Evolution of Cooperative Skills in Social Living Robots

By

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Contents

Abstract

Many animal species, including humans, live in groups, which means, in general terms, they “live together”. In general, we can interpret “living together” more specifically, depending on how two or more individuals live in spatial proximity to each others. In this respect, not all animal species live equally the group sociality. The social living is a matter of degree. Clearly, two individuals of the opposite sex must stay together for mating as well as, parents remain close to the children, in many species of animals. However, nowadays, it is also clear that some species tend to be more social than others, beyond the biological needs of mating and taking care of offspring. So some interesting research questions are: What are the adaptive advantages of the social living, beyond the reproductive needs or looking after the neighbors? In other words, why animals exhibit different degrees and types of sociality?

The advantages of living in groups have been extensively explored in ethology and biology, and they are generally related to the cooperation needs : (a) protection from predators, (b) feeding efficiency, (c) competition with other groups of con-specifics, and (d) possibility of information sharing.

Many authors argue that cooperation enables groups of individuals to reach common goals that are precluded to a single, as for example, in social grooming. Moreover laboratory dyadic cooperation has been analyzed with new simplified paradigms such as “The Loose String Task”.

On the other hand, living in non-dyadic groups (consisting of more than two subjects) poses a fundamental problem of social coordination: it is a not simple negotiation problem that in the examples. For the ethology, groups of animals are autonomous units which allow members to synchronize some activities, such as collective foraging and coordination in moving. For this reason, in animals world, especially in mammals and virtually always in primates, whenever there are groups, there seems to be a leadership / followership pattern emergence. Both in ethology and in biology, whenever there are moving groups of animals, a leadership arise. Evolutionary biologists use the

term leadership for behaviors that influence the type, timing and duration of group activity and generally they argue that the reason for the emergence of leadership / followership patterns is the need to coordinate.

A lot of theoretical works focus on how navigational information is exchanged between group members and how such information flow depends on the knowledge held by each member. Some open issues are : how do groups reach consensus and solve the problem of maintaining a collective moving? Is there a considerable variation in knowledge of the group members? Is the role of individual knowledge level determining for leadership in animal groups?

Furthermore, game-theoretical analysis has shown how, in some situations, the emergence of leadership is almost inevitable. Some experiments, conducted on humans, underline, not only how leadership can emerge in human beings as well as animals, but variation in temperaments may represent a prerequisite for the emergence of leadership. These studies suggest the thesis that evolution has fashioned a so large variation of individuals' personalities to foster the emergence of leader-follower patterns that are, in turn, essential for solving all the social coordination problems.

On one hand, our purpose is finding an answer to questions like: May really arise leadership in a group of genetically heterogeneous robots? Who is the leader? What are leaders made of? What are characteristics and skill of leader? All mentioned biological and ethological experiments are often hard to be performed in laboratory, since social species are not suitable for experiments performed in captivity. Therefore, in this approach we use artificial models from Embodied Cognitive Science literature and Evolutionary Robotics. In particular, we simulate groups of embodied and artificially evolved robots which must cooperate in order to reach a collective purpose. In every experiment, we try to maintain a strong link between "phenomenon" and "task" derived from experiments on animal behavior, in order to get insights from this kind of data reciprocally. On the other hand, we can contribute to build a new generation of autonomous robotics applications or a new generation of software agents which need a coordination and a leadership emergence to work properly. Examples are the design of new groups of robots for navigational

tasks in unknown environments where spontaneous leadership emergence could foster the coordination for the environmental exploration by robots. Similarly, evolutionary software could exploit leadership/followership patterns and hierarchic structures in order to guarantee the cooperation between different components. In this work I illustrate 4 different experimental setups, which examine the mentioned problems under different viewpoints.

Results show that sociality give the groups many advantage: 1) sociality facilitate the emergence of more probability to find the food in spite of the increased physical obstruction. Moreover, individual physical limits can be compensated by an increase of the population members number. The sociality fosters the intra-species or intra-race cohesion that allows members (belonging to one species or one race group) to be more successful respect to other species or other races groups; 2) in dyadic cooperative subjects, sociality contribute to the coordination of the group via many communication channels (visual or voiced); 3) in non-dyadic cooperative subjects (i.e. in groups of more than 2 member), social coordination causes the spontaneous emergence of flocking behaviors and leadership. Leaders seem to be the most explorative individuals, the fastest to reach the food areas, etc.

Introduction

Many animal species, including humans, live in groups, which means, in general terms, they "live together" [1]. In the common sense, all the individuals of same species that live together always share the same physical environment. However, we can interpret "living together" more specifically depending on how two or more individuals live in spatial proximity to each other, by perceiving others and by performing actions that change the environment or affect others' actions. In this respect, not all animal species live equally within group sociality. Therefore, the social living is a matter of degree. Clearly, two individuals of the opposite sex must stay together, in order to mate, in all sexually reproducing species. Moreover, in many species of animals, parents take care of the children to help them survive. Nowadays, it is also clear that some species tend to be more social than others, beyond the biological needs of mating and taking care of offspring. So some interesting research questions are: What are the adaptive advantages of the social living, beyond the reproductive needs or caring about the neighbors? In other words, why do animals exhibit different degrees and types of sociality?

The advantages of living in groups have been extensively explored in ethology and biology, and they are generally related to the cooperation needs: (a) protection from predators, (b) feeding efficiency, (c) competition with other groups of con-specifics, and (d) possibility of information sharing.

Many researchers have studied the principles underlying the cooperation in animal reign where various and outstanding examples of cooperation can be observed. In general, cooperation enables groups of individuals to reach common goals that are precluded to a single. For example, social grooming (or allo-grooming) [2] is an activity in which individuals in a group clean one another's body, as the reciprocal cleaning of hair. This practice, grounded on a tension-reduction mechanism [3], shows that primates exhibit some behaviours of reciprocal altruism [4], which means the mutual assistance such as "help me, so I will help you". This mechanism can bond and reinforce social structures, family links, and build relationships or the structured social organisation of insects such as ants, bees, wasps or termites where every subject covers a specific role that sustains the hierarchy feeding the entire group.

The ethological observation of these phenomena has been recently complemented with the study in controlled situation, by using specific experimental paradigms: these paradigms represent a simplified version of cooperation chances that animals encounter in natural environment. One of these, the *"Loose String Task"*, is an experimental paradigm to study dyadic cooperation (regarding to two subjects) developed [5] and used [6,7] in order to study chimpanzees, birds, and recently elephants.

On the other hand, living in non-dyadic groups (consisting of more than two subjects) poses a fundamental problem of social coordination. It is a complicated negotiation problem that is not often involved in the examples of dyadic cooperation. For example, in order to move in a large group, some members (not necessarily everybody) must choose the moving direction for the whole group and have to coordinate their movements.

Primatology has been dealing, for a long time, with what may be the conditions that lead to the formation of groups in primates. Several authors have suggested that grouping provides, to members, such benefits that differences in size of groups (either between different races or within the same race) must be sought primarily in the disadvantages that a given ecology determines on the group development [9]. As a matter of fact, some animals, which have to feed on larger areas, require an expansion of the group to match their nutritional requirements, with a consequent increase in time and travel costs for the entire group [10]. A study on "spider monkeys" has proved that the size of groups is conditioned by the distribution, density and size of the food patches spread in the environment where primates live and interact [11].

In ethology, groups of animals are autonomous units, this allows members to synchronize some activities, such as collective foraging and coordination in movements. For this reason, in the animal world (especially in mammals and virtually always in primates), whenever there are groups there seems to be a leadership / followership patterns emergence. For both ethology and biology, whenever there are moving groups of animals, a need for leadership arises. Evolutionary biologists use the term leadership for behaviours that influence the type, timing and duration of group activity [12] and generally argue that the reason for the emergence of leadership / followership patterns is the need to coordinate [13].

A lot of theoretical works focuses on how navigational information is exchanged between group members and how such an information flow depends on the knowledge held by each member [14]. Some open issues are : how do groups reach consensus and solve the problem of maintaining a collective moving? Is there a considerable variation in knowledge of the group members? Is the role of individual knowledge's level determining for leadership in animal groups?

Actually, a few experiments have attempted to provide the necessary empirical data about the social coordination [15]. These experiments demonstrate that during pairing flights, when two pigeons have a conflict in an individually preferred route, if they are significantly different (in knowledge), one bird will emerge as the leader and the other one as the follower. This means that, in order to negotiate joint routes, pigeons make use of a complex decision making system based on leadership mechanisms, where, in substance, less homing experienced birds are likely to follow more experienced con-specifics.

Furthermore, game-theoretical analysis has shown how, in some situations, the emergence of leadership is almost inevitable. Some experiments, conducted on humans, underline, not only how leadership can emerge in human beings as well as animals, but even how variation in temperaments may represent a prerequisite for the emergence of leadership. These studies suggest the thesis that evolution has fashioned (over many millions of years of trials and errors) a large variation of individuals' personalities to foster the emergence of leader/follower patterns that are, in turn, essential for solving of social coordination problems [16].

Therefore, some interesting questions come from a detailed analysis of literature: May leadership really arise in a group of genetically heterogeneous robots? Who is the leader? What are leaders made of? What are the characteristics and skills of a leader?

All mentioned biological and ethological experiments are often hard to perform in laboratory, since strongly social species are not suitable for experiments which are performed in captivity. These animals tend to need a long time to be trained and bred for the laboratory. So it is often difficult to set some experimental proves of theories about leadership and grouping emergence by the means of only using experimental animals or human subjects.

In this thesis, I propose an alternative approach (instead of the traditional statistical analysis of empirical data) to psychology scientists: this new approach is based on artificial models. The idea comes from my readings of Embodied Cognitive Science literature [17] and Evolutionary Robotics [18], which is the principal methodology that I use in this work for the design and implementation of control systems in simulated autonomous robots. In particular, I simulate groups of embodied and artificially evolved robots (khepera-like) situated in an environment where they must cooperate in order to reach a collective purpose.

In the past, several setups have been experimented with by the means of Evolutionary Robotics, for studying the emergence of some cognitive skills in robots. A series of experimental setups have been implemented to analyze the prerequisites for the emergence of different categorisation abilities in embodied agents [19] such as behavioural categorisation, categorical perception, etc. In another experiment, authors have investigated the possibility of aggregation and controlled motion of self-assembling and self-organizing robots, called swarm-bots [20]. Analysis of the evolved controllers shows that these robots have properties of scalability and display a swarm intelligence similar to groups of insects or other living beings belonging to the animal kingdom. Navigational skills of evolved robots have been examined in some setups [21] as well as the evolution and the emergence of language [22]. In all these cases there is a veiled link between the robots and the nature of living organisms.

In our view (of my research group), we try to establish a stronger link between “phenomenon” and “task derived” from experiments on animal behaviour, in order to get insights from this kind of data reciprocally. For this reason we try to model experimental setups, which have been widely used in animal behaviour literature. Recently, this approach has been successfully used to study phenomena like the evolution of mechanisms behind geometrical primacy, in order to understand whether it is innate or affected by the environmental interaction [23].

In my work I will focus on social coordination, decision making problems and emergence of Leadership, a new line of research that is not so much explored until today, by making use of Evolutionary Robotics. The results, that I have achieved, seem to be in excellent agreement with the biological and ethological observations. Apart from the scientific relevance in psychology, ethology and biology, the present research could provide insights to robotics and software design. The genetic differentiation of robots' control systems may contribute to build a new generation of autonomous robotics applications or a new generation of software agents where a coordination is needed and leadership is necessarily required. For example, the design of a group of robots for navigational tasks in unknown environments, such as the surface of a new planet. Unpredicted leadership strategies and spontaneous hierarchies could foster the environmental exploration by robots. Similarly, evolutionary software could exploit leadership/followership patterns and hierarchic structures in order to guarantee the cooperation between different components.

1 The Social Living

Social Living in groups is a well-known phenomenon within the animal kingdom and human societies, since the dawn of time. The question of social life among animals has fascinated biologists for centuries. Some of open questions are : How do we define sociality? When is it likely to occur? What are the patterns involved in social behaviour?

Sociality means group-living. Recently, the research in grouping behaviour has attracted considerable attention in a huge number of fields. The reasons of this growing interest in "living together" must be searched in the awareness that natural selection is not only concentrated at one single individual's level. Moreover, a lot of scientists have understood that all the aspects of structure and function of biological individuals are not solely a product of selection, but many of their peculiarities come from the direct relationship between selection, behaviour and sociality.

The first studies on primate social groups are dated from 1960s, when two ornithologists [24,25], brought home to primatologists the value of comparative analysis. These scientists have developed the first sophisticated system-analytical approaches to societal analysis in order to make predictions on mating modalities of birds, group formation, group size, etc. However, the avian models are not suitable for application to the situation of most of primates, because of the distances between the species. For example, more than 80% of bird species are monogamous. Other studies [26] have tried to classify primate social systems, grounding it on mating structure (solitary, monogamous, single male, etc.), with primary attention on finding associations between mating structures and feeding. A large amount of literature exists explaining the existence of grouping as self-organisation consequence [27], for reciprocal altruism [28] or producer–scrounger relationships [29]. Lately, the aims of researchers have been focused on the mechanisms that govern the evolution of grouping and the ecological factors that affect group size and group composition [30]. The general idea of these theories is that groups form and persist because all the members gain genetic advantages. The only exception, in this theory, concerns the sibling grouping which emerges because of reproductive needs. In general, authors of these studies suggest that group living only appears since the combination of group benefits, at some point, enhances the fitness of individuals (who accept the disadvantages of group living) above the fitness of solitary individuals.

The most accepted suggestions on group forming argue that the significant benefits for living in group are : a) more protection from predators, in other words, predation pressure fosters group life [30]; b) improving of feeding chances [31]; c) competing against con-specific groups [32] d) exchanging information [33].

The two most qualified theories are a) and b). First, when individuals aggregate, each of them is less likely to be captured since the probability of the predator to attack one member depends on the group size. All animals are seldom equally at risk and predators can choose according to the vulnerability, inexperience, weakness, etc. However, if the animals, in the group, actively cooperate, they have more chances of discovering the approaching of one predator. In this way, they can become able to transmit this information (predator proximity) by postures, chemical signals, vocalisations or other means, and everybody can eventually take evasive actions at an earlier stage. Second, all these mechanisms also affect, in the same way, the grouping behaviour for feeding needs. Group size can increase positively the number of chances of finding food in a land where it is scarce. More “eyes” that cooperate together in order to find food can discover it earlier. Third, inter-group competition for feeding sites is most intense when food occurs in spatially restricted patches, when such patches are rare, and when travel costs between patches are high. Some measurements have been made about the correlation between high rates of aggression and scarcity of resources. Fourth, the elective group size concept requires animals to be close enough for continuous information exchange between them. Elective group size concept regards to the fact that each individual is surrounded by an imaginary circle whose radius represents the maximum distance at which effective communication between individuals is possible. A circle is used because it is assumed that communication is purely a function of distance, which should be equally possible in all directions. Group size is given by the number of overlapping circles that are interconnected (see Figure 1.1).

Grouping could create some disadvantages : a) The cohesion between group members, constantly living in close proximity, should increase the dispersion of forces due to the consequent and unavoidable increase in the levels of intra-group competition. When individuals have different skills and motivations, the need, to move together in groups, compromises their ability to cohesion.

Subjects with different ages, sex and reproductive status may have different locomotive and nutritional needs, this requires different ways of foraging and strategies for defense from predators (lactating females); b) to move in groups, some members (not all) must choose the same direction for all and must coordinate their movements. This is a negotiation problem, often not easy to solve [34]. Other possible detriments, caused by grouping, are the increased likelihood of disease and parasite transmission, increased conspicuousness, etc.

Group life requires associations between individuals, which potentially can lead to interactions. Interactions have costs and benefits to each member.

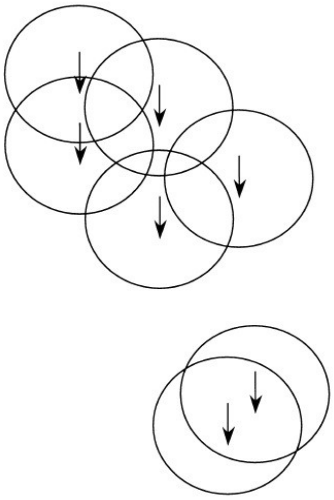


Figure 1.1: Elective Group Size concept.

It has been introduced a classification of social organisation : 1) groups of unrelated individuals, 2) groups of uniformly related individuals (not siblings), 3) groups of close and relatively distant individuals (perhaps containing siblings), 4) groups of siblings, 5) groups of genetically identical individuals (clones). Various definitions exist about what “group of individuals” really means. According to one first definition, a group is “any set of organisms, belonging to the same species, that remain together for a period of time interacting with one another to a distinctly greater degree than with other conspecifics” [35]. In another definition, a group is “a social unit of two or more animals living together” [36]. Searching for a perfect definition of grouping can easily produce a sterile list of criteria that are hard to apply and often arbitrary. Because of the great diversity of animal grouping behaviours, it seems difficult to find a definition that can be applied rigidly to all cases.

In a group of baboons, individuals forage together for the majority of the time, sleep in close proximity, exhibit and maintain friendly relationships within the group. Colonially nesting birds display aggregations of thousands of animals within a small area forming a compact mass, against the predators. It is possible to say that they are social animals. On the other hand, the orangutans of Borneo and Sumatra, forage separately, sleep alone, seldom live with the opposite sex mates, and mating process lasts no more than seven hours. Orangutans could be called solitary. Other species such as sloths, may also live together only for brief periods of mating, leading independent lives the rest of the time. Therefore, even in solitary species a period of parental care, association and interaction may be necessary. Unanimously, a degree of proximity in time and space seems to be an essential prerequisite for grouping. Anyway, the inter-individual distance between group members looks like a function of the trade-off between the costs and benefits associated with group-living. These costs and benefits have been extensively discussed in hundreds of studies [37,38] and it is not easy, even in this case, to comprehend what exactly they are and classify them. Indeed, costs and benefits depend on the differences between group formation (when and where individuals form a group), group size (when and where group of different sizes are created), group composition (which individuals aggregate), and the persistence of the group through the time.

As the result of the group formation, a social behaviour may evolve within groups for three reasons: First, sociality empowers the original advantage of group living. For example, predator attacks could be contrasted by social behaviour like the tightening of a flock, or by alarm shouts, by the clustering of females and juveniles near the large males, etc. Second, social behaviour may evolve because it can reduce disadvantages and detriments of grouping. For example, grouping could decrease the likelihood of disease and parasite transmission. Third, and most important, social behaviour can reduce the effects of intra-group competition. For instance, the dominant (or leader) individual gains some privileges if he has used his superior strength, agility or cleverness to maintain individuals grouped closely around him. The subordinate members also gains since the dominant is usually informed about the surrounding environment, and so they can stay alive by remaining in the group.

1.1 The Primatology

The first studies on wild primates were performed in the 1930s and 1940s, when on the basis of captive baboons and other species these studies proved that sexual instincts provide the social glue that lead to the cohesiveness of primate groups [39]. Ten years later, other researchers, analyzing the behaviour of howlers monkeys and orangutans, rejected the previous thesis, pointing out that the primate groups can remain stable even in species in which sexual activity is infrequent and limited [40]. Indeed, as we said, there are theories suggesting that the main selective forces for the evolution of group living primates are: predation pressure, feeding advantages, competition and exchange of information. However, none of these theories has been rigorously tested. Anyway, many efforts to identify the critical factors needed in the evolution of primate groups start with an original classification that focuses on the question of group size.

Primate social groups can be classified into three major types: a) monogamous pairs, b) single-male polygynous units and c) multi-male polygynous units [41, 42,43].

The issue of the group size is critical, since it seems that group size is correlated in some way with environmental resources and social behaviour. In fact, all the efforts to identify the critical factors in the evolution of primate societies has centered on implicitly and explicitly on the question of group size [44].

All large groups of primates are multi-male, and, in such concentrations of numerous females, the males have apparently evolved to maximize matings, accepting a low confidence of paternity and showing less parental care than in other social groups. Intermediate-sized and small groups correlate with the presence of single-male harems and, when such harems remain in close proximity to one another, with herding of females by males [45].

With regard to resources, a study on spider monkeys has shown that the size of groups is conditioned by the distribution, density and size of the patches of food spread in the environment where primates live and interact [46]. In particular, two simple general model have been expressed to illustrate two different situation of groups dependent on the distribution of food within the environment. First, uniform distribution, when food patches are uniformly distributed, this means that food is rare and small groups are favored. In that case, travel costs are high, and groups, in order to minimize costs, try to feed in a small patch for a long period of time and patches are depleted slowly (see Figure 1.2a). Second, clumped distribution, when food patches are massed in small areas, the average distance to the next patch is small and travel costs are consequently low. At such times, members form a large group and any costs can be easily recovered (see Figure 1.2b).

Some authors have suggested that an increase in group size determines an increase of the area that must be traveled to find food. Thus, group members travel and spend more energy, if they are in a large group respect to members

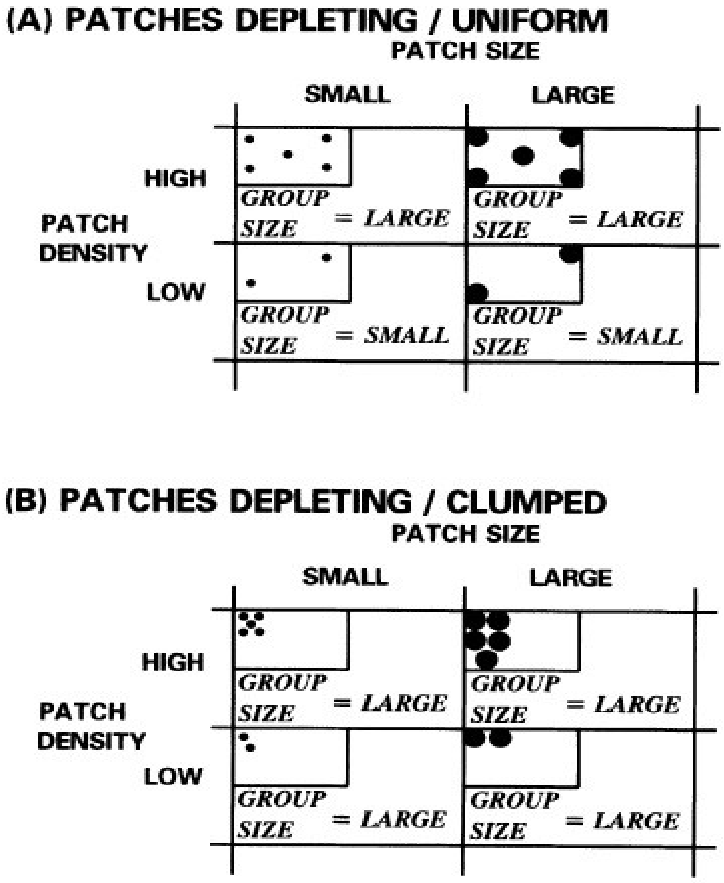


Figure 1.2: Dependency between group size and distribution, density and size of food, in spider monkeys. The predicted group size is indicated in the box.

of small groups [9]. Surely, travel costs are correlated with the distribution, density and size of patches available in the environment.

Some academics have proposed that the optimal group size for any primate species derives from a balance between the aggregation for safety from predators and grouping for access to high quality feeding sites [47].

On average, group sizes of any species are, in general, smaller than that which maximizes predator protection and larger than that which maximizes individual feeding success [48].

As pointed out earlier, ecology may affect social structure indirectly through its effect on group size. On the other hand, the majority of the variations in primate mating systems is directly related to differences in group size. Very often, an increasing group size is associated with a transition from solitary living to monogamy [49], to uni-male polygyny, and finally to multi-male polygyny [50]. However, recently, the relevance of ecology to primate mating systems has been supported by a lot of researchers [51,52,53].

1.2 Social living for cooperating

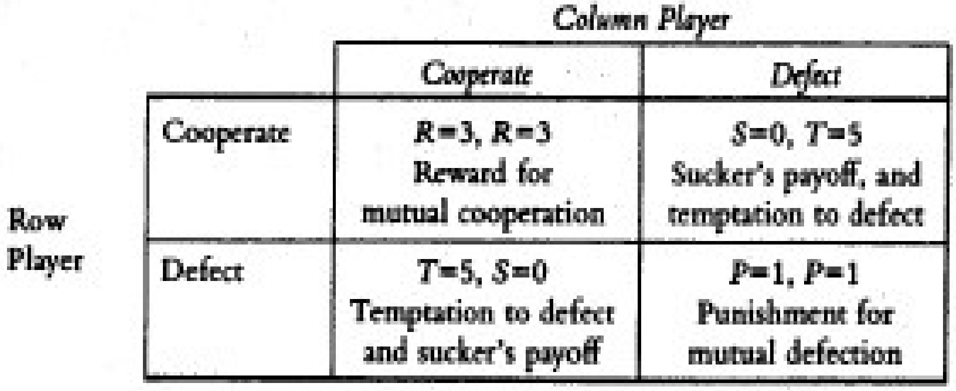
As we indicated earlier, the advantages of living in groups are generally related to the cooperation needs. But some important questions unavoidably raise: when should an individual cooperate? And when should an individual be selfish? Under what conditions, cooperation emerge in a world of egoists without central authority? Generally, it is difficult for each of us to find answers to these questions, due to the fact that the problem involves how individuals act in social, political and economic interactions with others. We have seen that in the primate kingdom, cooperation between group members, arises for protection from predators or for feeding needs.

Theoretically, in nature, the evolution of social living occurs when there is a contrast between conflict and cooperation [54]. For example, replicating molecules compete with their neighbors for resources. Moreover, every gene, every cell and every organism seem to be designed to promote its own evolutionary success at the expense of its competitors. On the other hand, every cell of multi-cellular organisms cooperate to hold in check some areas and do not cause cancer. Ants of many species sacrifice their fertility to take care of the queen ant and colony. Lionesses, belonging to a pride, may nurse cubs of another pride. Finally, human beings help each other reciprocally, to find food, attracting a mate or for the territory defense. Even though, individuals helping one another, do not necessarily risk their life, they could forgo some of their reproductive potentials to benefit the other. Humans are the champions of cooperation, it appears as the decisive organising principle of human society. However, for decades, cooperation has represented a great headache for biologists, as it is very hard to attempt to insert cooperation in an evolutionary perspective. Charles Darwin called this competition “an hard fight for surviving”, since only the fittest organisms will prevail: “survival of the fittest” is a famous phrase originating in evolutionary theory. In fact, natural selection implies competition, because evolution is based on a cruel and unscrupulous competition between individuals, the best reproduce more than the others and can spread in next generations. Thence, evolution should theoretically foster selfish behaviour. In other words, according to the Darwin theory, nobody should help contenders, and every single individual is justified if he tells lies and cons for a living. In the game of life the most important thing should only be the victory. As a matter of fact, an English philosopher, Thomas Hobbes has argued that, before governments existed, the world was dominated by selfish individuals who competed on ruthless terms, that life was “solitary, poor, nasty, brutish and short”. In his opinion, cooperation could not emerge without a central authority, such as a government. Nevertheless, the majority of today’s institutions and nations cooperate without a central authority. Then, why is there such a widespread selfless and cooperative behaviour everywhere? Last years, a new discipline has been involved in analyzing the paradox of cooperation and it is called “Game Theory” [55,56]. The modern Game theory is the study of mathematical models of conflict and cooperation between “decision makers”, that is the study of those situations in which two or more subjects interact with each other, and decisions of one individual may affect results of the rival by means of a retroaction mechanism. These decisions are finalized to maximize the payoff of an acting subject. Lately, some specialists of game theory, have indicated that, cooperation and competition work together for the evolution of living beings, rather than to be in contrast with each other [57]. No other life form on earth is engaged in the same complex games of cooperation and detection, like human life is. Some cooperation theories affirm that individuals that pursue self-interests by cooperating are not forced necessarily by a central authority.

A good example of the fundamental problem of cooperation, in the human world, is the case in which two nations have created trade barriers to each other's exports. Since there could be obvious advantages for both nations in free trade, these barriers should be removed in every circumstance. Although, if either country were to unilaterally eliminate its barriers, it would find that is is facing terms of trade that damage its internal economy. As a matter of fact, in any case, each country is better off by saving trade barriers. However, keeping barriers, could lead to a worse outcome than would have been possible if countries had cooperated with each other.

Clearly, regarding the cooperation, problems occur when the pursuit of self-interests leads to a poor payoff for all. To better understand the different situations that may happen in cooperation issues, a representation has been invented, called "Prisoner's Dilemma game" (see Figure 1.3). In this game there are two players, each one having two choices, namely cooperate or defect. Each player must choose without knowing the actions of the other player. One player can choose a row, either cooperating or defecting while the other player chooses a column, at the same time. If both players cooperate, both gain generous payoffs R=3 that are the reward for mutual cooperation. If one player cooperates and the other defects, the cooperator will get 5 points, whereas the defector will get 0 points. In the end, if both defect, they obtain 1 point, namely the punishment for mutual defection. So if both defect, both do worse than if both had cooperated. The Prisoner's Dilemma is an abstract formulation of common situations in which what is best for each person individually leads inevitably to mutual defection, whereas everyone would be better off with mutual cooperation.

It is denominated Prisoner's dilemma because, if we imagine that the two players are two prisoners and they must be judged by a public prosecutor, they have to decide, whether to cooperate or not. If one prisoner "blabs" while the other one collaborates, the cooperative one will be put in prison for 1 year, while the defector will be subjected to 4 years of prison. If both cooperate with each other they will be punished only with 2 years of imprisonment, whereas if each accuse the other one, both will get to prison for three years. Faced with the dilemma, it seems that the players (if they play once) will fall unavoidably



		Column Player	
		Cooperate	Defect
Row Player	Cooperate	$R=3$, $R=3$ Reward for mutual cooperation	$S=0$, $T=5$ Sucker's payoff, and temptation to defect
	Defect	$T=5$, $S=0$ Temptation to defect and sucker's payoff	$P=1$, $P=1$ Punishment for mutual defection

Figure 1.3: Prisoner’s Dilemma.

in the worse situation where they get less than if they had cooperated.

However, this is not true, if the players interact in the dilemma game an indefinite number of times. It is possible to prove that after some number of interactions, cooperation can emerge in an iterated Prisoner’s Dilemma. Some simulations have been implemented in order to understand the alternation of the evolutionary cycles of cooperation and defection [58]. The experiments begin from a randomly distributed population of individuals who are always cooperative or always defectors. After each game, winners generate a mutated offspring who take part to the next game. Each generation consists of a single game. After a few generations, it is possible to observe that all the individuals defect in every game. If suddenly a new strategy is created: players begin to cooperate and imitate movements of their opponents. This stage leads inevitably to communities of cooperators. This mechanism of cooperation is called “direct reciprocity”. One example of direct reciprocity is displayed in groups of vampire bats. In these colonies, whenever a bat has an empty stomach it calls to a bat that is full for help. Perhaps the full bat could share its food with the unlucky bat, by regurgitating a portion of its precedent meal. Some studies show that bats remember which companions helped them in times of need. When the day comes, in which a generous bat needs food, it will be likely to be helped by the bat which will return the favor. These kind of simulations can demonstrate the emergence of other types of direct reciprocity, as the possibility that cooperative players can help, not only other cooperative players, but also defectors for short periods of time. In addition to the direct reciprocity, another four mechanisms of cooperation may arise, but they will be discussed in the next paragraphs.

1.3 Bio-robotics

Recently, they have been developed a whole variety of bio-inspired robots which are able to operate autonomously in a physical environment. The field which deals with these kinds of bio-inspired robots is called Bio-robotics and it aims to produce robots with lots of features that could be commonly identified with natural organisms.

There are many successful robots which have been built using the principles of this approach. For example, mobile robots have been implemented and evaluated in order to study a hypothesized mechanism of phonotaxis in the crickets [59, 60]. Phonotactic behaviour is concerned with all those processes which enable a female cricket to get orientated towards a particular tone in order to recognize a possible male. The result of the research is a robot that successfully locates a specific sound source under a variety of conditions, with a range of behaviours that resembles the crickets (see Figure 1.4). Experiments has allowed researchers to clarify some hypothesis on real crickets, such as the neural mechanism for phonotaxis in crickets does not involve separate processing for recognition and location of the signal, as is generally supposed.

Sahabot (Sahara Robot) is a prototype of a robot capable of walking in the desert imitating the moving dynamics of Cataglyphis ants, which are a kind of desert ant [61]. In fact, one of the fundamental abilities required in autonomous robots is the homing ability. Desert ants solve the moving problem by integrating paths with a frame of reference. In order to perform this informational integration, ants employ a compass mechanism for determining

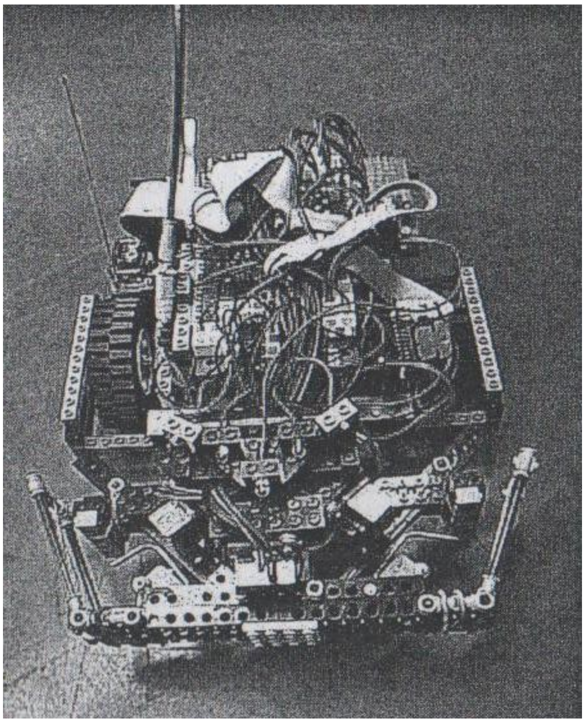


Figure 1.4: Robotic Cricket

direction and the compass precision will have a crucial effect on the precision of homing. For deriving compass information, these insects use the pattern of polarized light in the sky that arises due to the scattering of sunlight in the atmosphere (polarized light compass). The analysis of skylight polarization is mediated by specialized photoreceptors and neurons in the visual system. Thus, by inspiriting to the ants' polarized light compass, sahabot is equipped with a polarization compass which extracts compass information from the polarization pattern of the sky. The robot has been successfully tested in navigation tasks in one of the natural habitats of the desert ants in North Africa.

Some simulated robotic insects have been created in order to study the way a few insects walk[62]. In those simulations, they have introduced some exemplifications: for instance, insect legs are sticks with no mass and no joints. Moreover, these simulated robotic insects are called "esapods" since they are equipped with six legs, and each of them is able to get up or down. In this way, legs moving display two stages: a) a first stage, where a leg is down and supports the body of the robot; b) a second stage, where a leg is up, and any movement of the leg generates a move of the center of mass of the robot's body, and this consequently causes a move forward of all the trunk of the robot. Each leg is controlled by effectors, that is a subsystem needed to raise the leg up and down, and two effectors which control joint twisting forward and backward. After any robot change of position, body keeps placed on only three legs (see Figure 1.5a)., and its centre of mass "falls into" the triangle depicted by the three current front feet. Esapod robots researchers have been, for long time, looking at an artificial evolutionary process which suits the insect robots walk, and at the end they used a specific genetic algorithm for the evolution of the agent's control neural network (see Figure 1.5b). Each leg is controlled by a recurrent neural network provided with a proprioceptive sensor which measures the current angle of one of the joints. Insect robots have been evolved to be capable to walk in a natural way that is similar to that of the biological insects they aspire to.

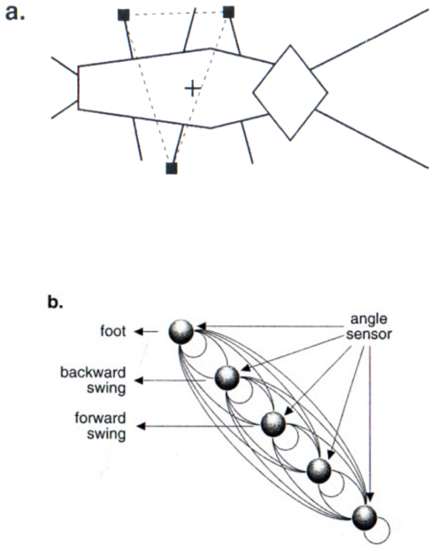


Figure 1.5: (a) Body and legs of the esapod robot. (b) Neural controller for each leg.

Another interesting example of bio-inspired robotics is a simulation of robotic fish which learn to swim under the water autonomously [63]. Researchers have developed an animation that can achieve the intricacy of motion typical of natural ecosystems, by means of advanced Computer Graphics techniques, such as "non-uniform B-spline curves" (see Figure 1.6). In order to achieve a naturalness of robots movements, they have been simulating all the interactions between agent and environment and fluid dynamics. The approach is to model each animal holistically as an autonomous agent situated in a physical world. After a short time of learning, the movements of these fish are surprisingly realistic. As in nature, the motions of artificial fishes in their virtual habitat are not predictable because they are not programmed. Some general behavioural patterns have been investigated such as: training, courting, mating, escaping and predator-prey interactions.

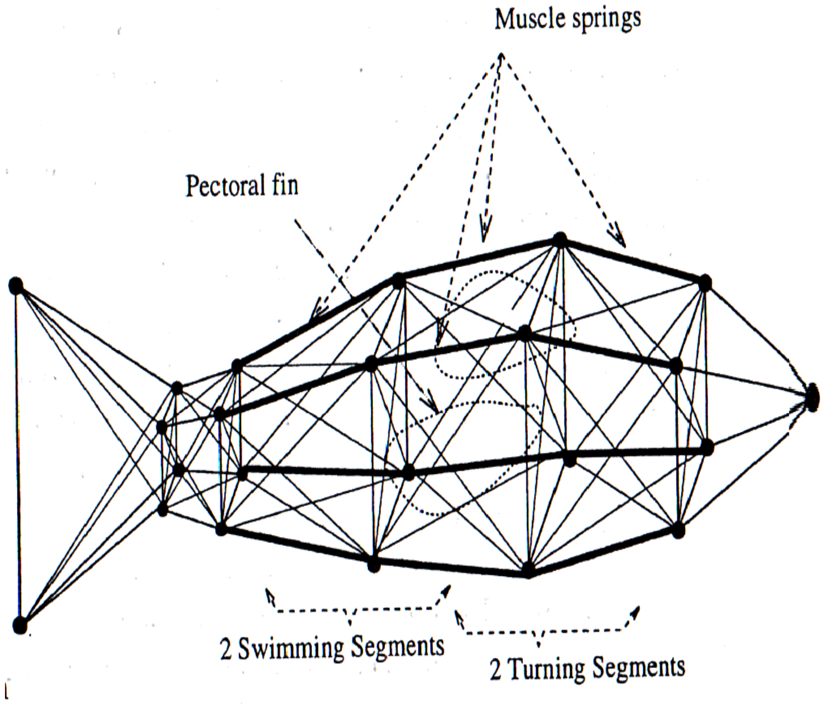
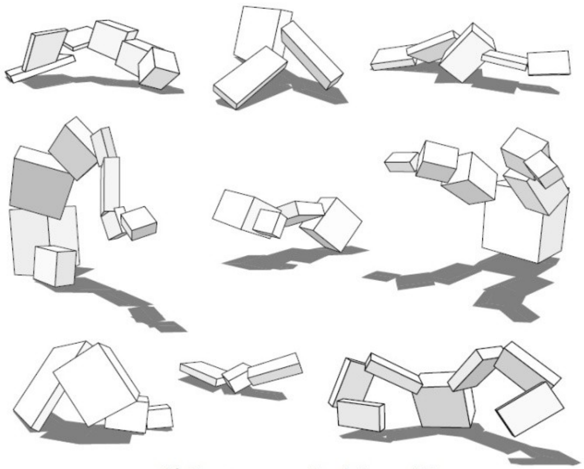


Figure 1.6: Artificial Fish diagram

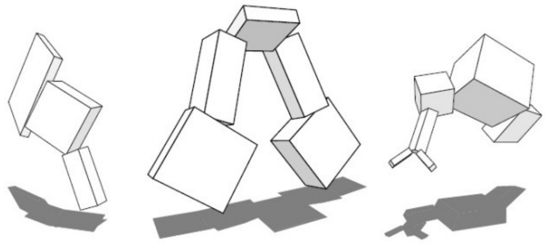
Lastly, another intriguing work on more abstract bio-inspired creatures has been developed by some researchers in order to build more realistic entities [64]. Frequently, the problem with these simulations is the complexity of the world that needs hard algorithms to control the dynamics of behaviour and morphology evolution. In this approach, researchers have adopted genetic algorithms which permit virtual entities to be created without requiring an understanding of the procedures or parameters used to generate them. The three-dimensional bodies of a creature can adapt to its control system, and vice versa, as they evolve together. The "nervous systems" of creatures are also completely determined by the genetic algorithm: the number of internal nodes, the connectivity, and the type of function related to each neural node are included in the genetic description of each creature, and can grow in complexity as an evolution proceeds. A genetic language is presented that uses nodes and connections as its primitive elements to represent directed graphs, which are used to describe both the morphology and the neural circuitry of these creatures. In this way, the genetic language is enabled to define an unlimited number of possible creatures with different behaviours and shapes.

In this work, the phenotype embodiment of a virtual creature is made of three-dimensional rigid parts represented by a directed graph of nodes and connections. These evolutionary creatures are evolved for behaviours like jumping, walking or swimming, that means in the case of jumping, for example, individuals are selected by measuring the maximum height above the ground of the lowest part of the creature, and so on. At the end of evolution a variety of successful and interesting locomotion strategies emerge, some of them are far from the strategies observable in nature, and many of them would be difficult to invent or build by design (see Figure 1.7).

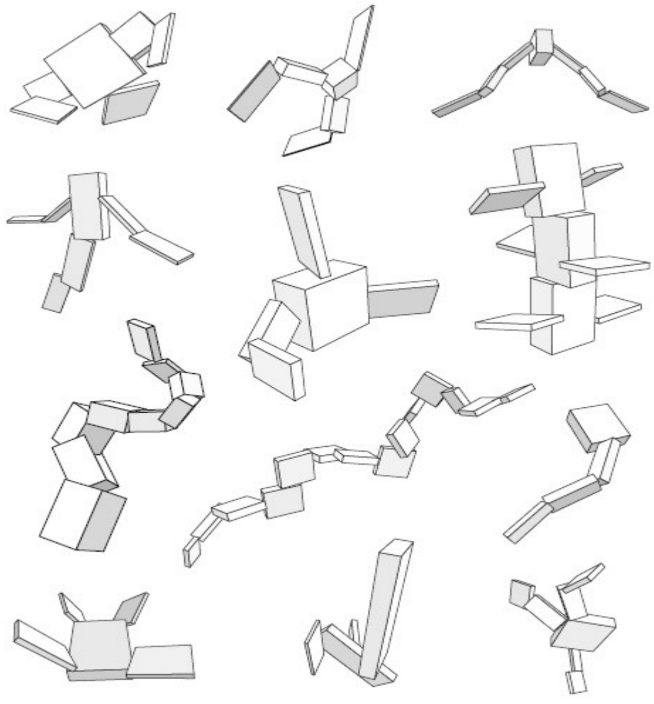
In another work, the same researchers, have investigated the evolution and co-evolution of virtual creatures that compete in the physically simulated three-dimensional worlds, as they have to contend to gain control of a common resource, such as a food-cube [65]. Most of evolutions have been performed using the "all vs. best" competition, including two species where individuals compete with members of the opponent species or a "single-species" where all



A) Creatures evolved for walking.



B) Creatures evolved for jumping.



C) Creatures evolved for swimming.

Figure 1.7: (a) Walking strategies. (b) Jumping strategies. (c) Swimming strategies.

individuals compete and breed with each other. Virtual entities are modeled in the same way as the previous work: gravity, collisions, and friction are simulated to restrict the actions to physically plausible behaviours and the morphology of these creatures and the neural systems are both genetically determined and represented into a directed graphs of nodes and connections.

After many independent evolutions, interesting and diverse strategies and counter-strategies emerge from the simulations (see Figure 1.8). Some evolved species display different skills in reaching cubes, as some needs few generations to reach it and others need many more. In one case, one species was successful quickly, under evolution, so the other species never evolved an effective strategy to compete with it (see Fig 1.8c). In other evolutions, more interactions occurred between the evolving species: a variety of methods for reaching the cube were founded, such as extending arms out onto the cube or crawling like an inch-worm (see Fig 1.8f). Interesting results have occurred when both species discovered method for reaching the cube, almost in the same evolutionary time, this forced a competition to emerge. For example, some creatures pushed their opponent away from the cube (see Fig 1.8e), some moved the cube away from the initial location and followed it subsequently (see Fig 1.8f) or some just kept covering up the cube in order to deny the opponent's access to it (see Fig 1.8g). In some evolutions, two-armed creatures use the strategy of batting the cube to the side with one arm and catching it with the other arm (see Fig 1.8i, 1.8j and 1.8k). Finally, there are cases, where the larger creature wins by a large margin against the opponent because it literally walked away with the cube (see Fig 1.8m). In conclusion, some observations of the authors are that the individuals with an adaptive behaviour could be significantly more rewarded if evolutions were performed with many species instead of few. Moreover, to be successful, a single individual would need to defeat a larger number of different opposing strategies.

However, in these simulations cooperation has not been investigated as well as the increasing chances of survival of adaptive individuals. So they could be examine the cooperation/competition patterns, speciation, mating patterns, and relationship between offspring production and ecological niche.

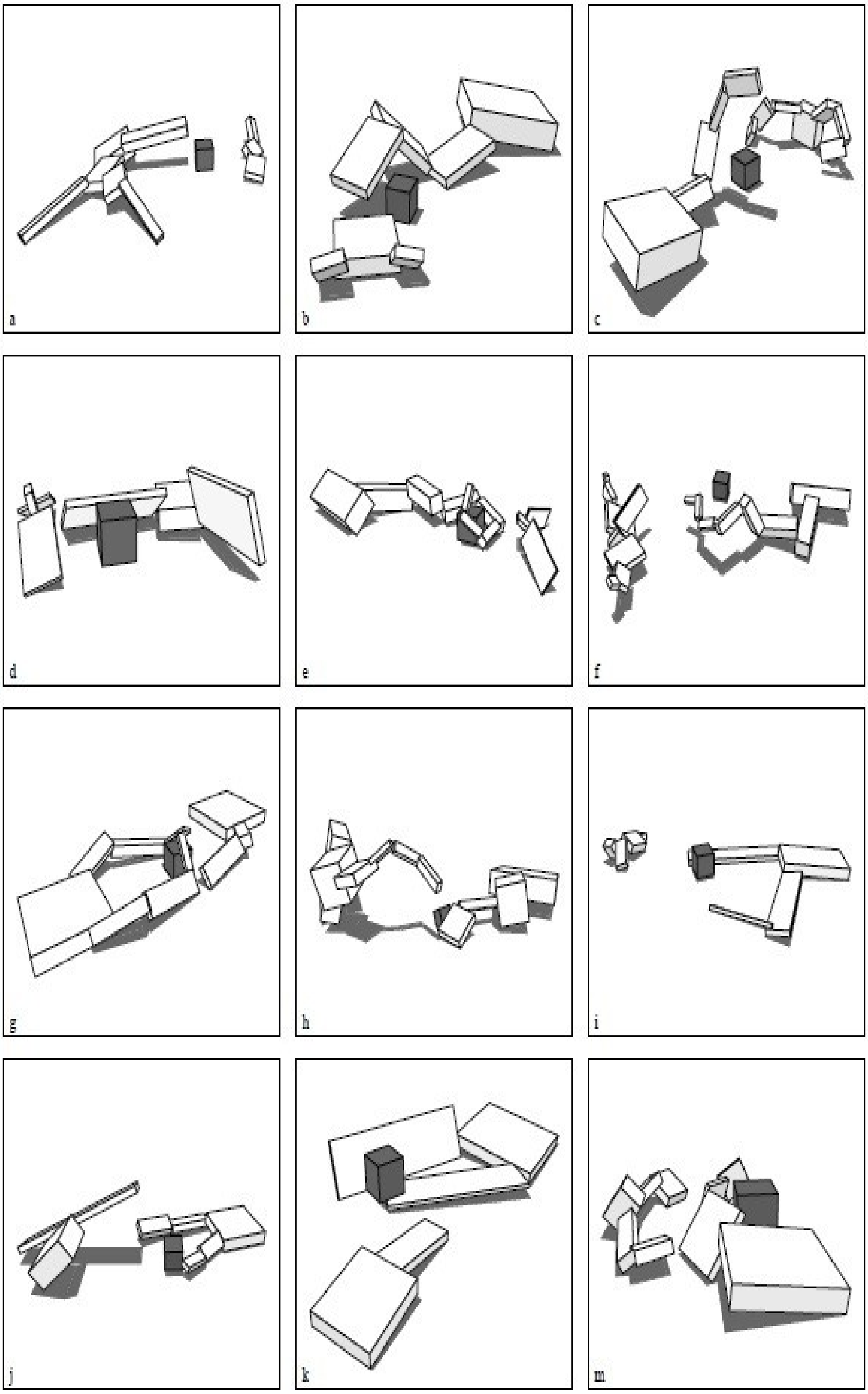


Figure 1.8: All the competition strategies evolved by Virtual Creatures with a common resource.

1.4 Embodied Cognitive Science

The “Embodied” approach in Cognitive Science draws inspiration from ideas and insights which have been originated by studies in the 1980s on the origin of the behaviour and the intelligence in living organisms. The main idea of “Embodied Cognitive Science” is that intelligent behaviour results from dynamic multiple interactions between the system which displays the intelligent behaviour and the environment where the system acts [66,67,68].

For the first time, the notion of embodiment has been introduced in order to characterise all the systems (artificial or natural) provided with a physical body [69, 70, 71]. Therefore, in the opinion of the embodied cognitive science, “embodiment” is a prerequisite of “complete” agents (such as living organisms) which are able to perceive the surrounding environment by means of a sensory system (vision sensors, acoustic sensors, etc…) that lets him derive some regularities in the environment. Another critical that complete agents have to exhibit is the “situatedness”, meaning they are located in a physical environment with which they can interact.

A consequence of embodiment and situatedness is that agents have to be able to display physical characteristics (weight, size and shape), they have to be submitted to physic laws (inertia, gravity, energy consumption) and finally they have to exploit the energetic exchange, material or informational so that they could properly interact with the environment.

Another effect of the situatedness is that agent’s sensors provide an “egocentric” information (that is dependent on the current position and from the orientation of the agent into the environment), a “local” information (that is related only to the portion of the observed environment), an “incomplete” information (for example, because of all the obstacles in the environment which prevent to perceive some features) and, at the end, a noisy information. The same issues are related to the motor system. Physical limits dependent on the embodiment requisite generating constraints for the agents’ movements, but on the other hand, they enable agents to exploit opportunities in order to adapt and find robust and parsimonious solutions for the tasks they have to deal with. So, from the embodiment standpoint, behaviour is the result of the interaction between the nervous system of the agent, the motor-sensory-skeletal system and the environment, and it cannot be dependent only on one of those three elements (see Fig 1.9).

To better understand the insights from embodied cognitive science, a metaphor has been proposed that is called "fungus eaters game" [72]. Fungus eaters are imaginary artificial creatures that have the purpose of collecting rough uranium on a far planet and they feed on a kind of mushrooms which grows up only on that planet. Those artificial organisms, are equipped with a motion system, and intelligence system capable of making decisions and actuators able to gather pieces of uranium. Moreover, fungus eaters have a vision sensor and a sensor able to perceive rough uranium. Since the extra solar planet is too far from earth, fungus eaters cannot be controlled from a remote station, so they have to be autonomous: the only information that these artificial creatures have is that which comes from their sensors. In other words, those creatures have been provided with a body (embodiment) with a means for them to collect rough uranium and, they are autonomous since they cannot count on an external intervention for the battery replacement, for example. Finally they live and work in a specific environment that is the planet surface (situatedness). Therefore, fungus eaters are a clear example of the complete agents theorized by the Embodied Cognitive Science. At the base of Embodied Cognitive Science there is a theorization called "Theory of Autopoiesis" developed to explain behavioural systems of living organisms [73]. According to this theory, an autopoietic organization is a dense network of recurrent interactions, which self-maintain and operate within clear physical confines. An example of an autopoietic system are the cells of living beings, that are characterised by a loop of internal chemical reactions on time step t, which produce the same type of chemical reactions on the instant time t+1. An autopoietic organisation must have two fundamental properties: a) *operational closure*, that means internal processes are independent from the external environment. The environmental

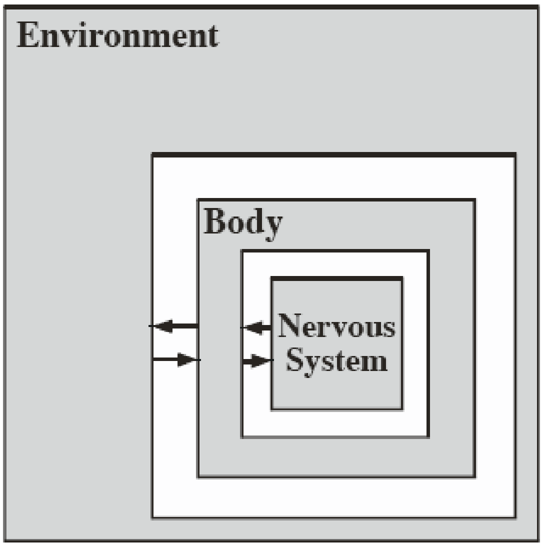


Figure 1.9: Schematisation of the interaction between nervous system, the body and the environment of an embodied and situated agent, in Embodied Cognitive Science.

structure is never reproduced inside the system's structure. For instance, in an organism's cell, the metabolism cannot be modified by all environmental processes; b) s*tructural coupling*, that means external environmental events are not capable of affecting an autopoietic organisation due to the fact the system can initiate a series of balancing actions that reset the initial state and preserve the integrity. In the cell example, it is always able to modify the membrane's permeability so as to counter-balance the dangerous chemical fluctuations that could happen outside in the environment. An autopoietic organisation, in living beings, is the outcome of long-running evolutionary processes which formed over millions of years and which are, in their turn, independent from the evolution itself. Concepts and ideas of autopoieses theory have been recently extended to the nervous system of living organisms, as it is made of local loop processes, which are structurally independent from the external environment (operational closure) and in balanced interaction with it (structural coupling). To better illustrate the autopoietic nature of a nervous system, a comparison has been conceived called “methaphor of the submarine”. According to this methaphor, a nervous system could be likened to the navigator placed inside of a submarine who moves all the control levers and handles all commands by following the indicators state and he does not pay attention to the external situation directly. In the same way, the nervous system modulates some number of parameters which are correlated with the external environment, but without any direct awareness of the external events.

In the Embodied Cognitive Science vision, a simple control architecture of a robot may exhibit complex behaviours. An evident example of that is the study on Braitenberg’s vehicles, where simple robots, equipped with direct sensory-motor connections, display complex behaviours like altruism and aggressiveness which could be seen as intentional [74].

There are 14 vehicles in all, a series of hypothetical, self-operating mobile machines that exhibit increasingly sophisticated behaviour similar to that in the real biological or neuroscientific world.

Braitenberg vehicle number 1, for example, is provided with a single sensor that is perceptive to a specific physical quantity and a motor directly connected to the sensor (see Figure 1.10). The higher the level of the physical quantity read by the input sensor, the faster the motor sweeps will be. If the physical quantity is the temperature, the effect is that vehicle number 1 will move faster in warm areas and slower in cold areas of the environment, by showing

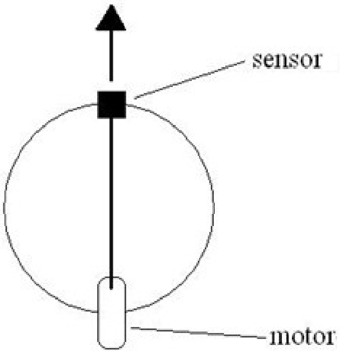


Figure 1.10: Braitenberg vehicle number 1.

apparently and intentionally to move in that way, that is the aim of avoiding areas with high temperature that could damage it. If in the environment some friction is present, the vehicle will deviate his rectilinear trajectory and it will draw a trajectory that for an external observer could be apparently a complex and senseless path.

A variation of the previous vehicle, is the vehicle number 2, that is equipped with two sensors and two motors directly linked to each other according to all the possible patterns of connections (see Figure 1.11). An example is the vehicle which has motors directly connected to light sensors, the right sensor to the right motor and the left sensor to the left motor. The effect of this configuration of links is that, in the presence of a light source that stimulates mainly the right sensor, the right motor is induced to rotate faster than the left motor, generating, in this way, the vehicle approaching to the light. By inverting the connections between sensors and motors, the effect is that the vehicle walks away from the light source. Therefore, the vehicles represent the simplest form of behaviour based on artificial intelligence or embodied cognition, (i.e. intelligent behaviour) that emerges from sensory-motor interaction between the agent and its environment, without any need for an internal memory, representation of the environment, or inference. One might think that Braitenberg's vehicles are like table-top toys but they behave like living creatures that an observing psychologist or philosopher might conclude were controlled by concealed human beings. They come to embody the instincts of

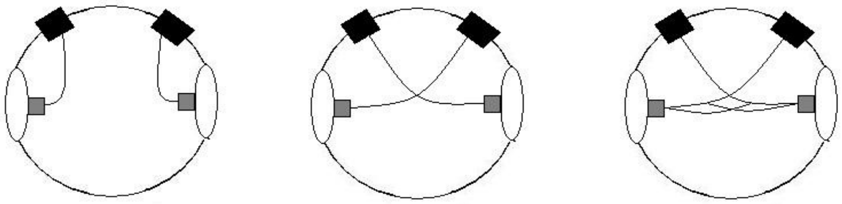


Figure 1.10: Braitenberg’s vehicle number 2.

fight or flight, the characteristic behaviours impelled by love and by logic, manifestations of foresight, concept formation, creative thinking, personality, etc.

1.5 Evolutionary Robotics

In general, robots are the entities closer to the complete agents theorized by Embodied Cognitive Science, as they are embodied (they have a body) and they are situated in an environment. However, autonomy is not present in every type of robot: for example, robotic arms of assembly lines are not autonomous because they could be remote-controlled or they could execute a preset program, without any particular decision-making. Moreover, very often, these robots are “blind”, when they interact with the environment. From this point of view, these robotic arms fully incarnate the concept of robots, which are pre-programmed devices for performing the same task in the time, these are tasks that could be boring and frustrating for a human executor, as well as too hard to do.

On the other hand, autonomous robotics deals with robots able to be free from strict programming and capable for performing multiple tasks, interacting with the environment by means of sensors, changing the behaviour depending on the context and learning from their errors. One of the first successful outcomes, from the autonomous robotics, is the robot Shakey, illustrated in Figure 1.11. This robot has been designed at Stanford Research Institute with the aim of accomplishing simple actions such as finding an object in the house or moving an object from a room to another room [75]. The control system of Shakey is based on a language and a search algorithm by means of the definition of expressions which translate symbolically to all the descriptions of the world. All the reachable solutions by the search algorithm must fulfill some properties like efficacy, completeness and consistency as the robot is not able to solve two

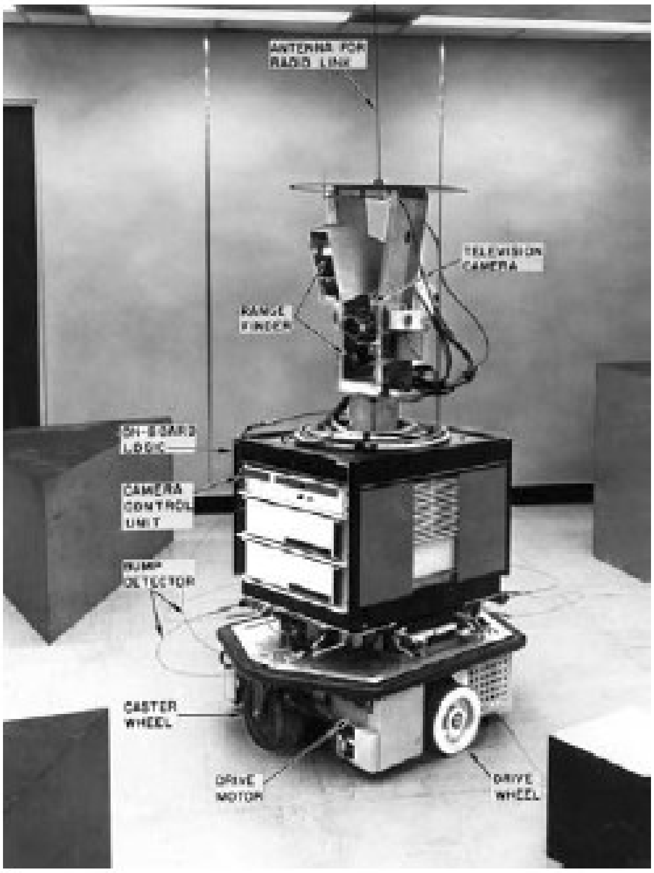


Figure 1.11: Shakey Robot

over the years, dissatisfying results for many reasons. The most important reason is that the planner of the robot's control system is not able to extract information from outside of the body, thus it cannot represent a correct and precise description of the world. In order to solve these and other problems and limitations, a new approach has been proposed and it is known as *"behaviour based robotics"* [76, 77]. This philosophy moves away from classical artificial intelligence and robotics approaches, but it underlines that intelligent systems design cannot disregard the embodiment. This means that an intelligent system must own a body equipped with a sensorial system and a motor system, at least. An intelligent system cannot be abstract and completely dissociated from the surrounding world. Definitely, according to the behaviour-based robotics, an intelligent system must have a world where "to live" and interact with other systems (situatedness). Therefore, in the conceptual elaboration, behaviour-based robotics has many points in common with the "Theory of Autopoiesis" and the Embodied Cognitive Science, in general.

In traditional Artificial Intelligence approaches, such as planning, robot brains are serial processing units as depicted in Figure 1.12a. The Behaviour-Based approach states that intelligence is the result of the interaction among an asynchronous set of behaviours and the environment. Therefore, from this viewpoint, robots brains are not designed by a series of modules that transfer information in a serial mode. Instead, in Behaviour-Based Robotics, robots' system controls are made of modules that define complete behaviours, modules are connected in parallel and have a direct contact with the external environment. This architecture is depicted in Figure 1.12b.

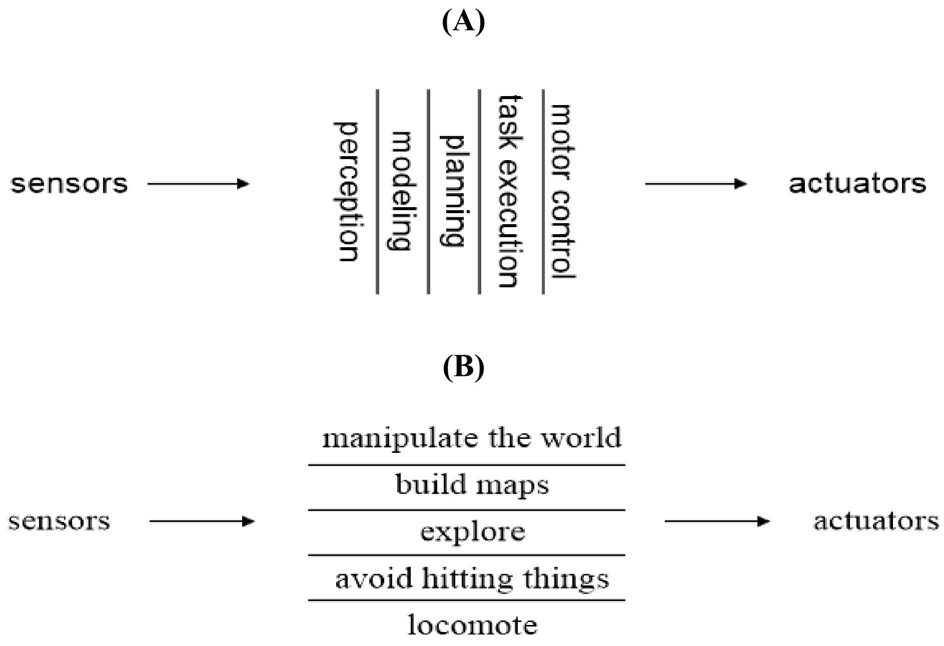


Figure 1.12: Traditional Artificial Intelligence Robots' Control System architecture (A) and Behaviour-Based Robots' Control System architecture (B).

One of the most popular applications in Behaviour-Based Robotics is “The Cog Project” [78] a humanoid robot building project based on physical embodiment, integration of multiple sensory and motor systems, and social interaction. The robot has twenty-one degrees of freedom and a variety of sensory systems, including visual, auditory, vestibular, kinesthetic, and tactile senses. A variety of visual-motor routines have been implemented such as smooth-pursuit tracking, saccades, binocular vergence, and vestibular-ocular and opto-kinetic reflexes, orientation behaviours, motor control techniques, and social behaviours such as pointing to a visual target, recognizing joint attention, etc. The robot is portrayed in Figure 1.13.

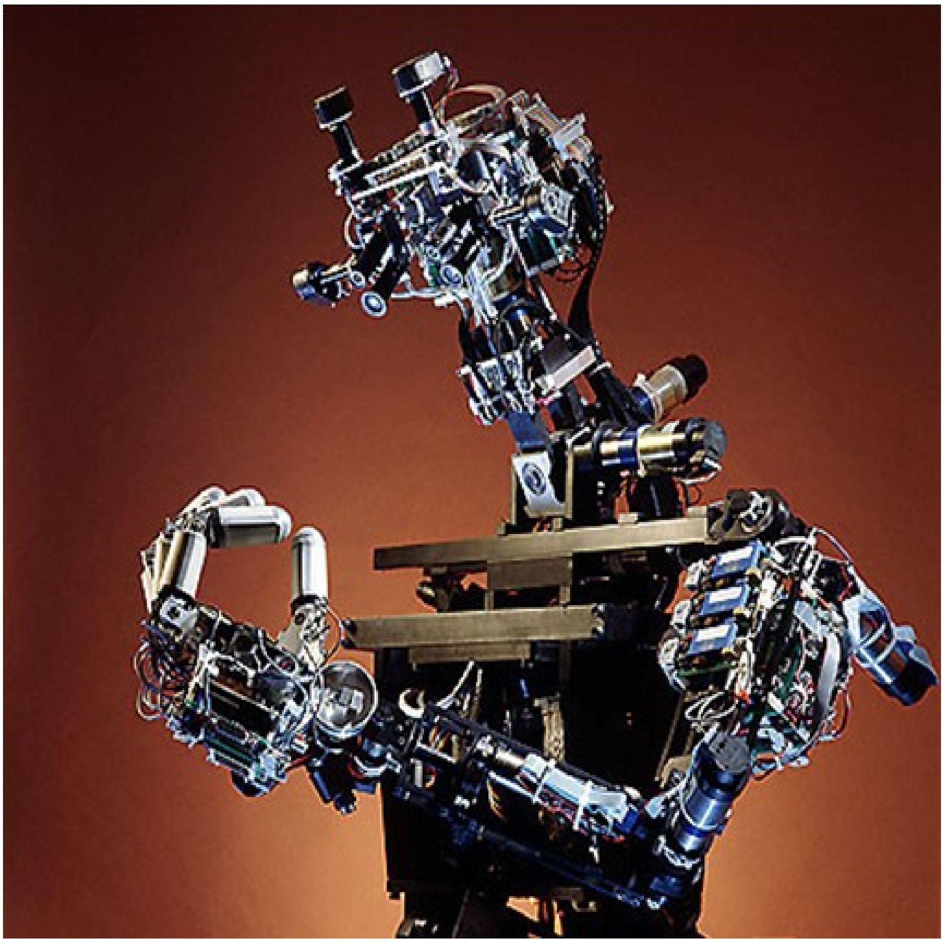


Figure 1.13: Cog Robot

Another interesting robotics approach is *"Developmental Robotics"* [79]. Developmental robotics is an emergent area of research at the intersection of robotics and developmental sciences, such as developmental psychology and developmental neuroscience. The methodology is interdisciplinary and two-pronged: on the one hand, it employs robots to investigate models originating from developmental sciences; on the other hand, it aims to develop better robotic systems by exploiting insights gained from studies on ontogenetic development. The research methodology advocated by developmental robotics is very similar to that supported by epigenetic robotics [80]. The two research endeavors not only share problems and challenges but also are driven by a common vision. One of the most important application of Developmental (and Epigenetic) Robotics is the Icub Project [81]. Icub is a humanoid robot platform, which has been designed to support collaborative research in cognitive development through autonomous exploration and social interaction. This robust humanoid robot that offers rich perceptuo-motor capabilities with many degrees of freedom, a cognitive capacity for learning and development, a software architecture that encourages reuse & easy integration, and a support infrastructure that fosters collaboration and sharing of resources. So far, each iCub is made of approximately 5000 mechanical and electrical parts and it has been delivered to several research labs in Europe and to one in the USA. In Figure 1.14 iCub Robot is portrayed.

All traditional robots' system control designing approaches require a general decomposition of the robotic system in sub-systems which are able to solve a single sub-objective. However, system decomposition does not always guarantee that general systems exactly execute the overall task since there is not always a direct correspondence between distal and proximal agent's behaviour. The proximal level is from the system point of view, whereas a distal level behaviour is from the viewpoint of the observer or the designer. Behaviours that appear complex from a distal point of view can be generated by a control system in a relatively simple way at a proximal level. On the other hand, a

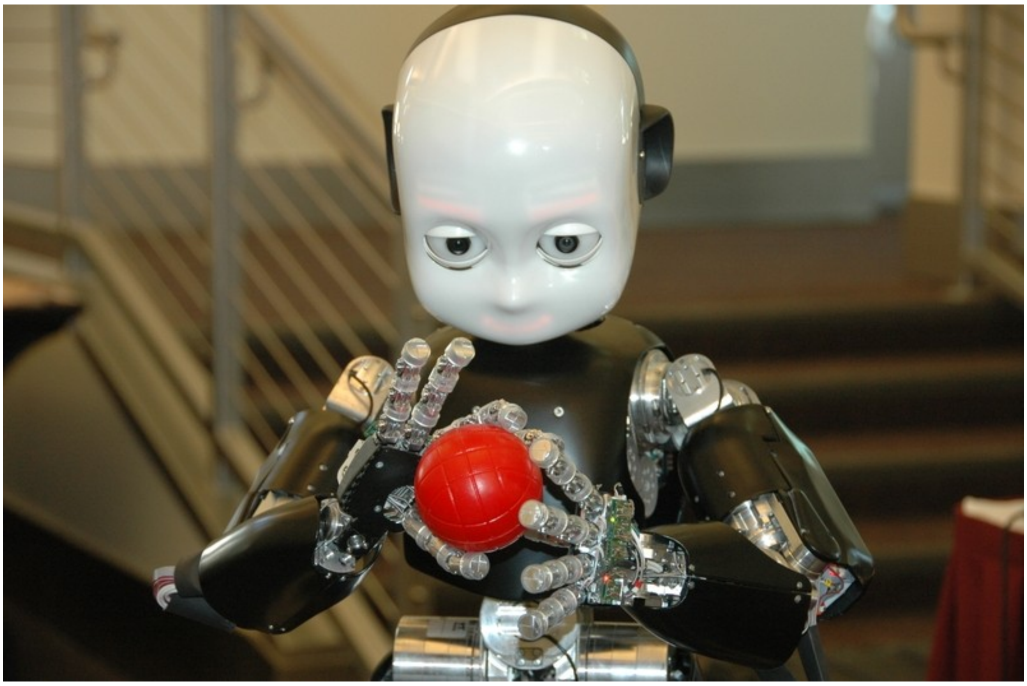


Figure 1.14: iCub Robot

solution seeming simple and effective from a distal point can turn out to be complex

and/ or ineffective from a proximal point of view. A way to overcome previous approaches' problems is the *"Evolutionary Robotics"* [82] where the robotic control system is able to auto-organise by itself without the requirement of a design system decomposition stage. In Evolutionary Robotics, adaptation process (i.e. the development of robot capabilities to solve the task in the environment) is achieved by means of genetic algorithms and neural networks, which are illustrated in Appendixes I and II, in detail.

In the past, a multitude of experimental setups have been performed by Evolutionary Robotics methodology. In one of the first works, authors explain how to evolve neural controllers for a Khepera robot (see Figure 1.15) in computer simulations and then how to transfer the obtained agents in the real environment [83]. In this way it is possible to reach: a) an accurate model of a particular robot-environment dynamics by sampling the real world through the sensors and the actuators of the robot; b) the performance gap between the obtained behaviours in simulated and real environment may be significantly reduced by introducing a "conservative" form of noise; c) if a decrease in performance is observed when the system is transferred in the real environment, successful and robust results can be obtained by continuing the evolutionary process in the real environment for a few generations. In further work, authors describe the evolution of a discrete-time recurrent neural network to control a real mobile robot [84]. The evolutionary procedure is carried out entirely on the physical robot without human intervention. Robots display the autonomous development of a set of behaviours for locating a battery charger and periodically returning to it. The emergent homing behaviour is based on the autonomous development of an internal neural topographic map (which is not pre-designed) that allows the robot to choose the appropriate trajectory as a function of its location and remaining energy. In another experimental setup, authors show how a group of evolved physically-linked robots are able to display a variety of highly coordinated basic behaviours (coordinated motion, coordinated obstacle avoidance, coordinated light approaching) and to integrate such behaviours into a single coherent behaviour [85]. In this way the group is capable of searching and approaching a light target in an environment scattered with obstacles, furrows, and holes and of dynamically changing its shape in order to pass through narrow passages. Coordination of the group relies upon robust self-organising principles based on a traction sensor that allows the single robots to perceive the “average” direction of motion of the rest of the group. A series of works have been performed on the categorisation capabilities in evolutionary robots [86,87,88]. Researchers show a set of experiments in which embodied artificial agents (namely robots) are evolved for the ability to accomplish simple tasks. In particular they focus on how categories might emerge from the dynamical interaction between the agent and its environment and on the relation between categories and behaviour [89]. Finally, theauthors introduce and discuss the notion of action-mediated categories, that is the notion of internal states that provide indirect and implicit information about the external environment

Figure 1.15: Khepera Robot

and/or the agent/ environment relation by exploiting the effects resulting from a stereotypic way of interacting with the environment. In a further experimental setup, the author investigates how embodied and situated agents perform tasks that require skills of categorisation [90]. The task is to categorise different shapes of objects using sensory-motor and linguistic input. Results show that the autonomous agents are able to solve the categorisation task by integrating the sensory-motor experienced states and employing “linguistic” input from the environment. This shows that autonomous agents are able to develop some "emerging" abilities by exploiting the information present in the environment in order to recognize and discriminate objects. Autonomous agents also exhibit a "social" behaviour, because they are able to categorize the objects in the environment, even when external inputs are unavailable. The purpose of this work is to prove the theoretical hypothesis that the “social” information (external labels), deriving from another agent or from the trainer, facilitates individual capacity to categorize, by the creation of internal representations. In other works, the authors investigate the emergence of communication in embodied agents or robots. In particular, in one study, researchers present the results of an experiment in which a collection of simulated robots, that have been evolved for the ability to solve a collective navigation problem, develop a communication system that allows them to co-operate better [91,92]. The analysis of the results indicates how evolving robots develop a non-trivial communication system and exploit different communication modalities. The results also indicate how the possibility of co-adapting the robots' individual and social/communicative behaviour plays a key role in the development of progressively more complex and effective individuals. In a further work, the authors examine an artificial vision system that is trained with a genetic algorithm for categorizing five different kinds of images (letters) of different sizes [93]. The system, which has a limited field of view, can move its eye so as to visually explore the images. The analysis of the system at the end of the training process indicates that correct categorisation is achieved by (1) exploiting sensory-motor coordination so as to experience stimuli that facilitate discrimination, and (2) integrating perceptual and/or motor information over time through a process of accumulation of partially conflicting evidence. Finally other authors have examined a few preliminary results on the emergence of leadership/followership patterns in a group of autonomous robots [94].

1.6 A neuro-robotic model for the social living

In the general introduction to the present work we have wondered whether social living is only a mating issue or if there are reasons behind living together. In particular, the questions we have asked are: What are the adaptive advantages of the social living, beyond the reproductive needs or caring about the neighbors? In other words, why animals exhibit different degrees and types of sociality?

However, there are many disadvantages of social living: resource sharing, competition, lack or personal security, social disapprovals, fighting, etc. Moreover there seem to be more disadvantages than advantages, as reported in literature. Therefore, beyond mating needs, individuals should prefer to live alone or in small groups instead of living together in very complex societies such as communities, cities or nations.

Obviously, the present work of course is not intended to explain all the reasons and mechanisms related to the biological beings' social living, this would be a difficult and complex challenge.

However, the simulative model, illustrated below, might be a first attempt to identify what could be the factors that lead to an increase of survival chances in social living organisms in comparison to the solitary ones.

1.6.1 Experimental Setup

A population of robots lives in a 550cm x 550cm squared area containing some food resources located in a corner without any motion (food zone). The food zone consists of a 110cm diameter. The environment is surrounded by walls. When a robot bumps against the environment's wall or against another robot, it bounces back in the neighborhood of the contact point, with a new random direction. Each robot is made of a circular chassis with a diameter of 5.5cm and it is equipped with two motors controlling the movements of two wheels. The robot simulated for this experimental setup is a Khepera-like robot. The Khepera is a small (5.5cm) differential wheeled mobile robot that was developed at the LAMI laboratory of EPFL (Lausanne, Switzerland) in the mid '90s [95].

In the simulation, robots are physically unfathomable but the food zone is navigable. Each robot is equipped with a smell system to detect the relative position of the closest robot. The smell system's perception distance is limited. According to the relative position of the closest robot with respect to a fixed

sector of the perceiving robot, smell sensors will be activated with a two digits binary code. Each robot is characterised by a green color of the body but they cannot perceive the color of the population mates. The robots' smell system code is depicted in Figure 1.12. Moreover, each robot has an additional smell system by separate sensors which perceives the relative food zone position. This food zone smell system is characterised by an unlimited perception distance too, that is it covers all the environment. The codification system of food zone smell system works in the same manner of the robots smell system.
Finally, the sensory system is made of a ground sensor to detect when the robot is placed on the food zone.

The control system (Figure 1.13) of each robot consists of a feed-forward neural network with 5 input neurons and 2 output neurons. So they are perceptrons. Each layer of neurons is connected to the next layer with a pattern of synaptic weights representing the strength of the connection. The input layer contains 15 neurons encoding the activation state of the corresponding photoreceptors RGB components, 2 neurons that receive smell signals and 1 neuron that receives output from ground sensor. The output layer is made of 2 neurons which control the speed of two motors, respectively.

They have been made for different experiments with this experimental setup, by modifying some parameters which have been considered "critical" for the

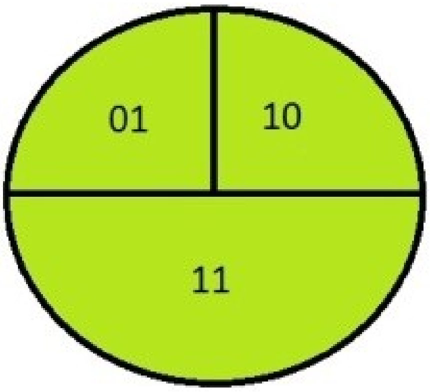


Figure 1.12: Representation of the codification of smell inputs.

sociality working. These critical parameters are: population size *(sub-experimental setup no.1)*, perception distance of robots *(sub-experimental setup no.2)* and number of races within one single population *(sub-experimental setup no.3)*. In this way it should be possible to understand how a variation in social living possibilities could affect performance of living (in terms of energy levels and assimilated food during the life) and so the survival likelihood.

Sub-experimental setup no.1

In the sub-experiment no.1, named *"baseline"* (since it will be used as basis for comparison for the further experiments), they have compared two robots populations: a) a population of robots who live alone in the environment; b) a population of robots who live socially in the environment, that is 100 individuals who act in the same time and in the same environments. The environment with robots is illustrated in Figure 1.13, for this first sub-experimental setup no.1. In both conditions, we have compared a sub-condition where the food zone smell system is enabled, with a condition where the food zone smell system has been disabled but has the ground sensor on instead.
In other words, robots have not been able to perceive the orientation of the food zone until they are on top of it. All the conditions are:

1. "Solitary" Evolution, food zone smell system off
2. "Social" Evolution, food zone smell system off
3. "Solitary" Evolution, food zone smell system on
4. "Social" Evolution, food zone smell system on

Basically, in the first condition a) individuals have been left to evolve in the environment according to the most traditional genetic algorithm version. That means each of 100 individuals of the population (reminding each individual is a candidate neural network for controlling the final robots) is singularly inserted into the environment. Then individual is allowed to "live" within the environment (by freely interacting with it) and its fitness is evaluated at the end. Finally, a ranking is performed on the whole population in order to select the best individuals and it is possible to produce a new generation's population starting from the best. Instead, in the second condition b) the whole population of 100 individuals is inserted into the environment. All the population's individuals live and interact with each other within the environment, in the same time. At the end the ranking is performed on the entire population. In both cases a) and b) the control system of each robot is a perceptron whose weights and biases are selected by the genetic algorithm throughout the evolutionary phase. The life time of each individual is set to 10000 cycles whereas the number of generations for each replication is set to 200. I need to underline that replication is a synonym of seed because seed is related to the random generator that in each replication produces different initial sequences of pseudo-random numbers (for genotypes, random positions, etc.). The sequence depends on the seed that is different in each replication. That is why I will refer to seed as a synonym of replication hereafter.

Mutation rate is 2%. Robots have been evolved for 20 replications which differ for the seed of random numbers generator of initial individuals' genotypes. Results are described in the specific section below.

Sub-experimental setup no.2

In this second sub-experiment we try to understand how physical encumbrance vary with the increase of the population size. So, 4 conditions have been compared by changing the number of population elements: 25, 50, 100 and 200 individuals. Robots have been evolved according to the same methodology already adopted in the sub-experiment no.1. All the parameters have been unchanged. The number of replications is 20 as well. Only the amount of population's members vary. The sub-experiment has been evolved in two stimulation conditions: in the first robots are not able to sniff the food zone at any distance (fz smell system disabled) and in the second they can sniff the

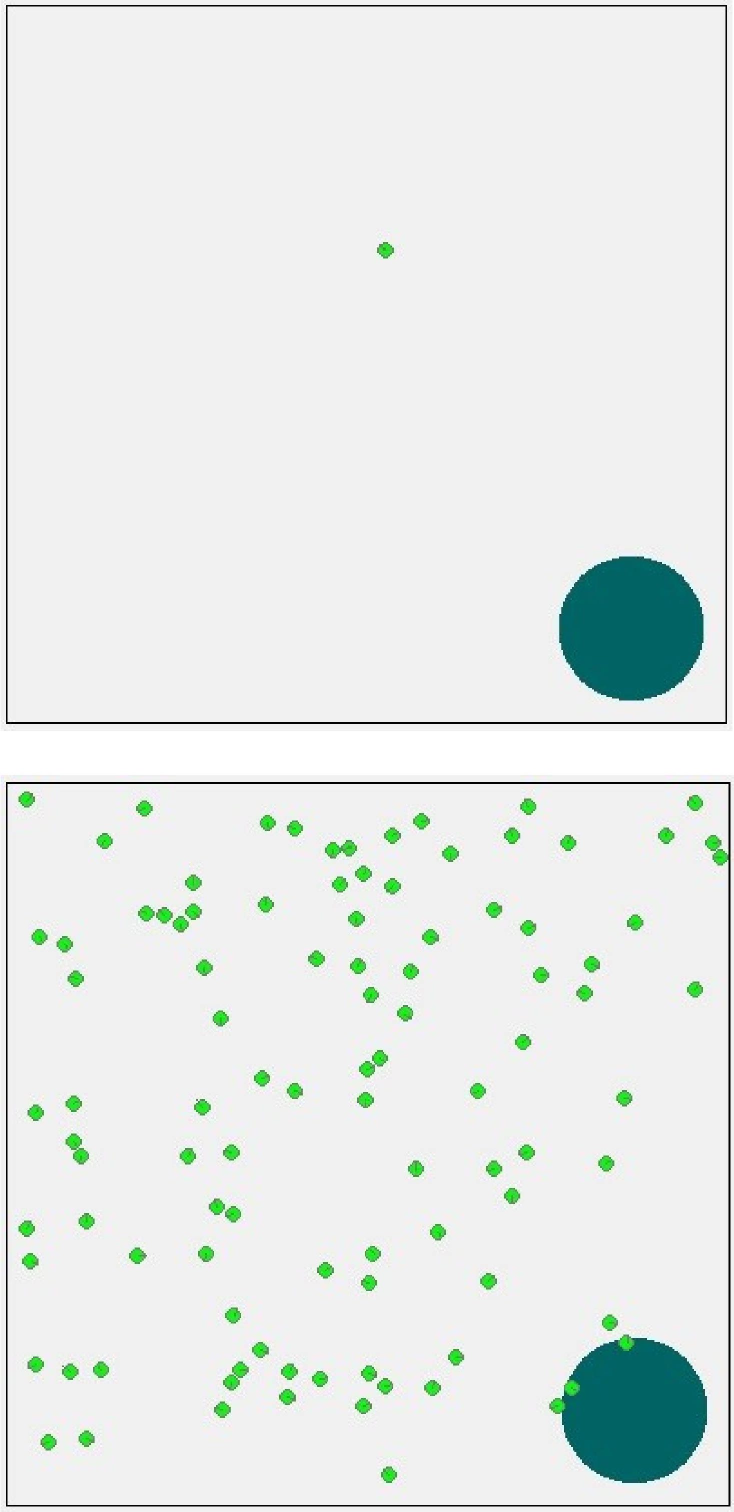


Figure 1.13: The environment and the robots of sub-experimental setup no.1 in two condizions: a) a population of robots who live lonely; b) a population of robots who live socially.

food zone from everywhere (fz smell system with no distance limit). In both cases they still can feel the presence of the food zone whenever they are on top of it by the ground sensor. Results are reported below.

Sub-experimental setup no.3

In the previous sub-experimental setups, the mechanisms of the physical obstruction and food interception probability have been investigated in order to understand how they affect fitness in a mono-race population. A third sub-experimental setup shed a light on how those mechanisms are modified in interactions between two different races in the same population. In order to reach this objective, we have modified the sub-experimental setup no.1 to have a population of 100 individuals divided into two different races. All of the two races' individuals must reach a shared food zone in order to survive. In substance, the robots of the two different races interact with each other in the same environment, but the final ranking, that is the selection of best individual is performed separately: one ranking for the first race and another ranking for the second race. In this way, on each generation, 10 of the best are selected from the first 50 individuals of the population (i.e. first race) and 10 of the best are selected from the last 50 individuals of the population (i.e. second race). For each race, each of 10 best generates an offspring of 5 individuals, which produce the second generation race. The first 10 produce the first 50 individuals of the population again, and so on. This mechanism keeps separately genetic lineages of each race and make them independent from each other. All the other parameters are unvaried from genetic algorithms of the previous experiments. However, the only considered condition in this sub-experimental setup is the "non-perceptual., this means the robots (in both races) are not able to sniff the food zone at any distance, but they only feel it when they are on top of it. Results are reported in the following paragraph.

1.6.2 Results

Sub-experimental setup no.1

By evolving robots for the 4 conditions, they have been produced results which mark robots develop two abilities, in the case of enabled smelling system: robot seem able to "feel" the food zone presence, and so (1) identify it for reaching it and (2) parking on the top of it. In other respects, when robots have the smelling system off (but the ground sensor), they develop only one ability: standing on it when they perceive it by the ground sensor, but they are not able to locate the food zone and reach it. However, we can see that with no smelling system evolved robots display marked exploratory inclinations in respect to robots equipped with food zone smell system which exhibit a "migration" behaviour towards the food zone, because they can perceive it. In Figure 1.16 Average Fitness Curves of sub-experiment no.1 are depicted, for each condition. These curves have been determined averaging Fitness Curves of all the replications and normalizing them in a range between 0 and 1 (1 represents the maximum number of edible food units in 1 life time, that is 10000). At the end, fitness curves have been elaborated with 10 period simple moving averages in order to eliminate the typical "ripple" of those tasks that are not easy to solve. Analyzing fitness curves is possible to show that the average of food quantity (food units) which is eaten by "smelling" robots is greater than the quantity of food eaten by "not smelling" robots (as can be expected). For this analysis, we consider only the average curve of fitness curves give that bests curves are essentially set to 1: this is explicable with the fact that there is always an individual who "is born" in the neighborhood of the food zone and so this individual needs few time to reach it and acquire almost the maximum quantity of food since the first generations. The second and more interesting information from charts is that solitary living robots eat more if compared to social living robots. If we try to understand reasons which lead to this discrepancy between solitary evolution and social evolution, we could suppose that physical impenetrability is the key factor which causes this variation. It is

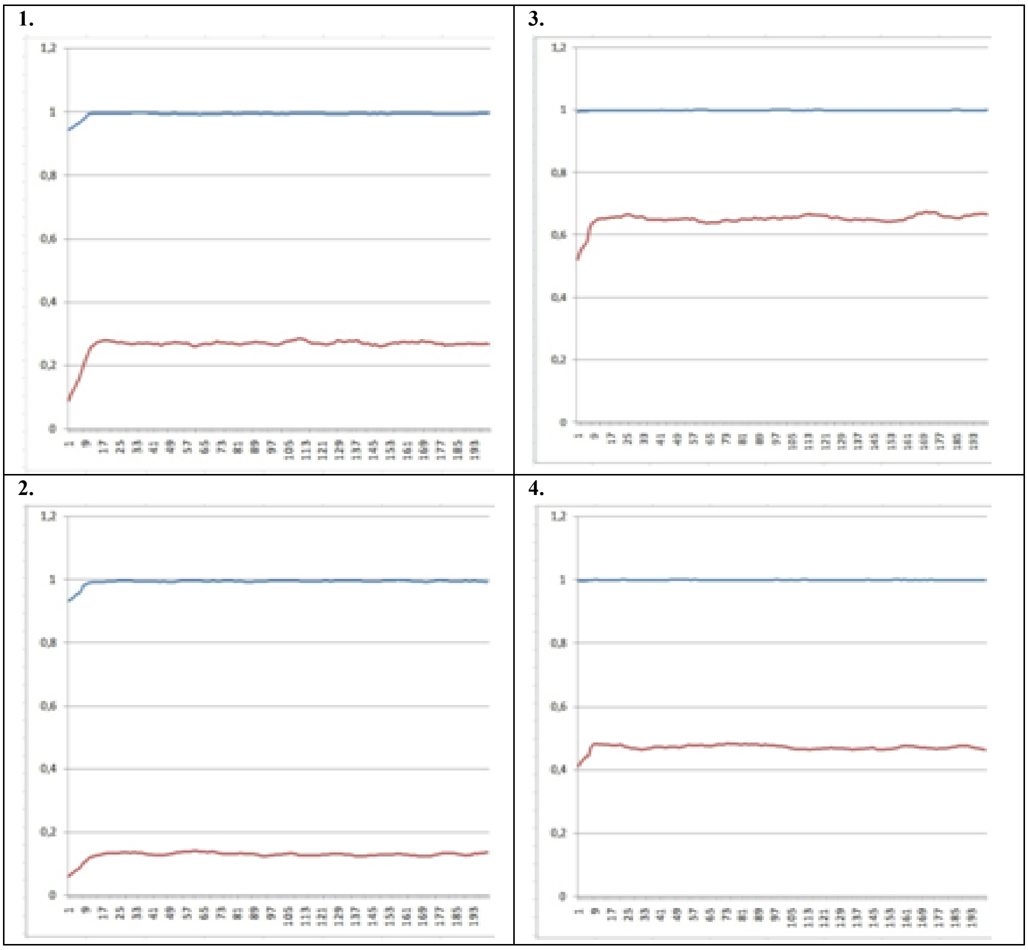


Figure 1.16: Fitness curves related to the 4 simulation conditions: **1.** solitary evolution/smell system off; **2.** social evolution/smell system off; **3.** solitary evolution/smell system on; **4.** social evolution/smell system on. Blue is the bests component and red is the average component.

possible to pinpoint two different reasons by way of which bodily impenetrability influence survival chances of an individual: a) in order to reach the energy source, any individual can be a real physical obstacle for other individuals, in a crowded environment, similarly to any other mobile obstacle into the environment; b) the other reason is that when an individual reaches a food zone, it tends to stand there as much as possible, but this causes a physical obstruction and finally probably a saturation of the energetic source, then even if it is unlimited in time it is not unlimited in space. In other words, a physical encumbrance causes the impossibility to enter the food zone for the other robots, in the course of the time. By these preliminary results it seems that it should be evolutionary convenience of living solitary rather than living socially (beyond of course mating needs that we have not considered in this study).

In Figure 1.17 it is reported a fitness gap between solitary evolution and social evolution in the same condition where robots are able to perceive the food zone at any distance (smell system on). In the light of these results we have wondered under what conditions the gap between solitary evolution and social evolution is not so intense anymore. Moreover, which are the factors involved in making sociality a weak point no longer (an obstacle) but a strong point?

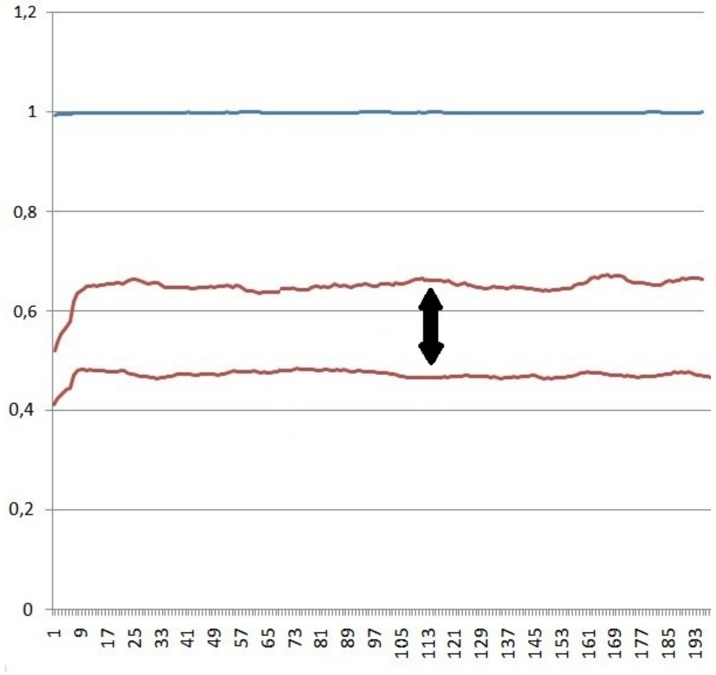


Figura 1.17: Visualisation of the gap between average fitness curve of socially evolved individuals (below) and average fitness curve of solitary evolved individuals, only for the condition where food zone smell sysyem is disabled. The average gap is 1785 f.u. (food units).

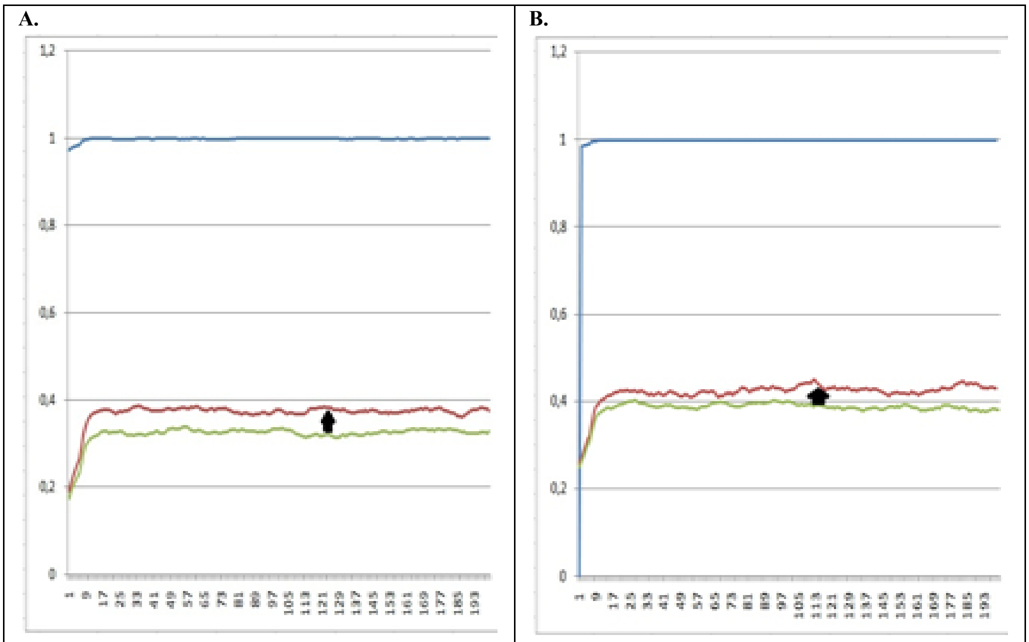
Therefore, we have thought to introduce a physic limit in food zone smell system's perception distance, that is we have evolved robots in four perceptual conditions of distance limit. In other words robots are able to sniff the food zone within limited distances of 55cm (experiment a), 110cm (experiment b), 137.5cm (experiment c) and 220cm (experiment d). The rest of each sub-experiment is executed with the same procedure of "baseline" experiment.

Each sub-experiment has been performed for 20 replications in two sociality conditions: solitary and social condition. At the end we have plotted the average of fitness curves for each condition overlapping solitary evolution's average fitness curve on social evolution's average fitness curve, for each sub-experiment. The outcome, of this elaboration, has been reported in Figure 1.18.

As we can notice in Figure 1.18a (perception distance 55cm) the gap between social evolution fitness and solitary evolution fitness is considerably reduced if compared to the "baseline", where there is an unlimited perceptual condition (see Figure 1.17). In this case the gap becomes 476 food units on average from 1785 f.u. in the baseline. From this first data, it seems that sociality is not such a great disadvantage such as in the "baseline" experiment, even though social evolution still has a slight advantage compared with solitary evolution.

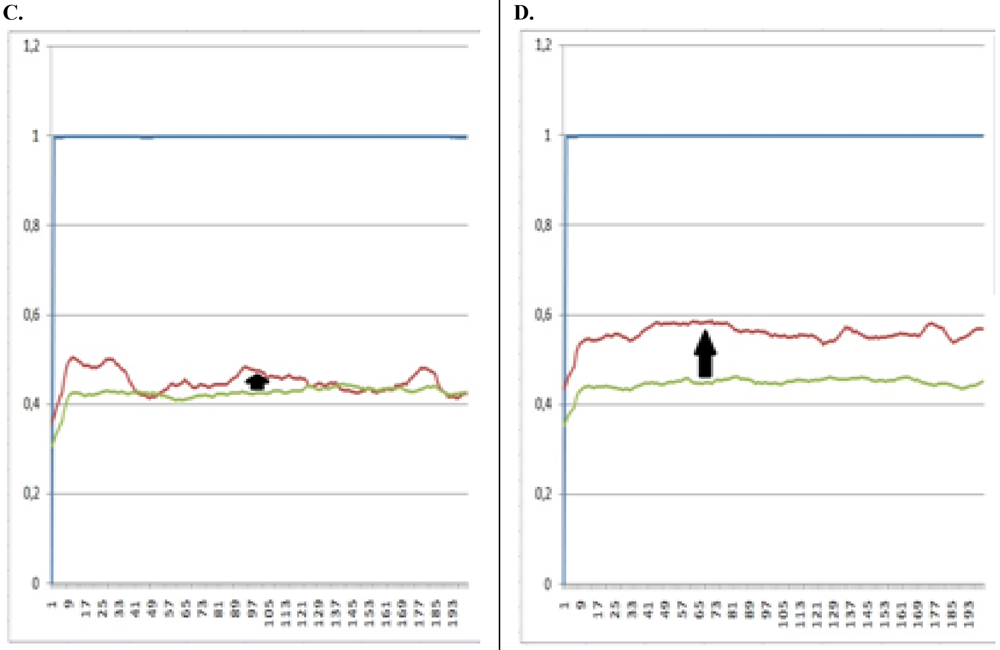
Surprisingly, the effect persists when perception distance is increased up to 110cm (Figure 1.18b) with a further reduction of the gap instead of an enhancement. Again, redoubling perceptual capability of robots, the cap further decrease (Figure 1.18c). Clearly, increasing perceptual distance of smell system (and consequently reducing physical limit) there is a reduction of the advantage of solitary evolution in respect to social evolution.

The fitness gap return to enlarge when the physical limit is almost not present anymore (220cm) that is the situation closer to the "baseline" (no physical limit). This last condition is depicted in Figure 1.18d. In Figure 1.19 is represented a bar-plot which marks the growing trend of fitness gap depending on robots' perception distance. Although it is clearly impossible to analyze the correlation between fitness gap and perception distance in continuum, we can still make some important observations from these discrete analysis that we have made.



Percep dist : 55cm
GAP : 476 u.c.

Percep dist : 110cm
GAP : 349 u.c.



Percep dist : 137.5cm
GAP : 249 u.c.

Percep dist : 220cm
GAP : 1098 u.c.

Figura 1.18: Representation of the different perceptual condition in the experiment no.1 (sub-experiments a,b,c,d). Below each perceptual distance is reported the related gap of fitness reached in that condition.

There is a threshold limit of distance beyond which solitary evolution shows a great advance in respect to the social evolution, this is when the threshold is close to omniscience (perceptual unlimited capabilities). Below this threshold, the social evolution is not so harmful and becomes almost equivalent at a certain point. We can claim that if there were other evolutionary advantages (mating, reproduction, etd.) then the social evolution could surely be advanced.

A detailed analysis of the simulation could permit us to understand the mechanisms of the last discussed effects of perception distance variation. In Figure 1.20 there are schematisations of two different evolutionary conditions: solitary evolved robots (100 individuals) and socially evolved robots (1 individual). In both cases the food zone smell system distance is limited to 55cm.

Although perceptual distance is limited, socially evolved robots are more likely to intercept the food zone presence compared with solitary evolved robots.

Clearly, those conditions are two outstanding situations of a range of possibilities in terms of population's size. But it can be trivially proved that the law is still valid when we compare populations with 10, 50 individuals on one side and 100 individuals on the other side. In summary of this experimental setup no.1, when individuals' physical limits are connected to body limits (i.e. perceptual distance) and/or to the environmental limits (i.e. food visibility) then the multitude of individuals increases the survival chances since this improves the likelihood of a successful perception, such as the probability of finding the food. Therefore a good question arising up to this point is: is sociality inevitable because it is a direct consequence of the physics laws of the world? Does sociality unavoidably derive from the probabilistic nature of individual – environment interactions? The question is still open.

Sub-experimental setup no.2

As it is possible to observe, in "non-perceptual" condition, from 25 individuals to 50 individuals, population shifts from 1120 food units to 1804 food units.

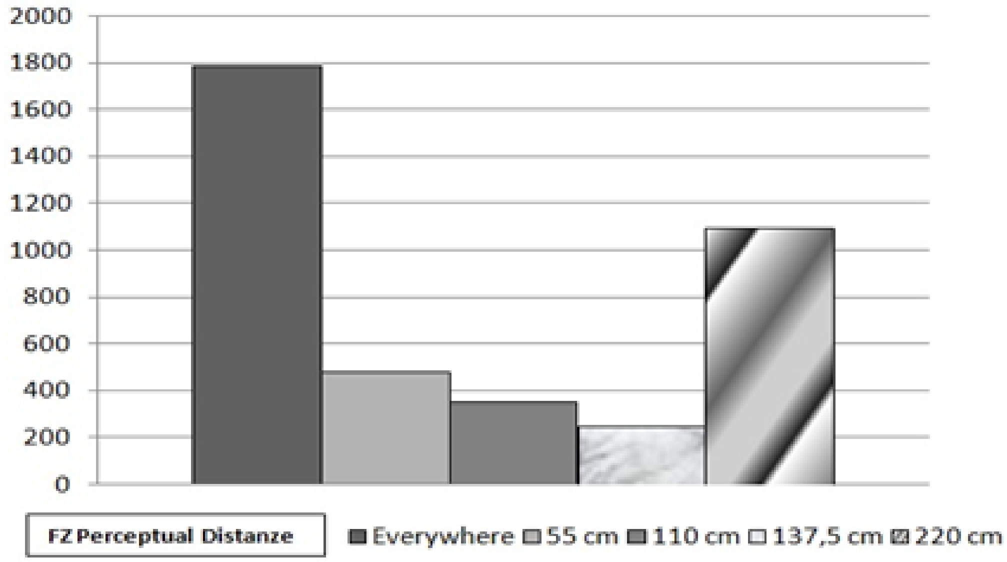


Figura 1.19: In this figure is drawn the variation of the fitness gap (between social and solitary evolutions) as a function of smell system perception distance.

Thus the population shows an increase of fitness (this is the fitness of the average population and it is still the average of 20 replications at the end) instead of a decrease as we have supposed, because of the increase of physical obstruction (i.e. 50 > 25). With 100 individuals the fitness decreased to 1287 f.u. and then to 763 f.u for 200 individuals. This trend is shown in the plot in Figure 1.21a.

Probably 200 individuals is a threshold limit since there are limits of food zone's physical capacity which is not possible to exceed. We can conclude that, in "non-perceptual" conditions, the fitness trend is not positively correlated with the population's size.

In the "perceptual" condition there is an inversely proportional trend of the fitness curve as a function of the population dimension. This is true because there is not a substantial increase of food units from 25 individuals to 50 individuals: fitness goes from 6060 f.u. to 5910 f.u. With 100 population's members the average fitness goes down to 4702 f.u.. With 200 individuals the

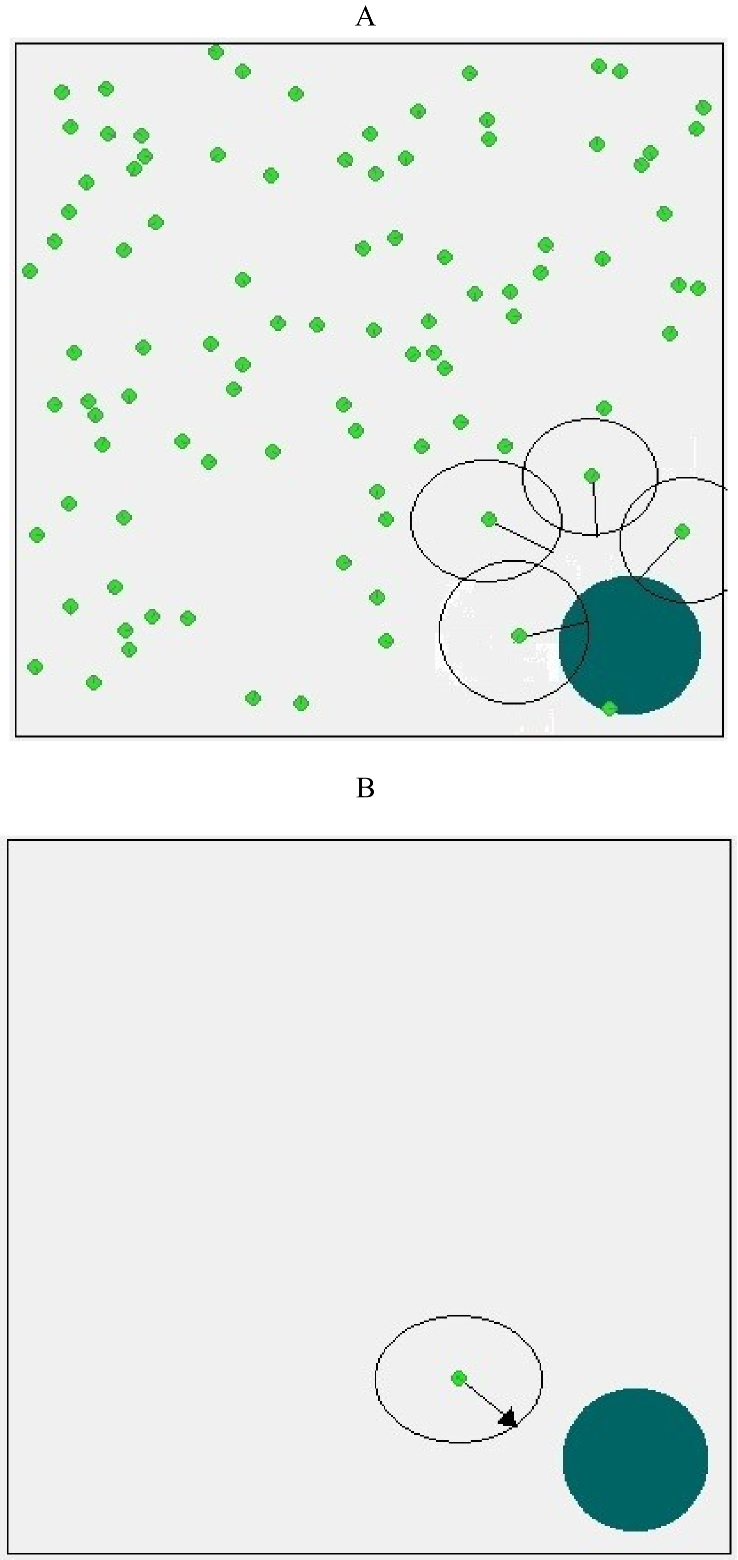


Figure 1.20: Schematisation of the perceptual distance's influence in solitary evolution and social evolution.

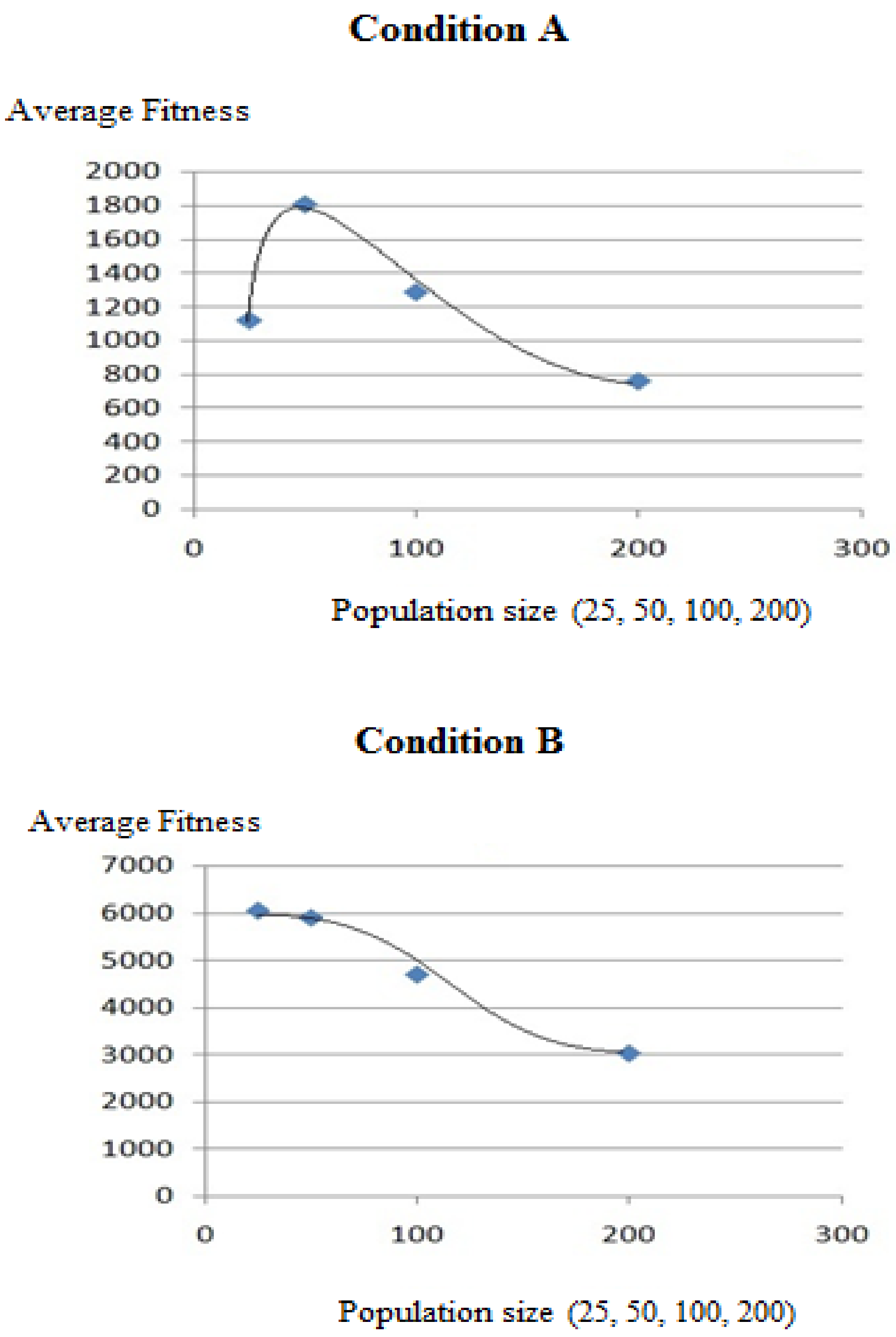


Figure 1.21: Average Fitness trend in “non-perceptual” condition (A) and “perceptual” condition (B).

fitness further goes down to 3024 f.u. Figure 1.21b shows the fitness trend of “perceptual” condition.

A simple graphical interpolation has been applied to the points to mark the probable curves’ trends.

These apparently inexplicable differences in the curves’ trends between the two conditions, can be elucidated by the effect of the presence of different factors which contribute to the production of fitness in condition A (no perception of food zone) and condition B (full perception of food zone).

In substance, in the second condition (B), the only factor that varies by increasing the population is the physical encumbrance, namely the obstruction deriving from the crowding. In this condition, as individuals can sniff the food zone at any distance, they have no troubles detecting the food zone in whichever position they are located. After the evolution, individuals learn to massively migrate toward the food zone, in this way the population’s size weighs on the time in which individuals need for the “migration”. Furthermore, the population’s size affects the capacity of the food zone to host individuals in any given time, because more individuals are in there, so the more crowded the food zone gets, meaning it is more difficult for the others to get in. In this way, the decrease of fitness with the increase of size, appears sensible.

Instead, in the first condition (A) there is not only the obstruction factor which affects the group dynamics, but there is also the probability factor of randomly reaching the food zone, as individuals are not able to perceive it from afar.

So the population members are not able to locate the food zone from a distance but only feel it when they are on the top of it. In this condition both factors, obstruction and probability to find the food zone, are in competition.

Increasing the population size will increase the chance of obstructions, however, conversely there is an increase in the probability of finding the food zone and so increasing the fitness. This is the reason that doubling the population from 25 to 50 increases the fitness instead of decreasing it: the increased probability of finding the food zone is a greater improvement than the disadvantage of obstruction. However, if the population is increased much more, then the physical encumbrance is more noticeable and so the fitness will decrease. This is clearly seen when the population is again doubled but this time from 50 to 100, at this point the detrimental effects of the obstructions have increased to the point that it cancels out the positive affect of finding the food zone, so the fitness decreases. This is further seen when the increase is from 100 to 200 individuals. These observations, with the varying populations, would seem to suggest that the optimal population would be somewhere in the middle, neither too numerous nor too few. In other words there is a threshold at which the trend of increasing fitness reverses and starts to decrease again.

In Figure 1.22 there is are depictions which are useful to explain the phenomenon of the apparently unpredictable fitness trend in condition A.

In conclusion, also in this second sub-experimental setup, it would seem that an increasing of sociality (i.e. increasing of population dimension) leads to a success probability increasing and so to more chances of survival. Although, this advantage of sociality is counter-balanced by the disadvantage of physical encumbrance deriving from an increasing size of population. Therefore where a physical limit exists such as in biological organisms (limited perceptual distance, environmental obstacles) sociality fosters an improvement of feeding chances, which means survival.

Sub-experimental setup no.3

Evolving robots for 20 different conditions, we can notice a remarkable difference of average fitness between the first race and the second, only in some replications. In Figure 1.23 there are represented the comparisons of the first 5 replications' fitness related to both two races. In particular, in replication no.1 and no.5 the first race gets a fitness far and away less than second race fitness. For this reason the second race can be named as "best" race. To understand why there is such a pronounced gap between races fitness in only a few replications, robots behaviours have been carefully examined. Immediately a dominance of the second race arise from robots behavioural analysis. In Figure 1.24 is illustrated the situation over some generations. It is clearly

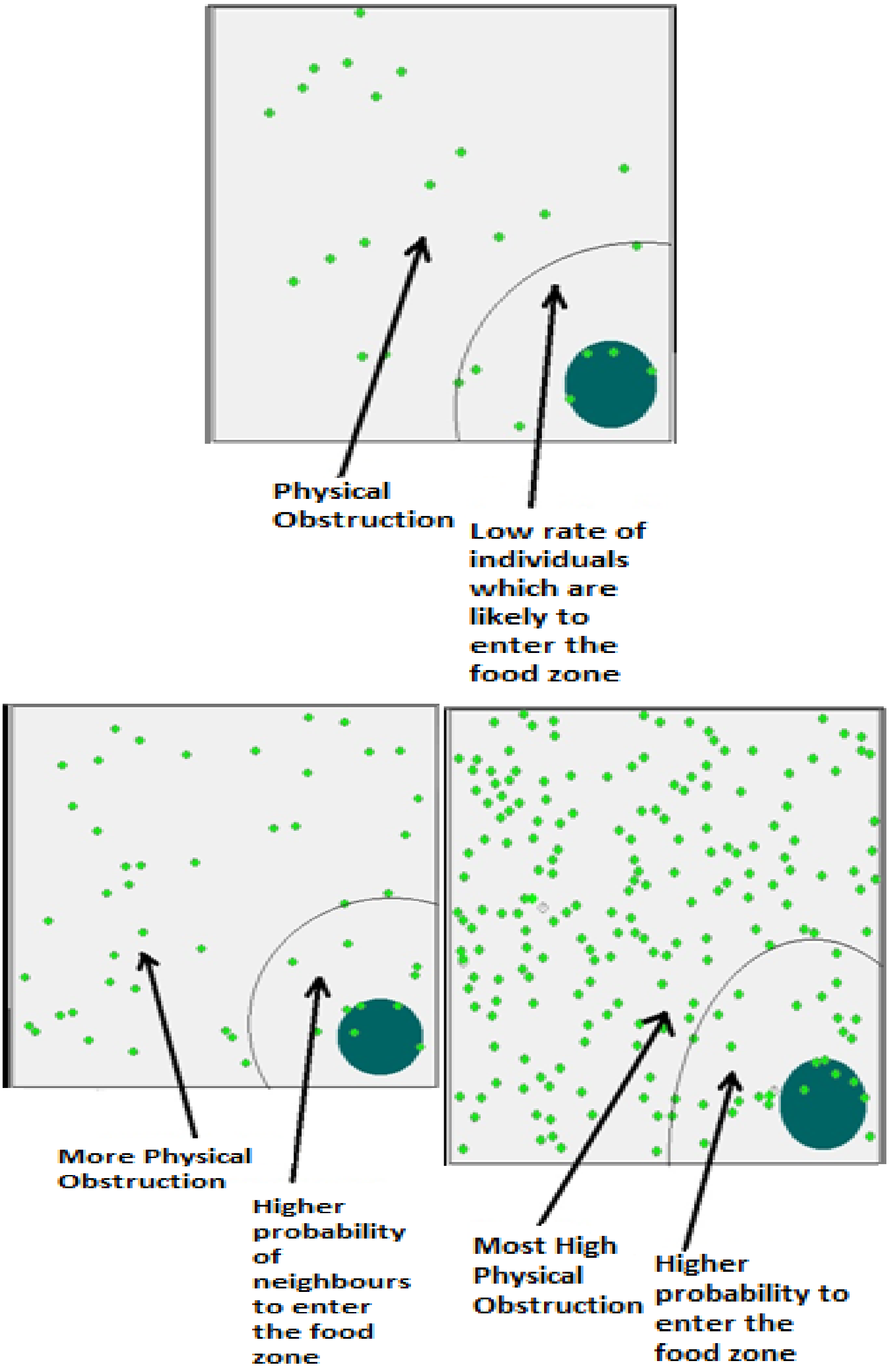
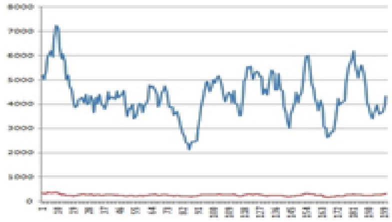
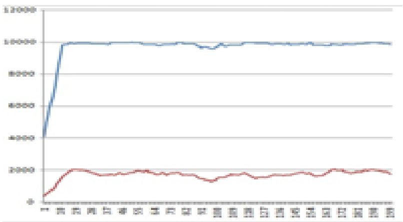


Figure 1.22: Graphical visualisation about how physical obstruction and the likelihood of catching the food zone change on varying of population dimension.

Replication 1.

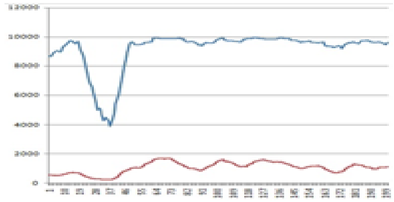


Green Race (First Race)

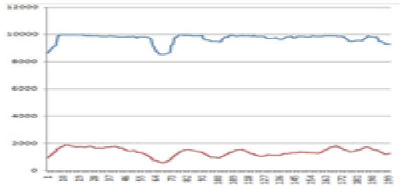


Blue Race (First Race)

Replication 2.

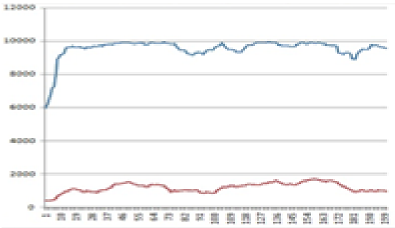


Green Race (First Race)

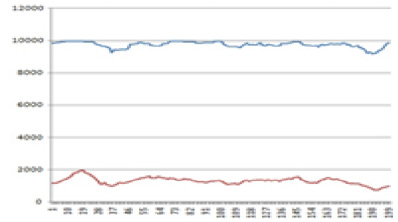


Blue Race (First Race)

Replication 3.

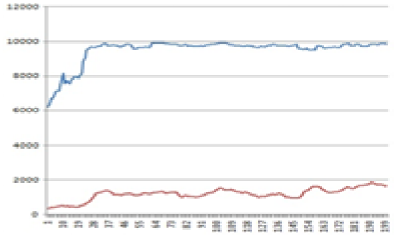


Green Race (First Race)

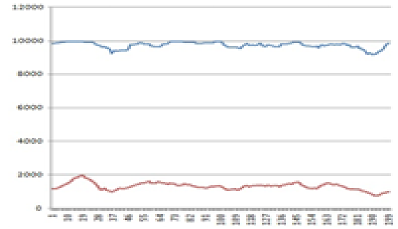


Blue Race (First Race)

Replication 4.

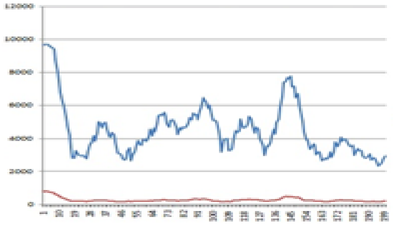


Green Race (First Race)

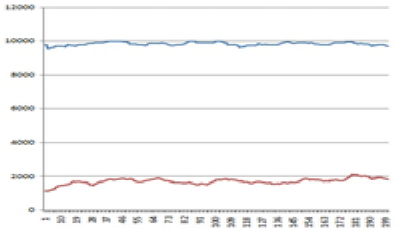


Blue Race (First Race)

Replication 5.

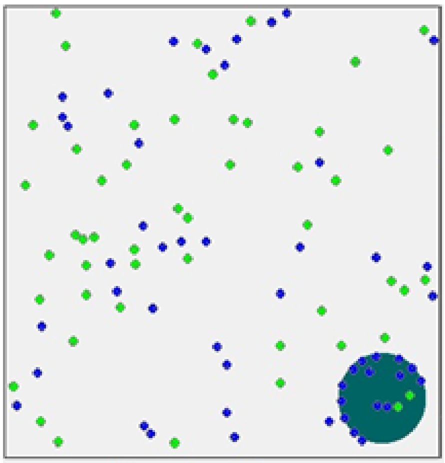


Green Race (First Race)

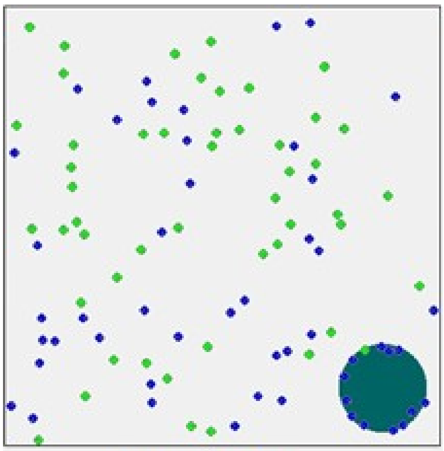


Blue Race (First Race)

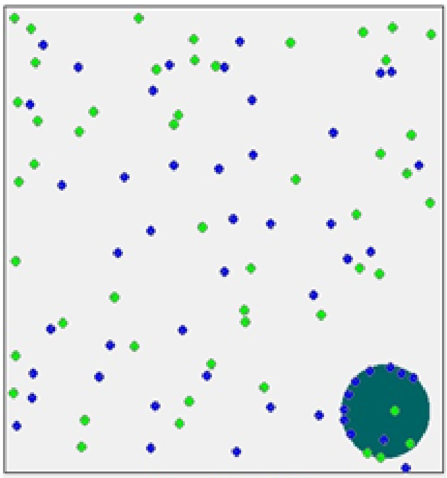
Figure 1.23: Fitness comparisons between both two robots races of some replications (over 20). In replication 1 and 5, blue race is dominant and green race is recessive. In the remaining 3 replications, races are on par.



Generation 20



Generation 100



Generation 200

Figure 1.24: Schmatisation of blue race's dominance mechanisms. Green race is obstacled to get in the food zone, over generations. Finally green race is not able to lie in the food zone when ground sensor signals the presence of it.

marked that blue individuals (race 2) tend to place themselves all around the food zone on the border. They evidently develop this strategy sooner than the green race (race 1). This is clear in the picture, as blue individuals tend to position on the border of the food zone, since first generations (see generation 20 and 100 in the Figure 1.24).

Obviously, if blue robots are faster in displacing all around the food zone they will create a “wall” for the green robots which will have denied the access to the food zone throughout the generations. In this way, green robots will not be capable to develop the only strategy robots can develop in this setup to get fitness: learn to stay in the food zone when ground sensor is on. In other words, at the end, green robots will not be able to lie in the food zone when they are in because their possibility to learn it has been precluded during the evolution, by the dominance of blue race. That is why there is a big gap between blue race’s fitness and green race’s fitness. Instead, in the other replications, blue robots do not generate a so efficient wall around the food zone making green robots able to penetrate in there, and vice versa. In this way, green robots learn to stand in the food zone when they find it, and average fitness is about the same for both races. Therefore, in this sub-experimental setup, a new information emerges on how physical obstruction can be exploited by competitive races to predominate on the other.

However, in this case, race’s dominance emergence does not come from differences in physical features but from the genetic difference of races from the begin of the evolution, because of the random choice of initial genotypes. This difference could make one race enough fast to reach the food zone and create a barrier to obstacle the other race’s penetration. In this case physical encumbrance can foster inter-race competition but at the same time it can enhance intra-race cooperation to increase survival chances of own race.

1.6.3 Future directions

So far, we have examined some advantages and some disadvantages of social living and these can be reduced or improved under some conditions. A new series of experiments could shed a light on all the advantages of sociality. We could investigate:

1. When individual tend to aggregate to each other?
2. Which are other factors who foster the cooperation and living in group? (predation protection, feeding efficiency, information and resource sharing, etc.)

2 Dyadic Cooperation

Cooperation allows to reach goals that are precluded to a single agent. This principle is well-known in animal reign where various and outstanding examples of cooperation can be observed. It is possible to consider for example grooming in primates, an activity in which individuals in a group clean one another's body by which animals who live in proximity can bond and reinforce social structures, family links, and build relationships or the structured social organisation of insects such as ants, bees, wasps or termites where every subject covers a specific role that sustains the hierarchy feeding the entire group.

In order to cooperate, sometimes, it is not needed being numerous. In nature, there are many situations where couples of individuals reciprocally help each other to achieve a common benefit. This type of cooperation is named "*Dyadic Cooperation*", since it is accomplished by two agents: dyad of agents.

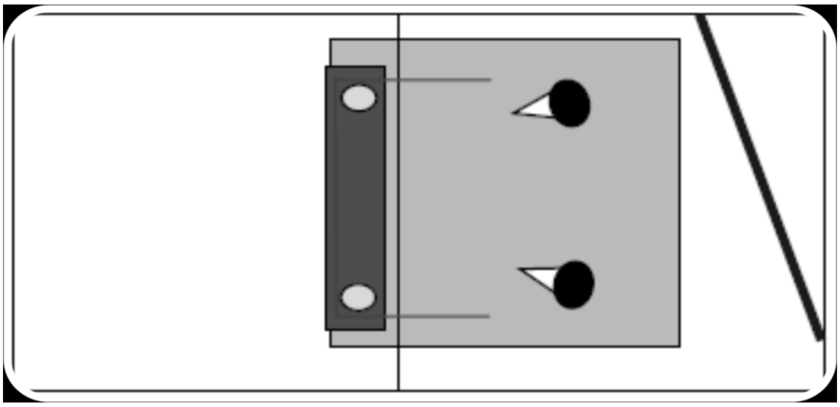
The ethological observation of dyadic cooperation has been recently complemented with the study in controlled situation using specific experimental paradigms: these paradigms represent a simplified version of dyadic cooperation chances that animals encounter in natural environment. The *"Loose String Task"* is an experimental paradigm to study dyadic cooperation and it has been explicitly developed for chimpanzees [5, 6], birds [96,8] and recently elephants [97].

2.1 Dyadic Cooperation in Corvids and "The Loose String Task"

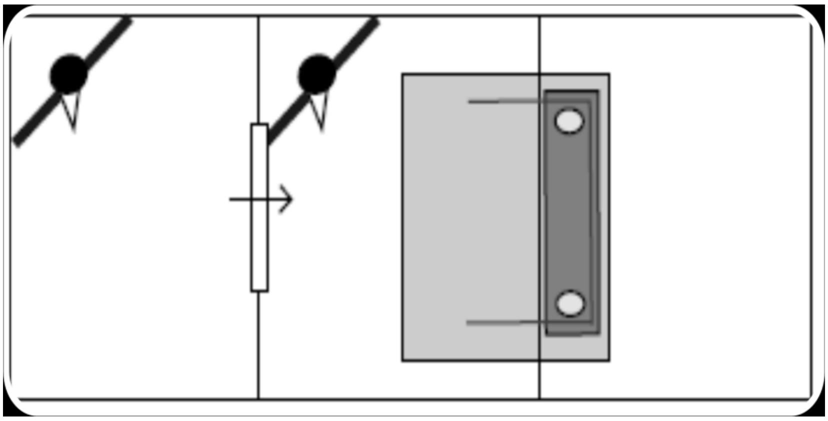
Recent works have shown that captive rooks are able develop dyadic cooperative alliances with their con-specifics. Furthermore, the pressures, hypothesized to have favored the social intelligence in primates, also apply to the birds family called "corvids" which contains: crows, ravens, rooks, jackdaws, jays, magpies, tree-pies, choughs and nutcrackers. Before, the same studies have been extensively conducted on monkey and chimpanzees. These studies, on primates dyadic cooperation, unequivocally prove that monkeys and chimps understand when cooperation is necessary. Furthermore, primates display behavioural coordination and they have a robust understanding of partners' requirements. These findings have suggested the importance of the role of temperament during the evolution of cooperation. Ultimately, the difference in the temperament between chimpanzees and humans might reflect an important evolutionary step, providing a platform upon which our cooperative culture and sophisticated cognition could have evolved. Starting from the cooperation results in primates, other authors have tested dyadic cooperative problem-solving in rooks to compare their performance and cognition with primates. Without previous training, eight rooks have been faced to a problem in which two individuals have to pull both the ends of a string simultaneously in order to reach a food platform. In literature this dyadic test is known as *"Loose String Task"*. The test is divided in 3 experiments: *"baseline"*, *"delay test"* and *"choice test"*. In the first experiment "baseline", two rooks (at a time) are trained to pull the string simultaneously. In the second experiment "delay test", the one-way flap is released (by the experimenter) once one of partners enters the test room. In this way, it has been possible to verify whether one of rooks waits the companion for the time necessary to enter in the testing room. In the end, in the "choice test" rooks must choose between a single and a double apparatus. When tested alone, the birds should prefer to pull the single apparatus because they are not allowed to individually get food from the double apparatus (which only works with two subjects). When tested with their partner, rooks should attempt to coordinate their group actions and pull in the double apparatus. The three experiments are depicted in Figure 2.1. The second and the third experiment have been developed to investigate whether corvids have an understanding of the partners' needs in order to have an effective cooperation by delaying acting or checking the presence of the partner.

Similarly to monkeys and chimps, rooks performance has been better when within-dyad tolerance levels have been higher. In contrast to primates, rooks

A - Baseline



B – Delay Test



C – Choice Test

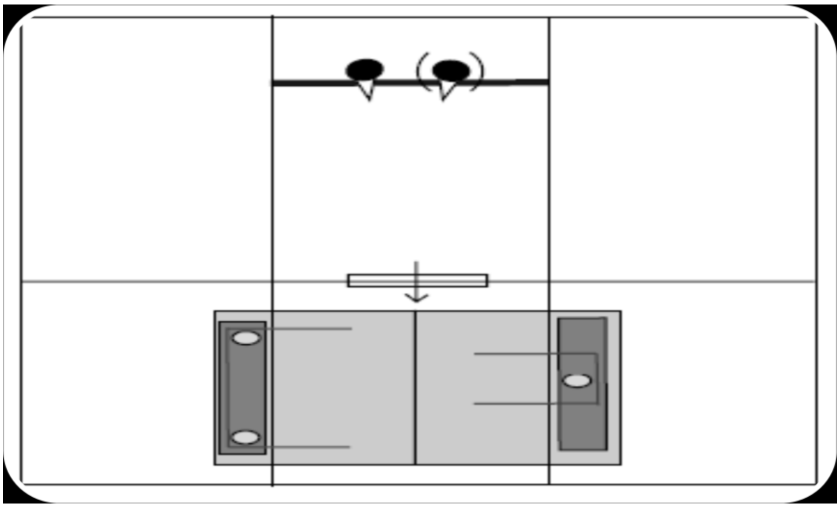


Figure 2.1: The Loose String Task: A) "baseline"; B) "delay-test"; C)"choice-test"

have not delayed acting on the apparatus while their partner gained access to the test room (delay test).

Furthermore, given a choice between an apparatus that could be operated individually over one that required the action of two individuals (choice test), four out of six individuals have showed no preference. These results may suggest that cooperation in chimpanzees is based on more complex cognitive processes than that in rooks. Such a difference may arise from the fact that while both chimpanzees and rooks form cooperative alliances. However, Chimpanzees, but not rooks, live in a more complex and variable social network made up of competitive and cooperative relationships.

2.1 Dyadic Cooperation in Robotics

All the “Loose String Task” experiments are often difficult to be executed on captivity animals such as rooks in laboratory. These corvids need a preceding long term breeding training. Moreover a long training for using the apparatus is often necessary for each single rook. Many times, this involves the wounding of the animals and sometimes even their death.

For these reasons, always more frequently, robots and simulations are being adopted in order to prove cognitive theories on cooperation in these animals.

In one of those artificial experiments, two robots e-puck are simulated within a rectangular arena where the robots are initially placed on a wide corridor [98]. Once the robots have reached the great central target area, this large area disappears and three smaller targets are placed in the corridor. In order to accomplish the task, robots have to drive towards one of three small targets. The setup is depicted in Figure 2.2. This experimental setup is a simple version of the "Loose String Task" (adjusted for the robots) and represents a situation in which the robots should coordinate themselves in order to cooperate and getting a reward. By evolving robots (by means of Evolutionary Robotics techniques), dyads display to be able to accomplish the task, showing

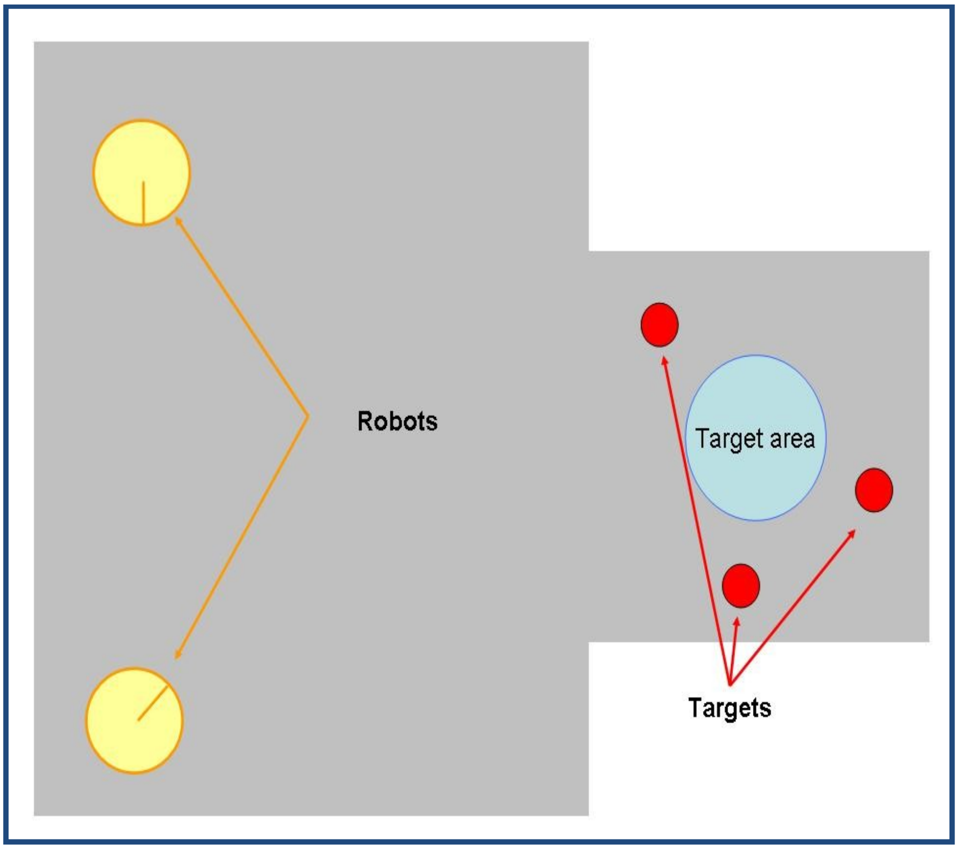


Figure 2.2: First Experimental Setup on Dyadic Cooperation in robots.

an efficient behaviour. Results underline that cooperation between robots is regulated by social interaction between robots, via communication as a medium. The emergence of communication leads to a coordinated cooperation behaviour that is anything like cooperation observed in natural organisms such as corvids.

In a second experimental setup, two robots e-puck situated in a rectangular arena, with two target areas, are evolved for the task of reaching areas almost simultaneously [99]. The experiment is schematised in Figure 2.3. The dyad is equipped with communication channels. Finally dyad, with enabled communication, becomes perfectly able to reach target areas in the same time. Whereas dyad evolved, without communication signals become able to reach the target area in different times: each robot enter the target area on its own.

Instead, the communicative dyad develop the capability to synchronize by the communication, in real time.

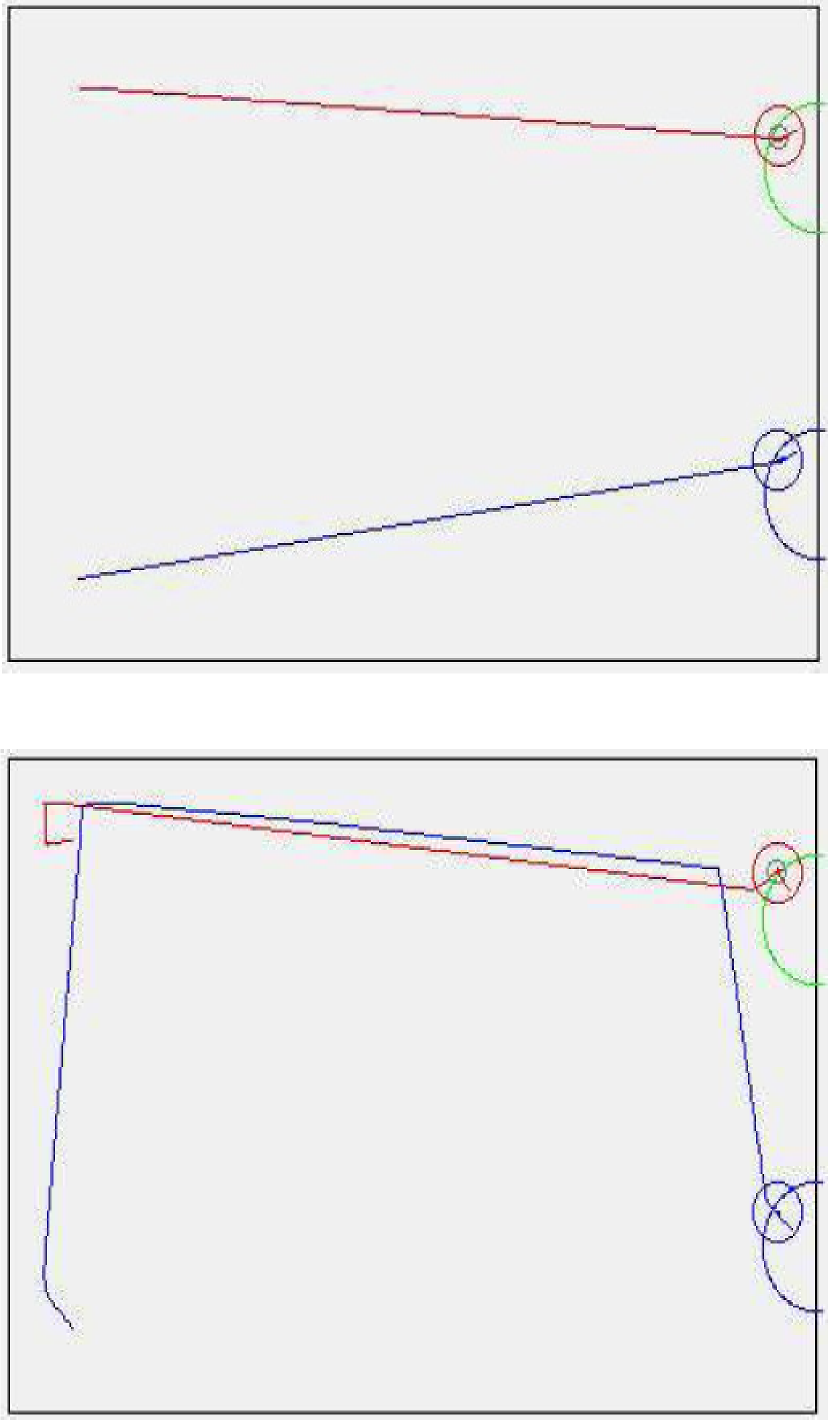


Figure 2.3: Second Experimental Setup on Dyadic Cooperation in robots.

2.2 A neuro-robotic model for “Dyadic Cooperation”

In our artificial approach we always attempt to set a strong link between phenomenon and task (that is derived from experiments) in order to obtain insights from this kind of data reciprocally. For this reason we model experimental set-ups, that has been widely used in animal behaviour literature. In others approaches, the main drawback is that attention is focused in verifying if a certain ability/capacity can be found in another species or not. In other words it seems that a catalogue must be compiled: dogs do this thing, cats don’t, etc, whereas there is no interest in understanding if there are different strategies in solving that task between species or rather a common underlying mechanism. Here, we try to overcome, at least partially, this issue with the present contribution in which we describe a dyadic cooperation task solved by artificial organisms whose we can analyze the solving strategies and mechanism.

In this new task we have extended previous experiments in order to make these simulations even more approximate to the real experiments (Loose String Task) on corvids.

2.2.1 Experimental Setup

Two wheeled robots (khepera) must cooperate for obtaining a reward, i.e. food, which is clearly visible, but not directly reachable. The dyad gets the reward if the two tips of a bar are pushed onto food zones. However, this is still a simplified version of the Loose String Task: a bar must be brought on two areas, by the two robots, at about the same time to receive a reward. The bar’s extremities must be simultaneously on two different areas to generate a reward, the setup is depicted in Figure 2.4. A delay of one robot causes the failure of both. The robots start from fixed positions inside a T-shaped corridor where, in the centre, there is a wall. The environmental arena has a size of 550cm x 1100cm The environment is surrounded by walls. When a robot bumps against

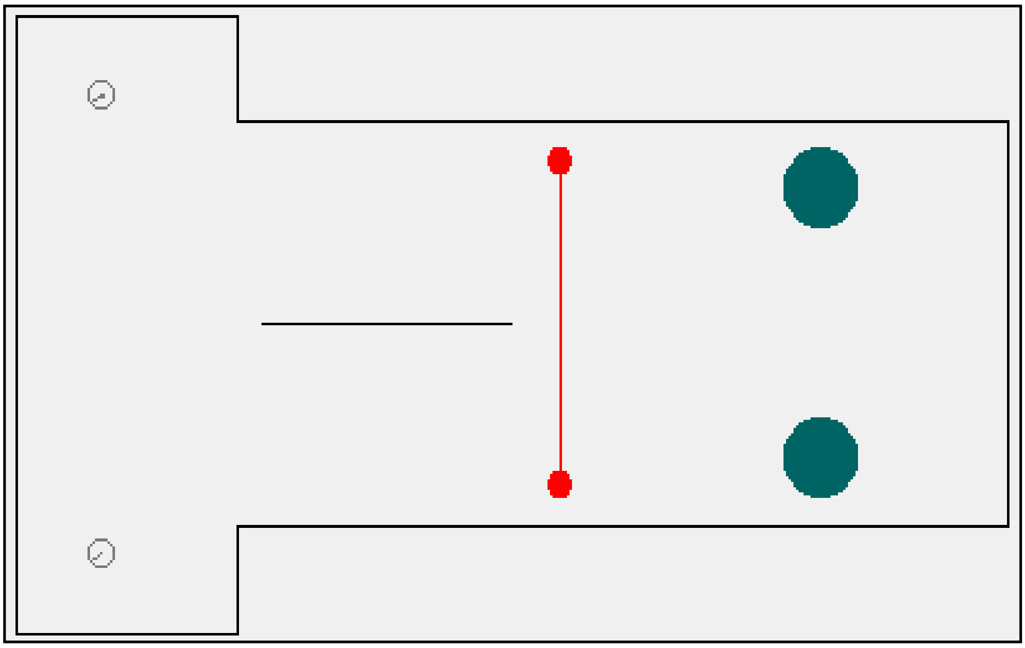


Figure 2.4: Robots and Environment.

environment's wall or against another robot, it bounces back in the neighborhood of the contact point, with a new random direction. Each robot is equipped with two motors on the bottom side and three bump sensors, as shown in the Figure 2.5. As we can see in the picture, each sensor encodes the stimulation in this way: 00 corresponds to no impact, 11 frontal impact, 10 and 01 lateral impacts. The robot control system consists of three layers: the input layers is made up by 2 bump neurons, 18 neurons associated to the visual system of the robots and by 1 neuron that encodes the ground sensor.

The visual system of the robot encodes on a gray-scale the input from the artificial retina of the robot whereas the ground sensor signals if the robot is on a specific area. The output layer is made up by 2 neurons that control the motors. The hidden layer is made up by 5 neurons. The layer that control the retina is formed by neurons that receive a value from 0 to 1 according to the gray-scale acquired from 1 of the 18 retina photoreceptors. The retina receptive field goes from -90 degrees to +90 degrees considering face direction so every

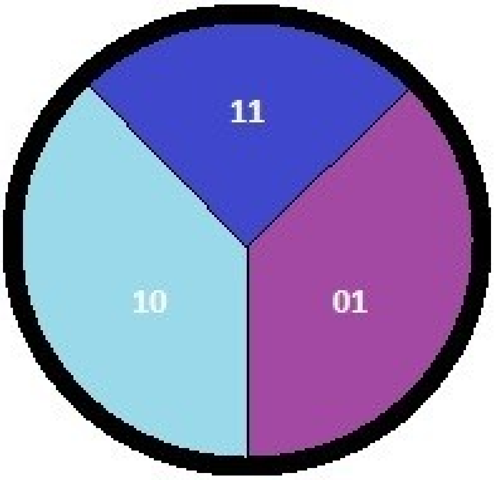


Figure 2.5: Representation of the codification of bumps sensors inputs.

photoreceptor cover an area 10 degrees wide. The neural control system is in Figure 2.6. Robots are evolved using a genetic algorithm with an initial population of 100 dyads of agents whose genotype is randomly varied. At the end of their life robots receive a fitness score according to their ability to solve the task described above (they can try 20 times) and their chance to reproduce themselves depends on this score. This selection procedure has been iterated for 300 generations. From one generation to the next, only the 2% of offspring genotypes are muted. The whole process has been replicated 10 times with different starting conditions. Each dyad consists of clones, that means each robot has the same genotype.

The main purpose of this study is to understand how cooperation evolves with different conditions of communication. The task we have described, in fact, implies that a subject in the dyad considers the presence of the other and that wait each other. It is moreover clear from the ethological observation that animal use some channel of communication to coordinate and solve the cooperative task correctly.

We have then compared 4 different conditions: a) no communication and no vision; b) communication (with an auditory signal) and no vision; c) no communication and vision; d) communication and vision.

2.2.2 Results

The first results is about the number of successes by the robots in the four conditions, illustrated in Figure 2.6. From the chart, it is clear that the most successful condition is the no-communication and vision. For each condition in the table in Figure 2.7 there are the average fitness values and standard deviation of the best dyads, for each condition. The difference between the 4 conditions (evaluated with t tests) is statistically significant.

The results are counterintuitive: one would expect that communication and vision together could be more helpful in solving the task. On the contrary vision alone works better.

If we observe the behavioural strategies, we can see that the robot, exploiting the lateral vision, sees each other in each moment. If a robot is late, the other wait for its partner and then they to go together to push the bar in order to reach the reward area simultaneously and solve the task. In other words they synchronize by the vision.

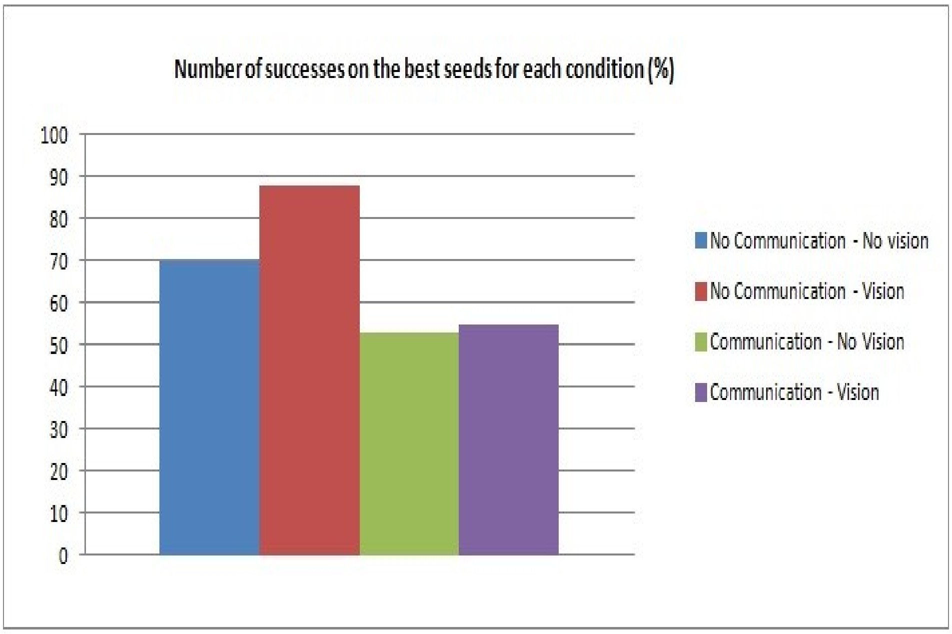


Figure 2.6: Number of successes, by the robots

	No Communication No Vision	***No Communication Vision***	***Communication No Vision***	***Communication Vision***
Average	**0,0485** (0,052)	**0,1291** (0,059)	**0,0738** (0,039)	**0,0805** (0,046)

Figure 2.7: Average Fitness and Standard Deviations.

On the contrary, the other three conditions do not produce strategies as efficient as the one described and this reflect also on the indexes reported above. Some examples of behaviours are reported in Figure 2.8.

How can we explain these puzzling data? In our opinion, the present evolutionary process does not allow the signal to become a communication signal: in other words, in no case, the dyad arrives to interpret the auditory signal as something that can be useful to understand others' intention. On the other side, vision automatically and naturally gives information about others' position, an information that is clearly relevant in this kind of task.

2.2.3 Future directions

What is relevant in our opinion, is that this approach allows us to study the cooperation issue trying to go deep inside the mechanisms that regulate it. In fact, with the artificial organisms we use, there is the chance to control more variables: how can you control the elephant vision? For us it is much easier to understand how vision determines cooperation and through which mechanisms. In the future, we propose to test other variants of the loose string experiment, for example the "choice test". Furthermore, we could investigate more deeply,

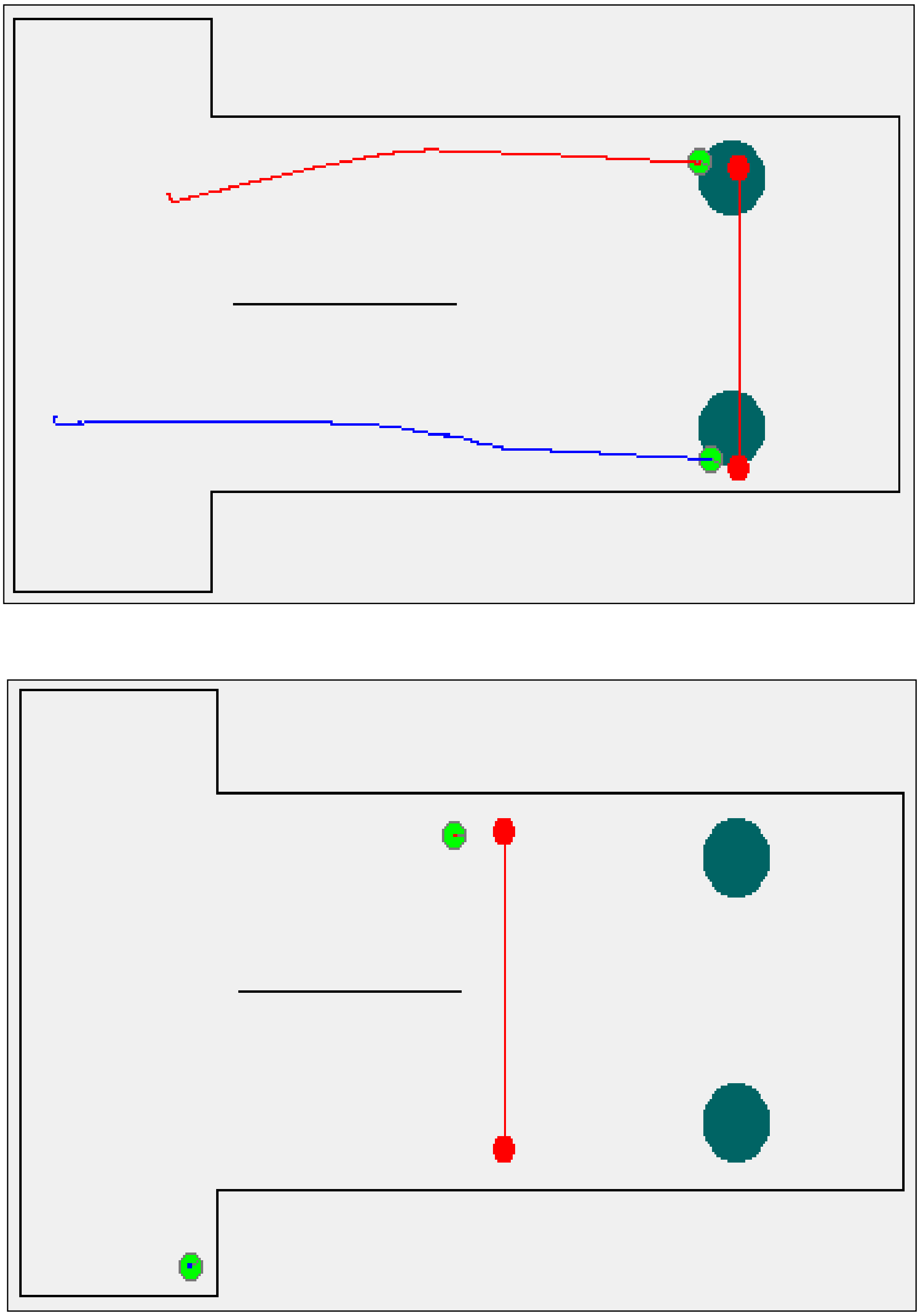


Figure 2.8: Behavioural strategy of synchronisation

the relation between information absence and communication needs in natural and artificial organisms.

3 Flocking behaviour and Leadership

As we stated in the Introduction to the present document, primatology has been dealing with the conditions which lead to the grouping in primates, such as monkeys and apes. Some authors have argued that grouping provides such benefits to the members that differences in size of groups must be sought mainly in the disadvantages of the ecology where the members are used to live. Beyond mating, reproducing and offspring caring, the most accepted advantages of social living in groups are: a) more protection from predators; b) improve the chances of feeding; c) compete against con-specific groups d) information sharing (resource sharing). However the most significant disadvantages of grouping are: a) Intra-group competition increase due to constantly living in close proximity; different motivations and skills could cause a compromising of group cohesion; b) Coordination needs proportional to the group size: in order to move in groups, some members (not necessarily all) should choose the same moving direction for all the group's members. Moreover those *"elected"* sub-set of individuals should coordinate the movements of the whole group. This is a negotiation problem, often not easy to solve [34].

Nowadays, evolutionary biologists generally argue that the reason for the emergence of leadership / followership patterns (over the years of evolution) is the need to coordinate [13]: they usually use the term leadership to indicate those behaviours that influence the type, timing and duration of group activity.

Specifically, the role of Leadership, that is identified in solving coordination and collective action problems, involves different degrees of conflicts. Across species, individuals are more likely to emerge as leaders if they have particular morphological, physiological, or behavioural traits increasing their propensity to act first in all the coordination problems.

3.1 Leadership in living beings

A review of the human and non-human leadership literature suggests five major transitions in the evolution of human leadership [100]:

1) Leadership emerged in pre-human species as a mechanism to solve simple group coordination problems where any individual initiated an action and others followed;

2) Leadership was co-opted to foster collective action in situations involving significant conflicts of interest such as internal peacekeeping in which dominant or socially important individuals emerged as leaders;
3) Dominance was attenuated in early human egalitarian societies that paved the way for democratic and prestige-based leadership facilitating group coordination;
4) The increase in human group size selected for powerful social cognitive mechanisms, such as theory of mind and language, providing new opportunities for leaders to attract followers through manipulation and persuasion;
5) The increase in social complexity of societies that took place after the agricultural revolution produced the need for more powerful and formal leaders to manage complex intra- and inter-group relations: the chiefs, kings, presidents, and CEOs. In some cases these new forms of leaders are best at providing public services, at worst they abuse their position of power to dominate and exploit followers.

In ethology, groups of animals are autonomous units, that enable members to synchronize some activities, such as collective foraging and coordination in moving. A lot of theoretical works have focused on how navigational information is exchanged between group members and how such information flow depends on the knowledge held by each member [14]. Some open central issues are: how do groups reach consensus and solve the problem of maintaining a collective moving, if there is a considerable variation in knowledge of the group members? Is the role of an individual's knowledge level determining for leadership in animal groups? Actually a few experiments have attempted to provide the necessary empirical data [15]. These experiments demonstrate that during pairing flights, when two birds (homing pigeons) have a conflict in an individually preferred route, if they are significantly different (in knowledge), one bird will emerge as leader and the other one will emerge as follower. In another study, the authors have examined the factors contributing to the formation of leadership / followership patterns in flocks of pigeons, focusing on the role of previous navigational experience [101]. The results prove that, in order to negotiate joint routes, pigeons make use of a complex decision-making system based on leadership mechanisms, where, in substance, less homing experienced birds are likely to follow more experienced con-specifics.

In order to coordinate group movements, primates evolution seems to have identified two strategies:

(1) Personal leadership: where a single individual uses its dominant status to impose its own choices. In this case, the spatial and temporal distribution of the group does not affect the initiation likelihood of movements. Moreover, the current leader does not constantly take under check its followers behaviour. He simply leads and the others follow. In this kind of leadership, the leader is the focal point of the group and all the group's members are constantly aware of its position and its activities. Before moving, the adult male signals its readiness to move, assuming a rigid posture and eyes fixed towards a given direction. He moves rushing in the direction chosen,

occasionally uttering grunts. Members of the group simply join him to follow [102];

(2) Distributed leadership: in this case, individuals continually exchange information to reach a collective decision. In this type of leadership, several individuals (not necessarily the dominant ones) may be the initiators of group movements. Spatial and temporal distribution of the group can strongly affect the probability of successfully beginning the group’s motion. In this context, every member constantly looks for an answer by tuning in sound and visual signals, from the other members. The greater the number of individuals involved in the decision making, the more types of communication signals are needed [103].

In the systems of distributed leadership, the leader is not chosen by status of dominance, especially in tolerant species. In this case, even older females may be selected. In the wild macaques "Barbary (Macaca sylvanus), for example, females usually lead the group, but males become more influential in cases of imminent danger. So there seems to be a distinction between a leader who guides (chief) and a “de facto” leader (leader). The social organization can influence the mechanisms of leadership: the asymmetry degree in dominance relationships may play a key role. Some studies have argued that white-faced capuchin monkeys which are more socially open and tolerant races of monkeys, rely on a distributed leadership [104,105]. Whereas brown-faced capuchin monkeys are characterised by a more central role of a higher-ranking male, who aggressively controls access to resources, and whose behaviour is constantly monitored by other members of the group. In this case, we may say that brown-faced capuchin monkeys display a more personal style of leadership than white-faced ones [106,107]. In some ethologically strong theories, whenever there are moving groups of animals, there always seem to arise a leadership/followership patterns emergence. That's a stronger restriction because it claims that motion is a necessary and sufficient condition for the emergence of leadership: in all cases a motion is needed, a leadership would arise [108].

Also the modern biology and psychology seem to agree with ethology on leadership operating principles. In species where individuals prefer to move together leaders and followers are more likely to be present in groupings, as a consequence of social and ecological pressure. Moreover, in the human case, a purely social environment may have selectively created the conditions for sophisticated leadership/followership patterns in human life [110]. However, literature on evolution of leadership, suggests that we can identify a first stage in the emergence of leadership in humans, when pre-human species, that tried to solve simple group coordination problems for foraging, developed a differentiation of roles, in this way some individuals initiated an action and others followed [111].

3.2 Flocking behaviour

Flocking behaviour can be defined as the capability of a group's members to follow other group's members drawing those typical "lines" of individuals that are exactly called "flocks". Those behavioural patterns have been extensively identified by biologists and ethologists in the animal world: researchers tend to make distinctions among the "shoaling" behaviour of fish, the "swarming" behaviour of insects or "herding" behaviour of land animals. Generally, flocking behaviour is used to mean groups of flying birds, and the lines they trace are named "flocks" for this reason [112]. Furthermore, flocking has been simulated in many computer simulations with the aim of understanding fundamental mechanisms [113].

3.3 A neuro-robotic model for “Prey and Predator”

The following work is meant to identify the possible mechanisms and conditions involved in the emergence of leadership, in socially living organisms. In order to achieve this ambitious purpose, we have simulated a neuro-robotics model based on evolving prey robots and predator robots. In particular, this “predator-prey” model might shed a light on the probable correlation between leadership and group moving (supposed in literature) and what is the leadership role in motion coordination. The most significant questions to which this simulation is intended to reply are: Under what conditions may grouping spontaneously emerge within a colony of robots? Does leadership need a group of genetically heterogeneous robots to arise?

3.3.1 Experimental Setup

The artificial system, that I present, consists of a simulation of Khepera Robots, whose body is made of a circular chassis with a diameter of 5.5cm, visual sensors and two wheels with which the robot moves in the environment. In Figure 3.1 there is a schematisation of the robot used in this experimental setup. The environment is a squared arena of 550cm x 550cm pixels bounded by walls. The environment contains 20 predator robots and 20 prey robots. The only physical difference between one predator and one prey consists in the color difference, blue for predators and green for prey. Both predators and prey are evolving robots by means of the evolutionary robotics methodology.

Another substantial difference between prey and predators is the different fitness function computation: when a predator bumps against a prey robot, this disappears from the environment (i.e. it is dead) and the predators fitness increase by +1. On the other side, predators cannot die. The Prey’s fitness is calculated by the number of time steps in which they stay alive, therefore, the

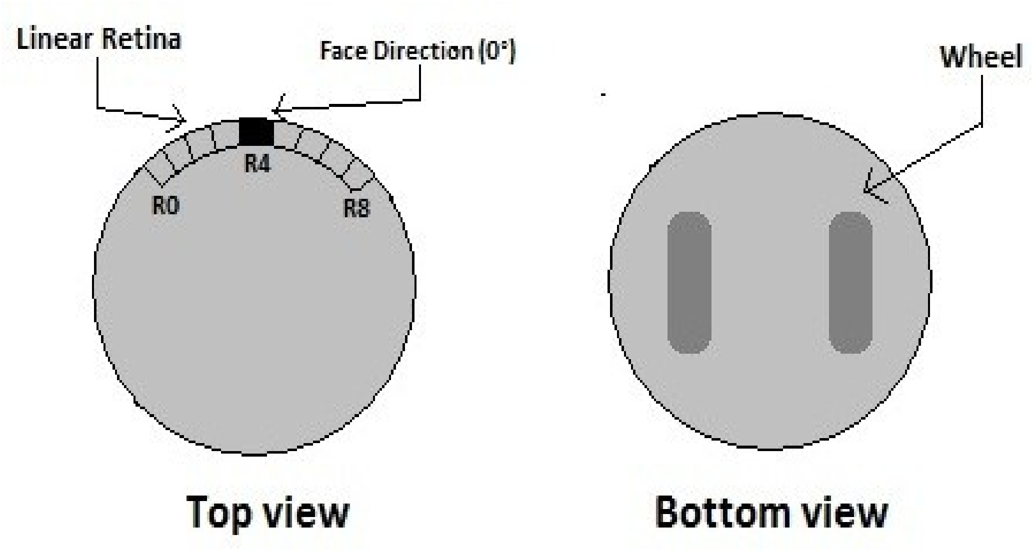


Figure 3.1: Visualisation of top and bottom view of the robot prey's and robot predator's chassis.

more the prey survive, the more fitness they gain. In conclusion, when a prey robot is eaten the total amount of prey ("living" in the environment) decreases. The possibility of eating one prey robot is the only behavioural difference between predators and prey. To survive and have offspring the predator robots must be able to approach and reach (i.e. eat) the prey robots whereas the prey robots must be able to avoid predator robots. In other words, predators should evolve the skill of running after prey, and prey should evolve the skill of escaping.

When a robot bumps against environmental walls or against another robot, it bounces back in the neighborhood of the contact point facing a new (i.e. randomly chosen) direction. This experimental setup is depicted in Figure 3.2.

The vision system of both prey and predators is based on a linear retina of 9 (R0-R8) photoreceptors that perceives gray scaled colors. The field of view (FOV) of each robot is 90 degrees wide, and it represents the extent of the observable world that the robot can see at any moment. The FOV ranges from -45 degrees to +45 degrees respect to the face direction (0°) that is the robot's moving direction. In this way, each photoreceptor manages a 10° wide portion

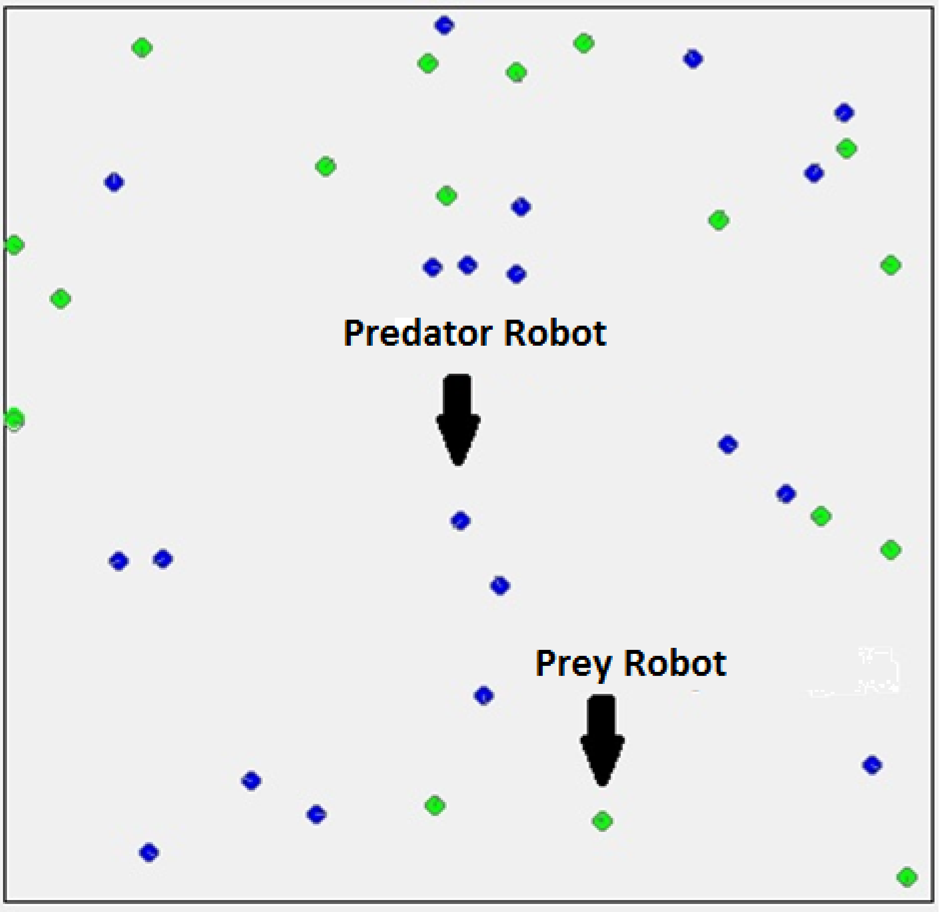


Figure 3.2: The environment and the predator robots (blue) and prey robots (green).

of the FOV, the first one is associated to a range of [-45°,-35°] with respect to the face direction, the second one to [-35°,-25°], and so on. When any object (such as another robot) is located in front of a photoreceptor (within its vision angle), it is activated to a value encoding the color of the object (translated into gray scale). So the green color of prey sets photoreceptors to 0.26, that is a normalised value (between 0 and 1) related to the gray scaled green. The blue color of predators sets photoreceptors to 0.97. This vision system is depicted in Figure 3.3. The maximum vision distance of vision sensors is 55cm. So if an object is further from a photoreceptor more than 55cm, it cannot be detected.

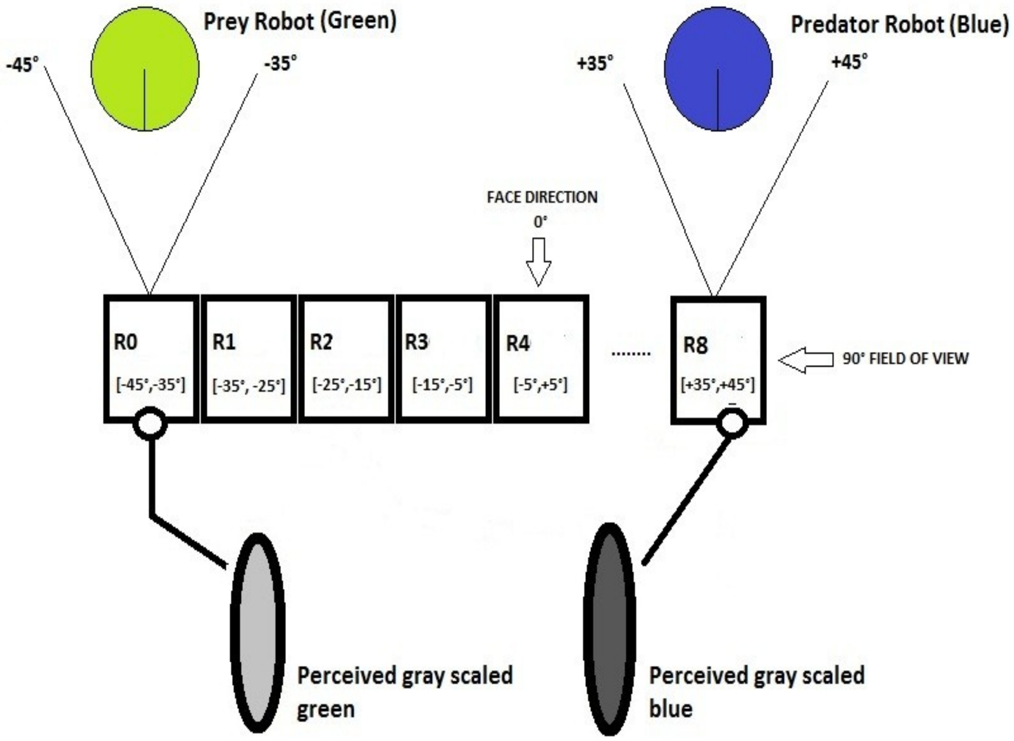


Figure 3. 3: A schematisation of Robot's Vision System.

Each predator robot can live a maximum of 3,000 time steps that represents 1 epoch of the entire life. Whereas each prey robot can die at any time so prey can live less than the maximum epoch's time.

As we have previously said, the robot's control system is evolved by a genetic algorithm, even though a different ranking system is applied to prey and predators, in order to simulate two different species. At the beginning of each epoch, every robot starts from a random position within the environment. Each life time is made of 20 epochs. At the end of their life, the 20 predators are ranked according to the average number of prey eaten in all epochs. Each of the 4 higher-ranking predators generates five predator offspring which inherit the genotype of their father. The first offspring individually preserves the father's genotype entirely (elitism) whereas the rest of the offspring receives a random mutation with a probability of 2% within the inherited genome. The total number of new predators (4 x 5=20) populates the next generation. Similarly, the 20 prey robots are ranked separately, generating 20 new prey robots for the next generation. This evolution carries on for 300 generations. The number of replications is 10. Each replication is characterised by a different initial genotype randomly selected before the beginning of the first generation.

The evolving genotype of each individual consists of a set of binary encoded controlling neural network's free parameters. The neural network (ANN) controls the behaviour of each robot. These encoded parameters are the synaptic weights of the connections and biases for the neural network. Furthermore, these free parameters of ANN are randomly generated in the interval between +5 and –5, and each parameter in encoded as a sequence of 8 bits.

The controlling neural network consists of 3 layers with 13 neurons for all, each one is connected to the other layers without recurrent connections. The neural network's topology is schematised in Figure 3.4.

The input layer contains 9 neurons which encode the output from the 9 retina's photoreceptors. In other words, input units receive values (normalised in a range between 0 and 1) from the retina's sensors depending on the gray level of perceived image. The hidden layer consists of 2 units, and the output layers are the controllers of the motor units: output neurons encode the speed of the two wheels that enable the robot to move in the environment. The activation of all the network's units are in the range [0,1]. Internal and output neurons are distinguished by a sigmoid activation function (logistics).

Initially, for the first generations, the predator robots are not able to approach the prey, to eat them. Similarly, prey robots are not good at avoiding the predators. During the generations, the best robots selection and the mutation operator cause the predators' to improve their capabilities to hunt the prey. On the other hand, the prey learns to escape from predators.

When a biological or artificial organism perceives food (prey robots or patches), the organism should approach to and eat the food because this is necessary for the survival. But when the organism does not perceive any food,

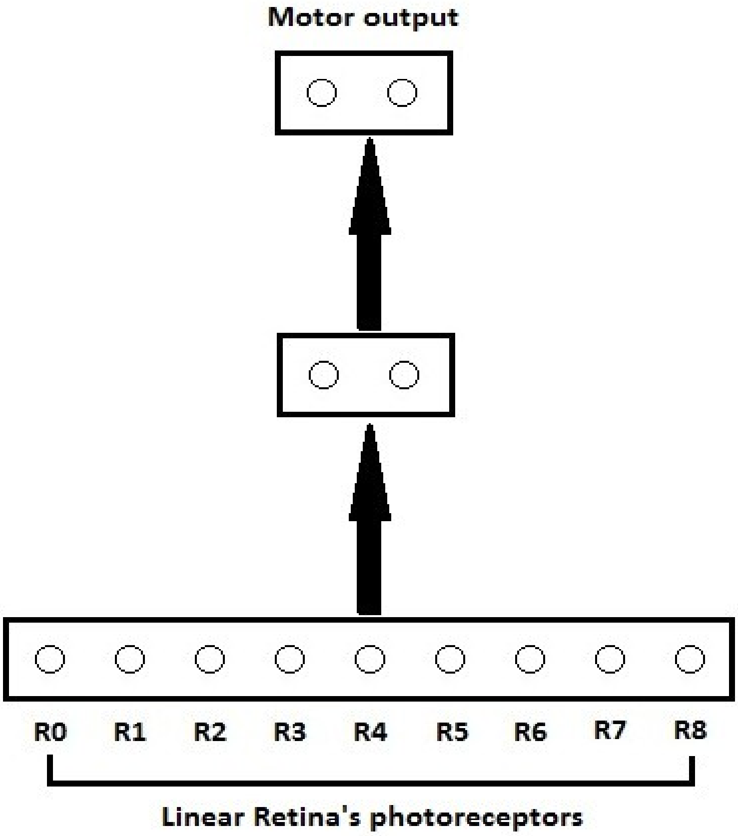


Figure 3.4: The control system of predator and prey robots.

what should it do? The organism should explore the environment and visit as many parts of the environment as possible, because this will increase the probability that it will perceive food. Therefore, the fitness score of a predator robot will depend on two distinct abilities: (a) the ability to approach and reach a perceived food token, and (b) the ability to explore the environment when there are no food tokens in view.

Two robots can achieve the same fitness score: but one robot could be good at reaching food and less good at exploring the environment. In opposition to this another robot could be skilled at exploring the environment and less good at reaching the food. We probably expect a specialization of skills like this, after the evolution. Both abilities could likely to be developed during evolution.

After the evolution phase, we are able to test the evolved robots in an artificial experimental laboratory.

3.3.2 Results

By evolving predator and prey robots, we observe that the former learn to follow and/or eat the prey, while the latter improve their ability to escape from the predators.

Moreover we observe the emergence of a flocking behaviour between predators. Instead, prey do not display any specific grouping behaviour, they just avoid predators. The flocking is schematised in Figure 3.4.

The motivation for the flocking behaviour emergence has been roughed out previously. As every predator robot has a limited maximum distance of vision, when they do not see anything around them they prefer to follow another predator robot instead of doing anything else. We have observed that predator's display a significant behaviour of following very different from the behaviour of hunting. The behaviour of following another predator because, in this case, predators do not tend to bump against the other predators, but they just limit themselves to follow with a safe distance. On the other hand, the behaviour of hunting consists of following the prey until the predator reaches and bumps against it, in order to finally eat the prey. Someone could trivially argue that flocking is facilitated by the evolution of a simple following strategy, namely chasing everything that is moving. This is not true, because as we have just explained, there is a differentiation between the behaviour of following one predator and following a prey.

In conclusion, by virtue of the previous behavioural analysis, we can strongly suppose that Flocking Behaviour in this model is caused by "vacuum vision", that is: when I do not see prey around me, I just prefer to follow another individual like me. This is generated by a limit of their vision capabilities.

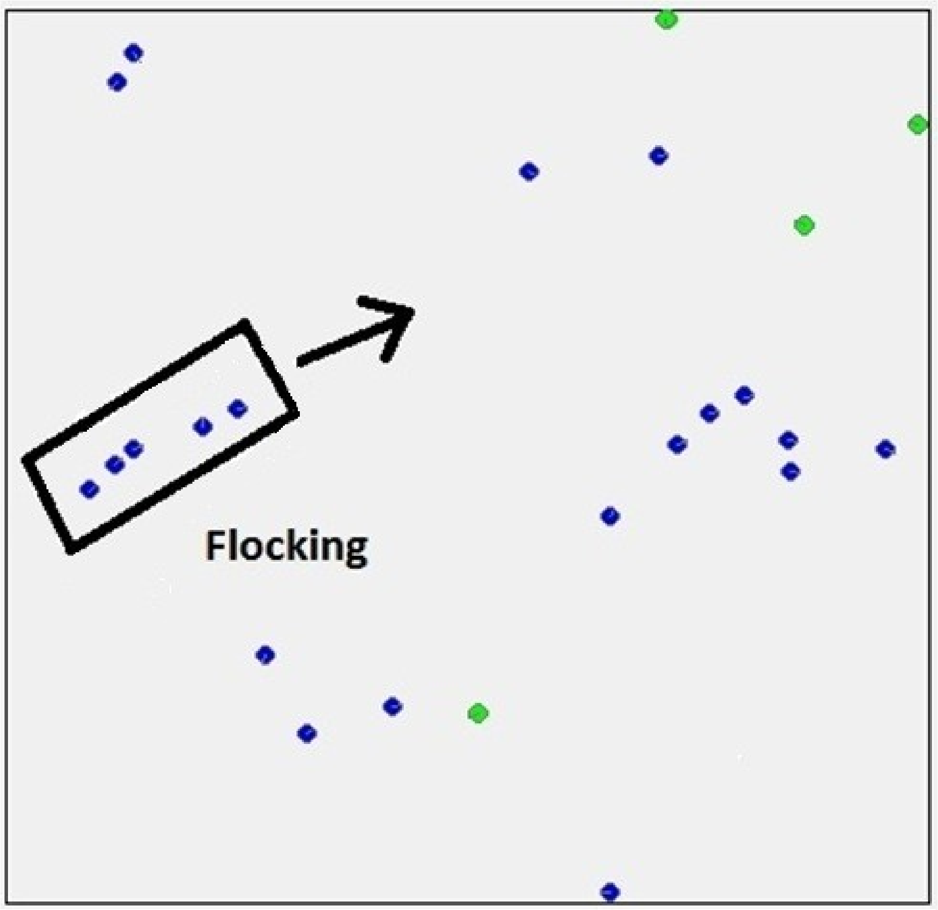


Figure 3.5: Illustration of the Emergence of Flocking Behaviour in the "predators-preys" setup.

Furthermore, if we take a look at the fitness curves (over the generations) of the best and the average populations, we notice that the curves are constant. Figure 3.6 is showed the average of the fitness curves of the predator robots.
The steadiness of fitness curves is true both for predators and prey. However, by watching the robots (both predators and prey) behaviours, they seem to improve their skills and performances throughout the generations. This effect has been explained in some past works by the *"arms-races"* mechanism that can arise in artificial evolution too [113]. Arms-races may emerge in every situation where a co-evolution of two species of organisms is involved: whenever two competing population of organisms co-evolve they may lead one another to increase reciprocally the behaviour complexity by producing an

evolutionary “arms-races”, to all intents and purposes. In this case, the efficiency of each single organism’s evolved strategies does not influence a co-evolved group enhancement. In this simulation, for example, prey robots become better and better at avoiding predators, meanwhile predators become better and better at hunting the prey. The result, is that the predator’s fitness score and prey’s fitness score does not increase over the generations, because the amount of prey the predators can eat, in one generation, is affected by prey’s skill enhancements: if prey get good at escaping the predators, the predators will not eat a larger amount of them. That is why the fitness curves appear stable. Through evolution, prey become increasingly good at escaping from predators, but predators also become increasingly good at hunting them. However, this does not mean that a robots’ strategies and skills do not improve and become more efficient during the evolution.

Another factor that makes the predators fitness curves constant is the fact that, at each generation, only 20 prey can be eaten in total, because the prey will not be born again after their death. Definitely, the number of prey eaten by predators (fitness), through the generations, cannot increase that much. Certainly, the speed of the predators to devour prey, can increase during the evolution.

In order to prove this fact, we have conducted an “ecological test” that means it was executed in the evolutionary ecological environment. We have measured the number of time steps in which predators eat all the 20 prey (i.e. predation time). The test has been repeated by loading the genotypes of all the robots over the generations. Not all the 300 generations have been considered, but only a sample of them, with a step of 10 generations. The test has been performed in 20 trials per generation, with 3000 time steps for each one. Then the 20 values obtained, have been averaged. We have then achieved 30 values (average time steps) per replication. In order to reduce the “arms-races” effect, the test has been executed with motionless prey, randomly spread in the environment.

Finally, we have calculated the average of all 10 replications and we have plotted these values on the chart depicted in Figure 3.7. The gap between the

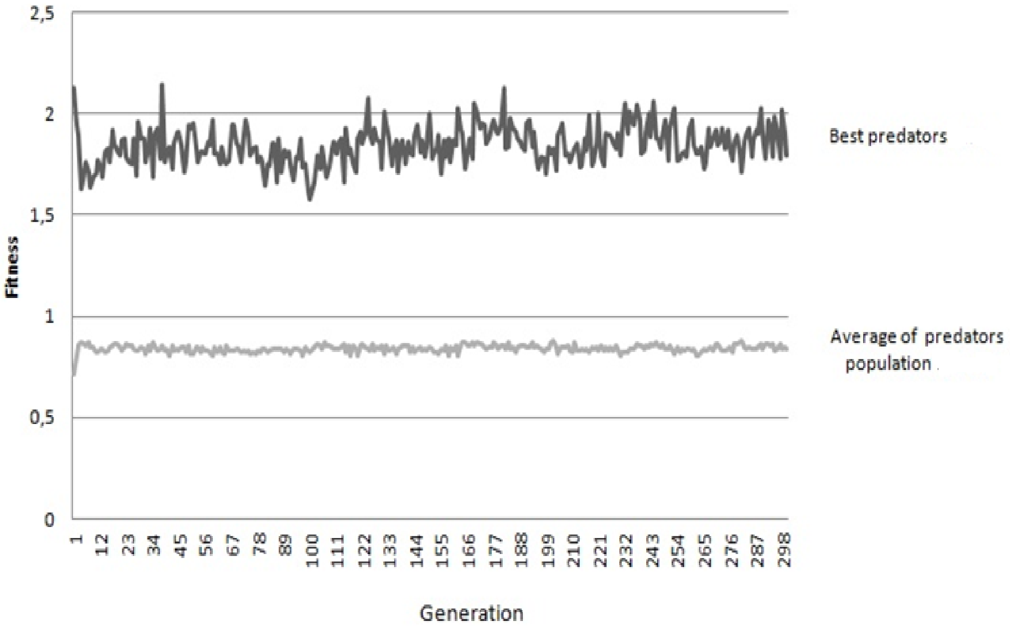


Figure 3.6: Visualisation of the average of all 10 predators' fitness curves, bests (black) and averages (light grey).

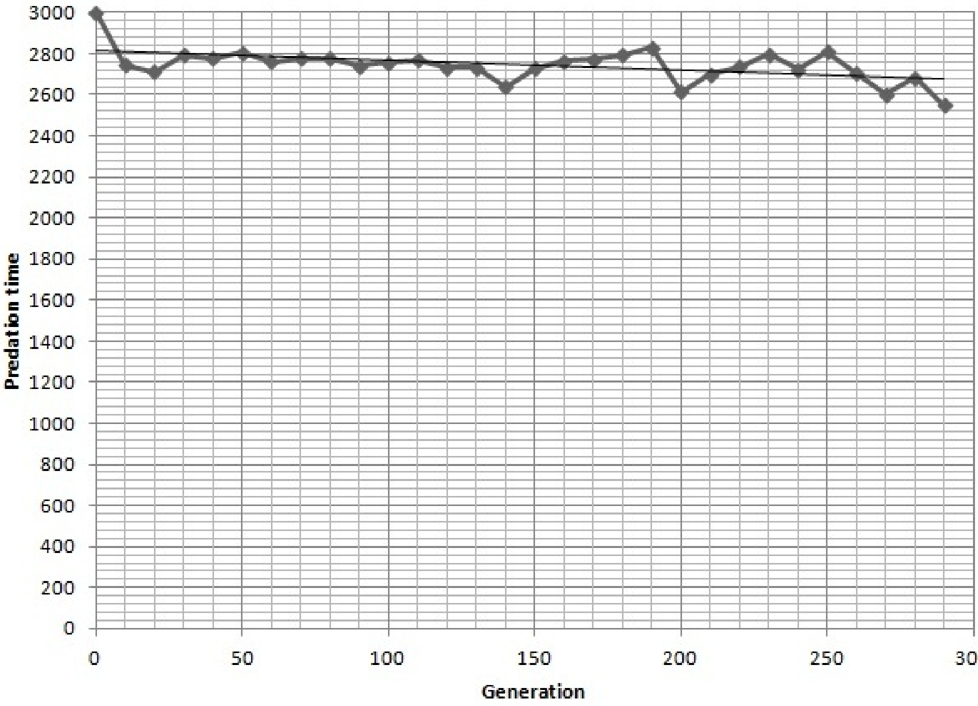


Figure 3.7: Average Predation time in ecology.

first generation and last generation time is 451, 57 time steps, that proves a decrease of predation time. This means an enhancement in predation skills, in spite of the constancy of the fitness curves.

Obviously, predation time cannot fall below a certain threshold because this depends on various factors: such as they cannot exceed the maximum robot's motors speed, there is a limit in the number of edible preys, the limited environmental size, and so on.

To find a single indicator on the fitness reached by robots in each replication, we have calculated the average of the last 20 generations' average fitness. In Figure 3.8 there is a bar-plot with all the 10 values of fitness per each replication that we call the "Fitness Indicator". We can observe that in replication no.10, predators achieve the highest average fitness, whereas they have the lowest average fitness in replication no. 7.

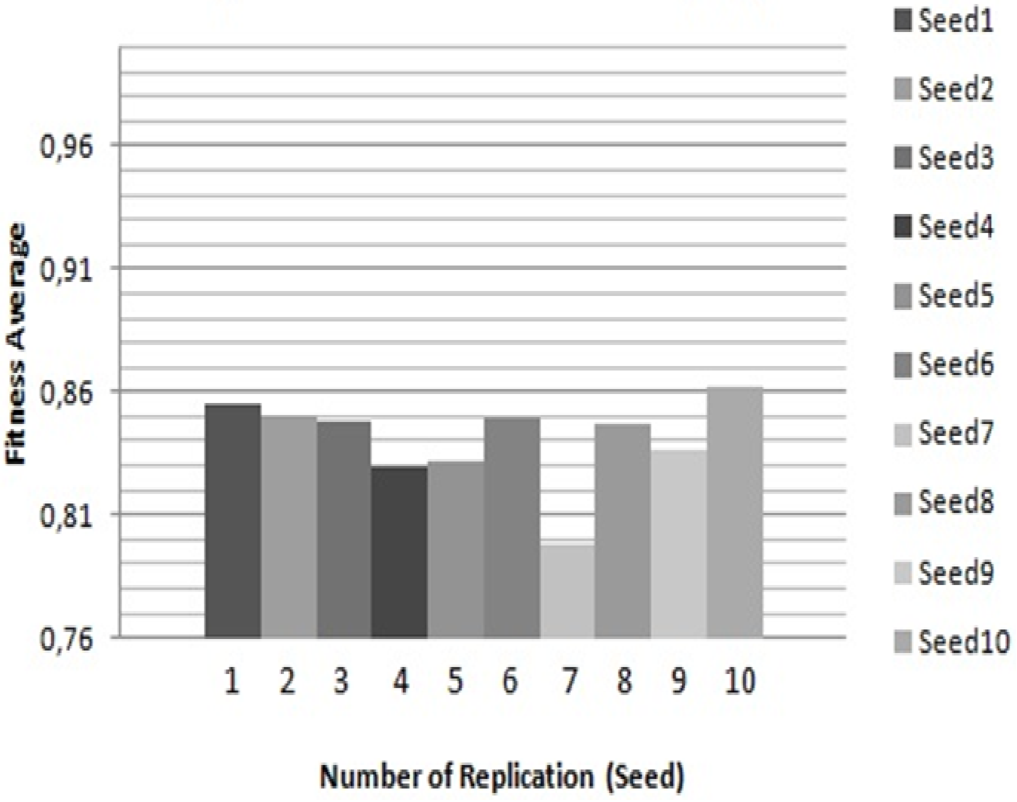


Figure 3.8: Fitness Indicator per replication.

Apparently there is an unexpected inter-replication variation of fitness. So the first question we have tried to answer is: What is the phenomenon behind this substantial variation?

In order to understand the why of this variation, we have tried to calculate a static aggregation measure of the predators' populations of in ecological environment. From this point we only consider the predators population for further analysis, as there are no interesting emerging social behaviours in the preys population. The "Aggregation Measure" has been calculating by measuring the distance between each robot and the nearest robot, in each time step. All the 20 measures of distance, for each time step, have been averaged returning, in this way, an average distance between each robot and the nearest robot, for each time step. Then all the time steps' distances have been averaged. The test has been executed on the last generation robots for 20 trials. So the average distance between one robot and the nearest robot has been averaged over all the trials. Finally, we have obtained an indication on the ability of predators to aggregate. The static Aggregation Measure per replication has been reported in a bar-plot in Figure 3.9. The lower values correspond to more aggregation and vice versa higher values correspond to less aggregation. This is because the aggregation value means the average distance of each robot from its neighbour, so the lower value is the average distance, the higher should be the aggregation. In this plot, we notice that (on the opposite of the Fitness Indicator Plot) in replication no.10, predators achieve the lowest value of average distance (higher aggregation), whereas they have the highest average distance in replication no. 7. Moreover, we can observe a variabilità between replications in the Fitness Indicator chart.

Therefore we have tried to understand whether there is a possible correlation between the Fitness Indicator and the Aggregation Measure, by calculating Pearson's Correlation Coefficient between those two series of data. The result has surprisingly returned a $\rho = -0.7$ that means high anti-correlation between Fitness and Aggregation (in statistics, $0.5 < \rho < 1$ means high correlation). This means that whenever there is a high aggregation then there is a high fitness probably, and vice versa. Anti-correlation had been expected as when there is a

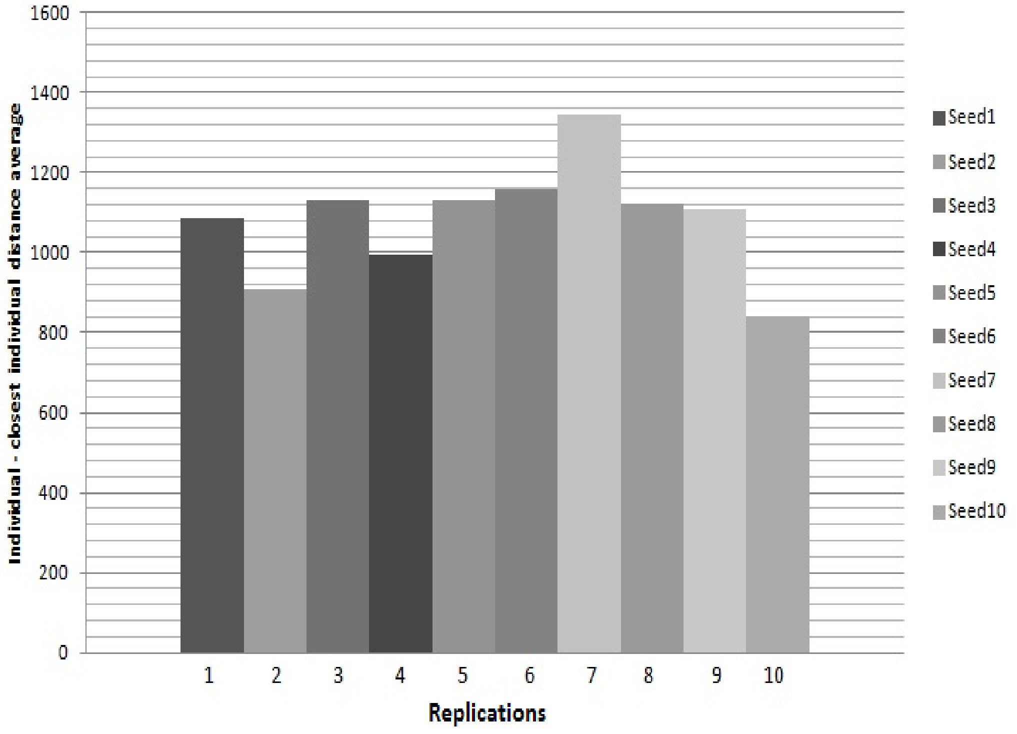


Figure 3.9: Aggregation Measure per replication.

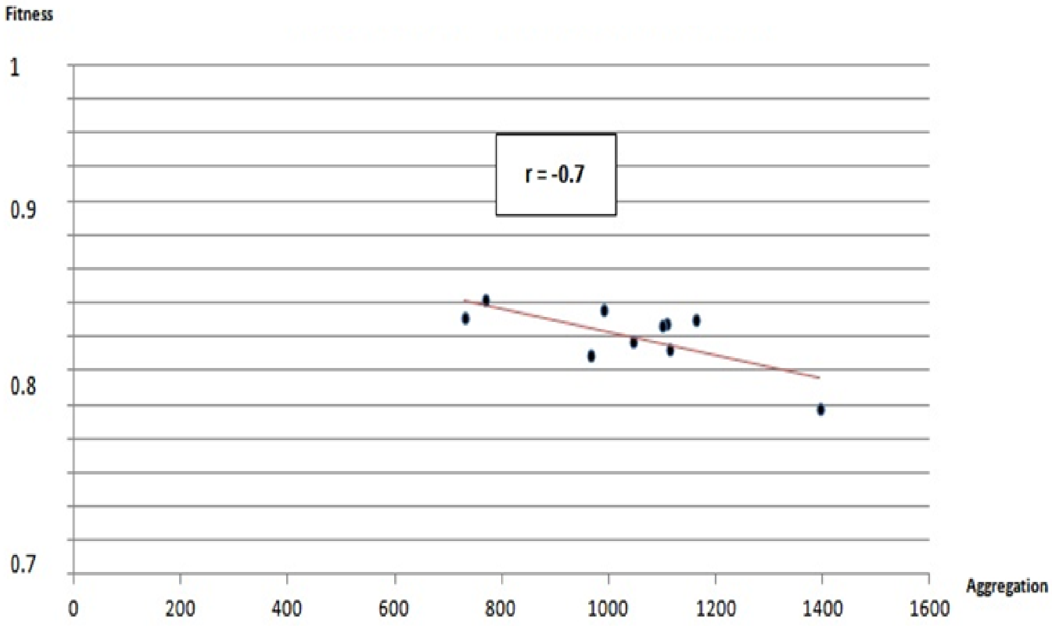


Figure 3.10: Correlation between Aggregation Measure and Fitness Indicator.

high aggregation, then the average distance between a robot and the closest robot is low. In Figure 3.10 all the series are reported on a plot with the correlation coefficient.

To better understand the dynamics of the robots aggregation through their life, we have plotted the average distance between a robot and the nearest robot on a chart in using the life time steps, as those reported in Figure 3.11. On X-axes we have the time-steps and on Y-axes we have the Aggregation (average distance). In Figure 3.11 there are two examples of aggregation curves related to replications no.7 and no.10. As we can see, the 7th replication curve appears constant whereas the 10th replication curve appears to be decreasing, that means the predators population tends to aggregate at the end of their life in replication no.10. Figure 3.12 illustrates the average aggregation curve, namely the average of all 10 replications' aggregation curves. Also in the average case, we observe an aggregation reduction at the end of the life. This could mean that the predators probably tend to increase the flocking behaviour and aggregation as a consequence of the increase of the prey's scarcity.

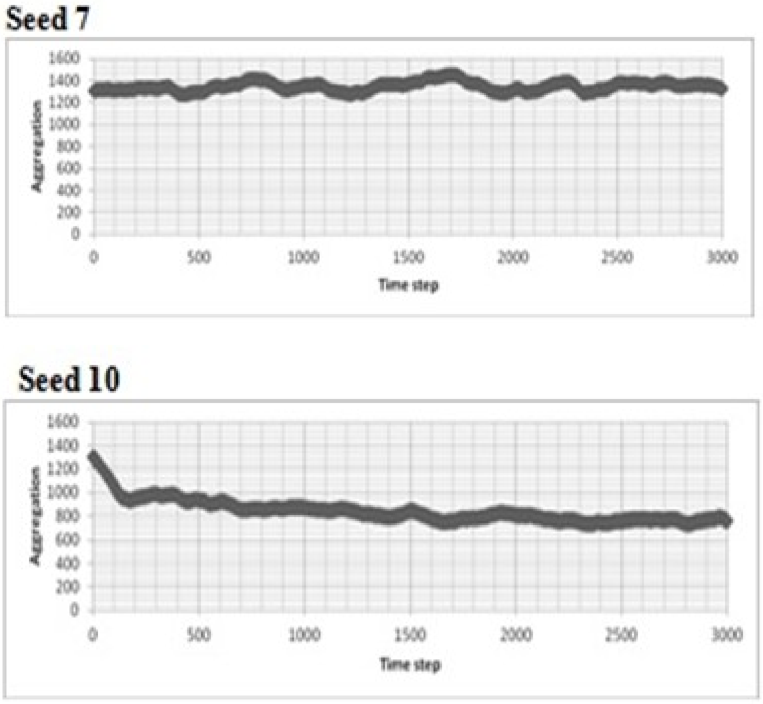


Figure 3.11: Aggregation variation through the life.

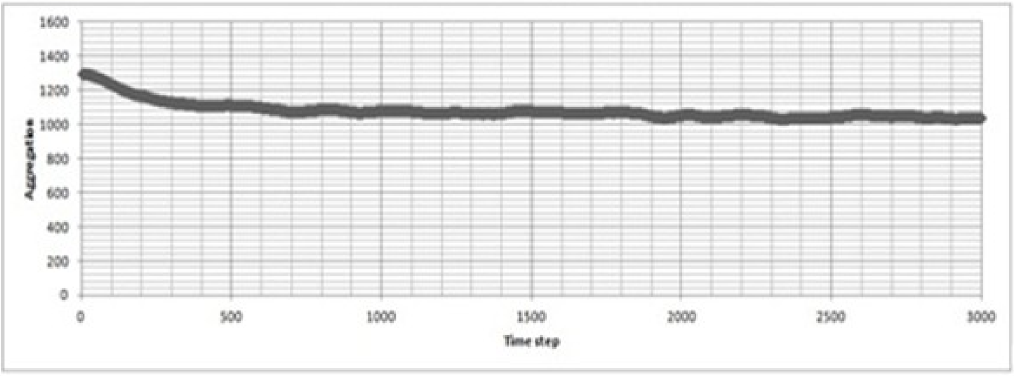


Figure 3.12: Average Aggregation over the replications.

As a matter of fact, after the predators eat the prey in the first part of the life cycle, then the prey supply become scarce.

In the first part of a robots' life, the average aggregation is always less than the average aggregation in the second half of its life, in every replication, but in replication no.7, where the aggregation trend is always constant as we have seen. This situation is clearly depicted in Figure 3.13. Each black bar indicates the average aggregation in the first 1000 time steps and the grey bar is the average aggregation of the last 1000 time steps. As we can see, in the first 1000 time steps the average distance between each individual and the nearest individual is greater than in the last 1000 time steps.

The first important issue, we have faced, is trying to understand why there is a substantial inter-replication variation, why there is a difference between seed 7 and seed 10. To find answers to these questions, finding a behavioural measure is important even before a behavioural analysis. But in this simulation, we have needed to analyze the behaviours before, for indentifying what we need for the following numerical analysis.

By examining the behaviour, we have comprehended that the predators' flocking behaviours are not simply a grouping of robots following each other. There are in many cases some special robots which lead the others in some way. To identify the underlying mechanism we have tested each single

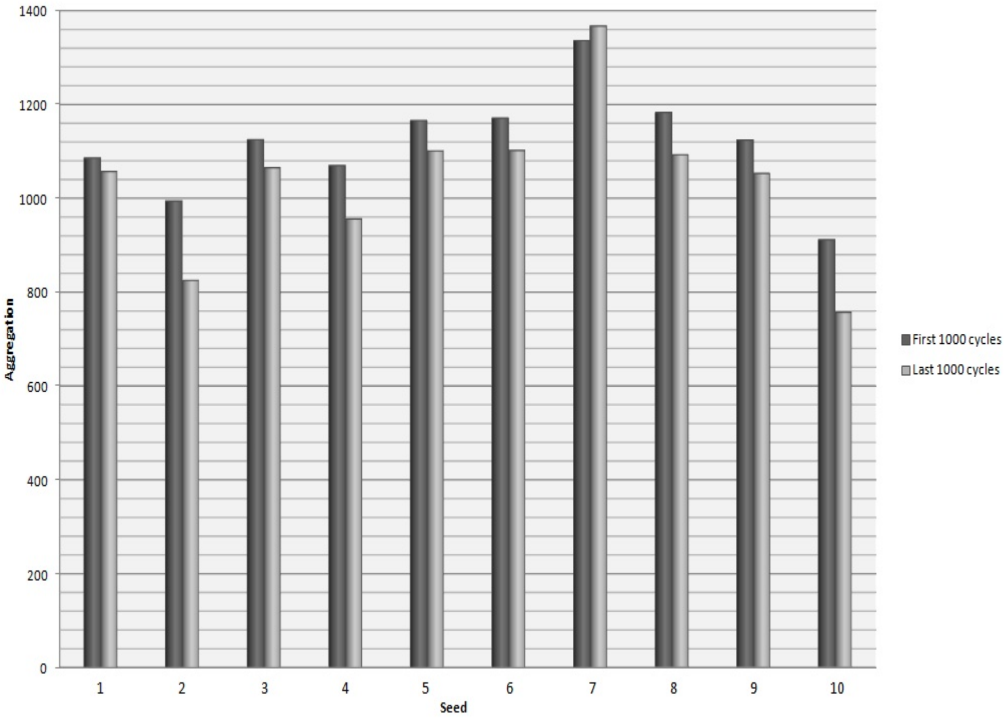


Figure 3.13: Average Aggregation over the replications divided into the 1000 life time steps and last 1000 time steps.

predator robot in a smaller environment called “Laboratory”. In this new Environment with size of 150cm x 150cm we have inserted one or two predators at a time, and we have studied their behaviour. In practice, before, we have inserted one single predator, and we have examined the trajectory as illustrated in examples in Figure 3.14. As we can notice, in the picture there are 3 predator exemplars: predator no. 29, 39, and 27. Each of them draw a different trajectory and we can say they display a different exploratory ability. The prey are numbered between 0 to 19 and the predators are numbered between 20 and 39. In all predators we have noticed different trajectories differentiated in groups depending on the exploratory ability: robots with a small exploratory ability, robots with a medium exploratory ability, and robots with a large exploratory ability. By placing the robots side by side in the same

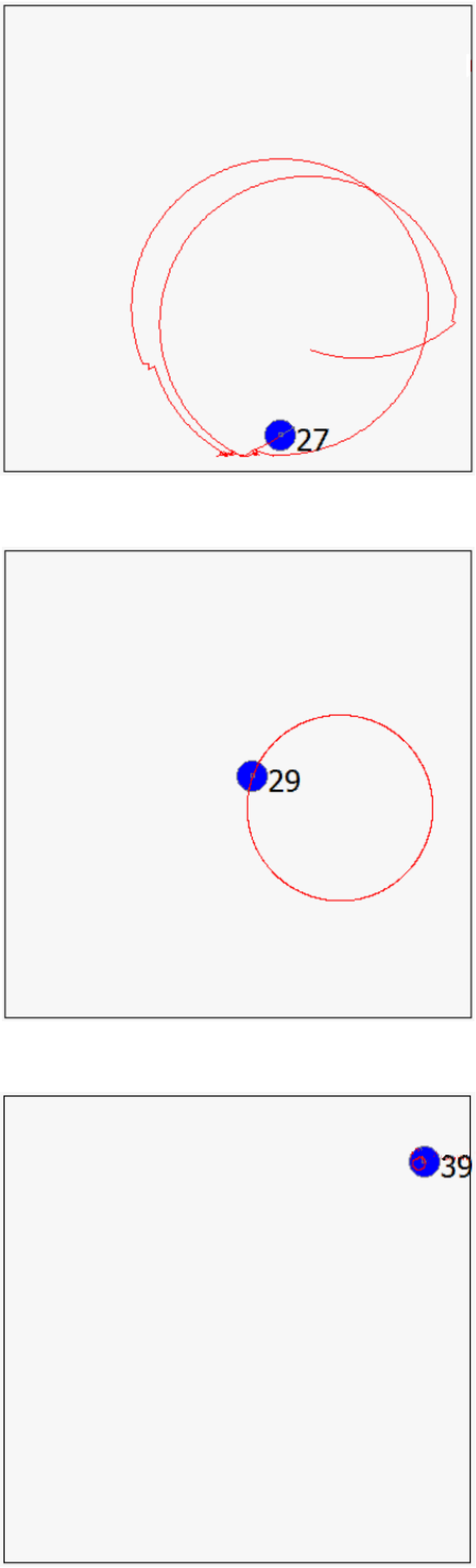


Figure 3.14: Trajectories of some predator exemplars. They are predator number 27, 29 and 39.

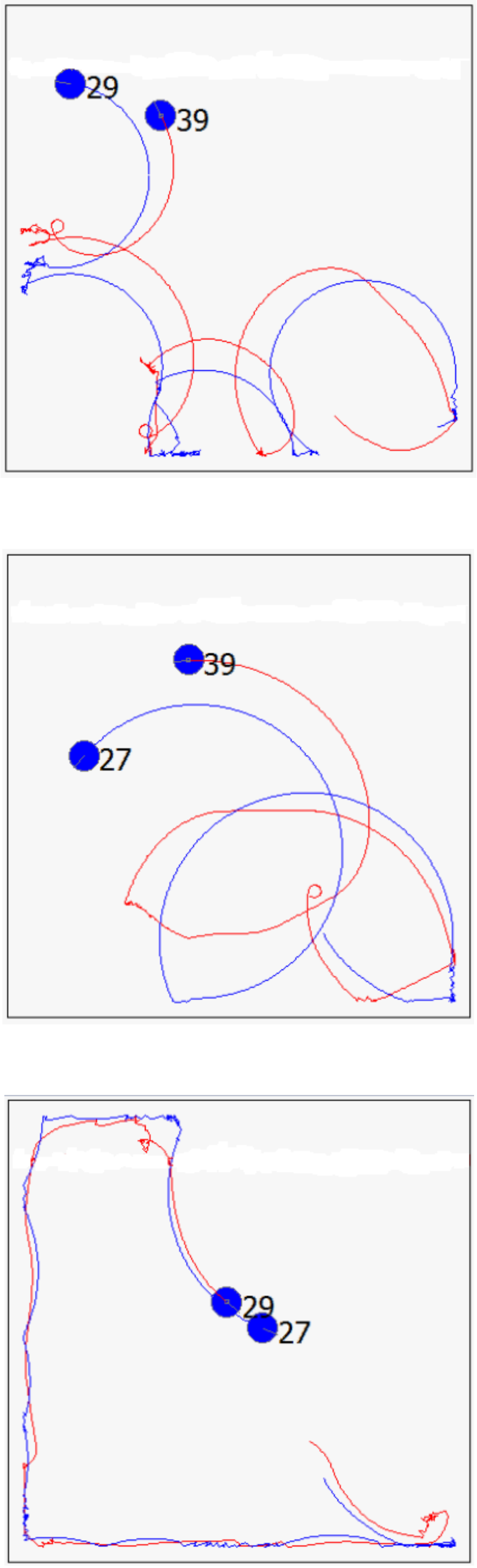
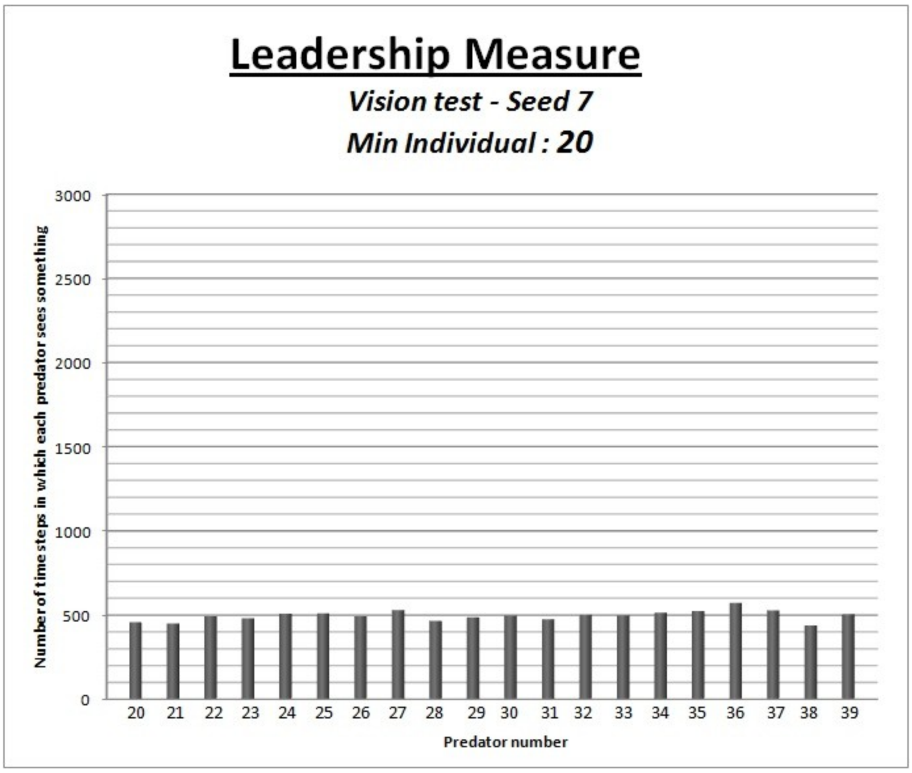


Figure 3.15: Trajectories of all matches between predators 27, 29 and 39.

environment, individuals 29, 39 and 27, we have obtained the behaviour illustrated in Figure 3.15. Basically, we have made all the possible couples between robots 29,39 and 27 and we have watched how they interact within the environment. Surprisingly, we have immediately noticed that in every couple one robot always leads and one robot always follows. This happens whichever trial we have run the test in. But fundamentally, there is a following hierarchy between predators and this is predetermined in advance. In any way we change the robots positions and orientation, this hierarchy always arises in the same preset manner. Furthermore, if we compare Figure 3.15 with Figure 3.14, we observe that all the robots with less exploratory capability (i.e. with draw small trajectories if tested alone) are the ones who tend to follow then. All the robots with more exploratory capability (i.e. which draw big trajectories if tested alone) are the ones who tend to lead. In other words, the following hierarchy appears to be regulated by every single trajectory, or exploratory ability. In fact, the 39 which is the less exploratory in the Figure 3.14 is a follower if coupled with the both robots 29 and 27 which draw bigger trajectories. Robot 29, which appears as leader with the robot 39 is a follower with robot 27. Robot 27 seems to be the absolute leader among these 3 robots. Indeed, 27 has the maximum exploratory ability. The hierarchy cannot be regulated by the color, because all the 3 robots have the same color. The hierarchy should be established by means of the angle of view: by exploiting the retina photoreceptors, each robot is able to recognize the angle of movement of another robot. So each robot is able to discriminate the arching amplitude of the curvilinear trajectory which another robot is able to draw. Exploiting this amplitude each robot can recognize the hierarchic degree of another robot. So in this way, one robot can establish if it has to follow or to lead. Obviously, the genetic algorithm shaped this mechanism to guarantee the emergence of leadership, since it is the only strategy we can imagine to reach this purpose.

Evidently, the leadership has been needed for the group coordination in moving toward one direction. In this way, we guess it is possible to conclude that a group of artificial agents, like those in the present simulation, needs leadership/followership patterns to solve a simple moving task in one direction this is the direction where the prey are. In other words, a peer-to-peer flocking behaviour is not enough on its own to guarantee a smart movement of the group in one direction, but it is necessary for the emergence of leadership. The evolution has fashioned the following strategies in this interesting way. Lastly, in this simulation, the leadership appears to be "relative", namely each leader is not an absolute leader but it is a follower of another robot. Since, the leadership position is correlated to the exploratory ability as we have argued, there could be an absolute leader among all the 20 predators, this would be the leader with the maximum trajectory amplitude. But this does not necessarily happen, there could be two maximum leaders of three and so on.

To support these ideas originated by the previous behavioural analysis we have studied a series of measures in order to prove the hypothesis we have made on the leadership hierarchy. The first Measure, that we have introduced, is the "Leadership Measure by Vision", that is a measure of each predators leadership level by exploiting the vision system. In practice, we have inserted all the possible predator couples, into the Laboratory environment. Each of the 20 predators have been coupled with each of the 19 others. For each sub-test, only 2 robots are present in the environment each time. Then we have counted how many time steps each predator sees something, namely how many time steps at least one retinoic photoreceptor is activated. For each predator, the number of time steps in vision, has been averaged for all the pairings with the other 19 predators. The hypothesis is that if there are only two individuals in a small laboratory environment, the leader will see less than the follower. The leader should more likely be at the head of the following line whereas the follower should be on the tail. Therefore, this turns out a sequence of vision parameters, for each predator per replication. Each parameter represents the leadership ranking of each predator in the group, and the lower the value of the "Leadership Measure by Vision", the higher the leadership effect of one predator. The Measure of Leadership by vision is depicted in Figure 3.16. This picture shows the values of Replication no.7 and Replication no.10, which are the ones with the lowest aggregation and highest aggregation respectively, according to the Aggregation Measure in Figure 3.9.



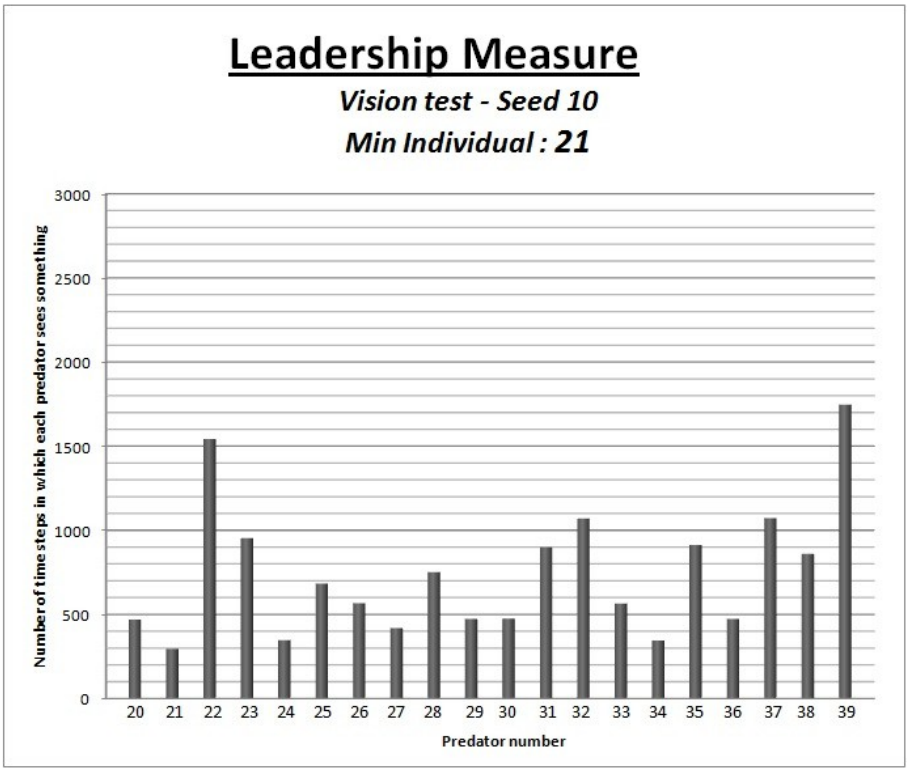


Figure 3.16: Leadership Measure by Vision. In the picture there are the values of Replication no.7 and Replication no.10.

Comparing the figures 3.8, 3.9, 3.11 and 3.16, we can argue that: whereas there is a low aggregation (replication 7) then the variation between predators leadership values are low, the fitness is low and the aggregation evolution during the life is constant. On the other hand, when the aggregation is high (replication 10), then there is a high variation between leadership values, the fitness is high, and the aggregation evolution during the life is decreasing. In other words, there is a great correlation between aggregation, fitness and leadership. Leadership parameters in replication no.10 suggest that leadership/followership patterns appear only when there is a high variation between the values: only some individuals are absolute leaders (namely, 21, 24, 34 in the picture), others are relative leaders (namely, 25, 28, 35, etc.) that means they are leaders for some predators and followers in regard to other predators. Lastly, only some predator robots are absolute followers (namely, 22, 39). Leadership variation suggests that leadership emergence is correlated with fitness: this should be a winning strategy because whenever there are strong leadership/followership patterns there is a higher average fitness indicator, and vice versa. All this indicates an operational way to extract a unique measure of leadership per replication: measuring the variation intra-seed of Leadership Measure by vision, we achieve a Leadership Measure per replication. For this reason, we have calculated the standard deviations of leadership measure for each replication, in this way we obtained a value of Leadership for each seed. For example, it should be that there is a high emergence of leadership/followership patterns, in seed 10 (high standard deviation) and seed 2, while in the seed 7 (low standard deviation) there should be a low leadership/followership emergence. Therefore, to measure intra-seed Leadership Measure by Vision’s variation, we have calculated the standard deviation of it for each replication. “Leadership Measure – standard deviations” per replication is illustrated in Figure 3.17. In excellent agreement with the previous comparisons between different measures, the Leadership Measure per replication draws a situation where replication no.7 (low standard deviation) displays a low leadership/followership pattern emergence; whereas replication no.10 shows a strong emergence of leadership/followership pattern.

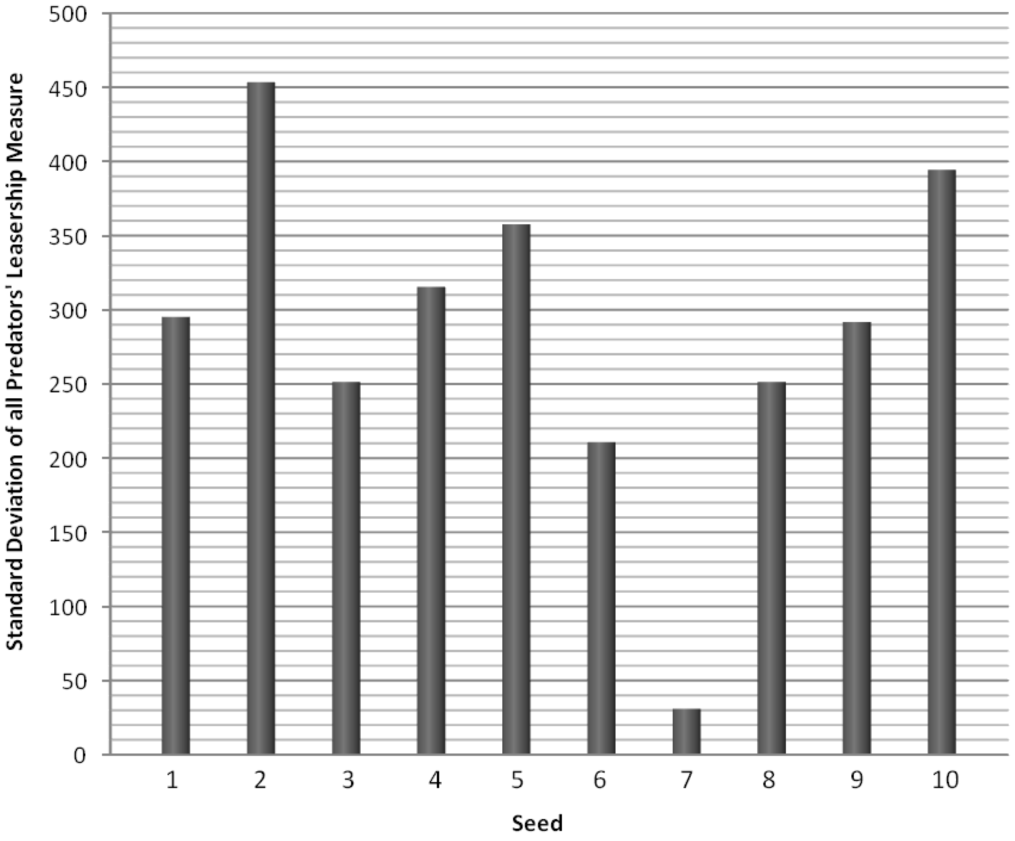


Figure 3.17: Leadership Measure by Vision per replication (standard deviation).

This is in accordance with behavioural observations because in replication no.10 we notice a strong presence of following with many special individuals who lead the group. Instead, in replication no.7 we observe that each individual displays a selfish behaviour and tends to explore the environment independently from others. In seed 10 robots tend to be more clustered than in seed 7.

Therefore we have tried to express formally (in a numerical form) the correlation we have foreseen (just before by comparisons) between Aggregation Measure per replication (Figure 3.9) and Leadership Measure per replication (3.17).

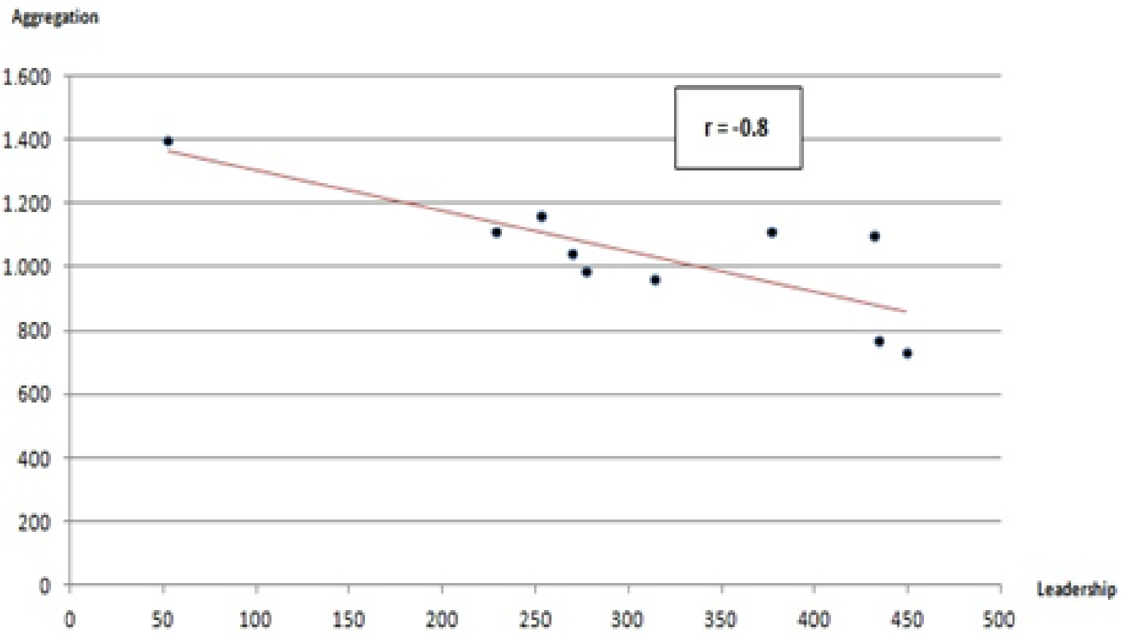
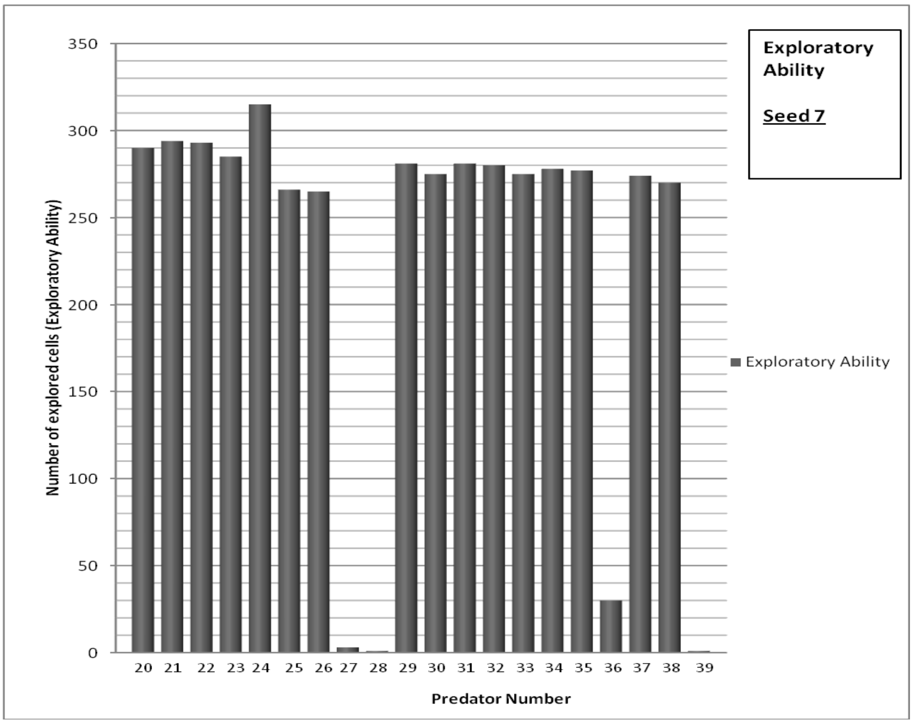


Figure 3.18: Correlation between Aggregation Measure and Leadership Measure.

The Pearson's Correlation Coefficient between those two series of data, has returned a $\rho = -0.8$ that proves a strong correlation. Figure 3.18 is shown this correlation. This means that the higher the leadership presence, the stronger the aggregation in the group and vice versa. Obviously, in this case, there is an anti-correlation because of the leadership measure design: the leadership is stronger when the vision value is lower.

Another interesting issue we have wondered about is: in what way is the leadership role connected with the exploratory ability? Predator robots seem to display different exploratory skills. Thus, we have calculated the exploratory ability for each single predator in the laboratory. Basically, we have counted how many 5.5cm x 5.5cm sized cells each robot visits in the lab environment only once. Each test has been performed on the last generation's predators for 20 trials lasting 3000 time steps. Each value has been averaged over all the trials and reported on a bar plot such as in Figure 3.19, where the "Exploratory Ability Measure" is depicted. As we can see in the picture, there is a substantial



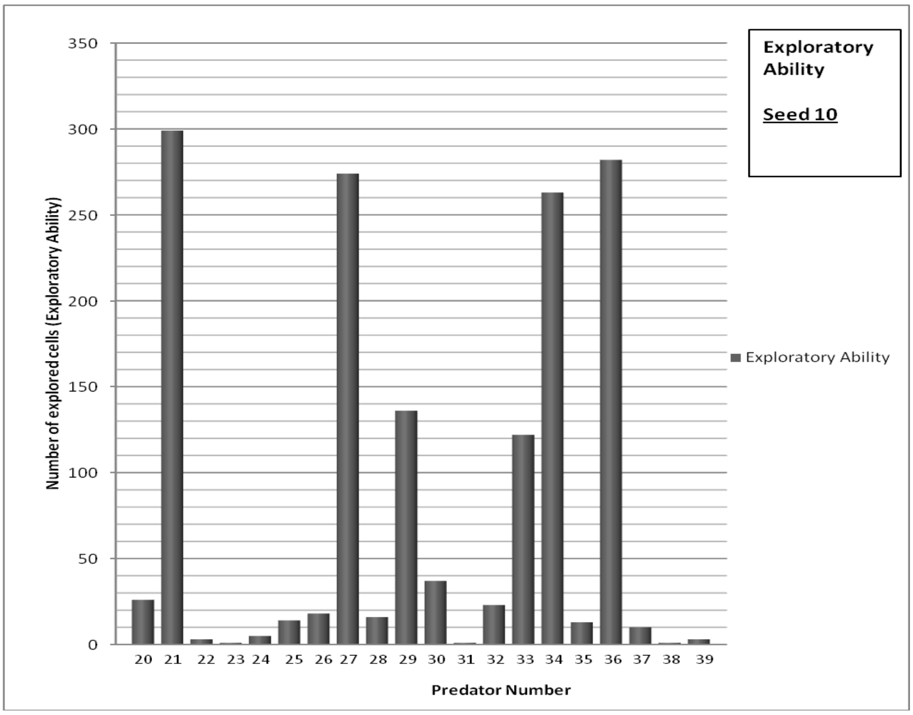


Figure 3.19: Exploratory Ability Measure. In the picture there are the values of Replication no.7 and Replication no.10.

difference between seed 7 and seed 10, also in this case. Intra-seed variation is low in seed 7, with all the predators appearing strongly exploratory. Again, in seed 10, variation between values is high, and only a few predators appear exploratory. Also in this case we have thought to find a resumptive measure for exploratory ability per each replication. However, in this case, we have tried to imagine and to calculate the average of all the exploratory abilities (instead of standard deviation) because we are interested in the average capabilities per seed. Therefore at the end we have the Figure 3.20 which shows the exploratory ability of the 20 predators in the last generation's population. As expected, replication no.7 displayed the maximum average exploratory ability whereas replication no.10 shows a low exploratory ability on average. This means that in seed 7 predator robots are selfish and independent of each other, they just deal with seeking prey on their own.

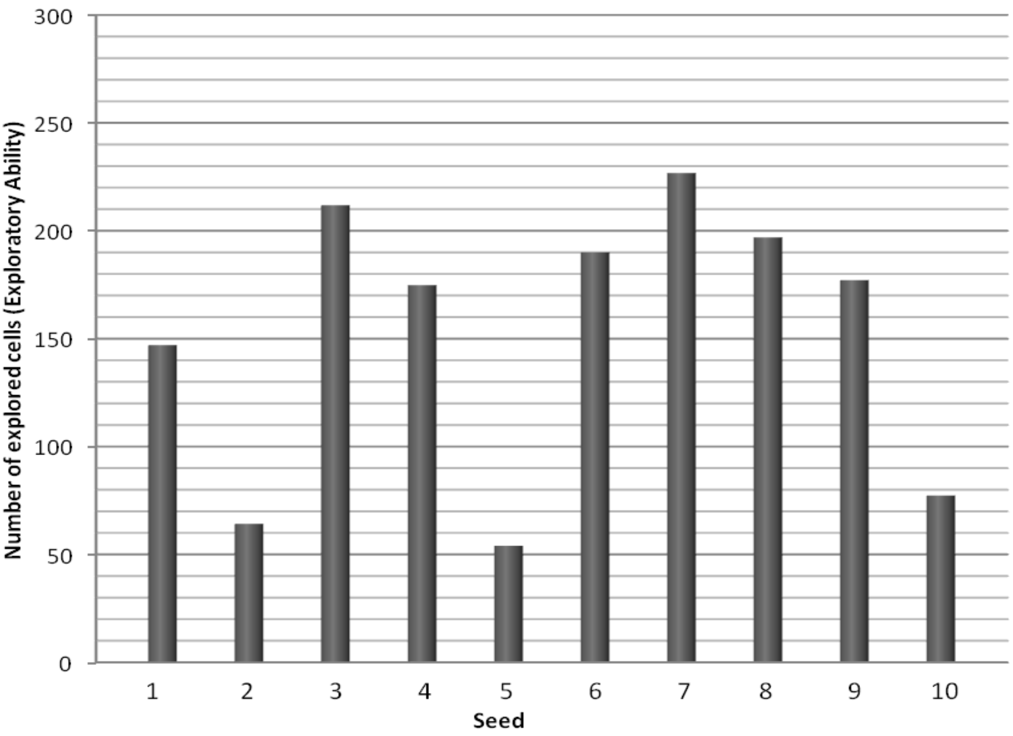
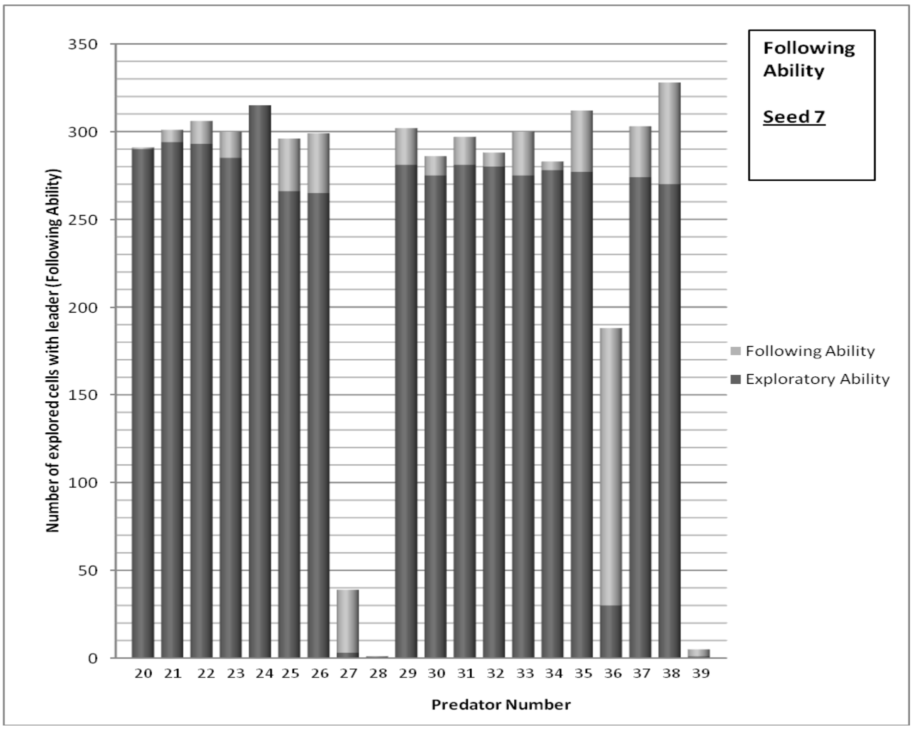


Figure 3.20: Exploratory Ability Measure per replication (average).

They do not follow and they do not have hierarchies. In the seed 10 predator robots are in strong relationship with each other, they follow the higher ranked robots basically, and they do not have high exploratory abilities. In this case, there is a leadership hierarchy. Moreover, this numerical analysis is in agreement with behavioural observations.

Another interesting point is understanding the following capabilities of each predator and trying to correlate these with all the other capabilities. In other words, so far, we have examined the predator's behaviours from a leadership point of view, now we are willing to study them from a followership point of view. To reach this purpose we have tried to identify a measure of following ability. Therefore we have measured the exploratory ability of each robot in ecology by inserting all predators in the ecological environment together. At this point we have disabled each robot's vision system to measure the exploratory ability without any influence from their neighbors. The results are in perfect agreement with the exploratory ability in the laboratory shown in picture 3.19, as expected. This test has been executed on the last generation's predators for 20 trials. Later on, the test has been repeated with the retina vision system enabled: in this case each predator starts to follow another one according to the leadership system we have earlier illustrated. This following behaviour unavoidably causes the increase of exploratory abilities in those replications where many robots were not that exploratory. The increase of exploratory ability has been schematised in Figure 3.21. In the picture, in grey is represented the increase of exploration of the environment from a "no vision" condition to a "with vision" condition. As we can observe, in replication no.7, most of robots were initially exploratory, so there was no evident increase of exploration. On the other hand, in replication no.10, only a few robots (leaders) were initially exploratory after the vision reactivation, so the less exploratory robots became more exploratory as they follow the leaders. In other words, the leadership seems to make followers able to become exploratory with regard to the situation in which they are alone. If we compare Figure 3.19 (seed 10) with Figure 3.16, all the leaders that emerge in the



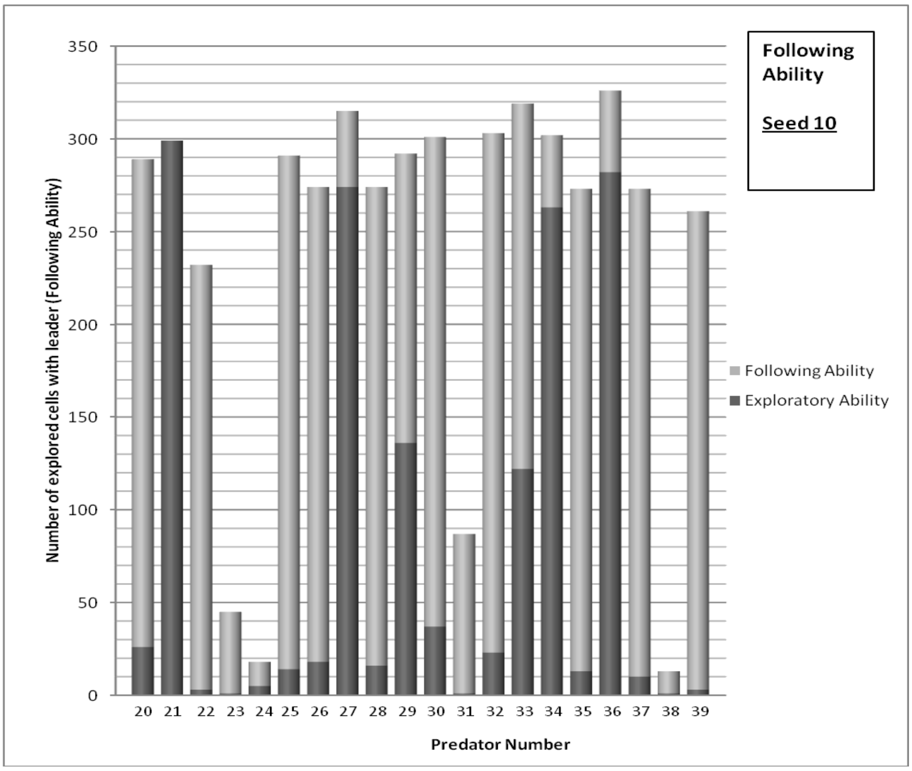


Figure 3.21: Exploratory Ability Measure after enabling the vision system. In grey the increase of robots' environmental exploration.

measure. In other terms, leaders turn out as the most exploratory robots, definitely.

They lead the less exploratory robots and they contribute to enhancing their exploratory capability in order to catch some prey. When leadership emerges there is a specialization of skills that is not present in seeds like no.7 where everyone is rather exploratory.

I guess, this is the most important information from this simulation. Another interesting insight comes from measuring the exploratory gap between the "no-vision" condition and the "with vision" condition, replication by replication. Basically, we have averaged all the values of the ecological "no vision" exploratory ability per replication. The result is the bar-plot in Figure 3.20.

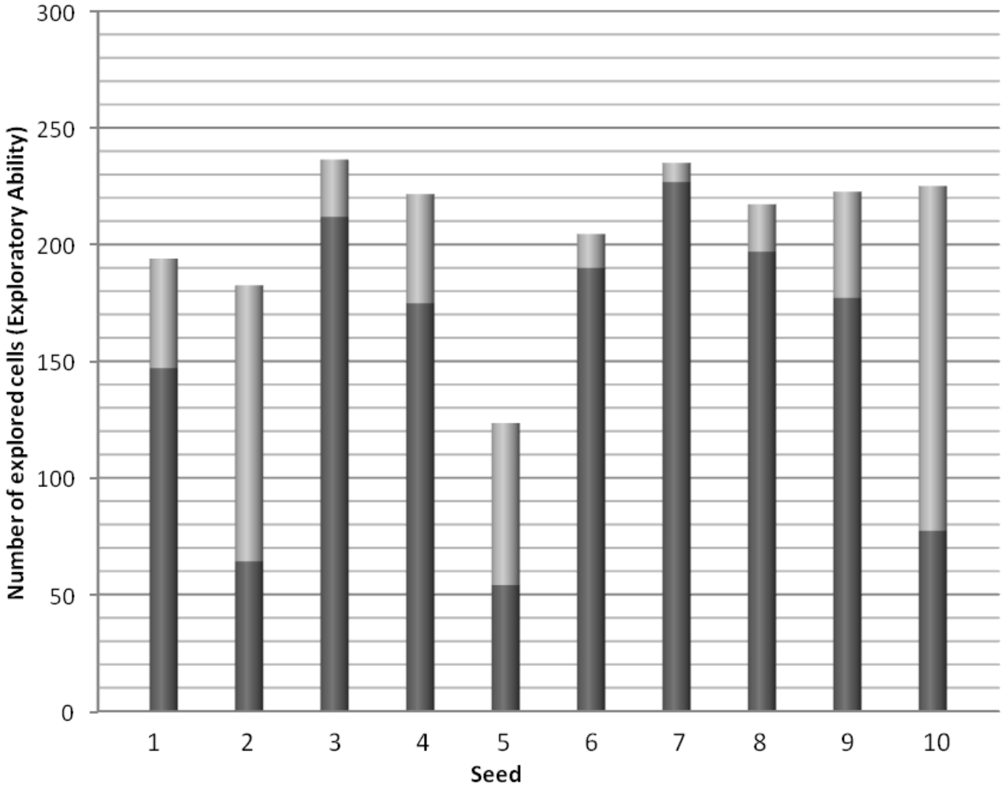


Figure 3.22: Exploratory Ability Measure after enabling the vision system. In grey the increase of robots' environmental exploration.

Thereafter, we have averaged all the values of the ecological “with vision” exploratory ability per replication. Overlapping the two charts, we can visualise the bar-plot in Figure 3.22.

A variable gap appears between replications; that gap can be assumed as the average following ability of robots in one replication. This is the following ability because from the “no vision” condition robots gain an increase of their exploration abilities which is directly proportional to the ability of the robot to follow.

In fact, the new exploratory capability in the “with vision” condition will be as high as the following of the robot, because the robot affects its ability to move and explore the environment. The grey gap visualised in Figure 3.21 shows this following ability per predator robot exactly. Therefore, if we “isolate” this gap, we obtain a measure of their following ability per replication, as illustrated in Figure 3.23. Absolutely, this is a reliable “Followership Measure”. This picture appears to be in agreement with the Leadership Measure by vision, as it shows a great following in replication no. 10 and a small following in replication no.7. This is what we had expected, as where there is a high leadership component, there should be a high followership component and vice versa. To numerically formalise this apparent correlation, we have calculated again the Pearson’s coefficient between Leadership Measure and Followership Measure and we have returned a $\rho = -0.79$ confirming a strong correlation.

In Figure 3.24 this correlation is graphically visualised. A careful analysis of the exploratory and following abilities by previous charts, shows another interesting piece of information: in this simulation, the exploratory ability and following ability are reciprocally exceptive, meaning that one ability excludes the other one. For example in seed 7 all predators appear to be explorers rather than followers, whereas in seed 10 they look like followers rather than explorers.

Therefore, we have implemented an analysis of exploration and following abilities depending on different perceptive conditions. Basically, we have evolved robots with different conditions of distance vision’s maximum limit: 13.75cm, 27.5cm, 41.25cm, 55cm, 82.5cm, 165cm and 220cm. Of course, we

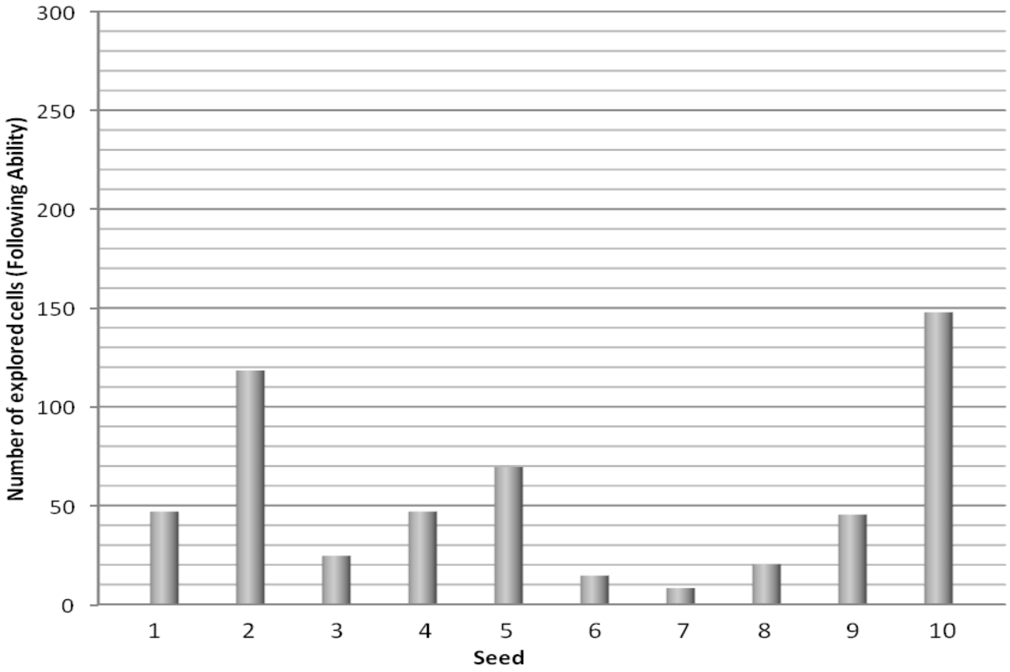


Figure 3.23: Following Ability Measure per replication.

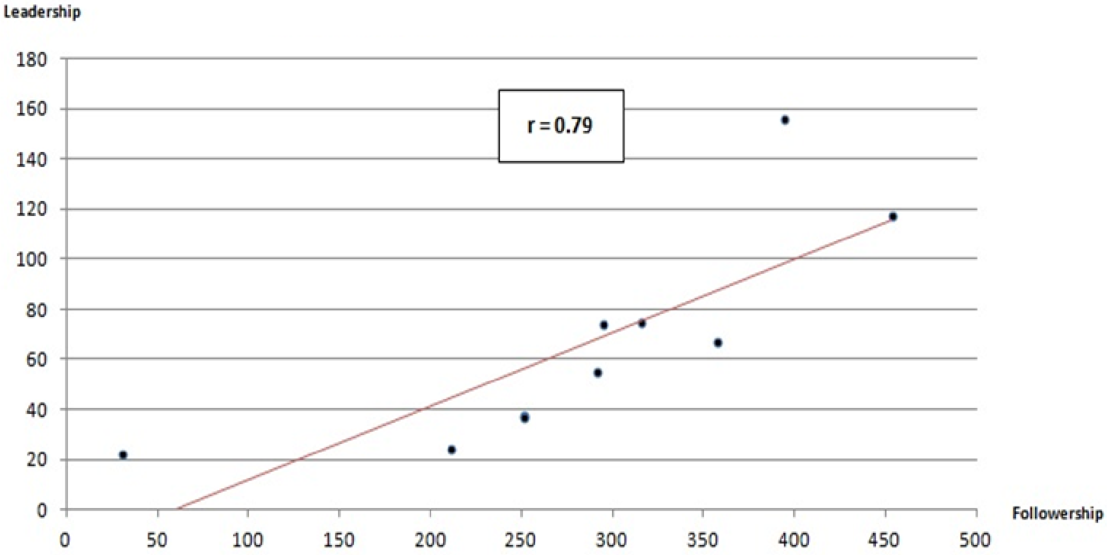


Figure 3.24: Correlation between Aggregation Measure and Leadership Measure.

have not been able to sample many more conditions of vision because of the elevated computational and time costs.

Anyway, the number of completed samples seemed to be acceptable for the present. The limit of 55cm is used as the default condition because it was used in the initial evolution. Therefore, we have considered the condition “55cm” as basis for comparisons. Again, every simulation has been evolved for 300 generations and with 10 replications for each one.

After all the evolutions have been accomplished, we have calculated the average of all the “Exploratory Ability Measure per replication” values (as in Figure 3.20) and all the “Following Ability Measure per replication” values (as in Figure 3.23) over the replications, for each perceptive condition. The result for the “Exploratory Ability” and “Following Ability” through different vision conditions are depicted in Figures 3.25 and 3.26.

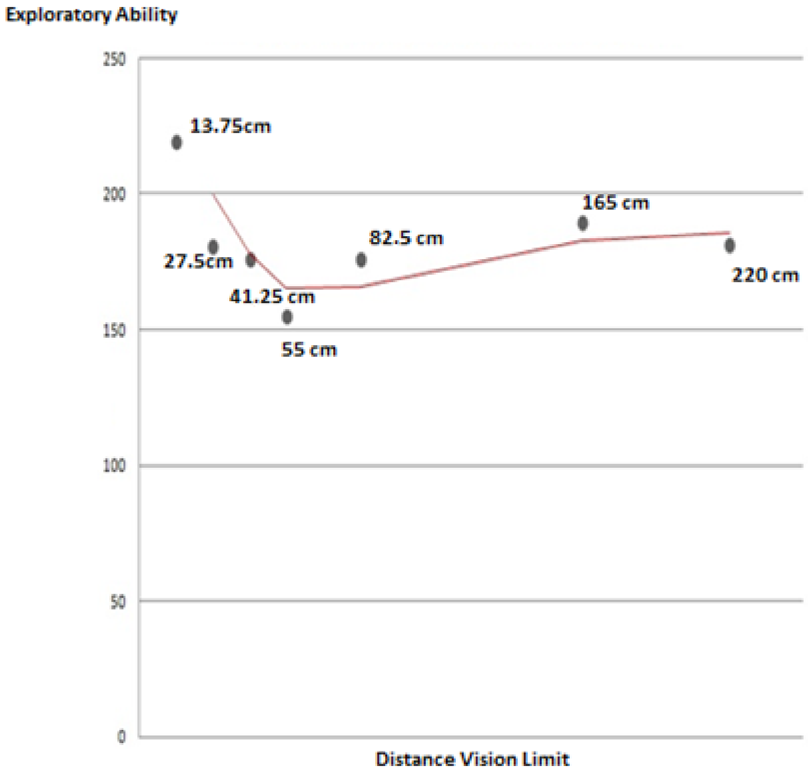


Figure 3.25: Exploratory Ability through different Distance Vision Limits.

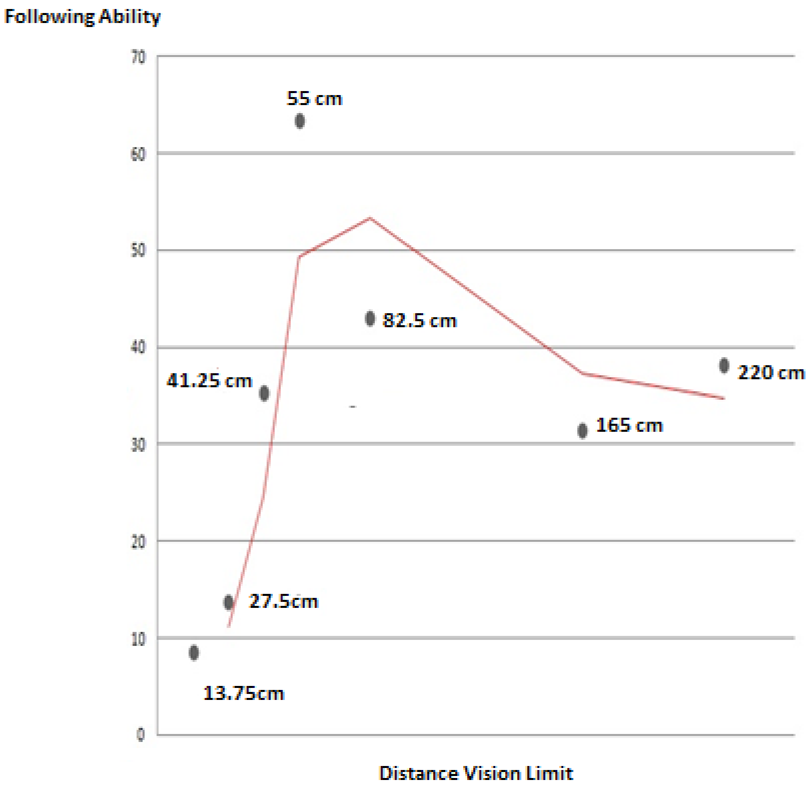


Figure 3.26: Following Ability through different Distance Vision Limits.

As we can observe in the Figure 3.25, "Exploratory Ability through different Distance Vision Limits" has not a linear trend, but after an initial decrease of the average exploratory ability, there is a new increase.

The condition with 55cm of limit, is the minimum of the curve. We have graphically interpolated all the points in order to highlight a data trend. This curve can be interpreted as the fact that the role of distance limit is not always crucial for the emergence of following (and leadership) abilities. In agreement with behavioural observations, we can say that limit of distance can foster the followership emergence, because of the "vacuum vision", as we have previously argued. But this is true under a threshold limit: above this threshold, vacuum vision is lower, because the robot's environmental vision is wider. This determine a reverse of trend since predator robots prefer to explore environment instead of following, because they are able "to see" more details.

For example they are able to see pretty more. Finally each predator can prefer to follow prey rather than follow other predators. This seems a good explanation of the phenomenon. In the matter of the following ability we can observe a totally opposite trend: the following has an increasing trend up to 55cm and then it starts to decrease again, later on. Definitely, following ability and exploratory ability appear in contrast: whenever there is a strong presence of one of those abilities the other ability is low and vice versa. This is another important information coming out from this simulation.

The last information (we have tried to extract from this experimental setup) is related to the number of leaders and followers which are present in every evolved population of robots. Moreover, we have tried to understand how the number of leaders affect the group's dynamics. From the interpretation of predator robots' behaviours and the exploration data in all replications (Figure 3.21), we have realised some clues about the types of individuals which the predators' population is made of:

- **Leaders:** which are predators characterised by an initial high exploratory ability (i.e. in non-social condition when they do not see the others). When they are in social condition (with enabled vision) they do not display a considerable increase of the exploratory ability. This because they are selfish and do not tend to follow other robots (for instance robots 21, 27 and 36 in Figure 3.21 - seed 10).

- **Followers:** which are predators characterised by an initial low exploratory ability (i.e. in non-social condition when they do not see the others). When they are in social condition, with vision enabled, they do display an elevated increase of the exploratory ability. This because they tend to follow other robots, and this makes them more exploratory (for instance robots 20, 39, 37 in Figure 3.21 – seed 10).

- **Non-socials:** which are predators characterised by an initial low exploratory ability (i.e. in non-social condition when they do not see the

> others). When they are in social condition (with enabled vision) they do not display a high increase of the exploratory ability. The exploratory ability keeps the same, more or less. This because non-socials do not tend to follow other robots and they are not exploratory initially (for instance robots 24, 38 in Figure 3.21 – seed 10). The non-socials' portion (in each replication) seems to be paltry with respect to the leaders and followers portions.

These considerations have provided us a "modus operandi" to count the exact number of leaders, followers and non-socials predators. We have defined some thresholds to separate all the three sets of robots: individuals with high exploratory ability initially in "no-vision" condition and with low increase of that in "with-vision" condition are the leaders; individuals with low exploratory ability initially in "no-vision" condition and with high increase of that in "with-vision" condition are the leaders; individuals which are not explorative in "no-vision" condition and with no increase of exploration in "with-vision" condition are the non-socials. The results of this analysis are reported in Figure 3.27 and 3.28 per replication. We can observe that non-social robots in every replication are a small part of the totality. On the other hand, all the replications which fit with high leadership (Figure 3.17) and high followership (Figure 3.23) show a small number of leaders with respect to the number of followers. In other words, every replication where a strong leadership (and followership consequently) arise, displays a small ratio leaders/followers, such as seed 2, seed 5, seed 10 (namely comparing in Figures 3.17, 3.23 and 3.27). These counting results are in excellent agreement with the literature which asserts this law**:** only a very small proportion of informed individuals (leaders) is required to guide a group and to achieve great accuracy [14]. In this case leaders are informed individuals since they are more explorative and can experience a wider portion of the environment. Namely, there exist a law (in coordinated moving groups) according to which, whenever there is strong emergence of leadership, only few individuals can lead big groups of robots. The larger the group, the smaller the leaders portion.

3.3.3 Future directions

Some improvements can be made in the simulation in order to examine, in depth, some unclear aspects such as the correlation between leadership emergence and fitness. Furthermore the connection between group size and leaders portion might be investigated.

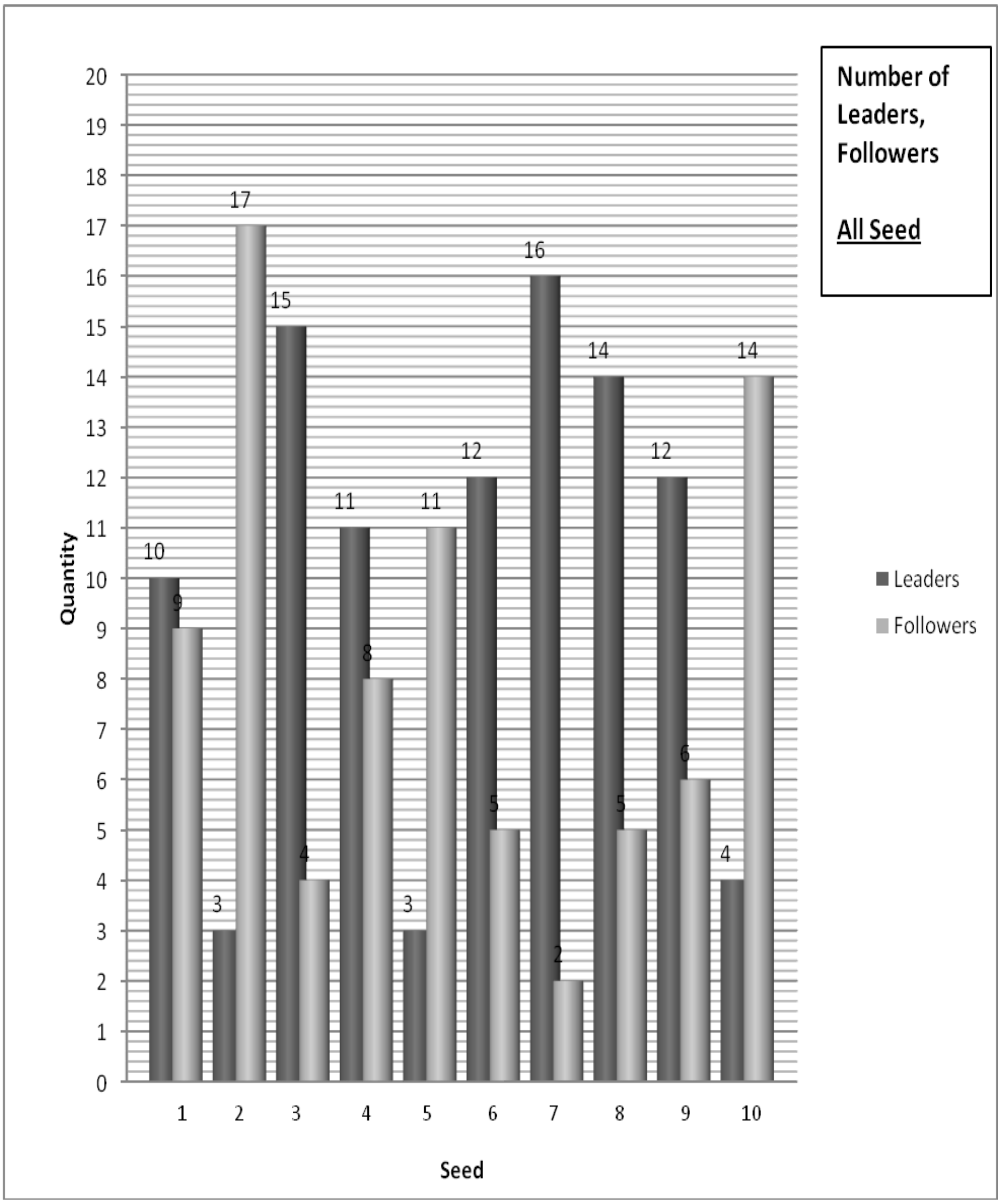


Figure 3.27: Count of Leader, Followers and Non-socials in the simulation.

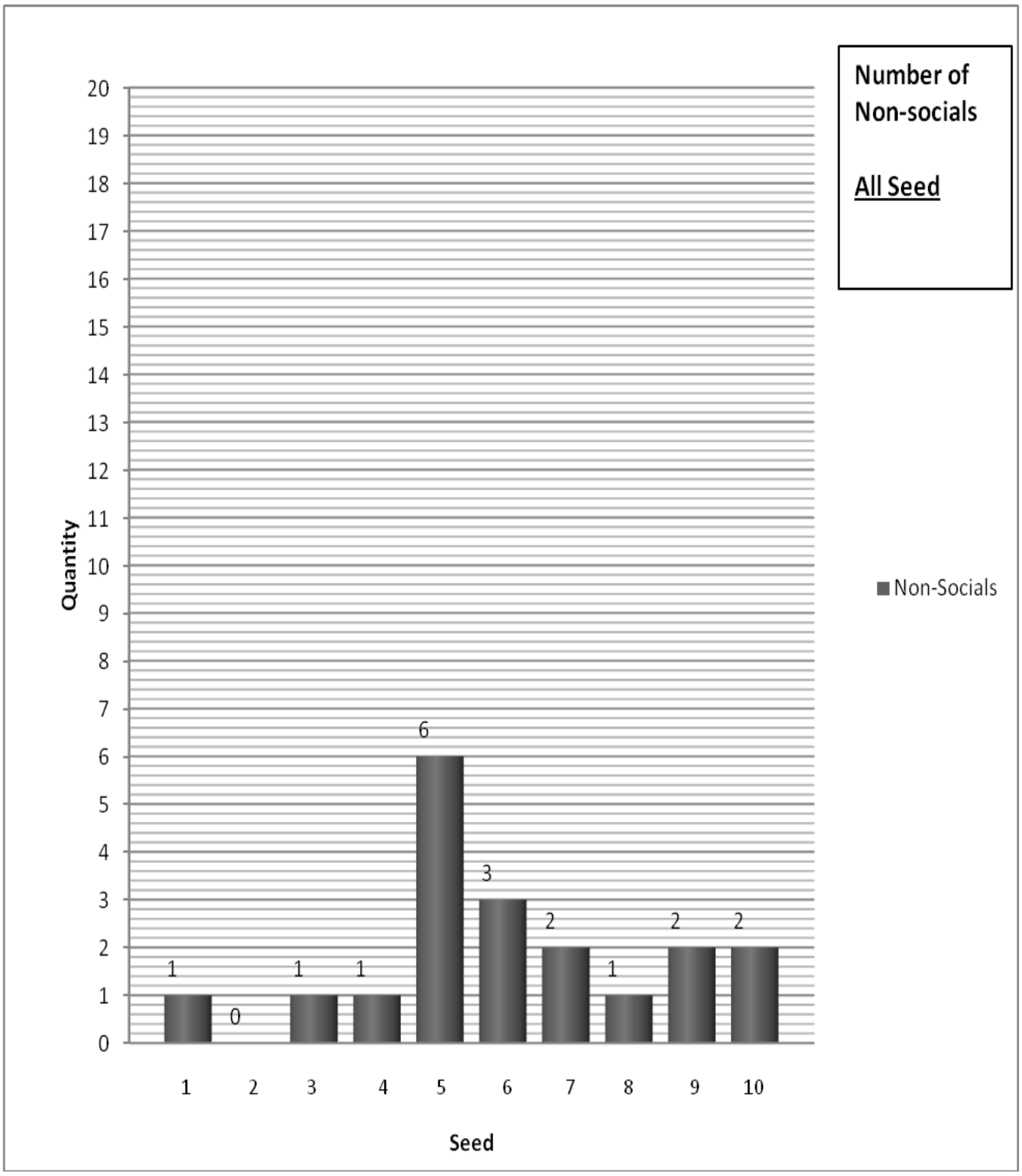


Figure 3.28: Count of Leader, Followers and Non-socials in the simulation.

4 The underlying mechanisms of the Evolution of Leadership

As I have stated in Chapter 3, the reason for the emergence of leadership / followership patterns in groups of living beings, is the need to coordinate, in evolutionary biology [12,13]. Moreover, I have underlined that a first leadership classification identify two categories of leadership: distributed leadership (democracy) and personal leadership (despotism). In some species followers accept the decision of a specific individual on a regular basis. In others, decisions can be achieved via a majority vote, or when a threshold number of followers agree with a potential leader's proposal.

Another interesting leadership classification is based on the modality according to which, the leader can lead a follower. This classification considers two categories: a) passive leadership, which occurs as a consequence of the group's emergent properties, such as differences in individuals' temperaments. This variation could determine a variation in information supplying for every member. Usually, in this case, leaders and followers do not need to communicate directly. Passive leadership is common in large and homogenous groups, such as insect swarms, fish, bird flocks, where individuals have little or no significant conflict of interest [14, 27]; b) active leadership, which occurs when potential leaders explicitly signal their intention to other group's members. Group members can choose to follow, or not. Active leaders' explicit signalling can operate at a global scale, via communication with all group members [114]. This type of leadership can be found in some species of animals such as ravens that inform group members about the food's location through acrobatic flights [115]. In monkeys species, it can be found a great amount of vocal and visual signalling for initiating group movements [103]. In human groups there are facial expressions, gestures, rituals, and complex language forms to synchronize group activity [116]. In the case of active leadership, followers need to agree with leaders to achieve coordinated group action [117].

Another classification suggest that could there be two types of leadership in dependence on environmental factors : structural leadership where the individual's leadership role is not affected social variations or environmental interaction. On the other hand, in contextual leadership, roles change depending on environmental and social conditions [14]

.

4.1 Intra-specific Temperaments Variation

Correlations between leadership and temperament are well documented in the animal and human literature. It has been argued that intra-specific differences in temperament (or personality) derive from a stable phenotypic or even genotypic variation. Personality differences have traditionally been assumed to be a non-adaptive variation which affect adaptive population behaviours [16].

In a recent experiment, pairs of sticklebacks have coordinated their foraging toward a food patch: personality differences have revealed themselves as crucial for achieving coordination. Bold fish have emerged as leaders and shy fish has emerged as followers. These differences have been enhanced by social feedback, namely bold leaders have always inspired faithful followership, and shy followers have facilitated effective leadership [118]. A review of the human literature shows that extroversion is correlated with leadership, and this trait (an indication of boldness) has a substantial heritable component [119]. Furthermore, experiments show that the most talkative members of a group often become the group's leader, more or less regardless of the quality of their inputs, this is referred to as the 'babble effect'.

To better understand what are the characteristics that make some individuals, leaders, and some other individuals, followers, a series of games have been invented which prove, without any doubt that, in many situations, leadership is almost inevitable.

In a simple two-player "coordination game", a pair of individuals have two simple goals to reach: one individual have to stay near the partner for protection, and the other individual have to seek resources such as food patches and waterholes. In this situation, any trait (physical or behavioural), that increases the likelihood of one individual moving first, will make them more likely to emerge as the leader, and the other player is left with no option but to follow. Furthermore, if this trait difference between players is stable (i.e. if the first individual is always hungry first) leadership-follower pattern will be stable over time [120]. So it seems that individuals are more likely to emerge as leaders if they have a particular physiological or behavioural trait increasing their propensity to act first to solve coordination problems. The consistent correlation between leadership and personality suggests the intriguing possibility that personality differences are maintained in populations, because they foster social coordination. In other words, these studies suggest the thesis that biological evolutionary process has fashioned individuals genetic temperaments differences (over many millions of years of trial and error) in order to foster the emergence of leader-follower patterns in animal groups. Then, these leadership/followership patterns had an essential role in solving of social coordination problems.

4.2 Leadership in Robotics

All these mentioned biological and ethological experiments are often arduous to be performed in laboratory. Frequently, highly social species are not suitable for supervised experiments because they typically need long time and laboratory breeding. So, getting some experimental proves, of theories on leadership and social behaviours, in general, is often hard by adopting experimental animals or human subjects.

Always more and more frequently a synthetic approach is bobbing up. This approach is based on the use of artificial models such as collective robots. In one of these artificial experiments, authors have evolved a team of four homogeneous robots for dynamically allocating roles through bodily and communicative interactions [121]. In particular, evolved robots show to differentiate both their communicative and non-communicative behaviours so that only one robot assumes the role of the leader of the group, sending high value signals, while all the other robots act as non-leader, almost ceasing their signaling behaviour.

In this experiment robots can rely only on the local information provided by their infrared sensors and by a one-tone communication channel. Definitely, after the evolution, robots are able to choose who is the leader of the group. This experiment proves in what way leadership could arise in a team of robots trying to accomplish a collective task, in which the presence of a leader could be critical. The outcomes from this experiment could facilitate the development of robots able to accomplish collective tasks which require the presence of a leader because this might significantly improve the performance of the group.

In another experiment, a group of agents has been simulated for reaching a target in a two dimensional environment [122]. The fitness is regulated by the time taken by the last agent to reach the target. The simulation compares groups with and without a leader. Whenever a leader is a member of the group, other members of the group follow it through the environment. Three factors have been examined to alter the group performance: (a) group size; (b) the presence or absence of an “able” individual which can detect targets at a greater distance than partners; (3) the existence of a communication network among group members. The results show that, in groups without communication, the leader has a positive influence on the group performance, especially in large groups. This is more evident when the “able” individual is the leader of the group. However, in situations where group members can communicate, the results are in conflict with the first results as leaders are damaging, rather than beneficial, for the group performance.

In another work, researchers have evolved a robot colony to study the possibility for the evolution of leadership patterns [123]. Each robot has a prearranged its own social position: leader, follower, and stranger. Leaders have the responsibility for the survival of the group while followers choose to go after their leaders. Strangers behave independently without a leader or a follower. Transitions between social positions are regulated by simple rules. Behaviours change adaptively to the environment by means of an evolutionary computation. Through experiments, authors have observed that a centralized structure with a leadership always emerges in the evolutionary robot colony: only few leaders with safety behaviour policies control the group in a difficult situation.

In my following experiment I have focused on some aspects that have not been investigated, in the past, in previous mentioned works. The aim of this experiment is to introduce further newness to the literature's results. In particular we have simulated and evolved a group of heterogeneous robots, that means they have not the same controller (on the contrary of [121]). This means, that each robot has got the same body shape, but it is characterised by a different colour and a different genotype which encodes the control neural network. So each robot is characterised by different controlling neural systems. A "Heterogeneous Evolutionary Algorithm" process is expressly conceived to maintain genetic variation between the robot, in order to reproduce conditions which can lead to a spontaneous (not pre-programmed as in [123]) leadership emergence.

This could enable us to reply to some questions derived from the previous readings on temperaments variation and the correlation with leadership/followership patterns emergence. In particular we have tried to reply to the following questions: May leadership always emerge in a group of genetically heterogeneous robots ? Is heterogeneity a fundamental pre-requisite for leadership emergence? Who is the leader ? What are leaders made of ? What are characteristics and skill of a leader ?

4.3 A neuro-robotic model for "Coordination and Leadership Games"

4.3.1 Experimental Setup

A group of four simulated robots live in an environment consisting of a 550cm x 550cm squared arena surrounded by walls. When a robot bumps against environment's wall or against another robot, it bounces back in the neighborhood of the contact point, with a new random direction.

The food source is located in two target areas placed in a fixed position of the environment. The food zone consists of a 110cm diameter. Each robot is made of a circular chassis with a diameter of 5.5cm and it is equipped with two motors controlling the movements of two wheels, respectively (Figure 4.1). Moreover, the robot is geared with two sensors which "smell" the relative position of the food zone in respect to the position of the robot body, as illustrated in Figure 4.2. According to the position of the food zone with respect to a fixed sector of the robot, smell sensors will be activated with a two digits binary code.

Each robot is characterised by a colour of the body: green, blue, light blue and yellow and it is equipped with a linear retina system in order to see the position and the colour of the other group members. The linear retina is made of five

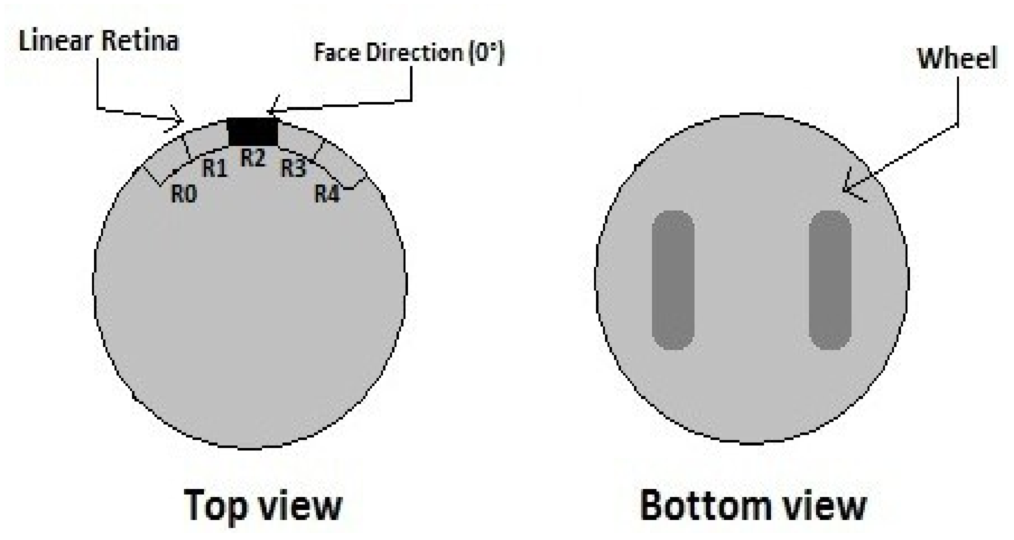


Figure 4.1: Visualisation of top and bottom view of the robot chassis.

RGB photoreceptors that manage a portion of the robot field of view, and it exactly works like prey-predators robots' retina illustrated in the Chapter 3. But in this experimental setup retina has less neurons (5) respect to the prey-predators setup, as they do not need a detailed information about angle of movements of other robots, as in the previous setup has been immediately needed.

The field of view (FOV) of each robot is 90 degrees wide, and represents the extent of the observable world that the robot can see at any moment. The FOV ranges from -45 degrees to +45 degrees with respect to the direction of movement (0°). In this way, each photoreceptor manages a 18 degree wide portion of the FOV, the first one is associated to a range of [-45°,-27°] respect to the face direction, the second one to [-27°,-9°], and so on.

Each photoreceptor consists of 3 colour sensitive components, respectively Red, Green, and Blue. When an object (such as a robot) is located in the front of a photoreceptor, within its vision angle, the sensor is activated to the corresponding RGB value for that object. The maximum vision distance of receptors is the environment size. The setup is illustrated in Figure 4.3.

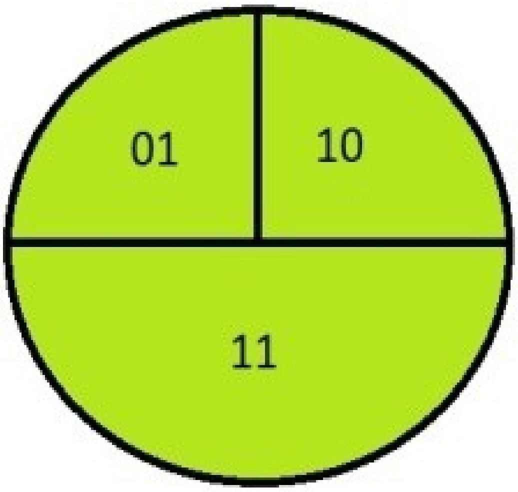


Figure 4.2: Representation of the activation patterns of the robot smell system.

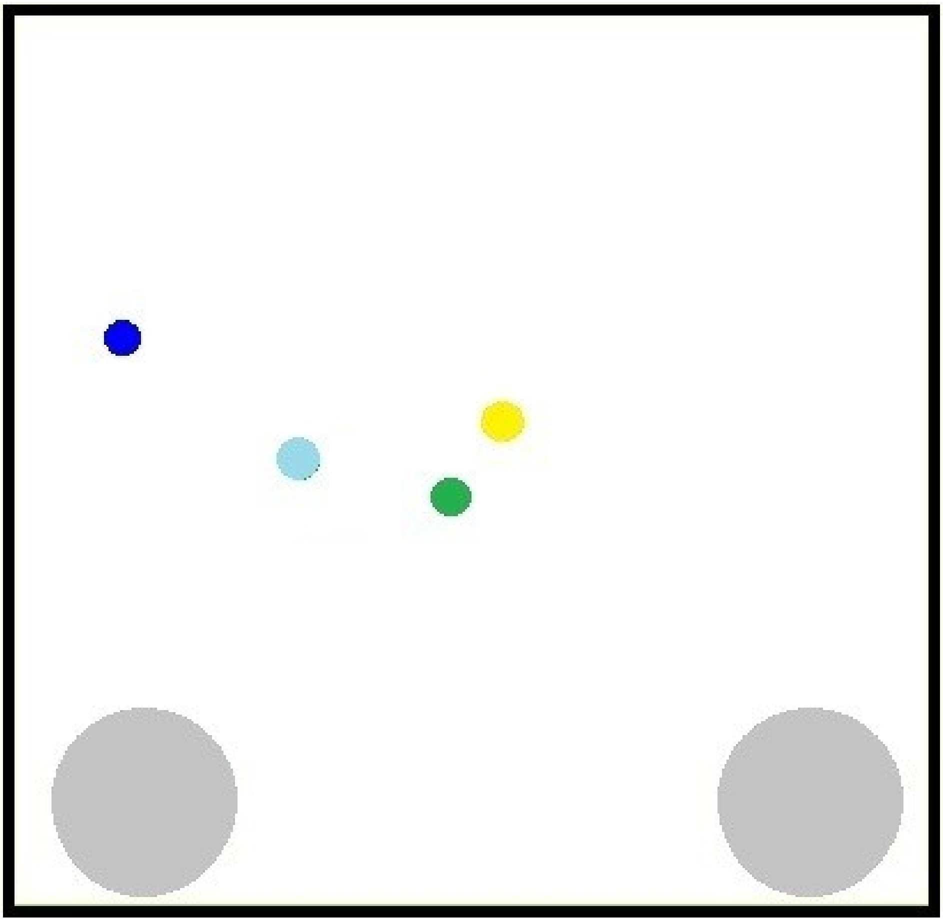


Figure 4.3: The environment and the robots.

The control system (Figure 4.4) of each robot consists of a feed-forward neural network with 18 input neurons, 2 hiddens, and 2 output neurons. Each layer of neurons is connected to the next layer with a pattern of synaptic weights representing the strength of the connections. The input layer contains 15 neurons encoding the activation state of the corresponding photoreceptors RGB components, 2 neurons that receive smell signals and 1 neuron that receives output from ground sensor. The output layer is made of 2 neurons which control the speed of two motors, respectively.

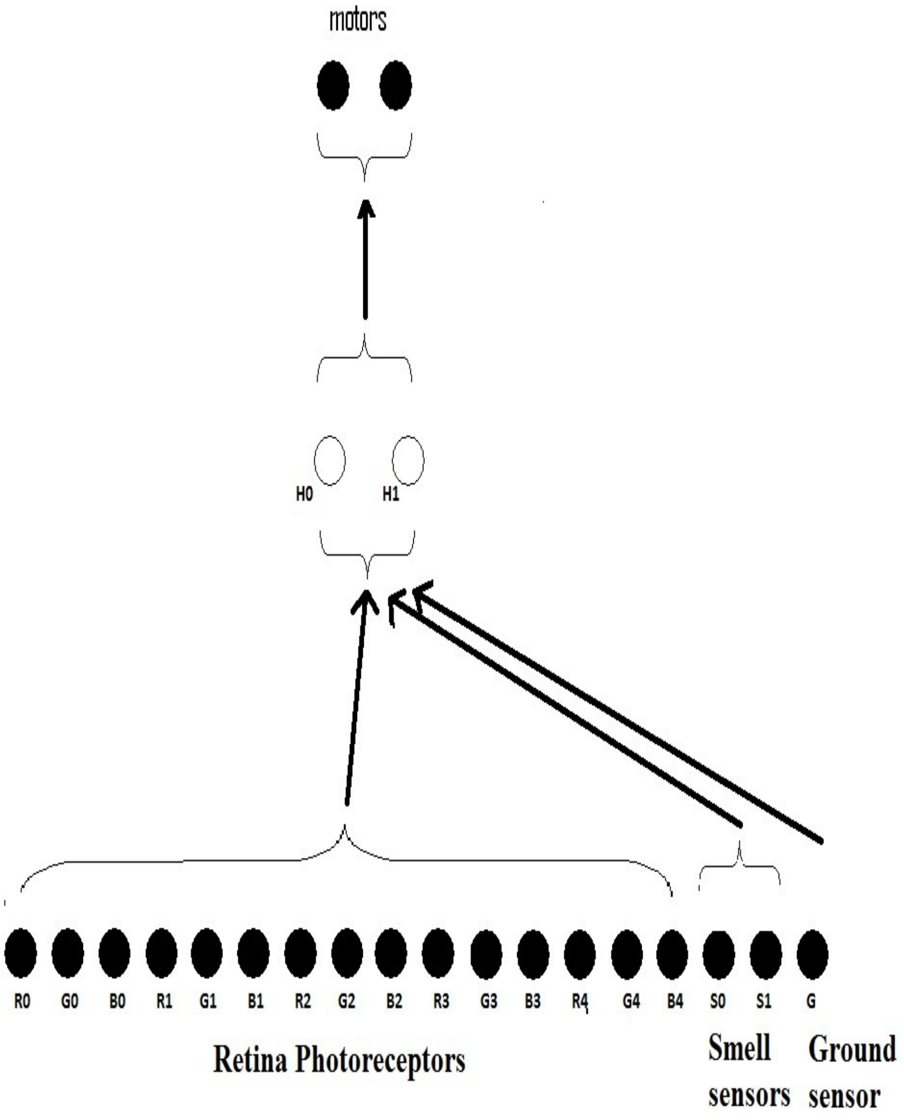


Figure 4.4: Neural network architecture

With regard to the adaptation algorithm, for this experimental setup, we have expanded a genetic algorithm that would foster the genetic differentiation between the evolving robots and so allowed the robots to distinctly evolve their behavioural skills. We have called it *"Heterogeneous Genetic Algorithm"*.

In this algorithm, the evolutionary process for the robots is based on the ranking type. Each individual is represented by a genotype that encodes the sequence of synaptic weights and biases of a neural network controller. Each parameter is encoded with 8 bits. In order to provide robots with different behaviours, each of the four robots belongs to a different population of 20 individuals. Thus, the evolution starts with 4 populations of completely “naive” robots (i.e. with randomly generated genomes) with no skills about how to move and identify the food sources.

Genotypes are randomly selected within each population: for each generation, individuals of each population is numbered by an index (0-19) and a sequence of indexes is chosen (i.e 3-4-5-4) from the four populations in order to extract the genotype that will control the robots. The first genotype (3), from the first population, controls the green robot, the second genotype, from the second population (4) controls the blue robot and so on. For 20 trials, a new different sequence of individuals is compared in the environment, and robots fitness is calculated at the end of life. The same index sequence never will be extracted twice. The same individual never will be extracted twice, so that each sequence extraction univocally corresponds to one trial. The extraction of sequences is depicted in Figure 4.5.

Each robot is rewarded with +1.0 at a given time step in which the entire group stays in the same food zone. Life time consists of 3000 cycles of neural network activation.

At the end of 100 trials (end of one generation), each individual (neural controller) is separately ranked according to the fitness score. The 4 higher-ranked individuals are selected from the list of genotypes, for each population. Every best generates 5 offspring individuals which inherit its genotype . The first offspring individual preserves entirely the genotype of the father (elitism) while the other four ones receive a random mutation with a probability of 2%. The total number of new individuals 20(bests) x 5(off) x 4(pop), will populate the next generation. Since, each population evolves separately: this mechanism fosters the genetic differentiation between the four robots and allows the robots to evolve distinctly their behavioural skills.

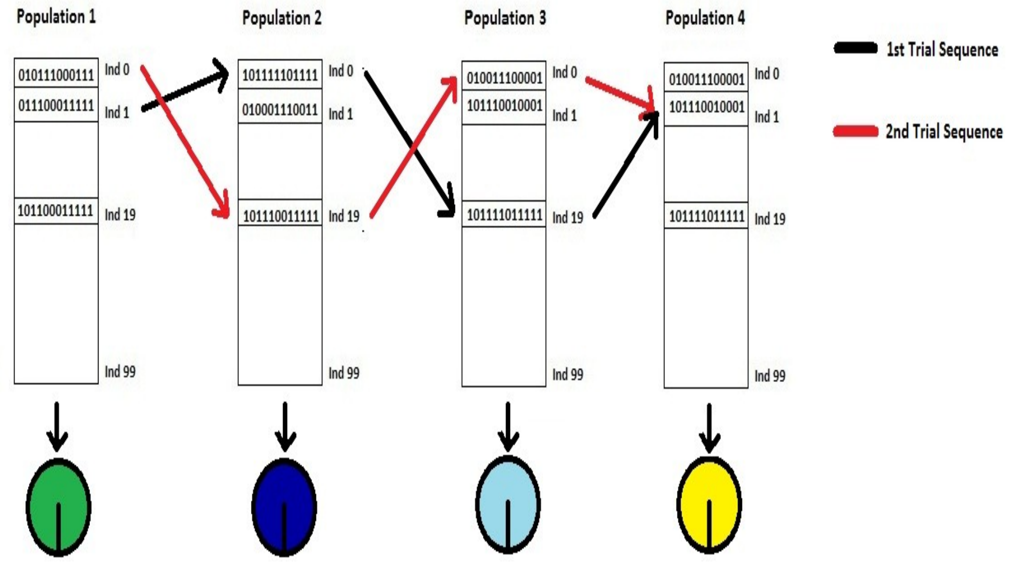


Figure 4.5: Schematisation example of index sequence selection.

4.3.2 Results

The populations of neural networks which are candidate to control the team of robots have been evolved for 30 replications by means of the genetic algorithm implemented to maintain an heterogeneity between populations (it has been described in detail in the previous paragraph). For each replication (which is made of 600 generations) it is possible to observe that robots are initially “naïve” that means they are not able to coordinate motion in order to solve the task. Furthermore, robots don’t exhibit an exploratory behaviour. After some tens of generation, robots become explorative. However, only after some hundreds of generations robots start to exhibit a *“flocking”* behaviour. In this new simulation, we have not focused much on the flocking but especially on a new aspect of group cooperation, that is the emergence of pattern leadership/followership. Looking carefully at the flocking behaviour of robots, it has been immediately noticed the presence of a special individual who lead all the team of robots, while other robots follow him. Individual in question changes in any replications (that is it has different colour) and it takes different behaviours in the direction of the group. At the begin of each trial, the leader seems to select one of two food zones on its own initiative, it moves toward the food zone, and it affects the behaviour of all the followers which come after it unconditionally, without any discretionary independence. The way of leading looks varying from replication to replication, in general two different leaders groups arise though: a) leaders that move forward, toward the chosen food zone, not minding of the fact they are followed by someone. This type of leader can be called *"passive"* for the reasons we will explain after in the chapter; b) individuals who moves backward (in reverse) and who constantly hold in check the behaviour of the followers. These leaders make use of some actions which are necessary for to modify, in real time, their behaviour in order to maintain the group cohesive and compact. These leaders are named "active".

In addition to the *"behavioural analysis"* of group's dynamics, however, it is always necessary to produce a *"quantitative analysis"* by calculating some behavioural indicators. Behavioural indicators are usually elaborated with some statistical techniques which point out some general rules on the dynamics of the simulation that is going to be implemented. These general rules must be true for all the replications (since the simulation is structured in different replications) and enable the user to derive some general conclusions that should be hopefully in agreement with the hypothesis.

A first needed representation are the fitness curves, which depict how much fitness each robot population gets throughout the evolution, generation by generation (food units eaten from the food zone in one generation). As each generation is repeated for 20 trials (with random robots start positions for each trial), each generation's fitness score, represent the average fitness of all the trial. Fitness values can be of two kinds: a) *"best"* fitness, which is the fitness got by the best robot, that is the robot that have totalized the maximum score, and for this reason it will be the first after the final ranking; b) *"average"* fitness, which represent the average of the fitness of all the population for each generation. Clearly, the average fitness is always less or at worst equal to the best fitness, because the population will never get an average fitness greater than the best individual, for the inner design of the genetic algorithm. In the current implementation of the algorithm, for each generation 4 populations of 20 robots are evolved (as previously said), so there will be 8 values of fitness in all, 4 values for the bests and 4 for the averages.

According to the design of the fitness, only groups of individual who reach the food zone in the same time are rewarded. In other words, each individual get fitness score whenever other individuals get it so the fitness function is exclusively made of a *"social"* component. Therefore, each population's fitness score appears to be identical for each of four populations, both in the part of bests and in the part of average. We have intentionally decided to eliminate the *"individual"* component of the fitness within the evolutionary fitness function, that is the increase of fitness when a single individual is alone in the food zone. Individual fitness has been introduced at the begin of the study, but with a double component (individual and social), it is very difficult to discriminate between the situation in which one individual is very "good" to solve the task individually (reaching the food zone) or the situation where the all the group is able to coordinate itself to reach the food zone together. This mix of components should involve some further difficulties for indentifying in which replications final fitness score depends on the a social coordination, and in which replications fitness score depends on the individual component, and so on individuals skills. Moreover individual component of fitness might contribute to the reduction of the *"evolutionary pressure"* to the social coordination. As a matter of fact, single individuals could be induced to acquire *"selfish"* behaviours for achieving the target going to the detriment of cooperative behaviours, that would mean the emergence of few situations of leadership/followership patterns. In other terms, with the only social component, it is possible to obtain a direct correlation between social coordination occurrences (that is the objective needed for the emergence of leadership) and higher fitness scores. This condition may simplify the identification of the different conditions to examine. Last and certainly not least, it is necessary to concentrate to the fitness curves asymmetry that may be resulting by an individual fitness component, since there should be a different fitness shape for each of 4 populations, that could imply a hard strenuous elaboration of fitness values, in so far as populations should be independently considered during the analysis phase.

Hence, a chart has been plotted with only one of the 4 possible fitness curves (for the four populations). In Figure 4.6 fitness curves are depicted for the first population of robots (the other ones are identical) for some of all 30 replications. Each curve represent the sequence of fitness scores got by robots for each generation and they are averaged on 20 trials. By this sample of curves it can be noticed an increasing monotone trend of the fitness function. The fitness growth is generally gradual, that means that the emergence of coordination is not instantaneous but a step-by-step process that stabilize during the evolution.

Moreover, it is clear that there is a *"ripple"* on the "surface" of each curve, especially as regards to the average fitness. It is possible to observe local trend inversions respect to the global increasing character of the curve. Those effects could be explained with the fact that social coordination depends on trial's initial conditions.

For instance, a non-coordination situation arise if initial positions are wide spread into the environment and they are far away and far from food zones. This is a situation that do not easily foster the social coordination of the robots, as they must look at each other from far, try to get closer and follow the leader to move all together toward the chosen food zone.

It is a different story for the robots who start close to each other and to the food zone. They will be obviously facilitated (since the begin) by being cohesive and compact and by moving closely to the food zone. This noise or ripple, is a component often present in such simulations, where the outcome of the fitness depends strongly on initial conditions. At this point, it is needed to open a parenthesis: a system of 4 robots which start from random positions within the environment (such as the model presented in Figure 4.3) is a classical example of *"chaotic dynamic system"*, that is amply discussed in literature over the years [124]

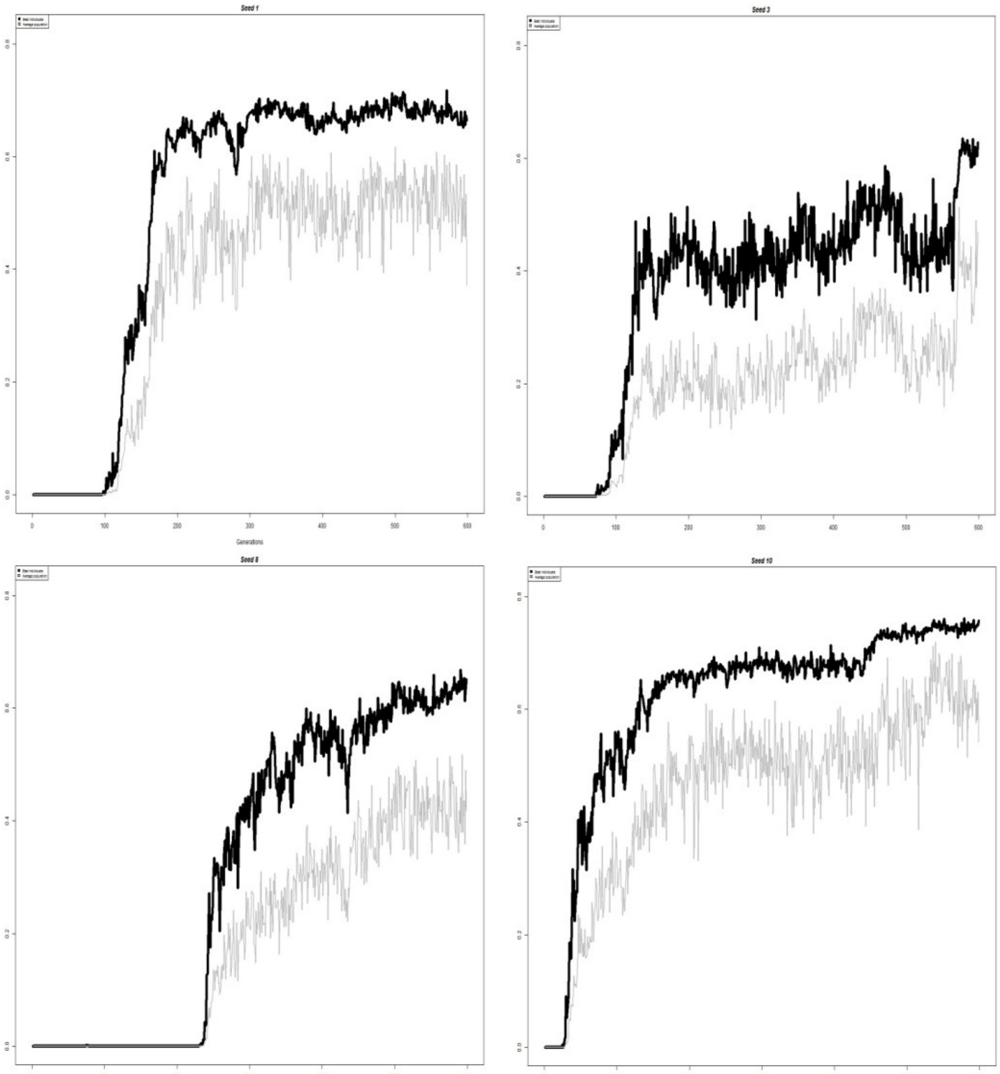


Figure 4.6: Representation of fitness curves of some replications. Best fitness are visualised in black, whereas average fitness are depicted in light grey.

A dynamic system is defined chaotic if it displays the following properties [125] :

1. Sensitivity to initial conditions, that means infinitesimal variations of surrounding conditions (or in generically of the inputs) produces finite variations of the outputs. As trivial example: the smoke of many

matchsticks, in glaringly similar conditions (pressure, temperature, flows of air) follows trajectories very different, from time to time;

2. Unpredictability, that is it is not possible to foresee, in advance, the trend of a system over a long period if they are compared to the characteristic time of the system starting from surrounding conditions;

3. The evolution of the system is traced, in the phase space, by innumerable orbits (state trajectory), very different from each other, with an evident stochastic component from an external observer's point of view. These orbits are all confined within a limited space: the system does not evolve to the infinite for none variable; in this case it is possible to define attractors or deterministic chaos.

The system described in this experimental setup glaringly suit all three the conditions, as a slight variation of initial positions of the robots and a slight variation of initial "face direction" produce a remarkable variation of robots' trajectories. Obviously, the process which manage all the system is stochastic (second property) as it is impossible to predict all the system evolution by a macroscopic point of view. Of course, in theory, it is possible to calculate all the states of the system since it is possible to calculate all the positions where robots are placed over the time, by determining the outputs from neural networks inputs.

Theoretically, in this way, system evolution could be calculated, and for this reason the system may be considered as a deterministic system and thus it meets the third requirement as well (deterministic chaos). To determine the system state, related variables are so many that the system results complex as any complex in real life, even though it can be calculated in theory.

In the real world, a social or economic system, such as the GDP of a country, could always be foreseeable in theory. Effectively, every country is made of institutions which deal with calculating the GDP that should recap all the economical interactions between imports, exports, etc. Nevertheless, last political happenings has shown that this indicator (GDP) hardly ever reflects the real productive context of a country just because one country's "economic cycle" is a chaotic complex dynamic system itself. All that is complex appears unpredictable since all variables in question are too many and they do not permit an elaboration with traditional informative systems. Anyway, all this does not mean that it will not be predicted one day with appropriate means.

Again with simulation, all this is needed that the evolution of the system of robots is unforeseeable without a precise and complex calculation. For this reason, simulation needs many trials per each generation with a random positioning of the robots, but this causes the ripple that it is possible to observe on fitness curves charts.

The level of noise is as lower as greater the number of trials is for each generation. However, we decided to use almost always a reasonable number of trials (20 in this model) both for computational costs and for the eventual inductive power loss (by increasing the number of trials, but this treatise lies outside of the purpose of this document).

Finally, observing fitness curves, it is possible to catch the presence of a "bootstrap problem", that is individuals start to solve the task (defined by fitness function) only after some hundreds of generations. This must be explained with the fact that all the 4 populations of the genetic algorithm evolve independently and they have separate rankings and they can "converge" relatively late throughout the evolution. For convergence is meant the fact that robots initially tend to solve the task individually, and so all the separate evolutionary processes tend to meet the solution independently. But at a certain point, it could happen that some totally unconnected behaviours in the four evolutions, could lead to reach a fitness score, not got until that moment, by means of essentially selfish behaviours. All this produces every single evolutionary process to stay on behavioural patterns which have leaded the whole group (of 4 populations together) to take higher fitness scores, that is cooperative behaviours that imply the social coordination. These patterns can be reached early or late during the evolution, according to the initial genetic conditions. Also the evolutionary process can be assumed to be a chaotic system as it can generate totally different effects as a result of a small variation of robots' initial genotypes. Anyway, in order to have a global view of fitness curves for all 30 replications, it has been calculated the average between each set of values (30 values, 1 per each replication) for each generation, both on the best fitness curves and on average fitness. The result is depicted in the chart in Figure 4.7 where there is an increasing gradual trend of the average fitness curves. This indicates, without any doubt, a step-by-step solution of the task via social coordination strategies (that will be examined later) which are probably acquired in a rather gradual manner.

This last statement can be justified with the design of the simulation since there is a strict correlation between fitness and social coordination (and so leadership emergence). Therefore a gradual increase of the fitness corresponds to a gradual increase of the social coordination capability during the evolution.

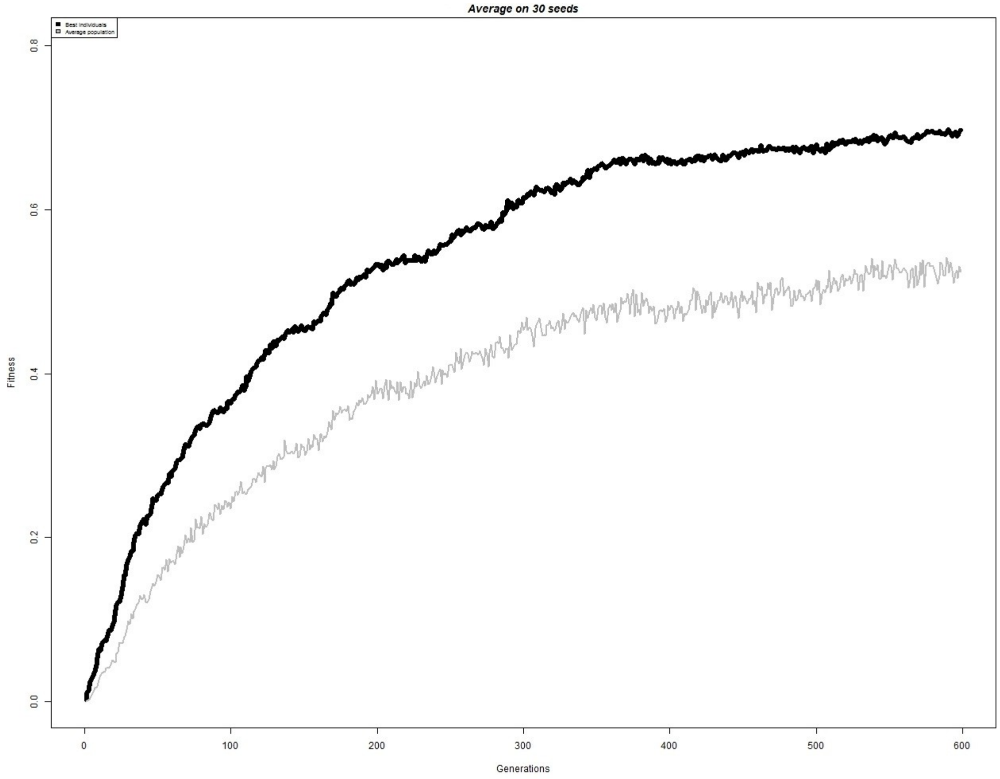


Figure 4.7: Visualisation of the average of all 30 fitness curves, bests (black) and averages (light grey).

An interesting visualisation of system are the “phase space” which is a cartesian representation of the system’s states. Phase space is useful to highlight the chaotic origin of the system. Clearly, there could be several phase spaces for one system according to the variables that are taken into account and to the states typology. In the case of this simulation, a possible phase state might be the set of all the positions that all the robots are able to cover in one test of 3000 cycles. To produce this phase space, all evolved robots (for each replication) have been left to act in the environment (in a test of example) and all visited positions per each time-step (x-axis and y-axis coordinates). The result is illustrated in Figure 4.8 where there are the phase spaces of some replications (the same of fitness curves plot’s ones). In the phase space chart, each colour is associated to the real colour of each robot into the simulation, green for the green robot, yellow is for the yellow robot, and so on.

Given that the simulation’s dynamic system is continuous, there are continuous curves in the phase space for each robot, and not a discrete sequence of points.

In the figure is possible to identify an attractor (described in the third property of chaotic system’s definition) for each replication. In mathematics, an attractor is a set toward which all the dynamic system evolves after a adequately long time. To define attractor a set of points, all trajectories, that get enough closer to it, must be close to each other even though they are slightly perturbed. Trajectories of a dynamic system get close up to the unlimited, after the system converges to an attractor. Therefore, in the simulation’s phase space picture, some small “vortexes” are the end of all the robot’s trajectories, and they are definitely the attractors of the spaces. Most likely, attractors correspond to the condition in which robots group reach one of the food zones. In the case of robots simulations like this, attractors are named “behavioural attractors” as every behaviour flows into the same behavioural pattern called attractor. Finally, of course, it does not have sense to calculate the average over the replications, in the case of the phase space, as it has been done on fitness curves. In effect, in the phase space analysis, all the robots’ positions are independent in every replications and they do not concern the other positions in other replications.

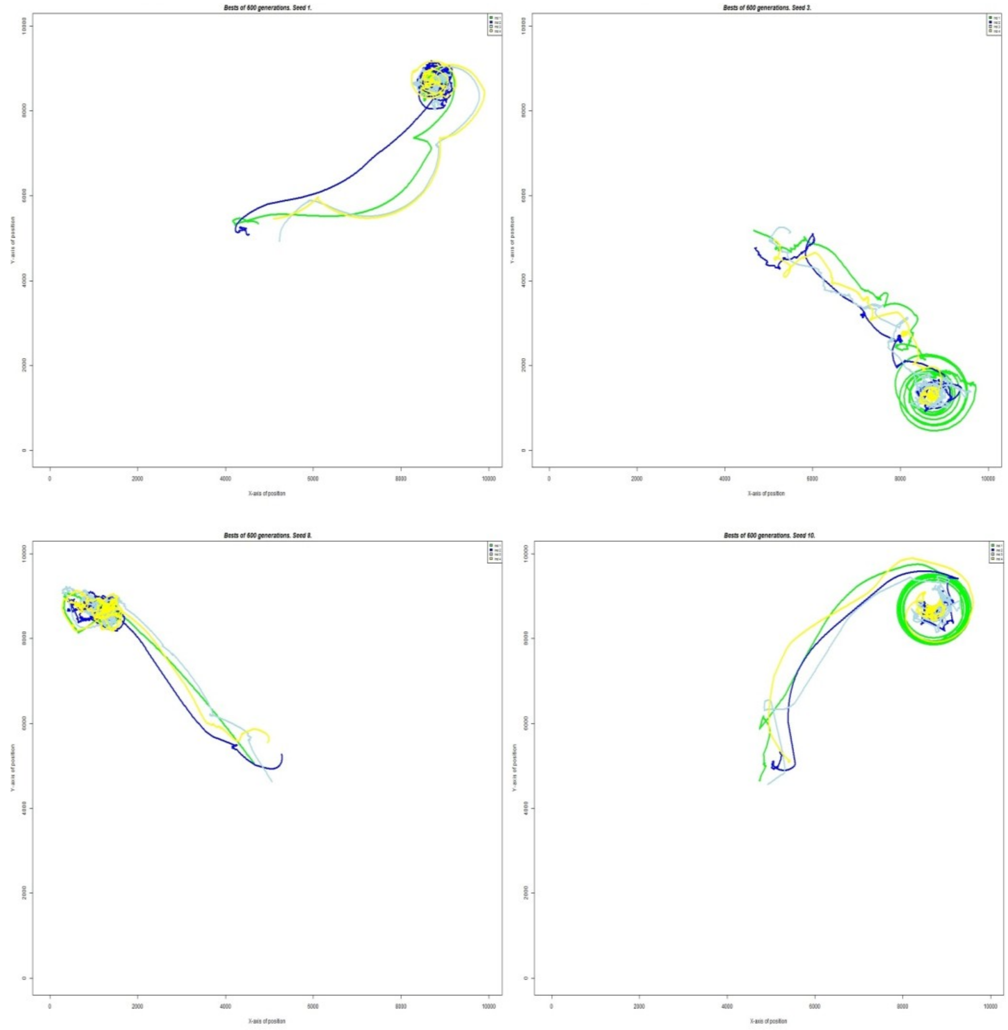


Figure 4.8: Visualisation of the phase space per each of 30 replications. Each colour is associated to the colour of each simulation's robot: green for the green robot, yellow for the yellow robot, and so on.

So a unique description of attractors for any replications is not possible to determine, it is necessary to examine phase space case by case.

To better understand inter-replication fitness differences, we tried to find a measure which the level of fitness score got by a robot in one replication. It in fact is difficult to compare single fitness curves which are usable at the end of the evolution per each replication. It has been noticed that, in the last 20 generations, every curve get stable on a constant value both regarding to the best fitness and to the average (basically it does not considerably increase or decrease). For this reason it has been calculated the average fitness of last 20 generations for each replications and that gives a measure which has been called “Fitness Measure”. In Figure 4.9 there is a bar-plot of fitness measures for each replications. As it is not difficult to observe, there is a variation between seeds which denotes a significant difference between fitness of a replication if compared to the other ones. This differentiation probably is associated to the extent of social coordination in a replication rather than another one. At this point, it has arisen the necessity to understand what happens inside each replication and why they differentiate in this substantial way.

As previously argued, a flocking behaviour arises in all the replications that implies robots follow each other in somehow. Moreover, there is always an individual who lead the group (leaders) and other individuals who follow

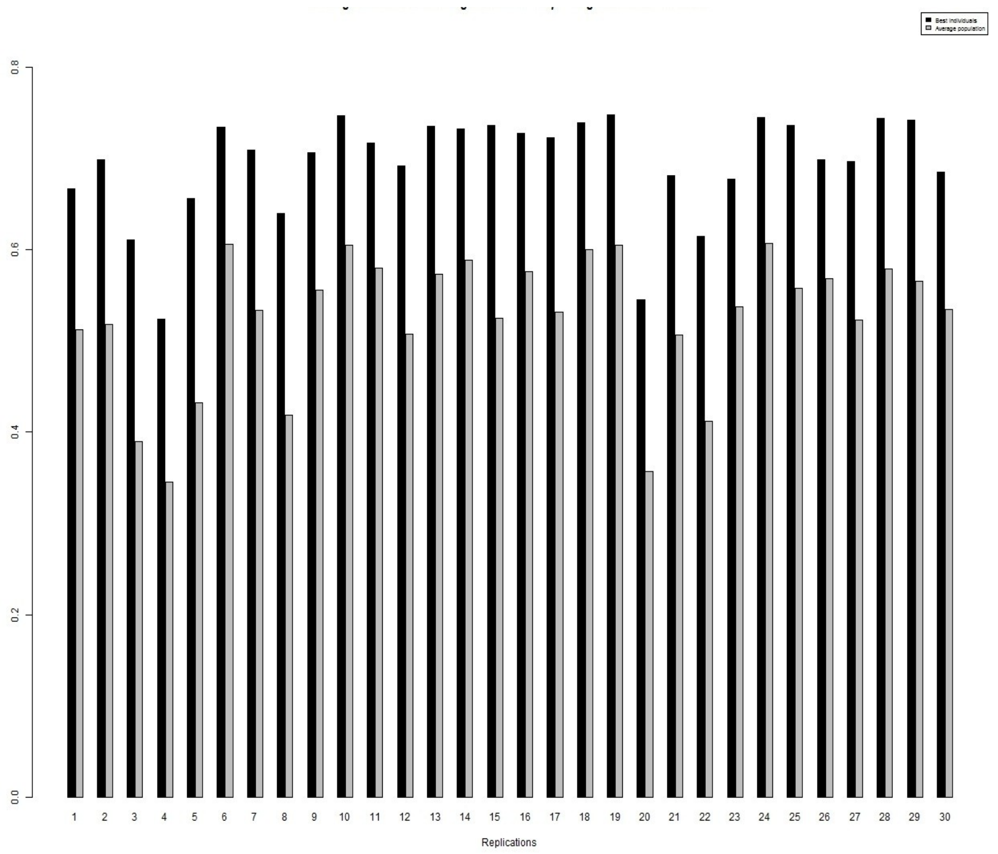


Figure 4.9: Bar-plot of “Fitness Measure” for each replication.

(followers). This behaviour bobs up in a simulation where a group of robots is faced to a simple decision-making problem, which concerns all the group. This decision-making problem is defined by means of the fitness function and the experimental setup. It is immediately appeared evident, so it is necessary to find one or more measures about "how much leadership" there is in a replications and if this have any sense.

In general, it is always difficult to capture what leader or follower mean for a group of robots. Thus it has attempted to find some numerical and statistical measures which enable to get more detailed information on the robots' behaviours from a mathematical point of view.

In order to achieve that purpose, some definitions are needed such as "who is a leader" in the simulation and not in the literature (it has extensively defined in literature). Which properties a robot must possess to be called leader? By and large, it is possible to define the following properties for an individual called "leader":

1. The leader must affect other individuals' behaviour in somehow in order to optimize the group coordination to solve the task;

2. The leader must aggregate all other individuals around him in a greater quantity respect to each other group's member is capable to do. In other words leader's distance from the group barycenter must be less than all other individuals' distance from the group barycenter.

The second condition provides an operational methodology to identify who is the leader at each replication. In effect, to understand "how much leadership" there is in one replication, it could be sufficient to calculate the gap between the minimum value of leadership measure (among the 4 individuals in 1 replication) and the average of the other individuals. Larger will be the measure's gap, larger will be the difference between individuals in terms of the leadership behaviour they display, in other words grater will be the influence of one individual on the others.

Hence, a first measure in this sense, which has been devised is by way of the calculating the distance between each robot in the group and the centroid (or barycenter) of the group itself. By determining which individual has got minimum distance from the group's barycenter it is possible to deduce that this group's member tend to deeply aggregate all the other members around him, and for this reason it could be definitely considered as leader of the group. This is because a leader is usually the cornerstone of the group since it leads the group and the others follow his actions in any moment.

The test has been essentially performed by holding one robot, in turn, in a fixed position into the centre of the environment, and by leaving the other 3 robots to act freely in the environment. Surely this test has been imagined to be performed on best robots of each different population (related to 1 generation).

It can be immediately observed, during the barycenter test, that when one leader (optically identified during a normal test) is stopped at the centre of the environment, all the followers crowd the neighborhood of the leader, waiting for an action from him to follow. Moreover followers are careless about the fact they have to go in the food zone for feeding and solving the task. On the other hand, every time whichever follower is motionless at the center of environment, the other 3 individuals group (leader included) go in the direction of the food zone, without any care of the motionless follower is not moving (with the exception of active leadership that will be examined hereafter). The two different situations are depicted in Figure 4.10. The situation is related to the replication n.1. In this context, the green robot is the leader of group whereas the others colours are followers. In Figure 4.10a the leader is motionless, and it is possible to observe the followers surrounding him. In the second square, the leader is movable, and it accurately solves the task going to one of the food zones whereas the followers follow him without caring for the stopped yellow robot. Every time one robot, is stopped, in turn, a sub-test is run for calculating the distance of the motionless robot from the barycenter of the group. Each sub-test has been performed for 20 trials, for each of 30 replications. Each trial is made of 3000 time steps, and in each time step the

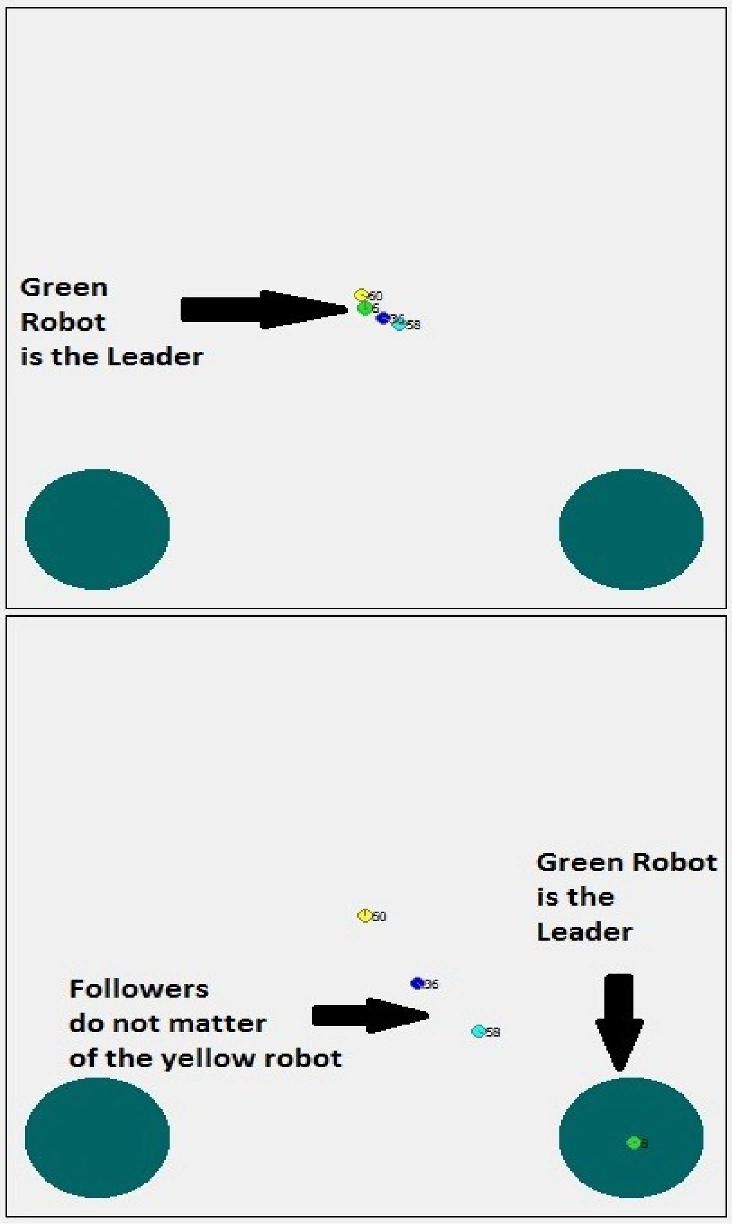


Figure 4.10: Depiction of the Barycenter Test. In Figure a) the Leader is stopped whereas in the Figure b) one follower, the yellow robot, is stopped.

distance of motionless robot from the barycenter of the group has been calculated. The group’s barycenter coordinates are determined by means of the following formula:

$$(4.1) \qquad x_b = \frac{\sum_{i=1}^{n} x_i}{n} \quad ; \quad y_b = \frac{\sum_{i=1}^{n} y_i}{n}$$

Where x_b and y_b are the calculated coordinates of the barycenter whereas x_i and y_i are the coordinates of each robot. Instead, the distance from the barycenter of each robot is calculated by *"Euclidean Distance"* formula:

$$(4.2) \qquad d_i = \sqrt{(x_i - x_b)^2 + (y_i - x_b)^2} \qquad \forall i = 1..n$$

Where x_b and y_b are the barycenter's coordinates, x_i and y_i are the coordinates of each robot, and finally d_i is the distance from the group's barycenter of the the robot ith.

All the 3000 distance values calculated in a life time are averaged returning a value for 1 single trial. At the end, it has calculated the average on all the values of 20 trials, getting 1 single value for 1 generation. The test has been repeated for the last 20 generations (loading the bests of the current generation, time by time). By averaging all the last 20 generations too, it is possible to get a single value which represent the level of individuals crowding around the motionless individual. In this way, it has been possible to obtain a sequence of 30 quadruples of values, where each value represent the distance from the barycenter of the group every time the corresponding robot has been fixed in the centre of the environment.

The 30 quadruples of values are plotted in a bar plot such as in Figure 4.11a. The green value coincides with the green robot, the yellow value with the yellow robot and so on.

Once the "Leadership Measure" (based on barycenters calculation) is determined, it has been necessary to understand another important question: Who is the leader? which are the features of a leader? Is the leader the more skilled individual in order to solve the task? Or not? To reply to these question an Individual Fitness Measure has been imagined to supply a general indication about the most capable individual: for example, the speed to approach to the food zone, the ability to not being affected by the behaviour of other individuals, etc. This individual fitness is a “virtual” fitness meaning that it represents the individual ability of each robot to provide for feeding by himself independently from the other robots. It is a virtual fitness as it has not adopted for evaluating the individual during the evolution, where a real fitness is applied, already illustrated in the previous section. To weigh the individual fitness, a test has been implemented, where all the robots move freely into the environment in the same way of the evolutionary phase. Although in this test, every time a single robot reach the food zone, the robot’s fitness is increased independently from the fitness of the other individuals or of the group (which is the real fitness used under evolution). In this way, individual fitness is correlated with the robot’s velocity to reach the food zone, the ability to feed , the ability to not be influenced by other individuals, and so on. Definitely, individual fitness measures the level of velocity and smartness of a robot, and greater will be the individual fitness, faster and smarter should be the robot.

Again, the test is executed for 20 trials calculated on last 20 generations. So each fitness value represents an average on trials and generations. Finally, a Measure of Individual Fitness is returned which is over again a set of quadruples of values for each replication. Each value is associated to a colour which is the colour of the corresponding robot as illustrated in Figure 4.10b. The main idea is that whenever a robot emerges as the leader according to the centroid measure, the same robot should have the maximum value according to the individual fitness measure.

Comparing each quadruple of the barycenter measure with the respective replication’s quadruple of the individual fitness measure, every time one robot has got minimum value for the barycenter measure then it has got maximum of individual fitness in the same considered replication. This mean that the leader (defined according to the barycenter measure) is the best member of the group to feed, the faster to reach the food zone, etc. This is true in the 100% of the cases, that is by comparing all the replications, as illustrated in Figure 4.11.

In other words, without any doubts, another important information that is returned by this simulation is that, every leader (defined by barycenter measure) is always the most skilled to solve the task individually.

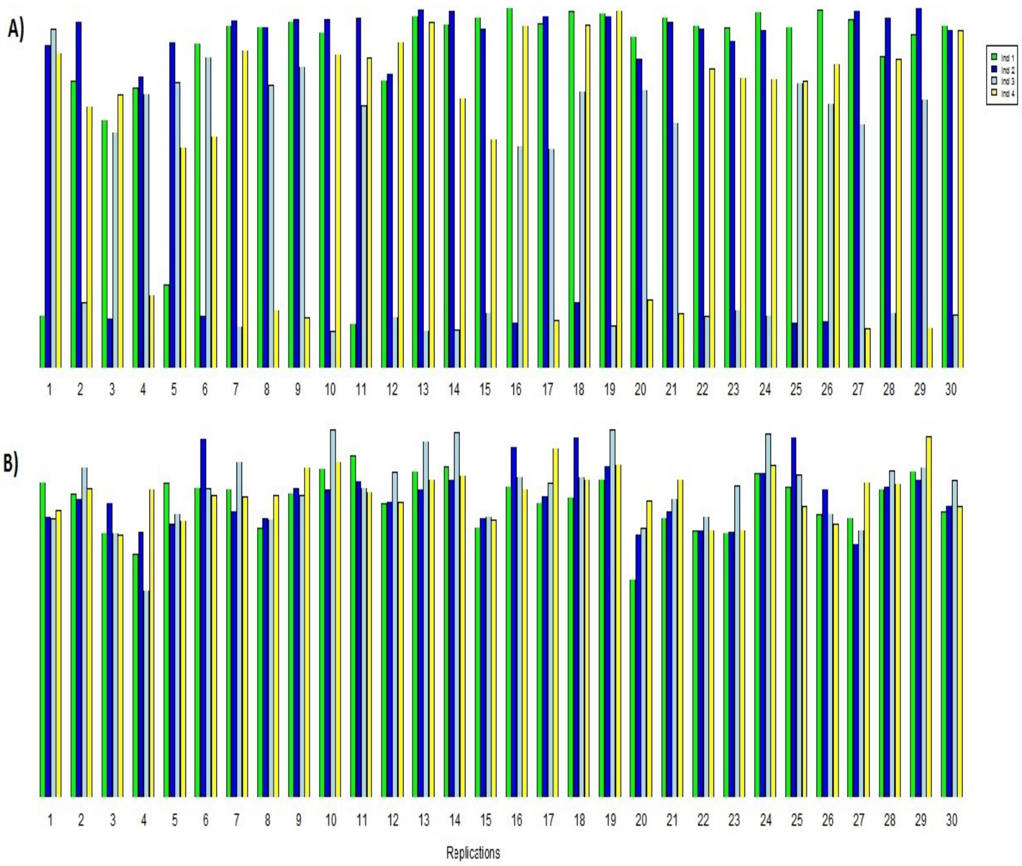


Figure 4.11: Comparison between the Barycenter Leadership Measure (A) and Individual Fitness Measure (B).

Another interesting measure has been drawn by calculating the average of all minimum values of the barycenter measure for all the quadruples. Then, the average of the second minimum has been calculated, the average of the third minimum and so on.

This elaboration is needed to understand if there is a substantial gap between individuals with minimum values (most likely leader?) and the values of other individuals. This might mean that in every replication there should always be a robot with the minimum distance from the group's barycenter, who is the main one able to collect all the other individuals around it. This new insight is depicted in Figure 4.12.

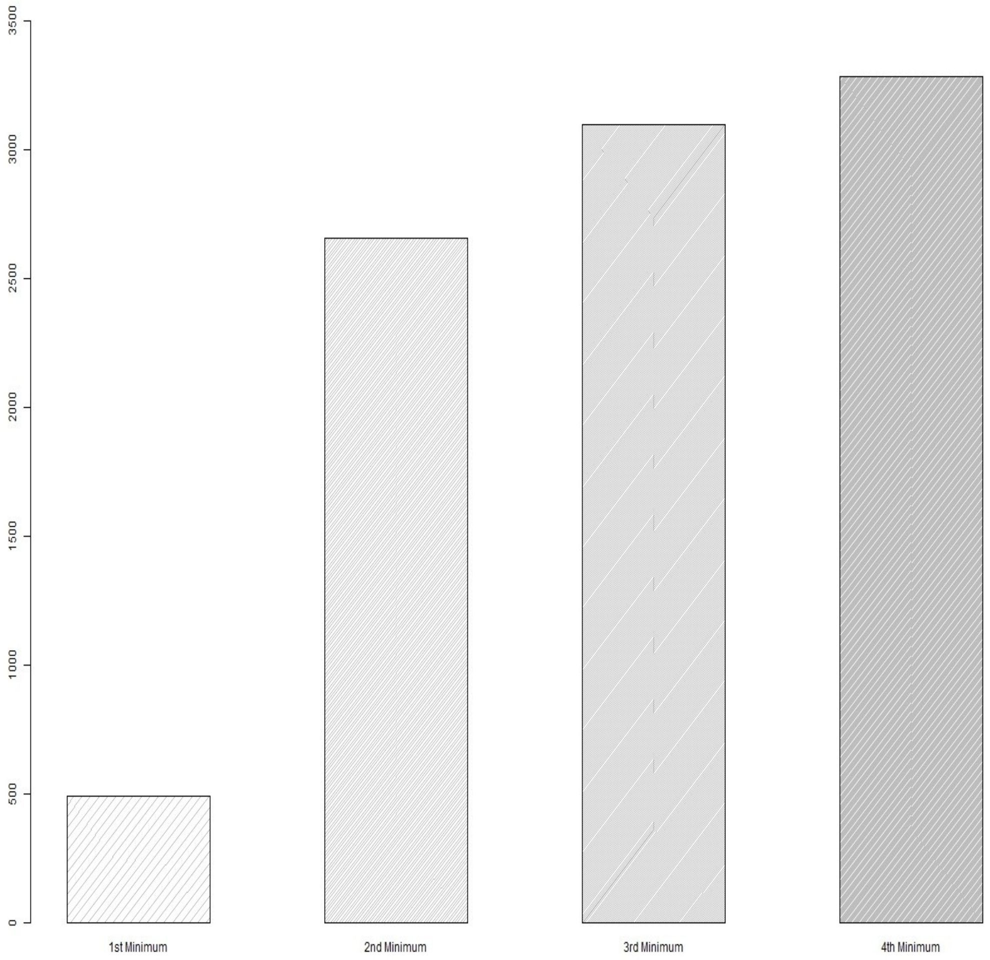


Figure 4.12: Representation of the gap between Individuals with minimum distance from the Barycenter and other Individuals. There is a significant gap between the two conditions in every replications.

Another interesting question that have been asked in the introduction, is whether the emergence of Leadership is a winning strategy or not. To respond to this question it is needed to understand if it is possible to correlate the quantity of leadership (in somehow), of the various replications, with the fitness level reached during the evolution. So, a first step is determining a measure which represent summarize the influence of the leadership effect in one replication, that is "how much leadership" there is in that replication. The insight has arisen by analyzing the barycenter measure and from the idea (already discussed) that less is the distance from the barycenter and greater is the capability of the individual to join all the individuals around it. Thus, the heavier consequence of this reasoning is that stronger is the variation between the values of barycenter's distances, stronger is the influence of leadership in a given replication. So it is possible to determine an indicator of the quantity of leadership for each replication by calculating the standard deviation of each quadruple of leadership measure by barycenters. The outcome of this calculus is reported in Figure 4.13, which represents a Measure of Leadership reliable enough. At this point it has been possible to evaluate the statistical dependence among "leadership – standard deviation" variable and "average fitness" variable (respectively taken from the Leadership Measure in Figure 4.13 and from Average Fitness Measure in 5.9). For this purpose, two different correlation coefficients have been considered: *"Pearson's Correlation Coefficient"* and *"Spearman's Correlation Coefficient"*. Correlating those two series of date (Leadership Measure – st. dev and Average Fitness Measure) has been returned a Pearson coefficient which shows a great correlation with $\rho = 0.67$ between leadership and fitness (in statistics, $0.5 < \rho < 1$ means high correlation). Moreover Spearman's coefficient shows a strong correlation with $\rho = 0.4754$ and $\alpha = 0{,}0079$. This correlation displays another interesting information about this experimental setup: leadership appear a winning strategy because whenever there is a strong leadership in one replication then there is a gain of high fitness and vice versa. The generally linear correlation between fitness and leadership is displayed in Figure 4.14, where on X-axes the Leadership Measure (st. dev) is reported whereas on Y-axes the Average Fitness is reported.

Another important issue is discovering how many kinds of leadership exist and in which way they influence the followers' behaviours and group's dynamics. For this fact, it has been distinguished between situations in which the leader is selfish and he moves independently from followers and situations where the leader take a careful look to the followers' behaviour every time. In the first case it is possible to talk about "passive leadership" (borrowed by literature on leadership in living beings) that means the leader is not barely affected by

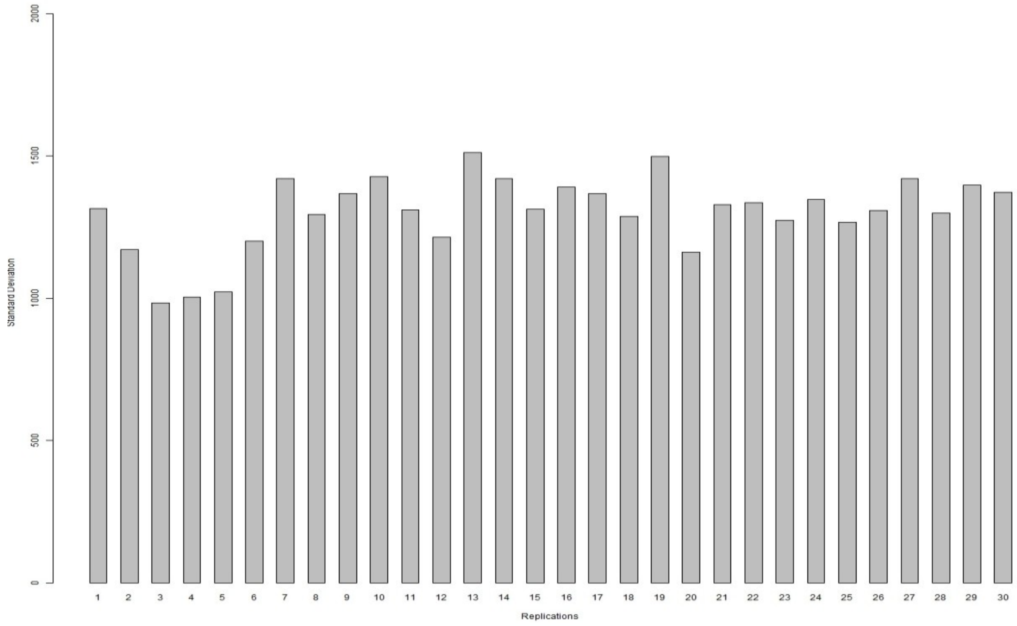


Figure 4.13: Standard Deviation of each quadruple of Leader Measure by Barycenters.

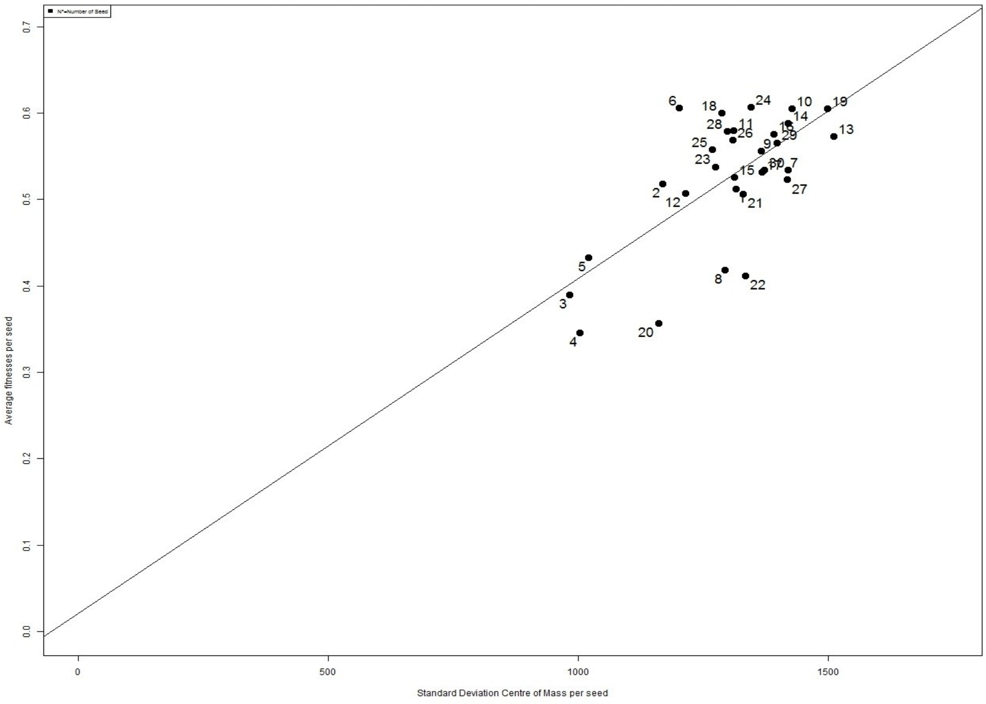


Figure 4.14: Visualisation of the correlation between Leadership Measure (Standard Deviation) and Fitness Measure.

followers and it does not profit of being followed, only the followers take advantage of following the leader.

In the second condition can be called “active leadership” since the leader take advantage of the following because this foster the group’s cohesion and so higher fitness. Thus the leader starts up all the necessary actions to make the followers able to follow him in any instant of time. To do this a test has been designed, where the 3 followers are placed in a fixed position in the centre of the environment without any possibility of motion. Then, it has not been difficult to distinguish among replications where leaders who totally takes no notice of the followers and replications where leaders approach to the followers to attempt to “convince” them to follow him. In Figure 4.15 there are some phase spaces related to 4 replications. They have been recorded keeping the motionless followers into the centre of the environment. As it is possible to observe to the upper charts, the leader (yellow in the first and blue in the second) does not pay attention to the motionless followers but he run toward the food zone which is identified with the attractor (vortex). Instead, in the lower charts, the leader (green in both charts) reaches the followers, at least once, in order to actively try to let the followers follow him (but it is worthless as they are fixed and motionless into the centre of the environment). In the first case, the leader approach to the motionless followers only once but in the second case the leader travel back and forth as a shuttle between food zone and follower positions, until life cycles finish. For this reason in the upper quadrants there is an active leadership behaviour whereas in the lower quadrants there a passive leadership.

4.3.3 Future directions

A possible of the illustrated experimental setup is in humanoid robotics. Indeed, the experimental setup has been originally designed by imagining it for a humanoid task, but as we have focused on the mechanisms behind the leadership more than robotics issues, we have decided to simplify the setup with *“khepera-like”* robots.

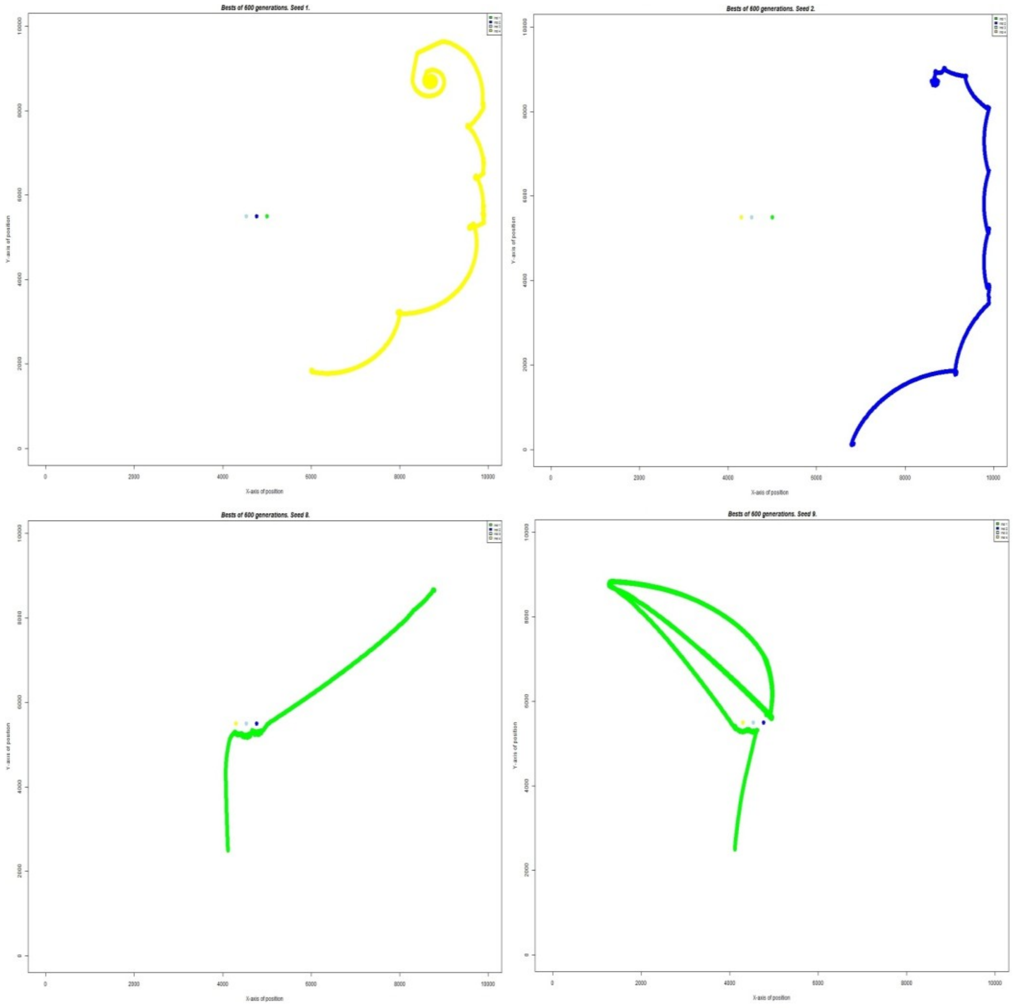


Figure 4.15: Illustration of phase space for some replications, with followers fixed into the centre of the environment without any motion. Upper diagrams depict a classical example of passive leadership and lower diagrams show an active leadership.

However, it is still possible to extend it to an equivalent setup with robots *"icub-like"* where the team is composed of 4 humanoid robots positioned around a table. With this setup some new interesting questions rise up: "What following does mean for humanoid robots?", "What leadership is made of in humanoid robotics?".

In order to reply to those question it has thought to implement a simulator (or use one already done, such as the official icub simulator) where it is possible to multiply the number of simulated icubs. Each robot joint and sensor must be controlled by a neural network like that one used for khepera robots in the previous experimental setup. The task consist in moving a small cylinder to the center of the table. Each robot is placed to one side of the table and it has 2 small cylinders in front of him. Each cylinder is numbered but none robot is able to read the number of the cylinder. In any time step, the group of robot is rewarded (of +1.0 as in the previous experimental setup) if they move the same corresponding cylinder (that is with the same number) from his cylinders source area to the middle area of the table in charge of containing those cylinders. As robots do not know the number of cylinder could exploit sensory-motor information to understand with cylinder is on the left of his body and which one is on the right. The adaptation algorithm is the same used in the experimental setup described in the previous paragraphs, that is an "heterogeneous genetic algorithm". In other words, each robot has a different genetic patrimony which makes him able to display different behaviours and different skills in reaching the cylinder, moving it, etc. A schematisation of the experimental setup with humanoid robots is depicted in Figure 4.16. In the figure is illustrated that each robot is governed by a different genotype.

In this humanoid experimental setup, the individual which sooner emerge as faster to move the cylinder into the middle of the table could arise as leader of the group, whereas the other individuals follow him in any instant of the life time, as well as the experimental setup with wheeled robots. As previously indicated, it would be interesting, in this case, understanding what following does actually mean for humanoid robots. They of course cannot follow each other with body motion, but they can follow partners' movements with eyes (cameras) by moving neck motors which produce head changing of position. In this way they can "elaborate" movements of the partners (leader?) and repeat their movements in order to make the same actions. From this point of view, in humanoid experimental setup, the following takes the meaning of imitating, since robots follow others' movements and reproduce them, that is to imitate. Clearly, it is a more complex process if compared to the wheeled robots task,

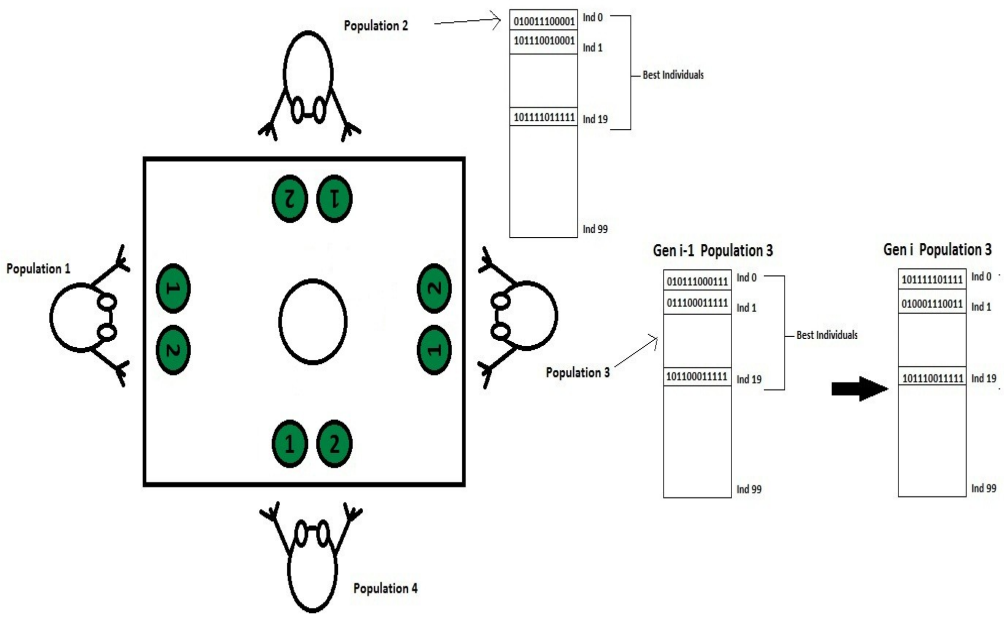


Figure 4.16: Robots and Environment of Humanoid Experimental Setup.

since the number of sensory-motor information to integrate in space and time is much more: camera photoreceptors are many more, a pre-elaboration of other robots' movements is needed, a translation of the observation in appropriate action is needed to follow (imitate), etc.

5 Conclusions

These studies have a two-pronged value. In robotics and software design: the genetic differentiation of robots control systems can contribute to building a new generation of autonomous robotics applications or a new generation of software agents where a coordination is needed. This coordination can be reached by means of leadership/followership patters emergence. For example, it is possible to imagine to use a robots' group for navigational tasks in an unknown environment such as the surface of a new planet. A spontaneous hierarchic organisation could arise among robots based on leaders/followers patterns that could make more efficient the environmental exploration. This might be as useful as more unpredictable are the decision-making problem details, which had not been foreseen in design phase. The Leader robot could be, for instance, the one who is genetically suitable for a faster exploration of the environment or a smarter selection of needed information. Analogous outcomes can be achieved with software controlled by evolutionary threads which are genetically differentiated through the medium of the same methodology adopted for the robots. In order to cooperate, these threads could interact according to a hierarchy using leadership/followership patterns. For instance, we may imagine a user interface controlled by different threads (i.e. agents in cooperation or competition) which have the task of user preferences personalisation (user profiling). Every agent is able to deal with one type of preference: icons positioning, windows sizing, widows displacement, events priority, etc. Depending on threads are genetically differentiated, some of them could emerge as leaders and the others could be the followers within the collaborative task of profiling user preferences.

On the other hand, in social sciences, it could be possible to explain that leadership is unavoidable. If we consider a group of genetically differentiated robots and they are faced to the choice of accessing a resource, the inevitability of leadership could come out. Access to the resource must be contemporary for all the group's members and resources must be correlated in some way to the individuals' survival chances (for example resources may be a food source, a water source, etc.). Actually, we are taking in account the necessity of a *"social decision-making"* that means a decision-making of the entire group. We can prove that evolving a group of individuals to a group decision-making problem, one or more individuals emerge as leaders moving toward the resource which is chosen unconditionally. Other individuals can follow without wondering about they have took the right choice or not. Other solutions might emerge in addition to leadership/followership one, such as solutions where the group coordinate by a minute by minute negotiation and a complex communication between individuals. But with this simulative model, it can be proved that the leadership is always the most efficient solution. All the alternative solutions (respect to leadership) appear inefficient because they are slower than a solution where one leads and others follow. At the end, distributed solutions end up to become extinct making way for leaders/followers in every experimental replication.

This reasoning might give some insight to those intellectuals who support the idea of societies without a central government, factories without a president or an administrative committee, etc: in other words groups without a leader. Indeed, there is more and more an open debate on the real benefits of leadership and on disadvantages. This is because of the fact that, nowadays, human societies continue to rely heavily on leaders (political, military, professional and religious leaders). However, there is still a consistently high rate of leadership failure: for example, 60%-75% is the estimated rate of business failures in corporate America [126].

Ultimately, all this discussion suggests that our modeling approach and simulations could be useful for understanding when and why human leadership succeeds or fails, and under which conditions it is indispensable or not. This is a topical issue.

6 Appendix I : Artificial Neural Networks

Artificial Neural Networks (ANN) were introduced, for the first time, by 1943, in a work on the formalisation of neural activity in propositional logic form [127]. In this analysis, authors argue that this new model, called "neural networks", can be described in terms of logical expressions under some conditions. Various applications of neural computation were discussed. We can define artificial neural networks as a simple model of biological organisms' nervous system. Depending on the way an artificial neuron is modeled and the connections' topology, we can identify different models of neural networks. In general, an artificial neuron consists of N inputs and M outputs y regulated by an "activation function Φ " and a threshold ϑ (see Figure 6.1). The activation of the neuron j-th is a linear combination of input signals, on the base of the following formula:

.

$$(6.1) \qquad A_j = \sum_{i=1}^{N} w_{ij} X_i - \vartheta_i$$

This is a weighted sum of every single neuron activation, where w_{ij} is a *"synaptic weight"* of the connection from the neuron i-th to the neuron j-th, X_i is the input of the neuron i-th (pre-synaptic activity) e ϑ_i represents the *"bias"* or *"activation threshold"* of the neuron i-th.

The j-th neuron's output is returned by an activation function which is expressed by the following formula:

$$(6.2) \qquad y_j = \Phi(A_j) = \Phi\left(\sum_{i=1}^{N} w_{ij} X_i - \vartheta_i \right)$$

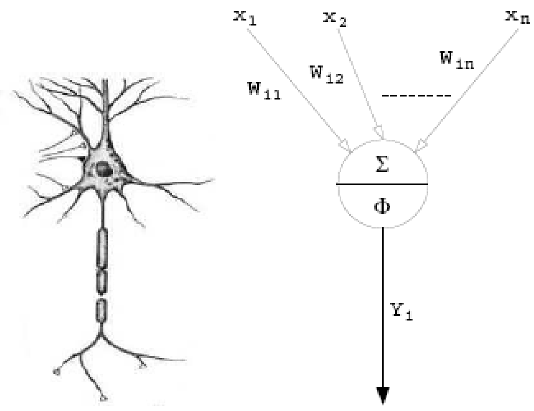


Figure 6.1: Graphical comparison between Biological Neuron and Artificial Neuron.

Where Φ is the activation function or *"logistic"*. The logistic function define the behaviour of the neuron's response to some stimulus. As often as not, the logistic is implemented by means of non-linear functions such as the sigmoid function (see Figure 6.2), which make neural networks a non-linear system.

The bias can be assumed a synaptic weight related to a virtual input called X_0, this input is always set to a constant value of 1.0.

Depending on the neural network's topology (the description of neurons connections) we can identify two different neural networks architectures:

- **Feed Forward Neural Networks** : namely, networks which are made of two layers of neurons (input layer and output layer) and some layers of internal neurons (hidden layer). There is a layers' hierarchy with oriented connections from input neurons to output neurons, with the one only constraint: loop connections within a layer are not allowed.

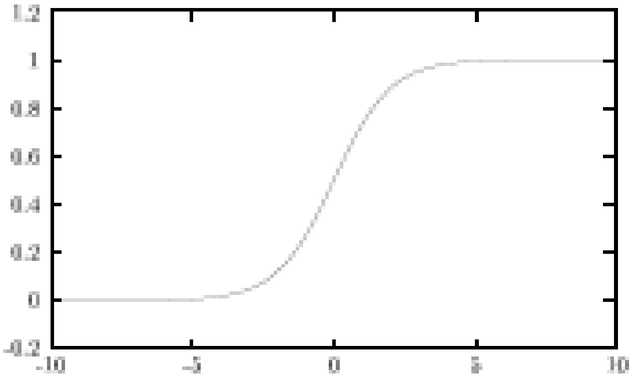


Figure 6.2: Sigmoid Function.

- **Recurrent Neural Networks** : that are neural networks, where connections within the same layer are allowed. These are called loop connections and they can be made on the same neuron. Moreover, recurrent connections are allowed from a layer to the previous layer. These links permit to take back a signal from output to input.

In practical applications, very often, “hybrid” topologies have been used such as feed forward neural networks with some recurrent connections. These networks can be useful in those applications where we need to provide the network with the possibility of create internal states.

Genetic Algorithms can be adopted with neural networks in a few applications such as Evolutionary Robotics (as stated in the paragraph 1.5). Genetic algorithms can generate a neural network (from a population of initially random neural networks) able to solve a required task. Depending on the parameters under evolution, we can identity three different ways to use a combination of genetic algorithms and neural networks:

- **Evolution of synaptic weights :** where evolutionary parameters are synaptic weights and biases. In this case, the network architecture is pre-arranged, that means the number of neurons and connections cannot be modified through the evolution, therefore they are not pre-codified into the genotype.

- **Structure Evolution :** where the number of neurons and connections are pre-codified into the genotype.

In 1994, some authors have implemented a genetic algorithm to evolve neural networks controlling a small mobile robot, in real time [128]. In this work, the robot can move autonomously into the environment while the neural network acquires signals from robot's sensors and send electrical signals to wheels' motors. A computer program constantly evaluate the fitness in terms of velocity and collisions avoidance. Each genetic algorithm's individual is identified by a neural network controlling the real robot. Next generations' individuals are tested one by one. After 10 hours (i.e. 50 generations) the genetic algorithm produces neural networks able to exhibit navigational behaviours and obstacle avoidance.

Because of the elevated computational cost, simulation programs have been devised to simulate the environment and the robot's body as close as possible to the real environment and the real robot.

After the evolution, the best control neural network can be transferred in the real robot control system (synaptic weight, bias, etc.). Then, a test of the real robot can be executed, by eventually submitting the robot to a further slower in the real environment.

7 Appendix II : Evolutionary Robotics and Genetic Algorithms

As we have stated, evolutionary robotics [129] attempts to build robots by means of an evolutionary process inspired to the biological evolution:

1. An initial population of control systems (which are named individuals) is randomly generated;

2. Only some control systems are selected and reproduced: those ones which display a behaviour that mostly approximate the wanted behaviour. Each reproduction generates a new generation of individuals similar but not identical to the previous generation's individuals.

3. Phases 1 and 2 are repeated until the control neural network reaches the desired accuracy. Thus, this candidate control system becomes the definitive control system of the evolved simulated robot and real robot, eventually.

The evolutionary approach relegate the programmer to a mere checker of the system behaviour, without any design role. Therefore, evolutionary robots are auto-organizing systems able to develop own abilities autonomously, by interacting with the environment. Since they are auto-organizing, evolutionary robots are characterised by two properties:

1. They can afford to deal with very complex tasks in an unexpected way for the trainer. However, very often, they can use simple strategies to solve complex tasks.

2. They can find parsimonious and unpredictable solutions. In this way they can provide new insights to the designer-programmer.

The Evolutionary Process, adopted in evolutionary robotics, is the *"Genetic Algorithms"* [130]. This methodology is based on the manipulation of "artificial chromosomes" belonging to an "artificial individual". An artificial chromosome (or genotype) is a string which encodes individual characteristics (or phenotype).

In general, the evolutionary process is structured in generations through the following phases:

1. For each generations, individuals are let live (that is interacting with the environment), and best genotypes are selected depending on the fitness score (selection operator);

2. Individuals are randomly joined by merging genetic material (crossover operator);

3. Individuals are mutated (mutation operator).

At the end of each generation, from population of individuals is generated an offspring which produces a new individuals populating the new generation. The process goes on until a good individual is generated according to the required task. The trainer-programmer defines the genetic encoding and the fitness function. Genetic encoding represents the relationship between genotype and phenotype. The choice of the codification is a critical point for the problem which is aimed to be solved and for a better exploiting of genetic algorithm functionalities.

In the case of direct codifications, phenotype parameters are translated in genotype values, which are finally encoded in binary code. Instead, in the case of indirect codifications, the genotype encode some developmental rules which determine how the phenotype is developed from the initial artificial embrion.

Evaluation function, or fitness, is a function which is used to evaluate individuals performances with respect to the considered problem or the designed task. The fitness function is calculated on every phenotype on the base of some critical parameters defined by the trainer-programmer. The fitness function returns a numerical value which is proportional to the accuracy of the solution provided by each individual.

In evolutionary robotics, the fitness function evaluates the robots' behaviour emerging during their interaction with the environment. Many fitness designing methods exist in order to selectively produce individuals. One of the most used algorithms is the *"roulette wheel"*. In roulette wheel, the probability for an individual to generate an offspring is given by the following formula:

$$p_i = \frac{f_i}{\sum_i^N f_i} \qquad (7.1)$$

where x_i is the considered phenotype, and $f_i = \phi(x_i)$ is its fitness score.

In other words, the likelihood to select an individual is a normalised function of the fitness score over the total fitness of a N individuals' population. The selection is accomplished as the individual is selected on a wheel, made of N slots and each slot is associated to an individual. The number of the offspring is $p_i \cdot N$.

An alternative is the *"rank based"* method , where all individuals of one generation are sorted by the fitness score. A number of bests are selected and the rest is discarded.

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