals clearly could not perform the given task, but in a flat terrain they are effective and also very simple to obtain.

Small and symmetric structures avoid the weight trade-off problem, so the best simple solution is to move the few motors to the maximum speed and the structure move as far as possible very quickly.

Key Point: The complexity of the environment represents a crucial prerequisite

	Covered Distance (cm)		N° DOF	N° Cyl	Signals
	Flat Terrain	Irregular Terrain			
$r0$	85.80	60.60	5	12	100%
$r1$	82.08	67.56	6	8	100%
$r2$	103.08	47.04	11	20	27%
$r3$	123.84	110.04	24	29	0%
$r4$	30.36	22.62	8	9	100%
$r5$	66.30	58.62	24	30	8%
$r6$	43.14	28.14	6	15	17%
$r7$	99.96	20.94	4	5	100%
$r8$	95.22	57.54	9	12	67%
$r9$	81.90	55.56	17	18	94%

Table 5.2: Performance and characteristics of the best individuals of each replication of the experiment Exp_onlyDist. Covered distances values indicate the average distance in cm covered by creatures during 4500 time steps ($6.75\,sec$) after 1500 time steps from the beginning of each trial. During the test, creatures have been situated for 50 trials on a flat terrain and 50 trials on a irregular terrain. $N°\,DOF$ and $N°\,Cyl$ indicate respectively the number of motorized joints and the number of cylinders possessed by the individual. $Signals$ indicates the percentage of signals detection by the motorized joints.

for the evolution of effective creatures displaying a non-trivial behaviour.

5.3.2 The role of Mutual Information in Fitness Function

To better understand which is the effective role of mutual information in the fitness function and in particular how this component affects the evolutionary process, a new experiment, named Exp_onlyDist, in which evolving creatures were only rewarded for their ability to locomote has been performed.

Ten replications of this evolutionary process have been run and the results are showed in figure 5.4 and in table 5.2.

By comparing these new results with those obtained from the experiment Exp_MI_half (table 5.1) it is possible to observe how mutual information component, according to preliminary hypothesis, favors the evolution of individuals with the ability to exploit signals in order to coordinate all movements produced by motorized joints.

Indeed observing values in *Signals* column ($n°$ of motorized joints using signals / $n°$ of all motorized joints in morphology) it is possible to see how in replications of experiment with mutual information component, all motorized joints of each best individual exploit signals to modify their own movements.

Instead, in replications of experiment without mutual information, in 6 cases on 10 the percentage is minor than 100 (in 1 case is 0%), meaning that there are several motorized joints that move independently from the others, each one with its own velocity.

Interestingly, the obtained results also show that only rewarding the distance produce comparable results in term of velocity and dimension of evolved agents even in those solutions that will not exploit signals on all motorized joints (see table 5.1 and table 5.2).

To explain this fact a study has been performed with the objective to understand how individuals can coordinate their movements to accomplish their objective despite the fact that their motorized joints did not interact to find a common strategy.

Looking at table 5.2, even if not always all motorized joints exploit signals to coordinate themselves ($r2$, $r3$, $r5$, $r6$, $r8$ and $r9$), corresponding evolved individuals display a good ability to locomote (*Covered Distance*) on flat terrain.

Joining these results with morphology (figure 5.4) and behaviour (see web page laral.istc.cnr.it/esm/phd_mazzapioda/3_exp) it is possible to identify a general rule that connects signals usage percentage and morphological symmetry detected in individuals.

Replications $r3$ and $r6$ display in figure and in simulation a perfect symmetry and as consequence a good balance. For this reason individuals do not need a good coordination among their motorized joints, it is sufficient that they move at maximum speed to perform given task. Indeed, $r3$ and $r6$ has respectively 0% and 17% of signal usage percentage among their joints.

More precisely, in the case of $r6$ this means that 1 joint of 6 uses signals, but
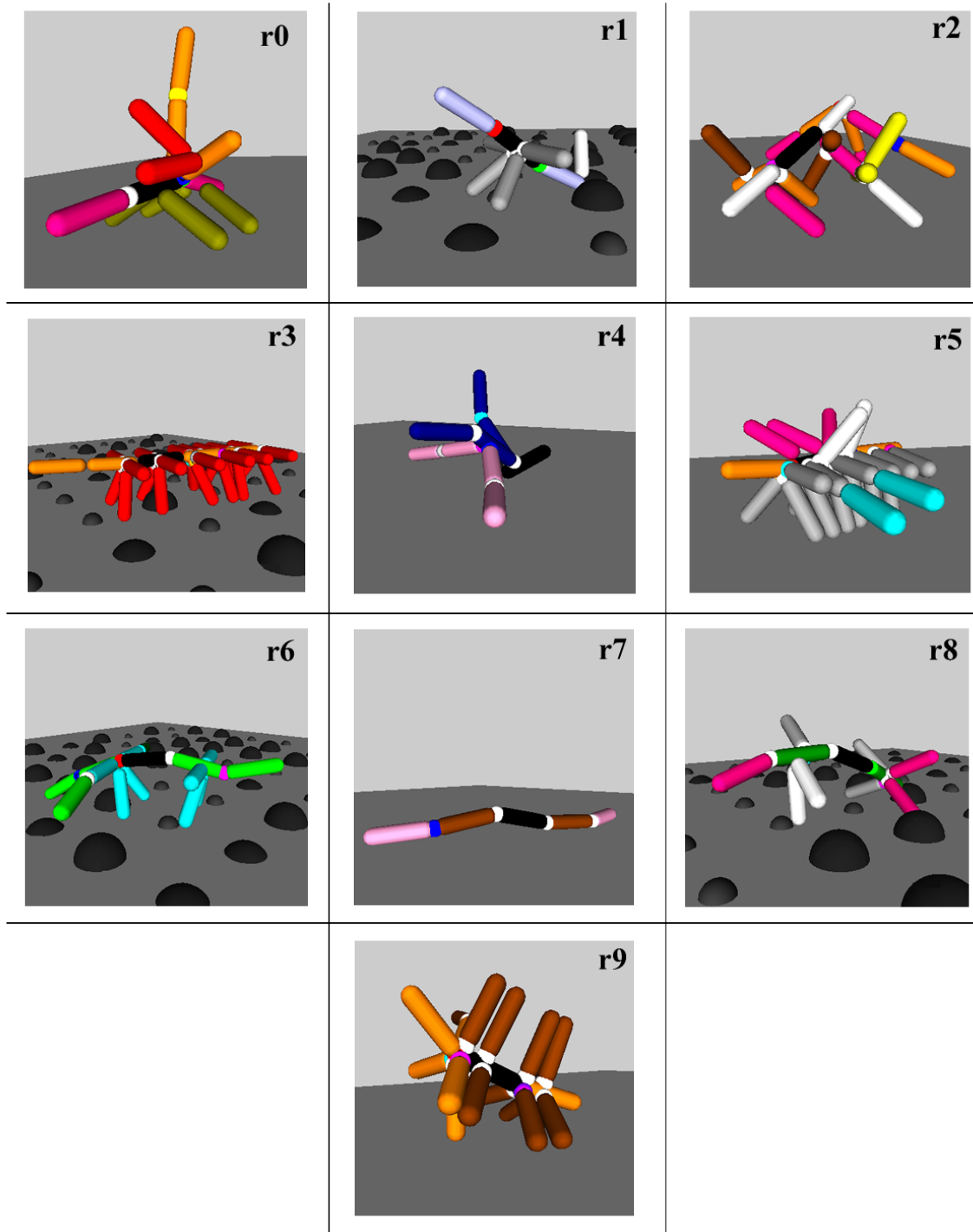
Figure 5.4: Morphology of the best evolved creatures of each replication of the experiment Exp_onlyDist. Some creatures are shown on the flat and some creatures are shown on the irregular terrain. The colours of the segments and of the joints correspond to the ID of the developmental rules which generated them. Joints of the same colour are provided with identical neural controllers.

deeply analysing its functioning it comes out that signal detection does not affect joint behaviour. It starts at random position with random velocity (according to evolutionary algorithm) and exploiting signals accelerate, reaching in few steps the maximum allowed velocity and never decelerate.

This behaviour should not surprise because, as already demonstrated in the literature (McGeer, 1990; Collins et al., 2001, 2005), passive walkers can display a clear ability to locomote without any controllers but merely by exploiting physical characteristics. In these cases happens an analogue situation: perfect symmetry compensate controller works that thus could be as simple as possible or completely disabled.

The clear disadvantage is that in case of environmental changes, evolved agents can not adapt their behaviours and as consequence they fail the task. Indeed, the best overall performance obtained with mutual information double the best overall performance obtained without mutual information.

Replications $r2$ and $r5$ display a good symmetry, are a bit less stable with respect to previous cases, but in any case are able to supply a balanced morphology. In these specific cases signal usage percentages are 27% and 8% (3 joints on 11 and 2 joints on 24) meaning that motorized joints on average do not need a global coordination. It is again sufficient that they move at maximum velocity to guarantee the achievement of the objective.

On the other hand, replications $r8$ and $r9$ do not display a good symmetry, and as supposed, they have an high percentage of signals usage among their motorized joints. More precisely $r9$ has 94% of usage (16 joints on 17) while $r8$ has 67% (6 joints on 9). Further analysis have showed that, in these latest cases, joints that do not use signals have not a direct role in locomotion, indeed, in both cases these joints are external appendages and never touch the ground.

In cases in which evolved individuals exploit signals for all motorized joints ($r0$, $r1$, $r4$ and $r7$) it is possible to observe how morphologies have both few cylinder and

few motorized joints and display the same simple behaviours, dragging and lateral rolling, already found and described in the experiment with evolution on flat terrain only (see section 5.3.1). The reason is that, as shown in previous replications, neural coordination is not necessary to perform the given task so when it happen, the only case in which it can evolve is when there are few controllers to coordinate.

In general, this experiment generated 2 classes of individuals:

1. **no adaptation ability group** ($r2$, $r3$, $r5$, $r6$, $r8$ and $r9$). These individuals do not exploit signals and coordinate their movements using morphological characteristics of their bodies. They have completely lose the ability to modify their behaviour in new different environments, for examples where obstacles are bigger and the only way to overcome them is to reorganize all motorized joints (see the column related to *Covered Distance* in rugged terrain - table 5.2)

2. **simple and little effective behaviours group** ($r0$, $r1$, $r4$ and $r7$). These individuals display a clear ability to coordinate their movements favoured from the fact that their morphologies are very simple and small. They are also able to interact with the environment, however, individual physical characteristics are so poor that they can only exhibit relatively trivial behaviours.

In conclusion, this experiment has showed how in fitness function, mutual information component favour the coordination among motorized joints avoiding evolutionary process to converge towards big morphologies that are not able to coordinate themselves or towards small morphologies that are not able to produce an adaptive behaviour (for example overcoming any obstacles).

Key point: Mutual information favours an active coordination among motorized joints and this let evolved individuals adapt their behaviour on different terrains.

This study confirms one more time how morphological characteristics play a key role in evolution of corresponding neural controller. In particular, having an high degree

of symmetry let individuals stabilize their own body on the terrain and balance the corresponding motor forces, but also having a large number of cylinders let individuals exploit their weight to regulate all movements (more weight carried by motorized joint produces low movement).

This ability of executing actions or, more in general executing processes, by a physical body instead of by a neural controller is already known in the scientific area as Morphological Computation (Paul, 2004, 2006; Pfeifer and Bongard, 2007). A further deep study of this aspect is not one of the goals of this work, however it could be an interesting spin-off practicable in future works.

5.4   Analysis of the Evolutionary Process

In order to understand how the performance, the morphology, and the behaviour exhibited by the best individual vary throughout generations, for each replication of the experiment a new kind of analysis has been performed.

Rather than analysing the characteristics of the best individuals of each generation, it has been reconstructed the lineage (that is the 499 ancestors) of the best individual of the last generation, making particular attention in those genetic variations which have been retained in successive generations.

Analysing direct relationships from father to son, instead of only taking into account fitness obtained from best individual throughout generations, it is possible to identify:

- type of variation (morphological or neural) that occurred in genotype,

- effects on individual behaviour (both related to distance covered and to coordination).

In order to carry out this kind of analysis, for each best individuals obtained from all replications of the experiment Exp_MI_half (previously described), this procedure

has been applied:

1. All 499 ancestors, for each best individual, have been identified,

2. Each ancestor has been tested 10 times for 6000 time step (3 seconds),

3. Obtained fitness has been analysed separating the 2 specific components,

4. Correlations between morphological and behavioural changes has been identified and analysed.

Next section will show obtained results from this kind of analysis, considering the lineage of replication $r7$.

5.4.1 Analysis of Best Individual Lineage - replication r7

Figures 5.5 and 5.6 show how fitness components (travel distance and mutual information) of the ancestors of best individual vary throughout all generations (top part of figures) and which are the major morphological and neural transitions occurred during the lineage (lower part of figures).

Focusing the attention on major morphological transition, it has been observed how they always coincide with significative variations in fitness function components. Leaving out first generations in which any morphological changes are due to variability of initial environment (see section 5.2.1) rather than evolutionary process, major variations occurred at generations: 51, 64, 218, 251 and 297 (fig. 5.5 and 5.6 - lower part).

In regard to these generations it is also possible identify in fitness components curves significant variations both in covered distance and in coordination. This aspect does not surprise because any morphological variation is caused by:
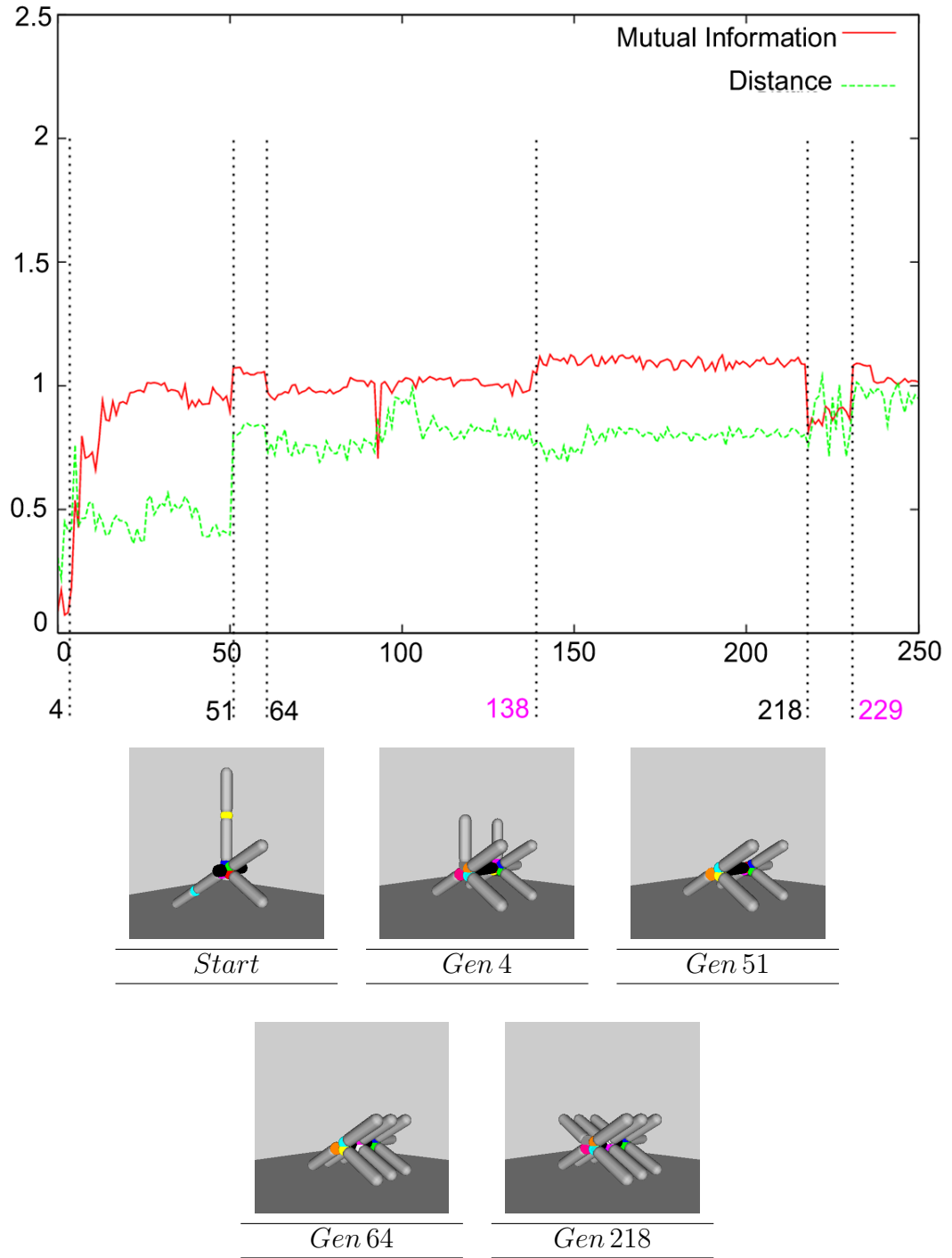
Figure 5.5: Average distance traveled and average mutual information of the ancestors of the best individual of the last generation of replication $r7$ throughout first 250 generations. The dotted green line indicates the distance traveled whereas the full red line indicates the mutual information (both normalized in the range [0.0, 1.5]). The x-axis indicates the number of generation and the 6 vertical lines at generations 4, 51, 64, 138, 218 and 229 indicate the 6 major transitions with respect both to morphological and neural changes. Morphological changes are indicated in the pictures at the bottom, whereas neural changes are simply indicated with pink reference (generation 138 and 229) on the graphical representation of fitness.
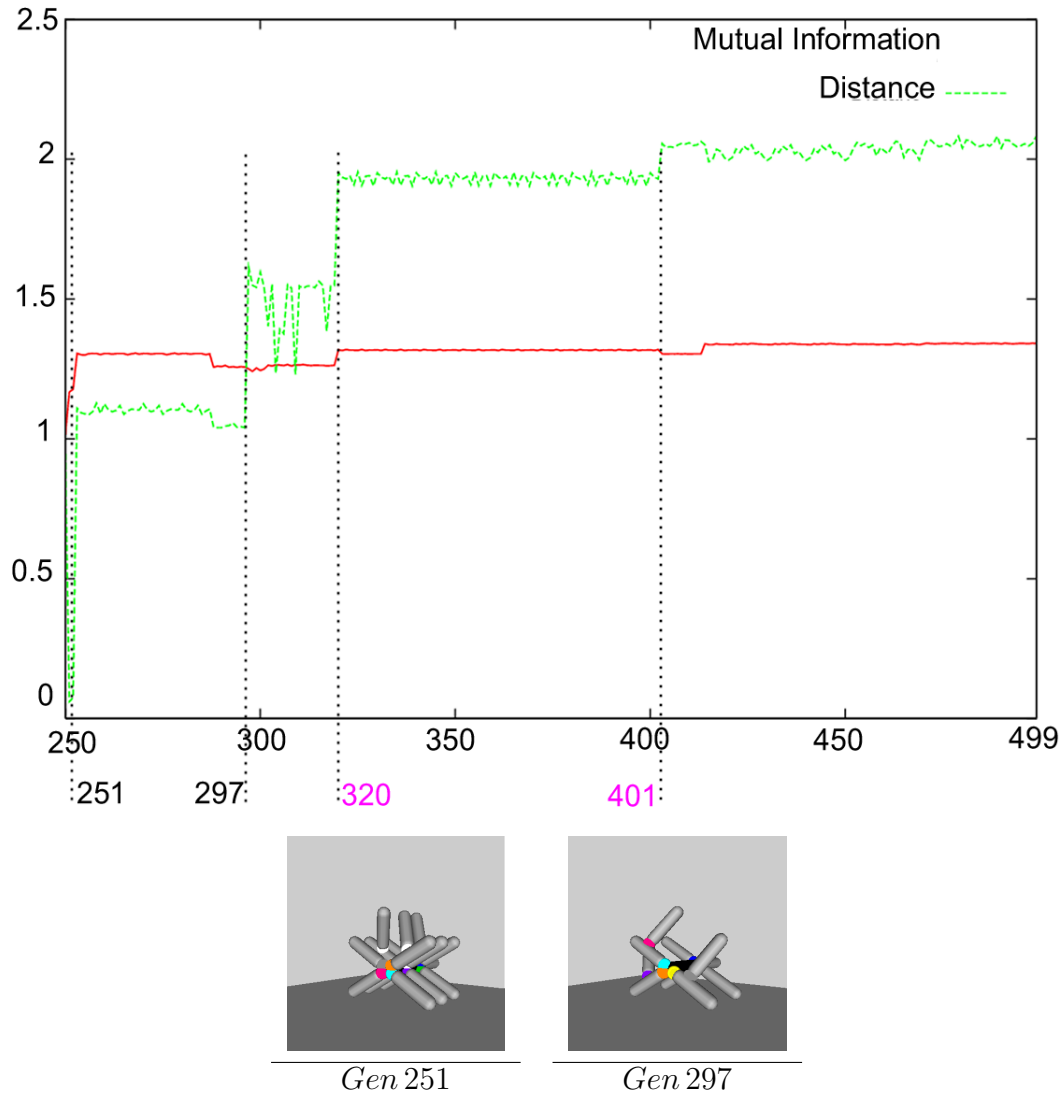
Figure 5.6: Average distance traveled and average mutual information of the ancestors of the best individual of the last generation of replication $r7$ throughout generations $250-500$. The dotted green line indicates the distance traveled whereas the full red line indicates the mutual information (both normalized in the range $[0.0, 1.5]$). The x-axis indicates the number of generation and the 4 vertical lines at generations 251, 297, 320 and 401 indicate the 4 major transitions with respect both to morphological and changes. Morphological changes are indicated in the pictures at the bottom, whereas neural changes are simply indicated with pink reference (generation 320 and 401) on the graphical representation of fitness.

(1)	adding/removing elementary unit with motorized joint	$\Rightarrow$	increasing/decreasing global weight
		$\Rightarrow$	increasing/decreasing motor power
		$\Rightarrow$	increasing/decreasing coordination among neural modules
(2)	adding/removing elementary unit with fixed joint	$\Rightarrow$	increasing/decreasing global weight
		$\Rightarrow$	improving/decreasing morphological symmetry

As consequence, every morphological change always has a significant effect on global behaviour. Looking in detail for each mentioned generation:

Generation 51 − physical structure become lighter and better balanced respect to the previous one causing a remarkable increasing of covered distance and improvement of global coordination.

Generation 64 − physical structure increases the number of motorized joints without loosing its morphological symmetry. This causes a minor decreasing of covered distance due to loss of coordination (more neural modules) that will be quickly recovered, as show in the figures, in next generations.

Generation 218 − physical structure increases the number of motorized joints improving its morphological symmetry. This cause a decreasing of coordination among motorized joints and, in contrast to *Generation* 64, an increasing of covered distance. This is due to the fact that a more stable symmetry compensates the uncoordinated movement (see section 5.2 and (Paul, 2004, 2006)).

Generation 251 − physical structure increases the number of motorized joints losing its morphological symmetry. In contrast to the previous two generations, this causes a minor increasing of covered distance and a major increasing of coordination. The reason is clear looking at the movies (available on dvd enclosed with the hard copy of this thesis or on the web page: http://laral.istc.cnr.it/esm/phd_mazzapioda/3_exp) where it is possible to clearly understand the new locomotion strategy.

Generation 297 − physical structure decreases the number of motorized joints improving its morphological symmetry. This causes an increment in covered distance and no significant variation in coordination, meaning that only unused motorized joints have been removed.

Moreover, focusing the attention on fitness function curves, not only in correspondence of morphological variation it is possible to identify remarkable jumps, they appear also at generations: 138, 228, 320 and 401. In these cases, as there are no morphological changes, it means that an important neural variation has occurred affecting general coordination.

In generations 228, 320 and 401 it is possible to observe a significative improvement of covered distance clearly due to a better coordination of motorized joints. On the other hand, at generation 138 the opposite happens: improvement of mutual information and decreasing of covered distance.

This fact should not surprise because, as already shown in sections 4.5 and 5.3.2, a high value in mutual information means not only a better coordination but also a general slow down of motorized joints (equiprobability conditions forces motorized joints to exploit all frequencies, also the slower ones).

This kind of analysis is not specific only for replication $r7$, it could be executed for each replication of the experiment. Avoiding to give, for each replication, a list of the same observations, here will be reported the general trends emerging from the full data analysis:

(*i*)   After the first generations, the morphology of the creatures became stable and undergoes a few crucial adaptive changes (at generations 51, 64, 218, 251 and 297 in the case of replication $r7$), which represent crucial transitions in the evolutionary process while remaining rather stable between the phases that precede and follow transitions.

(*ii*)   Once the performance of creatures increases, the probability of observing variations of the morphology which are adaptive become progressively lower. For this reason, after the first part of the evolutionary process, the occurrence of a major transitions which produce a significant modification of the morphology often arise as a result of variations which are retained despite they are maladaptive but which later become adaptive thanks to the adaptation and retention of further changes (as in the case of the variations occurring between generation 218 and generation 229 in the case of $r7$).

(*iii*)   Each significant variation in fitness value is followed by an adjustment phase in which morphology and neural controller co-adapt to each other. This behaviour supports the validity of preliminary hypothesis (see 4.4) in which mutation operator is applied to morphological or neural characteristics but not together.

For a further validation, a spin-off experiment has been executed in which mutation is applied, according with corresponding percentage, to neural and morphological characteristic at the same time.

Results obtained from this experiment have showed that no evolved individual was able to perform given task in an effective way.

(*iv*)   Mutual information tends to increase during the initial phase of the evolutionary process and then tends to decrease (or hold steady) during the final phase. This can be explained by considering that the optimization of the distance travelled tends to interfere with the need to vary the

desired speed of the joint in a coordinated manner.

These data confirm the observation reported above which indicate that the attempt to maximize mutual information channel the evolutionary process toward the evolution of creatures which are able to coordinate the movements of their parts, which in turn tend to lead to effective solutions.

On the other hand the attempt to optimize mutual information interferes with the need to optimize the locomotion behaviour (see also sections 4.5 and 5.3.2).

5.5   Summary

The analysis of the obtained results has demonstrated how the proposed method allows the synthesis of effective and robust solutions which let evolved creatures effectively locomote both on flat and irregular terrains after a relatively short number of generations in all the replications of the experiment. This general ability involves:

(a)   a capacity of assuming a preferred posture (by avoiding to fall on a side or to tip over),

(b)   a capacity of coordinating the movement of several body parts so as to produce a coherent behaviour which allow the creatures to locomote,

(c)   a capacity to keep moving in a coordinated manner while compensating the perturbations which arise during motion and during the interaction with obstacles of variable size in the uneven terrain.

The fact that evolving creatures display good performance in all replications of the experiment indicates that the model proposed guarantees a good level of evolvability in this setting.

The fact that the evolved creatures display a variety of different morphologies and a variety of behaviour strategies indicates that the model proposed displays a good level of expressiveness.

Furthermore, the relative simplicity of the model allowed us to test several variations of the model itself in order to identify the features and the parameters of the model which play an important role.

Environmental Complexuity - the analysis of the obtained results indicates that increasing the complexity of the task/environment (that is by asking the creature to locomote both on a flat and an irregular terrain rather than only on a flat terrain) might improve the performance of the evolved creatures also with respect to their ability to walk on a flat terrain.

Task Independent Fitness Function Components - the analysis of the obtained results also demonstrates how the use of a task-independent measures (in the case of the experiment reported in sections 5.3.2, the possibility to reward evolving individuals on the basis of the average mutual information computed between the output of each couple of neural controllers) combined with task-dependent measures (in this case the distance traveled by creatures within a limited time interval) can facilitate the maximization of the task dependent criteria.

Finally, the analysis of the evolutionary process indicated how, after the very first generations, the morphology of evolved creatures tend to remain rather stable apart from few significant changes which represent major transitions in the evolutionary process.

Chapter 6

Discussion and Future Works

The attempt to evolve complete artificial creatures (that is embodied and situated agents in which both morphological and control characteristics are adapted during the evolutionary process) has been and still represents a key long term goal for the Artificial Life and Evolutionary Robotics community.

The possibility to make progress crucially depends on the possibility of identifying a genotype-to-phenotype mappings with the following characteristics:

Evolvability - that is the probability that genetic variations lead to improvements of creatures' adaptive skills should not be too low;

Expressivity - that is the variations at the level of the genotype should potentially lead to a large number of possible alternative solutions with respect to both the space of possible morphologies and the space of possible control systems;

Simplicity - that is the rules that determine the relation between the genotype and the phenotype should be as simple as possible in order to deal with not too many parameters.

The aim of this thesis is giving a valid solution to this problem proposing a new genotype encoding schema which permits the evolutionary co-adaptation of mor-

phology and control system of realistically simulated artificial creatures. For this reason, the following has been proposed:

- an indirect encoding, inspired by cell chemistry and formal grammar rule approaches in which a genotype does not directly specify the characteristics of the phenotype but rather the way in which an initial element develops into a full formed individual in a realistic 3D space;

- a selection criterion defined with the objective of facilitating the evolution of required skills without being selective (either too much or to little);

- a distributed neural controller chosen in order to maintain simplicity and scalability characteristics. In particular, highly distributed independent neural controllers, embedded in different body parts with the objective to keep the model as simple as possible and the number of parameters as small as possible has been adopted.

The model proposed is globally inspired by ancient biological organisms and by simple organisms such as stick insects.

After defining and verifying a valid genotype encoding, the interest of this thesis moved toward understanding which:

(a)   mechanisms can lead to obtain a distributed neural controller able to coordinate all its own modules according to the requested task (see chapter 3),

(b)   mechanisms can lead to the autonomous design of complete and evolvable artificial systems based on local distributed controllers (see chapter 5),

(c)   mechanisms can lead to achieve co-adaptation during the evolutionary process, between morphological structures and neural controllers (see chapter 5).

The experimental chapters presented in this thesis clearly display how these mechanisms emerged from the evolutionary process, in particular

Chapter 3   showed how the proposed distributed neural controllers can coordinate 6 legs of a simulated hexapod robot both converging towards the same coordinated gait and selecting an appropriate gait (tripod or tetrapod) on the basis of different environmental conditions.

Chapter 5   showed how the proposed encoding displays a good level of expressiveness: high variety of different morphology and high variety of behaviour strategies. Furthermore, the simplicity of the model allowed us to execute new tests in order to identify which are those mechanisms that lead to co-adaptation of body and neural controller during the evolutionary process and which are those features that play a decisive role in evolutionary process (environmental complexity and fitness function components).

6.1   Contributions of the thesis

In this section, in order to show the advantages of the proposed model, which allows evolutionary co-adaptation of morphology and neural controllers of realistically simulated creatures, several contributions in the field of evolutionary robotics have been presented.

More precisely, in this section will listed the main contributions given in the sub-field investigated in this thesis will be listed: distributed neural networks and development of genotype encoding.

Distributed Neural Networks

In Section 3.3 it has been demonstrated how a simulated hexapod robot, controlled by a distributed neural network, produces a coherent and coordinated

behaviour exploiting a local distributed communication system among all its own neural modules.

In Section 3.4 it has been demonstrated how, increasing the number of emitted and detected signals (that is the communication systems among modules - see section 3.3) simulated hexapod robots not only produce a coordinated behaviour but can adapt "on the fly" their behaviours on the basis of different presented environmental condition.

In Sections 3.3 and 3.4 those mechanisms that allow coordination and adaptation among robot's legs have been shown. More precisely, the role played both by the local distributed communication system (that is to coordinating different legs with each other) and by the physical interactions between robot and environment has been identified (for example coordinating the movement of a single leg: femur and tibia).

On average, having small networks allows to cope with a very little number of parameters and as a consequence it is possible to deeply understand the specific role of each element present in modules.

Moreover, having a scalable network that does not exponentially grow with respect to the number of corresponding actuators, allows to obtain, as showed with experiments, the same global behaviour with a higher number of neural modules (i.e. with a higher number of legs in simulated hexapod robots).

Body-Controller Evolutionary Co-Adaptation

The design of genotype encoding has been subjected to deep analysis in order to define a genotype-to-phenotype mapping that respects these three characteristics: expressivity, simplicity and evolvability.

Inspired by the ontogenetic process, the proposed method (described in chapter 4), allows to generate and evolve individuals with the ability to locomote on flat and

irregular terrains exploiting a distributed neural controller.

In Section 5.2.1 it has been shown how the proposed encoding can generate a wide range of different morphological structures at first generation, ensuring in this way a better investigation of the space of solutions (expressivity) and as a consequence avoiding direct convergence toward simple trivial solutions (evolvability).

In Sections 5.2.2 and 5.2.3 it has been demonstrated how, in each replication of the experiment, evolved individuals achieve the given task, that is those mechanisms that allow them to show a clear ability to effectively locomote in a physically simulated environment.

Different locomotion styles, joined with different morphologies display how genotype encoding is able to produce very different individuals, each with its own evolutionary heritage.

In Section 5.3.1 it has been showed how the complexity of the environment strongly influences the entire evolutionary process of artificial agents. Test experiments have indeed displayed how in too simple environments individuals tend to evolve very simple morphologies and very simple behaviours, whereas, when individuals are evolved in a more complex environment, they can also exploit all the environmental characteristics and thus evolving new abilities.

In Section 5.3.2 the importance of choosing an appropriate fitness function to evolve individuals during the evolutionary process has been demonstrated. In particular, the proposed test experiment has shown how an indirect fitness component (in this thesis the mutual information has been proposed) affects the behaviour of artificial agents increasing the space of possible solutions that at the end of the evolutionary process obtain a wider set of different solutions.

133

In Section 5.4 those mechanisms that allows morphology and neural controllers of artificial agents to evolve together during the evolutionary process have been shown and in particular how they work to co-adapt to each other in order to perform the given task.

All these analysis are the results of small adjustments applied during the evolutionary process to genotype encodings and environmental parameters. The possibility of performing, for each variation a deep and well defined analysis demonstrated the concept of simplicity that was introduced at the beginning of this thesis: "avoiding to deal with too many parameters that have to be chosen, optimized and analyzed".

6.2 Future Directions

All experiments performed during these last years and reported in this thesis have answered many questions and at the same time have opened the door to several directions for future works:

- In order to favour co-adaptation between the body and the control system of individuals, rules defining artificial development could be modified. Inspired by biological organisms a possible modification could be to "grow the element" instead of "adding a new element". In this way an individual could extend its body without adding either new elements or new joints but simply by enlarging the existing ones. As consequence, existing joints have to specialize themselves, modifying frequency and force, in order to deal with elements with different dimensions.

- Always inspired by biological organisms, the concept of "Energy Consumption" applied to motorized joints could be added. In this way individuals should avoid moving at maximum velocity in order to save energy and as a consequence live for a longer time. This feature could substitute the indirect

component in the fitness function and a specific analysis could underline the differences among emerging behavious.

- The ability of a physical body instead of a neural controller of executing actions, or, more generally, executing processes could be quantified and formally analyzed exploiting the morphological computation theory.

- In order to increase biological realism, fitness evaluation could be done, not only at the end of individuals life, but also during the ontogeny (Quick et al., 2003; Knabe et al., 2008).

- Distributed neural controllers could be investigated in completely different evolutionary experiments with different fitness functions, with the objective of comparing their behaviours and thus fixing strengths and weaknesses.

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Appendix A

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Synchronization within Independent Neural Modules Controlling a Simulated Hexapod Robot

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Abstract

In this paper we illustrate a system consisting of a collection of identical neural modules, that communicate by exchanging signals, that control a simulated hexapod robot with twelve DOF. The evolved neural controllers display an ability to generalize their ability to different environmental and body conditions. Synchronization and phase differentiation between joints and legs is achieved through simple acceleration/deceleration mechanisms based on local interactions.

1. Introduction

Synchronization, i.e. coordination with respect to time, is a phenomenon of interest to disciplines ranging from astrophysics (e.g. celestial mechanics) to laser physics, and from biology and neuroscience to communication (Strogatz, 2003). In most of the cases, syncronization can be characterized as a self-organizing process, i.e. as a property at the global level of the system that results from local interactions among lower-level components (Camazine et al. 2001, Strogatz, 2003).

In living beings, syncronization processes occur both at the level of the individual (as a result of the interaction between elements that constitute the individual) and at the level of group of individuals (as a result of the interaction between individuals). Examples of the former category include the syncronization between the pacemaker heart cells, and that between the nerve cells generating locomotion (Glass, 2001). Examples of the latter category include syncronized flashing in fireflys and syncronized foraging activities in ants (Camazine et al. 2001).

In this paper we investigate how syncronization processes might be exploited in design of artificial agents (robots). More specifically, we investigated how six independent neural modules that control the six corresponding legs of an hexapod robot with twelve degrees of freedom can coordinate in time so to allow the robot to walk effectively.

Rather than following a bio-mimetic approach (i.e. observing a specific natural organism exhibiting the target behaviour, identifying the crucial elements and the rules that govern their interactions, and reproduce the elements and the interaction rules in an artificial system as accurately as possible - Cruse et al, 2002; Calvitti & Beer, 2000) we used on an automatic process based on artificial evolution (Nolfi and Floreano, 2000). The number of char-

acteristics of the system that are hand-crafted is reduced as much as possible, and the rules that govern the behaviour of the six independent neural modules and their interaction are left free to self-organized during the evolutionary process (for related approaches, see Gallagher et al., 1996; Ijspeert and Cabelguen, 2003).

2. The experimental setup

In this section we describe the simulated hexapod robot used in the experiments, its control system, and the evolutionary algorithm used to set the free parameters of the robot's control system

2.1 The hexapod robot

The simulated robot (Figure 1) consists of a main body (with a length of 20 cm, a width of 4 cm, and a height of 1.5 cm) and 6 legs.
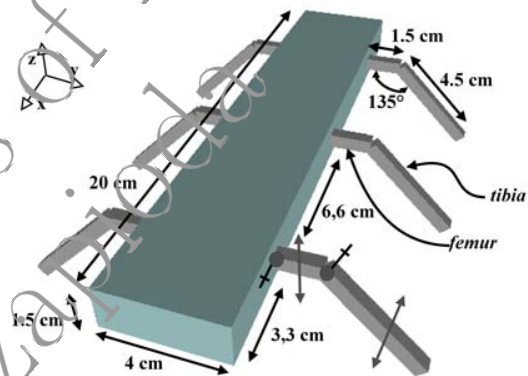

Figure 1. The simulated hexapod robot. The grey circles on the leg shown on the bottom-right side of the picture indicate the position of the joints. The two grey arrows indicate the rotational axis of the corresponding joints.

Each leg consists of two segments (a "femur" and a "tibia" with a length of 1.5 and 4 cm respectively) and has two motors controlling two corresponding joints (the body-femur and the femur-tibia joints). The femur and the body-femur joint allow the robot to raise its central body from the ground and to move the tibia up and down. The body-femur joint is a motorized hinge joint with rotational axis parallel to the x-axis that can rotate from $-\pi/16$ to $+\pi/16$ rad. The femur-tibia joint allows it to move the tibia forward or backward. It is a motorized hinge joint that rotates

from - π/8 to + π/8 rad with respect to its own axis (i.e. an axis rotated of π/4 rad with respect to yz-plane). The motors controlling the joints can apply a maximum torque of 0.03*Nm* at maximum speed of 3100 rpm in both directions. For each leg, two simulated position sensors detect the current angular position of the corresponding joint. The total weight of the simulated robot is 387g. Gravity force is –9.8 m/sec². The environment consists of a flat surface. The robot and the robot/environment interaction was simulated by using the VortexTM toolkit (Critical Mass Labs, Canada), that allows to realistically simulate the dynamics and collisions of rigid bodies in 3D.

2.2 The control system

To robot is controlled by a distributed control system consisting of six independent neural modules, located at the junction between the main body and the legs, that control the six corresponding legs (see Figure 2). The six neural modules are identical (i.e. have the same architecture and the same free parameters) have access to local sensory information only. More specifically, each neural module has access to the current angular position and controls the frequency of oscillation of the two joints of the corresponding leg. Neural modules communicate between themselves by producing signals and by detecting the signals produced by other neural controllers located within a given Euclidean distance. Signals thus are analogous to gaseous neurotransmitters such us nitric oxide that are released by neurons and affect other neurons located nearby in a diffuse manner (see Elphick et al., 1995, 1996; Husbands *et al.* 2001).
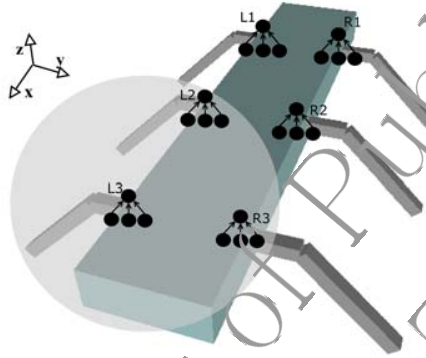

Figure 2. The robot and its control system consisting of 6 neural modules. L1, L2, and L3 indicate the front, middle, and rear leg located on the left side of the robot. R1, R2, and R3 indicate the front, middle, and rear leg located on the right side of the robot. The grey circle represent the range of diffusion of the signal produced by one neural module (i.e. the neural module controlling the L3 leg).

Each of the twelve motors neurons produces a sinusoidal oscillatory movement with a variable frequency of the corresponding joint, within the joint's limits. More specifically, the current desired position of a corresponding joint is computed according to the following equation:

$$pos(t) = \sin(V(t) \cdot t + \varphi) \qquad (1)$$

where pos(t) indicates the desired angular position of the joint at time t, V(t) (that ranges between 7 and 14 Hz) indicates the current frequency of the oscillator, and φ indicates the starting position of the joint. The desired position is normalized within the range of movement of the corresponding joint. Motors are activated so as to reach a speed proportional to the difference between the current and the desired position of the corresponding joint.

Each neural module has four input neurons directly connected to four output neurons (Figure 3).
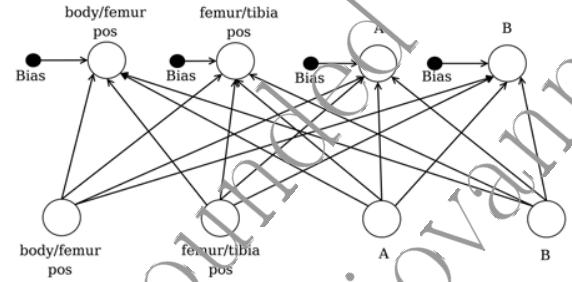

Figure 3. The topology of each neural module. The four input neurons indicated in the bottom part of the picture encode the current angular position of the two joints of a leg and signal A and B (see text). The four output neurons are indicated in the top part of the picture. The first two modulate the frequency of oscillation of the two corresponding motorized joints and the others two determine whether or not the signal A and B are produced.

The input neurons encode the current angular positions of the two joints of the corresponding leg (normalized in the range [0.0, 1.0]) and whether signals A and B, produced by other neural modules, are detected. Each neural module can produce two different signals (A and B) that diffuse and can be detected up to a certain distance (D_a and D_b, in the case of signal A and B, respectively). The intensity of the signal detected is linearly proportional to the number of neural modules that are currently producing the corresponding signal located within the corresponding maximum diffusion distance.

The activation of output neurons is computed by using a standard logistic function. The first two output neurons determine how the frequency of oscillation of the two corresponding joints varies. More specifically, each time step (i.e. each 1.5ms), the frequency of oscillation of a joint can vary within [-1.4Hz, +1.4Hz] according to the following equation:

$$V(0) = Val \qquad 7 \leq Val \leq 14$$

$$V(t) = V(t-1) + \begin{cases} (Out-0.75) \cdot 1.4 & Out \geq 0.75 \\ 0 & 0.25 < Out < 0.75 \\ (Out-0.25) \cdot 1.4 & Out \leq 0.25 \end{cases} \qquad (2)$$

Where Val indicates the initial value of frequency of a joint that is randomly set within the range, Out indicates the output of the corresponding motor neuron, and V(t) indicates the current frequency, V(t-1) indicates the frequency at the previous time step. Frequency is bounded in

153

2

the range [7Hz, 14Hz], i.e. variations that exceed the limits are discarded.

The other two output neurons determine whether or not signal A and B are produced. More specifically, signal A and B are produced when the output of the corresponding output neuron exceeds the corresponding threshold (T_a and T_b, in the case of signal A and B, respectively).

2.3 The evolutionary algorithm

The free parameters of the neural modules are evolved through an evolutionary algorithm. Robots were selected for the ability to walk along a straight direction as fast as possible. Each robot was allowed to "live" for 2 trials, each lasting 3000 ms (i.e. 2000 time steps of 1.5 ms). The state of the sensor and motor neurons, the torque applied to the motors, and the dynamics of robot/environment interaction are updated each time step (i.e. each 1.5 ms). At the beginning of each trial: the main body of the robot is placed at a height of 4.18 cm with respect to the ground plane. The initial position of the twelve joints and the initial desired velocity of each corresponding motor is set randomly within the corresponding range. The fitness of each robot is computed by measuring the Euclidean distance between the initial and final position of the centre of mass of the robot during each trial. The total fitness is computed by averaging the distance travelled during each trial.

The initial population consisted of 100 randomly generated genotypes that encoded the connection weights and the biases of a neural module, the maximum distance of diffusion of the two signals (D_a and D_b), and the thresholds that determine when signals are produced (T_a and T_b). Each parameter is encoded as real number. Connection weights and biases, diffusion distances of signals, and thresholds that determine signal emission are normalized within the following ranges: [-15.0, +15.0], [0.0, 10.0], [0, 1.0], respectively. Each genotype is translated into 6 identical neural modules that are embodied in the robot and evaluated as described above. The 20 best genotypes of each generation were allowed to reproduce by generating five copies each, with 3% of their genotype value replaced with a new randomly selected value (within the corresponding range). The evolutionary process lasted 300 generations (i.e. the process of testing, selecting and reproducing robots is iterated 300 times). The experiment was replicated 15 times starting from different, randomly generated, genotypes.

3. Results

By analysing the results of the evolutionary experiments we observed that evolved robots display an ability to walk effectively, in all replications of the experiment. Figure 4 shows fitness through out generations.
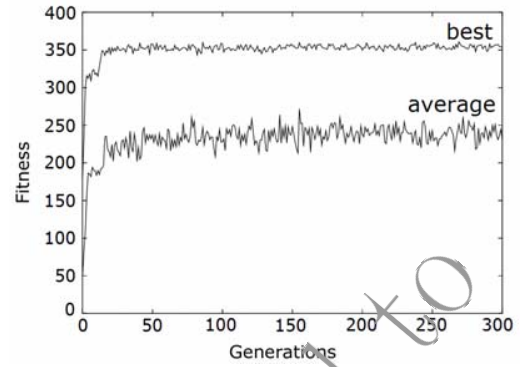

Figure 4. Fitness (i.e. average distance in cm travelled during two trials) of evolving individuals through out generations in a typical replication of the experiment. The curves indicate the fitness of the best individual of each generation and the average performance of the population through out generations.

By visually inspecting the evolved walking strategy we observed how, in all replications, evolved robots display an ability to quickly coordinate the phases and the frequency of oscillation of their twelve motorized joints by converging toward a tripod gait, a type of gait used by all fast moving insects, independently from the initial position of the joints (see Figure 5, 6, and 7).
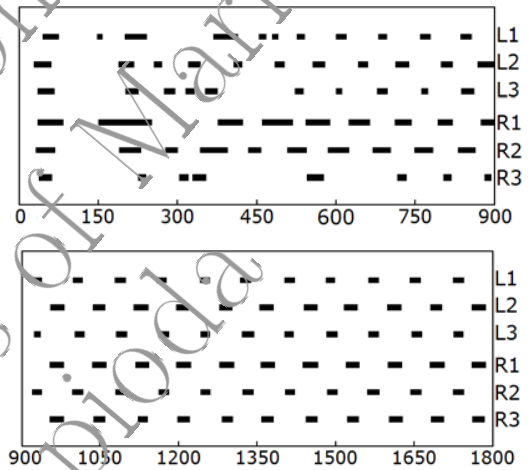

Figure 5. A typical behaviour exhibited by an evolved robot during a trial. At the beginning of the trial the position of the joints and frequency of oscillation are randomly initialised within limits. The black lines indicate the phases in which the tibia of the corresponding leg touch the ground. Legs are labelled with L for left and R for right and numbered from 1 to 3 starting from the front of the insect. The horizontal axis indicates time in millisecond.

The analysis of the evolved robots indicates that after an initial coordination phase (that last about 1000 ms, on the average):

- the 12 joints converge on the same average frequency,
- the body-femur and femur-tibia joints of each leg coordinate so that the tibia touches the ground during retraction movements (in which the tibia moves to-

154

3

ward the rear of the body) and do not touch the ground during protraction movement (in which the tibia move toward the front of the body), see Figure 6 and 7.

- the two groups of legs (L1, L3 and R2) and (L2, R1, R3) are in phase within the group and in anti-phase between groups, see Figure 5, 6 and 7.

Once the twelve joints coordinate, they tend to keep the same frequency of oscillation (on the average, over a time span of 100 ms) but also slightly accelerate or decelerate, with respect to each other, to compensate for misalignments arising during motion.
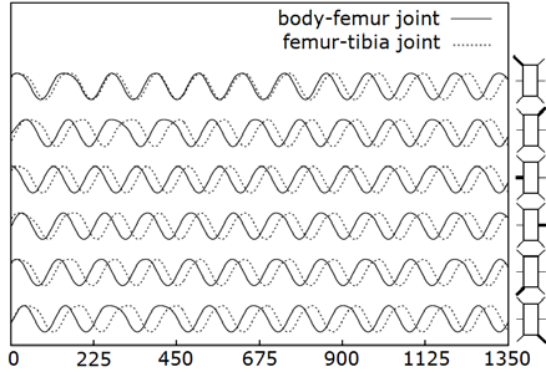
Figure 6. Desired angular position of the twelve joints during the same trial shown in Figure 5. Each line indicates the position of the joints of the leg indicated with a dark line in the right part of the Figure. Full lines and dotted lines indicate the position of the body-femur and femur-tibia joints, respectively. High values indicate positions in which the femur is elevated with respect to the main body and positions in which the tibia is oriented toward the front of the robot.
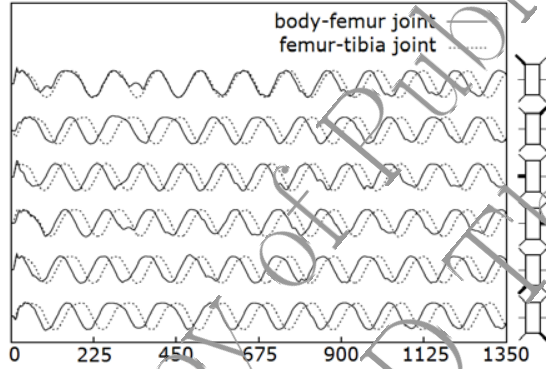

Figure 7. Current angular position of the twelve joints during the same trial shown in Figure 5 and 6. Each line indicates the position of the joints of the leg indicated with a dark line in the right part of the Figure. Full lines and dotted lines indicate the position of the body-femur and femur-tibia joints, respectively. High values indicate positions in which the femur is elevated with respect to the main body and positions in which the tibia is oriented toward the front of the robot.

The dynamical behaviour produced by the walking robots does not only result from the interaction between the six neural modules that control the six corresponding leg but also from the dynamics originating from the interaction between the robot body and the environment. Indeed, the way in which the actual position of the joints vary in time (Figure 7) is influenced not only from the variation of the desired joint position (Figure 6) but also from the forces arising from the collision between the legs and the ground. These forces are influenced by several factors such us the actual orientation of the robot with respect to the ground, the current velocity of the robot, the characteristics of the ground, etc. As shown in the figures, the effects of the robot/environment physical interaction are much more significant during the initial phase in which the legs are not yet coordinated.

4. Analysis of the mechanisms that lead to legs' coordination

To understand the mechanisms that lead to the synchronization of the twelve joints, we analysed the interaction occurring within each neural module and between different neural modules (i.e. the conditions in which signals are produced and the effects of signals detected). Here we report the analysis conducted in the case of the evolved individuals already described in Figure 5-7.

As could be expected, the synchronization between the two joints of each leg is achieved within each single neural controller. More specifically: (a) the body-femur joint decelerates when it is elevated and the tibia is oriented toward the rear (Figure 8, top-left picture), and (b) the femur-tibia joint decelerate when the body-femur joint is elevated and the tibia is oriented toward the front of the robot (Figure 8, bottom-left picture). The combination of these two mechanisms leads to a stable state, that correspond to the synchronized phase, in which the protraction movement of the tibia is performed when the body-femur joint is elevated the retraction movement is performed when the body-femur joint is lowered.
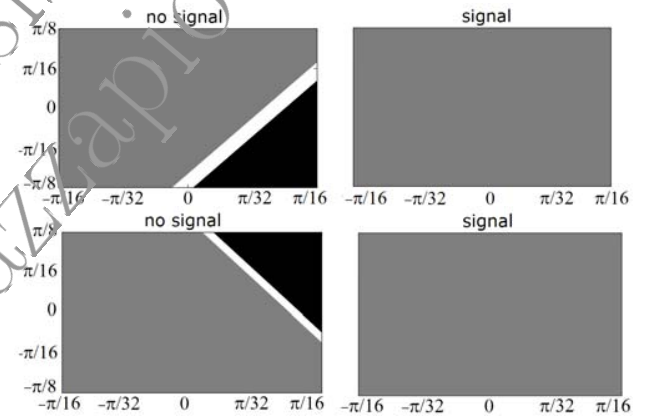

Figure 8. Conditions in which joints accelerate (grey area), decelerate (black area) or maintain the the same frequency (white area), as a function of the current joint positions and of whether the neural module detects signal A or not. The vertical and horizontal axes indicate the femur-tibia and body-femur joints, respectively. Top: acceleration/deceleration effects on the body-femur joint. Bottom: acceleration/deceleration effects on

the femur-tibia joint. Left: effects when signals are not detected. Right: effect when 1,2, or 3 signals are detected.

Although neural modules can produce and detect up to two different signals (i.e. signal A and B), this individual only produces one of the two signal: signal A. By analysing the signals used during the course of the evolutionary process we observed that, in all replications of the experiment, evolving robots use both signals during the first evolutionary phases. However, after 150 generations, robots use one signal only. Since the maximum distance of diffusion of signals A is 7.12 cm (in the case of the individual shown in Figure 5-7), the signal produced by each leg affects the contra-lateral leg of the same segment and the previous and succeeding leg of the same segment (when present). This means that the signal produced by a leg of one group ([L1,L3,R2] or [R1,R3,L2]) affects only the legs of the other group that should be in anti-phase in a tripod gait. The legs that are affected by a signal are 2 out of 3 legs in the case of legs [L1,L3,R1,R3] and 3 out of 3 legs in the case of legs [L2,R2].
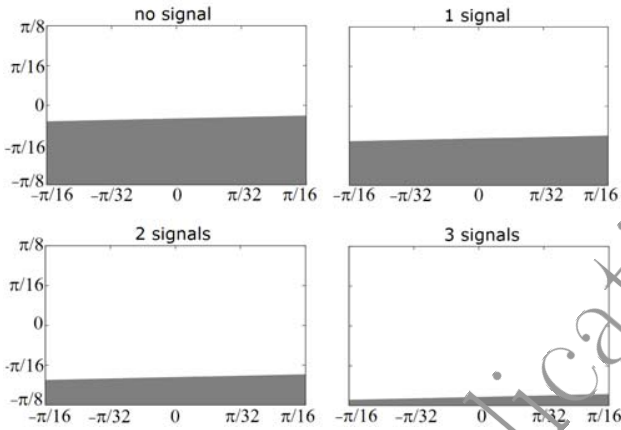

Figure 9. Conditions in which the signal A is produced (grey areas) as a function of the current current joint position and of the number of detected signals. The vertical and horizontal axes indicate the femur-tibia and body-femur joints, respectively. The four pictures indicate whether the neural module detects 0, 1, 2, or 3 signals produced by other neural modules.

To explain how the six legs coordinate we should explain why uncoordinated states are unstable and lead to coordinated phases (through relative acceleration/deceleration of the joints) and why coordinated state are stable.

The latter aspect can be explained by considering that when legs belonging to the two groups are in phase within the group and in anti-phase between groups. The effect of the signals produced by the leg of the two groups does not produce a relative acceleration/deceleration of the legs of the two groups.

A leg produces a signal when its tibia is oriented toward the rear (Figure 9). This implies that, when the legs of the two groups are in anti-phase, signals are produced in an alternate way from the two groups. This signal produce by the leg of the first group accelerate the joints of the legs of the second group (i.e. it prevents the deceleration that oc-

curs when the signal is not detected, see Figure 8). However, the legs of the second group later produce a signal that accelerate the legs of the first group, so that the original relative frequency is restored.

To explain the former aspect (i.e. why uncoordinated phases are instable) let us consider the case in which, when the leg of the first group completed their retraction movement, the legs of the second group did not completed their protraction movement yet. Since signals are produced by the leg that have their tibia oriented toward the rear (see Figure 9) and produce an acceleration only on legs that have their tibia oriented toward the front (see Figure 8) the acceleration effect produced by the legs of the first group on the legs of the second group is lower than in synchronised conditions. This lack of deceleration of the legs of the second group increase their delay with respect to the leg of the first group. This implies that, the signals produced by the legs of the second group later on produce a larger lack of deceleration on the legs of the first group. This asymmetrical effect reduces the amount of de-synchronization between the two groups, until a synchronized state is reached.

Finally, the instability of the cases in which, the legs of the two groups are erroneously in phase or almost in phase can be explained by considering the effects of the signal produced by one group of legs on the body-femur joints of the other group of legs (see Figure 8).

The way in which the legs of one group tend to synchronize and phase within the group is an indirect effect of the processes that lead to synchronization and anti-phase between groups, described above.

5. Generalization

By testing the evolved neural controllers in new conditions we observed how they generalize their ability to produce an effective walking behaviour to new environmental and body conditions.

Evolved robots display an ability to coordinate by exhibiting a tripod gait and to effectively walk also when tested on uneven terrains (see Figure 10) or on inclined surfaces. The average speed of the robot after the initial coordination phase in these test conditions decreases of about 35% and 15%, in the case of the rough terrain and in the case of an inclined surface with a slope of +15°, and increases of about 15%, in the case of an inclined surface with a slope of -15°.
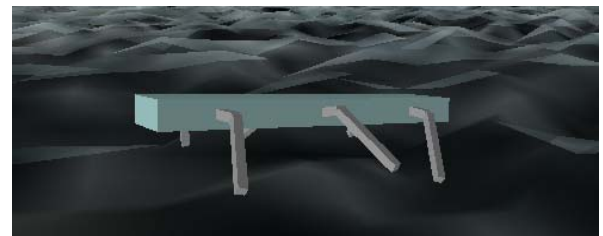

Figure 10. A robot evolved on a flat terrain tested on a rough terrain (i.e. an uneven terrain with variation in height up to 5 cm).

Evolving robots also show an ability to carry additional weight. Indeed, in test conditions in which the weight of the robot is duplicated we observed that the robots are still able to coordinate and to walk. In this test condition, speed decreases of about 25%, with respect to the normal condition.

Finally, by embedding the neural controllers evolved in robots with six legs in robots with a different number of legs, we observed that robots keep an ability to coordinate on a tripod gait. Robots with a larger number of legs are able to walk at higher speed and to coordinate faster than hexapod robots. For example, a robot with 20 legs provided with 20 identical copies of the neural modules described in the previous section (see Figure 11) is able to walk with a speed that is about 10% higher and to coordinate in a time that is about 25% shorter than hexapod robots.
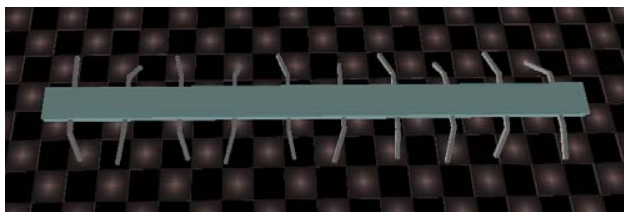

Figure 11. A robot with 20 legs and a body length of 67 cm controlled by 20 neural modules identical to that evolved in robots with 6 legs.

In future research, we plan to evolve robots in varying environmental conditions to verify whether, by being selected for their ability to cope with environmental variations, they can develop even more effective strategies.

6. Discussion

Syncronizazion is a widespread phenomena in the universe and occur in a large variety of animate and inanimate entities at different space and time scales. This generality can be explained by considering the inevitability of syncronization (Strogatz, 2003) providing that two simple conditions are met: syncronizing elements spontaneously exhibit an oscillatory behaviour with a given intrinsic frequency, and each oscillatory element appropriately increases or decreases its frequency of oscilation on the basis of the output of the other elements (that provide an indication of their actual phase) and of its own phase. When the differences between the intrinsic frequency of oscillation of the elements do not overcome a given threshold, sincronization will always occur, independently from the initial condition of the system and of the number of interacting elements (Strogatz, 2003).

In this paper we demonstrated how an automatic process based on artificial evolution can develop the rules that determine: (a) the output of oscillatory elements, and (b) how frequency of oscillation of a given element is affected by the output of other elements.

Moreover, we demonstrated how, by leaving the system free to determine the range of interaction and whether the interaction is local or global, the system converges towards a local interaction modality. This local interaction form combined with the fact that oscillatory elements are located in space with a given spatial configuration, allow the system to produce both a syncronization of the oscillatory elements and a differentiation of the phases of oscillation of the different elements. This phase differentiation, in turn, allows the system to produce a tripod gait, i.e. a coordinated movement in which contra-lateral legs of the same segment alternate in phase.

Further research might investigate whether this surprising result can be generalized to other problems and domains and whether distributed system consisting of collection of homogeneous elements located in space and interacting locally can produce complex coordinated behaviour in which individual elements or group of elements play different complementary roles.

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Abstract

In this paper we present a distributed control architecture for a simu- lated hexapod robot with twelve degrees of freedom consisting of six homoge- neous neural modules controlling the six corresponding legs that only have ac- cess to local sensory information and that coordinate by exchanging signals that diffuse in space like gaseous neuro-trasmitters. The free parameters of the neu- ral modules are evolved and are selected on the basis of the distance travelled by the robot. Obtained results indicate how the six neural controllers are able to coordinate so to produce an effective walking behaviour and to adapt on the fly by selecting the gait that is most appropriate to the current robot/environmental circumstances. The analysis of the evolved neural controllers indicates that the six neural controllers synchronize and converge on an appropriate gait on the basis of extremely simple control mech- anisms and that the effects of the physi- cal interaction with the environment are exploited to coordinate and to converge on a tripod or tetrapod gait on the basis of the current circumstances.

Abstract

In this paper we present a model which allows to co-evolve the morphology and the
control system of realistically simulated robots (creatures). The method proposed
is based on an artificial ontogenetic process in which the genotype does not specify
directly the characteristics of the creatures but rather the growing rules that deter-
mine how an initial artificial embryo will develop on a fully formed individual. More
specifically, the creatures are generated through a developmental process which oc-
curs in time and space and which is realized through the progressive addition of
both structural parts and regulatory substances which affect the successive course
of the morphogenetic process. The creatures are provided with a distributed control
system made up of several independent neural controllers embedded in the different
body parts which only have access to local sensory information and which coordi-
nate through the effects of physical actions mediated by the external environment
through the emission/detection of signals which diffuse locally in space. The anal-
ysis of evolved creatures shows how they display effective morphology and control
mechanisms which allow them to walk effectively and robustly both on regular and
irregular terrains in all the replications of the experiment. Moreover, the obtained
results show how the possibility to develop such skills can be improved by also se-
lecting individuals on the basis of a task-independent component which reward them
for the ability to coordinate the movements of their parts.