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ON THE DESIGN OF A BOOLEAN-NETWORK ROBOT SWARM
COLLECTIVE RECOGNITION OF GROUND PATTERNS

Tesi di Laurea elaborata nel corso di:
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I still remember the first time I was given a personal computer. I was six and the first thing that I asked was “Can I write my name?”. I hope that now, after some years of studies, I can be able to respond to also more interesting questions.

Contents

1. Introduction

Under the 7th RTD Framework Programme of the European Commission, several grant agreements (about 75) fall in the remit of the ICT Challenge "Cognitive systems and robotics". The phenomenon demonstrates the still lively interest in artificial intelligence for the European scientific community. In particular, such projects concern issues about endowing artificial systems with *cognitive capabilities* including: recognition, reasoning and planning, learning and adaptation. The term "cognitive capabilities" is used with good justification to indicate skills that can make a robotic device able to control its own actions. Simple cognitive capabilities like establishing and recognising patterns are prerequisites for higher level operations like conceptualization, reasoning, planning, intelligent control and complex goal-oriented behaviour.

Moreover, the trend outlined in Strategic Research Agenda (SRA) issued by the European Robotics Platform in 2009, predicts that by 2020 robots should be programmable by learning (e.g., from observation or imitation). Such systems will operate in non-deterministic environments and will regularly be confronted with novelty and change. In order to work robustly and adaptively, they not only have to be able to extract information from their environment but also to reason and learn about it [44].

To accomplish such features, the employment of automatic design procedures is needed since such procedures can make the process more robust and flexible with respect to a customised one.

In this work, we treat the automatic design process as a search problem identifying two main components: the model that represents the robot behaviour and the optimisation algorithm that shapes the model according to specific requirements. Generally, the most commonly used model is the *artificial neural network* (ANN) which attempts to simulate either the structure or functional aspects of the biological central nervous system. ANNs and genetic regulatory networks in general, have interesting features like robustness and flexibility typical of biological systems. For these reasons, ANNs are used in the field of Evolutionary Robotics where the network is trained by means of techniques inspired by the Darwinian evolution. However, because of their complexity, it is impossible to analyse the solutions found and to reverse-engineer them.

We can try to overcome the problem using a simpler model of genetic regulatory networks called Boolean network (BN). BNs have been introduced by Stuart Kauffmann in 1969 in order to study the mechanisms of evolutionary processes in nature. With their compactness and simplicity we can nevertheless obtain complex behaviour and, moreover, we can study their internal dynamics.

The second element of the design process concerns the optimisation algorithm. An appropriate choice can be a specific metaheuristic technique which, exploring immense search spaces, can find a viable solution in a limited amount of time.

In this work, developed in collaboration with the Institut de Recherches Interdisciplinaires et de Développements en Intelligence Artificielle (IRIDIA) of the Université Libre de Bruxelles, we apply the automatic methodologies to a swarm of BN-controlled robots in order to obtain a specific collective behaviour. Until this moment, the design in swarm robotics has been empirical, tailored to the specific case. However, because of the growing interest of the research in this field, a more formal methodology is needed in order to engineer the design of such systems.

Our goal is to program a set of robots with same controllers, in such a way that they collectively can decide a specific action to perform in accordance with the environment. The environmental features are distributed and this make the communication necessary to accomplish the task.

The specific task concerns the recognition of two different patterns drawn on the floor. The robots are placed in order to uniformly covering all the peculiarities that emerge from the floor. Robots must reach a consensus only using local communication and signaling their status through the LEDs.

At first, we validate the automatic design methodology on a given instance of the problem; this is necessary for determining a suitable optimisation algorithm and a good evaluation criterion for the swarm. Subsequently, the methodology is applied on a simpler case to better investigate the factors that can increase the performance.

The abstract scenario depicted in our work is only a simple example of swarm robotics applications which, however, can provide a proof of concept for more concrete applications (e.g., the exploration of hostile environments such as oceans, Mars, human body, etc.).

The thesis is structured as follows:

In Chapter 2 we introduce the Boolean networks as model used for representing the robot behaviour. We focus on their dynamics detailing also the analysis of a special kind of BNs used in our experiments: the Random Boolean Networks. Finally, we provide an overview of previous works about BNs design.

In Chapter 3 we define the concept of Boolean Network Robotics relying on the basics of general robotics. We depict the methodology in all its aspects and we report recent studies about this field.

Chapter 4 contains the description of the task highlighting the main emerging aspects, the description of the chosen robots, environments and initial conditions for each experiment. We also include a brief overview on the research areas which partially deal the same issues.

In Chapter 5 we report a sequence of preliminary experiments discussing for each case the correlations between the achieved results and the chosen experimental settings.

In Chapter 6 we simplify the problem for a deeper study of the swarm behaviour. In particular, we focus our analysis on the exchanged communications among robots.

Finally, Chapter 7 draws some conclusions and gives an outlook for future works.

2. Boolean Networks

In this chapter we define the Boolean networks as model to represent the robot behaviour. After a brief introduction in Sec. 2.1, we discuss their dynamics in Sec. 2.2 while in Sec. 2.3 we focus on a special kind of BN used in our experiments: the Random Boolean Network. Section 2.4 reports a brief of previous works on BNs design.

2.1 Introduction

Boolean Networks (BNs) have been introduced by Stuart Kauffman in 1969 [23] as a simplified model of genetic regulatory networks (GRN) and as an abstraction of complex systems in order to study the mechanisms of evolutionary processes in nature. Despite their simplicity, BNs are very important because, for many systems, the on-off Boolean idealization is either accurate or the best idealization of the nonlinear behaviour of the components in the system [27].

BNs consist of binary variables, each with two possible states (1 or 0). The variables are connected such that the activity of each element is governed by the prior activity of some elements according to a Boolean switching function. The set of these variables is structured like a directed graph with N nodes. Each node x_i has K ingoing arcs and an associated Boolean variable. The values of the variables are determined by the function $f_i = (x_1, \ldots, x_K)$

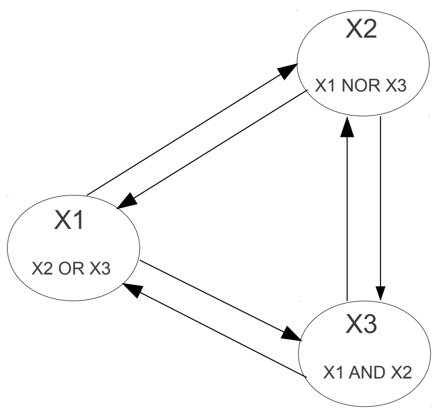


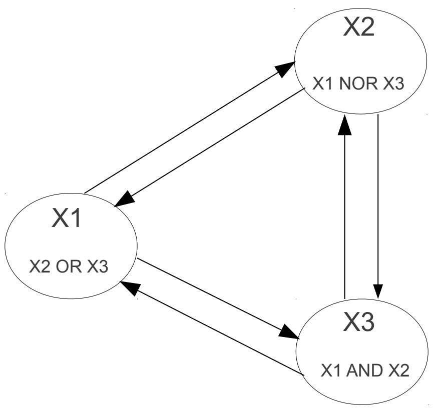
Figure 2.1: An example of Boolean Network with $N = 3$ and $K = 2$.

where the arguments are the Boolean variable value of the nodes whose outgoing arcs are connected to i. A simple example of BN is showed in Fig. 2.1.

We call *state* of the BN the sequence of the Boolean variable values $s(t) = (x_1(t), \dots, x_N(t))$ in a given instant of time t. Since a Boolean variable can assume only two different values, the state space size is finite (2^N) and the dynamic behaviour is characterized by a sequence of state updates. Furthermore, several kinds of update rules and dynamics have been proposed [19] like *synchronous* (the Boolean variables are all updated at the same time), *asynchronous deterministic* (variables do not change their states all at the same moment, but some do it earlier than others) *asynchronous non-deterministic* (not only the nodes do not march in step but these nodes are non-deterministically updated) etc... The one we consider in this thesis is *synchronous* with a *deterministic* nodes updating.

2.2 Boolean Network Dynamics

The state space of Boolean networks is discrete. Thus, it is possible to enumerate all the possible states of the network and study interesting dynamics



X1	X2	X3	X1	X2	X3
0	0	0	0	1	0
0	0	1	1	0	0
0	1	0	1	1	0
0	1	1	1	0	0
1	0	0	0	0	0
1	0	1	1	0	0
1	1	0	1	0	1
1	1	1	1	0	1

t **t+1**

Figure 2.2: The table describes the dynamics of the BN showing the successor of each state.

using concepts such as *state* (or phase) *space, trajectories, attractors* and *basins of attraction* [6].

Since the state space is finite and the dynamics are deterministic, the state succession assumes this structure:

- When the BN starts its progress, the *trajectory* (i.e., the evolution of the BN into the state space) is a succession in which each state is different from all the previous ones. This sequence of different states is called *transient* and the number of states of the transient is called *lenght of the transient.* The transient can have length 0.

- Since the network dynamics are deterministic and the state space is finite, eventually a sequence of states will be repeated. Such sequences are named *attractors* of the BN and they can be classified in *cyclic attractors* with period $t > 1$ or *point attractors* whether $t = 1$. Point attractors are also known as *fixed points.* The set of states that leads towards an attractor is named *basin of attraction.*

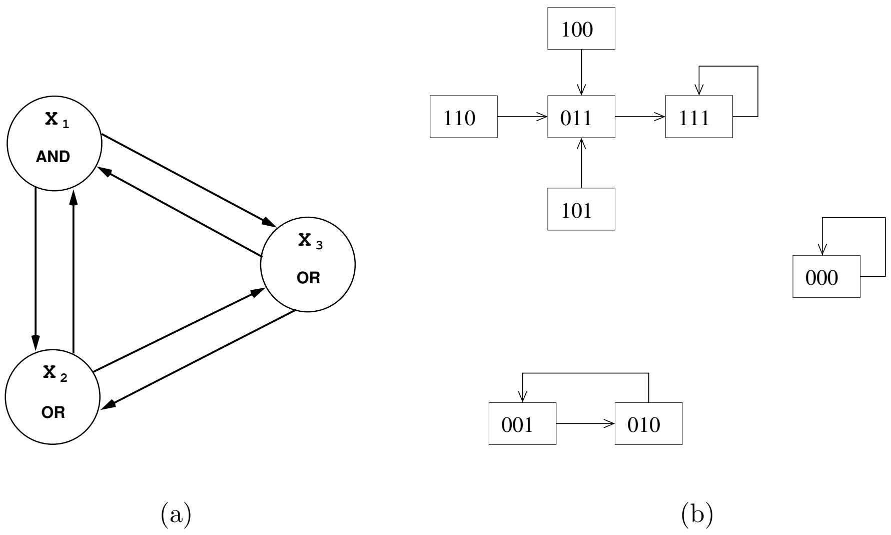


Figure 2.3: The figure shows a simple Boolean network (a) with three attractors (b): 2 fixed point and 1 cyclic attractor.

In Fig. 2.3 is shown the state space of a simple Boolean network with $N = 3$ and $K = 2$. In particular, we can see that several states join to the same successor state. According to the Boolean functions of each node and initial conditions, the trajectory can converge into three different attractors. Two of these are fixed points (the states *111* and *000*) while the other one is a cyclic attractor (states *001* and *010*).

The attractors are very important because they house the stable behaviour of many complex systems. The remaining space in state space are visited only along transients leading to such attractors. Dynamical systems ranging from genomic cybernetic systems to immune systems, neural networks, organ systems, communities, and ecosystems all exhibit attractors [27]. Thus, the characteristics of attractors in complex systems with hundreds, thousands or millions of interacting elements are inevitably of basic importance.

2.3 Random Boolean Networks

Starting from the original definition of BN, many variants exist that differ according to dynamics and updating rules. The most studied are the *Random Boolean Networks* (RBNs). RBNs have been used to model living organisms to provide evidence over the hypothesis that such entities could be constructed through processes that display some degree of randomness rather than being precisely programmed [23]. Because of their peculiarities, RBNs have been also used as models in many different areas, such as evolutionary theory, mathematics, sociology, neural networks, robotics, and music generation [19].

RBNs are a generalization of Boolean cellular automata (CA) [47], where the state of each node is not affected necessarily by its neighbours, but potentially by any node in the network. Differently from the general model presented in Sec. 2.1, RBNs presents randomly generated Boolean functions and connections among nodes. If we try to imagine all possible networks, for each node there will be 2^{2^K} possible functions [21]. Each node has $N!/(N-K)!$ possible ordered combinations for K different links. Therefore all the possible networks for given N and K will be:

$$\left(\frac{2^{2^K} N!}{(N-K)!}\right)^N \tag{2.1}$$

From Eq. 2.1 we can see that the space of networks increases exponentially with the number of nodes N. Thus, the cardinality of such space is very big also for small N values. However, general properties can be extracted from this huge universe of possible networks. Indeed, as well as in many dynamical systems, it is possible to identify three dynamical regimes: *ordered*, *chaotic*, and *critical*. A good way to visualize what happens would be the plotting of the states of a network in a square lattice where the state of a node depends topologically on its neighbours, and let the dynamics flow.

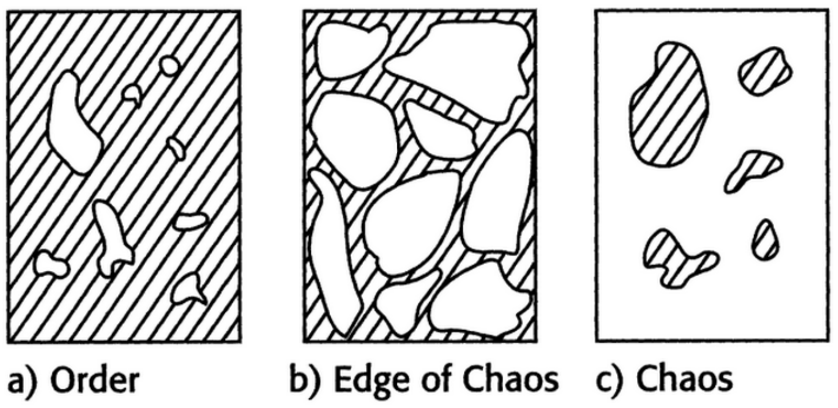


Figure 2.4: Schematic view of the ordered, edge of chaos and chaotic regime in Boolean networks with genes arranged on two-dimensional square lattice.

To show which states change and which ones are stable, we indicate changing states with white, and static ones with hatch marks (see Fig. 2.4). We observe that:

- in the ordered phase, initially many states change, but quickly the dynamics stabilise, and most of the nodes are static. At convergence, what remains is a small number of white "islands" of nodes changing state surrounded by a striped "sea" of static nodes.
- In the chaotic regime, most of the states change constantly, so the long-term dynamics of the system converges on a white sea of nodes constantly changing state dotted by a few striped islands of static nodes.
- In the critical regime, the dynamics of the system settles on a mid point between the two previous regimes. Indeed, similarly to the chaotic regime, the dynamics starts with a white sea of changing nodes is dotted by striped islands of static nodes, but, as these islands join, they grow in size so as to look like a sea, in which white islands appear. This phase transition from the ordered to the chaotic regime is also known as the *edge of chaos*.

Given these regimes, it is possible to observe the *stability* of a network after a perturbation (e.g., flipping the state of a node) and how the perturbation spreads. In the ordered regime, usually the perturbation does not spread. This is because changes cannot propagate from one green island to another. In the chaotic phase, these small changes tend to propagate through the network, making it highly sensitive to perturbations. Finally, for the edge of chaos, changes can propagate, but not necessarily through all the network.

Order arises also as a result of *forcing structures*. Consider the Boolean OR function. This function asserts that, if at least one of the two input nodes is active at a given moment, then the node state will be 1 at the next network update. So, if a node input is constantly 1, the value of the other input does not affect the state of the node. This kind of functions are called *Canalizing Boolean functions* and their presence inside a network can force the achievement of steady states.

Several RBN simulation experiments show that the networks with $K \leq 2$ are in the ordered regime, and networks with $K \geq 3$ are in the chaotic regime. Furthermore, it is possible to identify analytically and statistically the critical line in the edge of chaos. Different solutions exist. One of these is the Derrida annealed approximation [11] that measures the Hamming distance of consecutive randomly chosen configuration of networks. In this way, it is possible to find a relationship between K and p where p is a parameter called *homogeneity* or *bias*. The Boolean function of a node can be represented by a *truth table* in which a Boolean value is assigned to every combination of input values. Homogeneity is defined as the probability p to have an truth table entry with 0 as output value. Then, the critical line is defined by Eq. 2.2 and the related plot is showed in Fig. 2.5.

$$2p(1-p) = 1/K \tag{2.2}$$

The importance of the complex regime, which represents the phase transition between order and chaos, is due to the fact that it combines the inherent

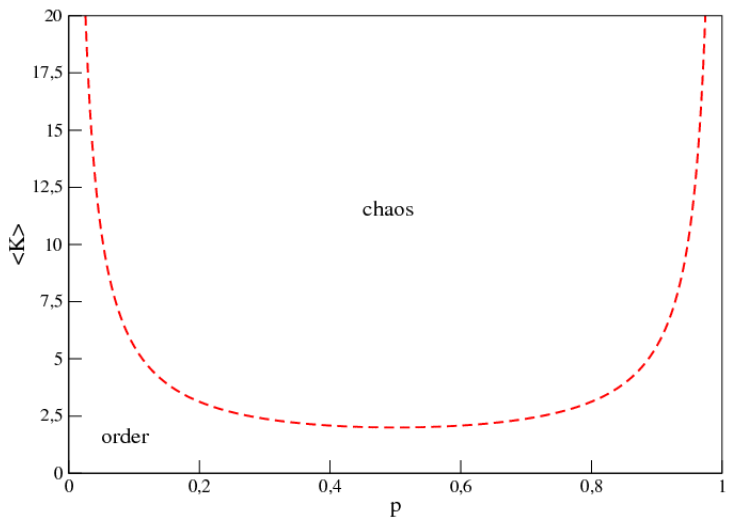


Figure 2.5: Relationship between p and K in Derrida annealed approximation.

robustness of ordered regime and the flexibility of the chaotic one. Thinking about living systems, they require certain stability to survive but also flexibility to the environmental changes. This has lead people to argue that life and computation occur more naturally at the edge of chaos [25].

2.4 Boolean Network Design

The emergence of interest in Boolean networks was motivated by the rapid accumulation of genetic information and advancement of experimental techniques, which led to studies on the engineering of artificial gene regulatory networks and their respective models. Even if BNs derive from genetics, they have also been studied as computational learning systems [34, 24, 12] and proven capable of tackling hard problems [31]. Many analytical studies about the properties and dynamics of BNs exist, but their synthesis has not been deeply studied. The first contribute in this direction is due to Kauffman and Smith [26] where they proposed some issues that arise in applying Darwin's idea to the problem of designing adaptive automata. Subsequently, Lemke et al. [28] investigate the adaptation of RBNs considering a general genetic algorithm and a fitness function that takes into account the full network dynamical behaviour. Interesting inferences emerge related to the analysis of the scenario that describes the adaptation on the proposed fitness landscape. Some studies on the evolvability and robustness are conducted [2, 7, 13]. Szejka and Drossel in [45] focus on networks with canalizing functions where the evolution is obtained with an adaptive walk. They found that in spite of having a high degree of robustness, the evolved networks still share many features with chaotic network. Fretter et al. [16] investigate the propagation of perturbations in Boolean networks by evaluating the Derrida plot and modifications of it. They conclude that the simple distinction between frozen, critical and chaotic networks is no longer useful, since such evolved networks can display properties of all three types of networks. In addition, Roli et al. [37] found some differences among the three kinds of networks. They discuss the results of an experimental analysis in the design of Boolean networks by means of genetic algorithms. The target of the evolution is to find a network able to reach an attractor of a specific length. Initial populations composed of critical or chaotic networks are more likely to reach the target. Moreover, the evolution starting from critical networks achieves the best overall performance.

3. Boolean Networks Robotics

This chapter first introduces the Boolean Network Robotics (Sec. 3.1) providing some basic concepts useful tu understand the reasons of interest for this field. After, (Sec. 3.2) it describes in detail the methodology that underlies the automatic design procedure. In Sec. 3.3 we report some recent works that validate such methodology.

3.1 Basics

The very recent concept of Boolean Networks Robotics refers to the design of robotic or multi-agent systems. To date, only a few preliminary studies exist that focus on this problem [40, 18, 3, 39, 41, 38].

As in classical robotics, we consider two principal actors: the *agent* and the *environment* where the agent acts. The agent (in its most general definition) interacts with the environment using *sensors* and *actuators*. The former ones are needed to sense the environment and the latter ones to act in function of the goals and the sensed environmental information (see Fig. 3.1). A robot is a special kind of agent that operates inside the real world. One of the hardest problems in the design of a behaviour for a robot is the unpredictability of the real world, stemming from complex, non-linear phenomena. In general, non-linear systems implies that we can no longer, as we can with linear systems, decompose the systems into subsystems, solve

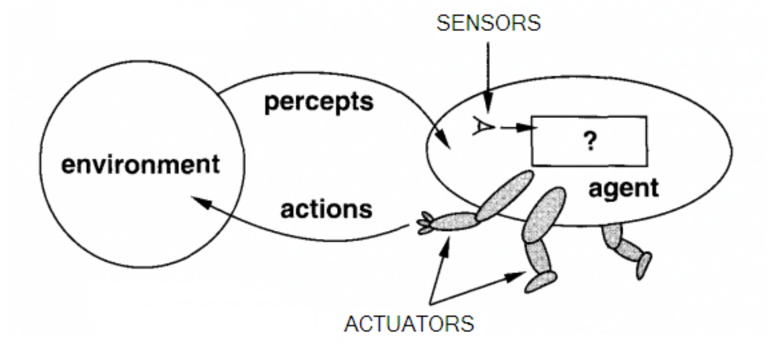


Figure 3.1: Interaction between agent and environment.

each subsystem individually, and then reassemble them to give the complete solution [35].

Thus, in real world scenarios, adaptation to constantly changing conditions is often necessary, rendering rule-based strategies likely to fail. Darwin suggested that adaptation and complexity could evolve by natural selection acting successively on numerous small, heritable modifications [15]. That said, the first proposal that Darwinian selection could generate efficient control systems can be attributed to Alan Turing in the 1950s. He asserted that intelligent machines capable of adaptation and learning would be too difficult to conceive by a human designer and could instead be obtained by using an evolutionary process with mutations and selective reproduction [46]. The idea hinted by Alan Turing has been actually tried in a methodology called *evolutionary robotics*. In this approach, genetic regulatory networks can evolve to obtain the intended behaviour by means of a specific learning process. BNs are extremely interesting because they are capable of producing complex behaviours, notwithstanding the compactness of their description. For this reason, we believe that BNs can effectively play the role of robot programs [40].

3.2 Methodology

The proposed approach consists in using BNs as robot controllers. In this way, the robot behaviour can be described in terms of trajectories in a state space, making it possible to design the robot program by directly exploiting the dynamical characteristics of BNs, such as their attractors, basins of attraction and any dynamical property in general. For the design of BN robot, several interrelated issues have to be tackled.

3.2.1 BN-Robot Coupling

The first issue is called *coupling* and concerns the mapping between sensors and network inputs and between network outputs and actuators. Many researchers treat BNs as isolated systems neglecting aspects of interactions with an external environment. However, some important exceptions exist [4, 12, 24, 34]. In our case, we divide the network in three specific sets of nodes: *input nodes*, *hidden nodes* and *output nodes*. The input nodes are nodes whose state is completely insensitive to the network dynamics (hence the name) but updated by the sensors readings. Conversely, output nodes are subjected to the network's dynamics and their state is observed and used as signal to trigger or adjust the robot's actuators. All the remaining nodes are hidden, i.e., they do not interact with the environment and we conjecture that they could house processes related to memory and reasoning. The output nodes' states depend on such hidden nodes. The choice of which nodes to use as input, output or hidden could be fixed a priori or updated by means of a learning process. Fig. 3.2 shows the scheme of the coupling between BN and robot. According to the type of sensor or actuator, the mapping signal-state/state-signal can be one-to-one or obtained as result of determined function (e.g., the output could correspond to the moving average of the state values in time).

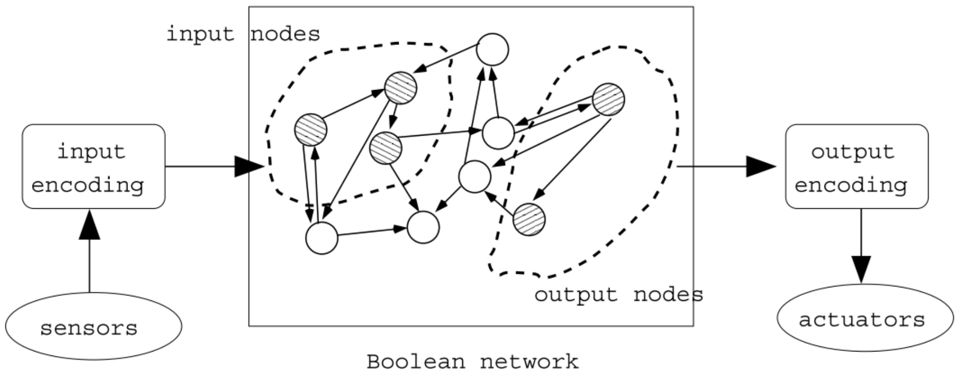


Figure 3.2: Coupling Between BN and robot.

3.2.2 BN-Controller Design

Once the input and the output mappings are defined, we have two ways to design the resulting Boolean network. The first way is to design a BN such that its dynamics satisfy given requirements. For example, in correspondence of attractors with largest basins of attraction the robot exhibit high-level behaviours and the transitions between attractors would correspond to transitions between behaviours. In this way, the robot is driven by the dynamics of its Boolean network. The latter possibility consists in modelling the BN design process as a search problem, in which the goal is maximising the robot's performance. These two ways are not alternative and can be combined. For example, once the basic behaviour is obtained with the latter approach, we can use the former one in order to improve the robot's behaviour [41].

We use a design methodology based on metaheuristics. In fact, the design of a BN that satisfies given criteria can be modelled as a constrained combinatorial optimisation problem by properly defining the set of decision variables, constraints and a evaluation function for reward and punish according to the network behaviour. This approach is illustrated by the scheme in Fig. 3.3. In our work, the decision variables manipulated by the metaheuristic algorithm correspond to the Boolean functions contained inside the nodes while the

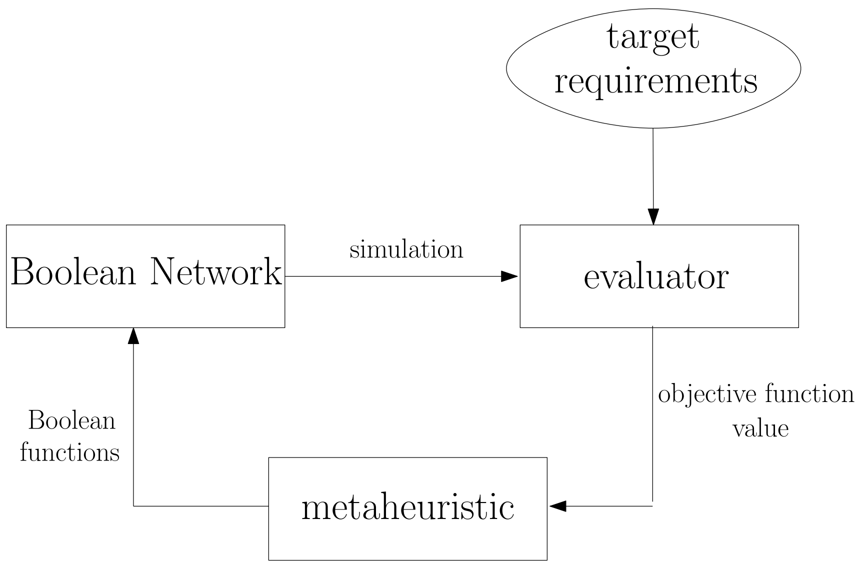


Figure 3.3: Metaheuristics for BN Design.

network topology is fixed at the beginning and never changed. A complete assignment of decision variables defines an instance of a BN. Subsequently, this network is used as robot control code and evaluated according to the specific target requirements, either on its dynamics or on the robot's behaviour, or both. Since real robots are expensive and prone to fail while simulations are faster to execute a large number of experiments, we prefer to use a modular, multi-engine simulator for heterogeneous swarm robotics called *ARGoS* [36]. The simulation parameters are controlled in real time by a specific software application which, in function of the values of such parameters, evaluate the behaviour of the network. Thus, when the simulation ends, we have a specific performance value that will be used by a metaheuristic algorithm. The metaheuristic algorithm, in turn, proceeds with the search.

The metaheuristic algorithm chosen for this work is a Stochastic Local Search method called *Iterated Local Search* (ILS) [30, 22]. Below, we find a more detailed description of this algorithm.

3.2.3 Iterated Local Search

As all the stochastic local search algorithms, the Iterated Local Search (ILS) starts at some location of the search space, representing a possible solution, and try to improve it by iteratively move from the present location to a neighbouring location. For preventing iterative improvement from getting stuck in local optima, the ILS essentially alternates two types of search steps: one for reaching local optima as efficiently as possible, and the other for effectively escaping from local optima. The landscape that contains these local optima is defined by an objective function that, in our case, we want to maximize. Alg. 1 shows an outline for ILS.

Usually, the search process can be initialised in various ways, In this work we start from a randomly chosen network. For each evaluation, the network starts from the same randomly chosen state. From this initial candidate solution, a locally optimal solution is obtained by applying a subsidiary local search procedure *localSearch*. Subsequently, each iteration of the algorithm consists of three major stages: *perturbation*, *local search* and *acceptance criterion*. These components need to complement each other for achieving a good trade-off between intensification and diversification of the search process.

Perturbation a perturbation (*perturb*) is applied to the current candidate solution s obtaining a modified candidate solution s'. The role of *perturb* is to modify the current candidate solution in a way that will not be immediately undone by the subsequent local search phase. This helps the search process to escape from local optima, and the subsequent local search phase has more possibility to discover different local optima. In our case, the perturbation consists in flipping a single bit randomly chosen into the truth table of each node.

Local Search The next stage is the application of a subsidiary local search *localSearch* until a local optimum s'' is obtained. The local search procedure has a significant influence on the performance of any ILS

Algorithm 1 Iterated Local Search

```
1: input: a problem instance $\pi' \in \Pi'$
2: $s \leftarrow init(\pi')$
3: $s \leftarrow localSearch(\pi', s)$
4: $\hat{s} \leftarrow s$
5: while not $terminate(\pi', s)$ do
6:     $s' \leftarrow perturb(\pi', s)$
7:     $s'' \leftarrow localSearch(\pi', s')$
8:     if $f(s'') \geq f(\hat{s})$ then
9:         $\hat{s} \leftarrow s''$
10:    end if
11:    $s \leftarrow accept(\pi', s, s'')$
12: end while
13: if $\hat{s} \in S'$ then
14:     return $\hat{s}$
15: else
16:     return $\emptyset$
17: end if
```

algorithm. Considering the simplicity of the model and the reduced number of nodes, we believe it is sufficient to use a simple Stochastic Descent (SD) method. Starting from an initial candidate solution, the SD choose at random both a node of the BN and an entry in the truth table of the Boolean function characterising such node. Then, the value of such entry is flipped. If a given move does not lead to an improvement (i.e., a greater or equal value of the objective function to maximize), such move is retracted; otherwise, the move is accepted and the modified BN becomes the new candidate solution.

Acceptance Criterion The acceptance criterion, *accept*, also has influence on the behaviour and performance of ILS. A strong intensification of the search is obtained if the better of the two solutions s and s'' is always accepted. Conversely, if the new local optimum s'' is always accepted regardless of its solution quality, the behaviour of the resulting ILS algorithm corresponds to a random walk in the space of the local optima of the given evaluation function. For our work, we prefer to choose s'' if it is better than or equal to s. Here, for exploring more of the search space, we accept also a new candidate solution which performance is the same performance of the previous best solution.

3.3 Related Work

In this work we employed the automatic design methodology seen in Sec. 3.2 in order to synthesize BN-based programs for robots able to perform a given task. Even though BN robotics is quite recent research field, it is important to summarise recent work in this area in order to provide its motivations and perspectives.

Below, we report a summary of the first three works in this direction where are shown different ways to validate the methodology.

3.3.1 A Proof of Concept

The first contribution in Boolean network robotics comes from Manfroni [40]. In this work, the methodology has been validated by experiments on abstract case studies (e.g., design of a BN whose trajectory must reach a given a target state at least once within a certain temporal interval). In these cases, the networks obtained by automatic design process tend to the critical regime, that is the most interesting and studied one.

After the validation, the methodology is applied to two robotic tasks: *path following* and *phototaxis & antiphototaxis*. In the former, the robot selects its actions only on the basis of the current sensory inputs. In the second task, more difficult than the previous one, the robot needs to keep a sort of internal memory to achieve the goal. The result attained show that BN dynamics is suitable to produce complex behaviours notwithstanding the simplicity of the model. However, this work provide only a proof of concept, without focusing on statistical properties of the methodology, such as its success rate on robotics case studies.

3.3.2 Improving the Search Method

Garattoni [18] tests the methodology directly on two simple robotic tasks: *phototaxis* and *obstacle avoidance*. The robustness of the methodology is proven by the good results obtained utilising only a simple stochastic technique i.e., the stochastic descent. Subsequently, he studies some properties of the search landscape showing that the dynamical regime of the initial solution can impact the performance of the search process. For instance, initial solutions in chaotic regime cause a deterioration of the search performance. Moreover, the choice of the number of nodes can be decisive for the performance of the process. In general, a small search landscape make the search easy, but it is crucial to consider also the required computational capacity for the target task. Another aspect carried out in that work concerns the link between the improvements during the training and the network properties. He shows that relevant improvements in the search landscape correspond to particular effects on the dynamics of the networks, as the number of states visited. Finally, the methodology has been employed for a *sequence learning* task, more complex due to the form of memory required to be performed. In this case, the difficulty of the simple stochastic descent emerges in tackling the task. He proposed different methods with features of search diversification, such as the iterated local search and variable neighborhoods search. From the analysis on the results obtained it is possible to achieve a good trade-off between intensification and diversification.

3.3.3 State Space Analysis

The method is validated also in the work by Amaducci [3], experimenting the obstacle avoidance and the phototaxis task but the focus of the work is on the state space structure of the resulting networks. His studies show that the networks tend to use a low portion of state space to achieve the target task. In particular, he focuses attention on the relationship between the number of used states and the quality of results. For example, in the ordered regime, where the number of used states is lowest, he obtains better results compared with the chaotic regime in which the number is highest. Furthermore, from the analysis of the the state distribution during the design process, it emerges that the number of states is subjected to an exploration phase (i.e., where the number of visited states increases) and exploitation (i.e., states decrease). He calls this phenomenom *states compression mechanism*. The results have been confirmed with networks of different size. Subsequently, he plots the entire state space structures showing that the network's knowledge stored within the state space is organized in hierarchies that increase the stability and reliability of the network. From this analysis he states that such large amount of information can not be extracted just by studying attractors.

The same studies are conducted on the sequence learning task where the robot is required to keep an internal memory to achieve a given goal. In this case, he observes a different behaviour in the state space, probably due to the memory requirements to perform the task. The network realizes memory by duplicating some portion of its state space and placing it in the right position of the hierarchy. This mechanism is realized by the states reuse together with the state space compression and duplication. Finally, he demonstrates that, independently of the nature of the task, the network behaviour can be represented by a finite states automaton.

4. Task Description

Starting from the outcomes reached in the previous BN-Robotics works [40, 18, 3], we now define new objectives to push the limits of this research. The most important scientific question we want to address is: what happens inside a system consisting of many BN-controlled robots interacting with each other? This question is very important, because it moves towards new unexplored research areas, such as the interaction among Boolean networks and new design techniques for *swarm robotics*. Swarm robotics is an important application area for *swarm intelligence*. This concept refers to the emergent collective intelligence of groups of simple autonomous agents, in particular, autonomous robots [29]. An autonomous robot is viewed as a system that acts independently on its environment interacting with other robots around it. The peculiarity is that an autonomous robot does not follow commands from a leader [14]. With a swarm of robots we can achieve some tasks that would be impossible for a single entity.

As we saw in Chapter 3, a methodology exists in order to automatically design the behaviour of a single robot. The goal of this work is to verify if such methodology works when applied to a set of interacting robots. In doing this, we need to define a specific task where collaboration is necessary. In Sec. 4.1 we introduce the requirements chosen for such task, in Sec. 4.2 we describe in detail all its parts and in Sec. 4.3 we report some similar work from the field of distributed computation.

4.1 Task Requirements

The task that we want to consider needs *distributed computation* and *simplicity.*

Distributed computation is realized by *distributed systems* which consist of multiple autonomous computational entities that communicate through a network for achieving a *common goal.* The distributed computation takes place to solve large computational problems which are too demanding for a single computational unit. Moreover, the information needed to achieve a common goal could also be distributed among the nodes of the network. According to the swarm robotics definition, for our task we use a set of robots with simple computational capabilities. Such robots can only exchange their limited perceptions with the neighbourhood. The goal is to recognize a certain environment, whose characteristics can not be fully collected by local perceptions of a single robot. Here, it is necessary that each robot communicates its local information until a consensus is reached.

Simplicity is a key issue when, as in our case, we do not have full knowledge of the systems that we want to use. Indeed, although recent studies have provided the tools to analyze the internal dynamics of Boolean networks, such systems are yet partially unknown and many aspects are still unexplored. For this reason, we use simple BN with a small number of nodes. Furthermore, we employ such networks into simplified environments where the noise component does not exist. In these conditions, the computational complexity is reduced and it is possible to execute a large number of experiments. This means that we can test the networks on a considerable amount of cases in order to obtain a complete and thorough picture of the network behaviour.

4.2 Description

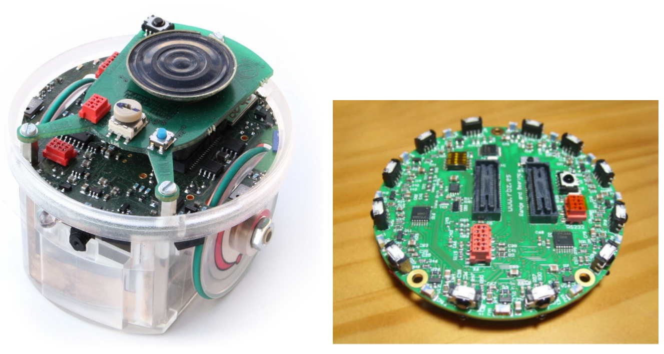
The task on which we want to validate the methodology consists of a swarm of robots that communicate locally among them trying to recognize two different floor patterns. Each robot can only sense the portion of floor below itself and then send this information into the environment. Each robot, both transmitter and receiver, perceives the information of the closest robot from each cardinal point so that is also potentially able to understand what comes from where (e.g., the northern robot perceives black floor, the southern one a white floor, etc...). Each robot is equipped with LEDs which can be perceived from an external observer. The goal is to design controllers able to keep off all the LEDs of the entire swarm if the robots are placed on a certain floor and turn on all the LEDs whether the swarm is located on the other one.

Below, we report a more detailed description of the robots used for this task, in particular the mapping between BN network and controller. Subsequently, we report a description of the floor patterns and of different initial conditions on which we train the network.

4.2.1 Robots

The robot used for our experiments is called E-puck and it is showed in Fig. 4.1(a). The E-puck is a simple robot designed for educational and research purposes. The full access to knowledge at every level of this robot improves both the quality of the support to the students and the diffusion in the research community [33].

A standard E-puck is equipped with several sensors and actuators but only a small part of them is necessary for our issues. Moreover, we integrate the robot structure with an open hardware/software board called *E-puck Range & Bearing* that enables the robots to communicate and at the same time obtain the range and bearing of the source of emission. Now we describe the utilized sensors and actuators.



(a) (b)

Figure 4.1: The E-puck robot (a) and the Range & Bearing (b).

E-puck Range & Bearing

The E-puck Range & Bearing board (RAB) (Figure 4.1(b)) was designed to increase some communication features needed into a multi-robot scenario. In particular, the board permits high communication range and speed, automatic managing of modulation and demodulation and different communicating sensors that work in parallel [20]. To communicate, the board includes 12 sets of IR emission/reception modules. Each of these modules is equipped with one infrared emitting diode, one infrared modulated receiver and one infrared photodiode. The modules are uniformly distributed on the perimeter of the board (Figure 4.2).

With the RAB it is possible to transmit a 16 bits data frame. The robots which receive the frame can also simultaneously calculate the distance (range) and orientation (bearing) to the emitter robot. It is also able to receive and transmit data from/to different directions at the same time and simultaneously identifying the location of several sources of emission. Therefore, the range of transmission is parameterized from 0 cm to 80 cm. In this way, one can tune the communication range according to the experiment needs. For instance, in our experiments we set always the maximum

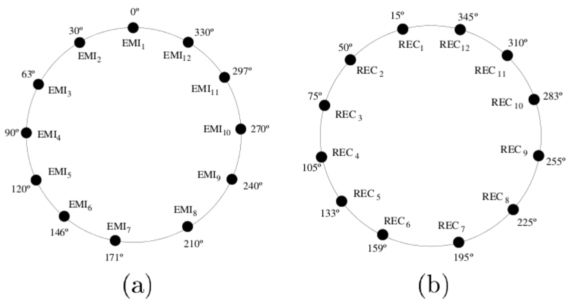


Figure 4.2: (a) Emitters and (b) receivers distribution around the perimeter of the RAB.

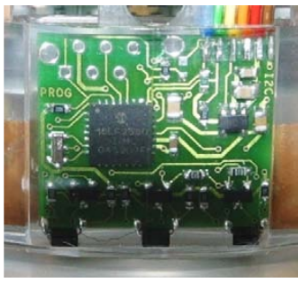
range in order to be sure that each robot can sense at least a neighbour.

Ground Sensors

The ground sensors (GS) are composed of three active IR proximity sensors placed in the front of the e-puck pointing directly at the ground [9]. These sensor elements are mounted on a small printed circuit board (PCB) which includes a microcontroller that continually samples the IR sensor elements. Each IR sensor consists of an IR-emitting diode and a phototransistor. The IR diode is used to emit a constant amount of infrared beam while the phototransistor detects the amount of signal reflected by the surface. A white surface reflects much more IR signal than a black surface. The e-puck Ground Sensors can be used for several different applications. In our case, we employ the sensor simply to understand whether the surface below the robot is black or white.

LEDs

The E-puck is equipped by eight red light emitting diodes (LEDs) placed all around the robot. These LEDs are covered by a translucent plastic and it is possible to modulate their intensities. In our task, the LEDs are used as a visual interface for the user to evaluate the correct behaviour of the robot.


(a)

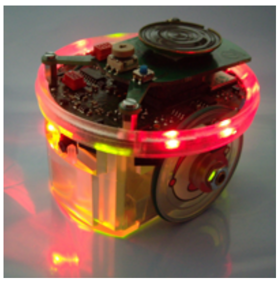

(b)

Figure 4.3: In (a) is showed a close-up view of the e-puck Ground Sensors module while in (b) the E-puck with LEDs on.

BN Coupling

Given the requirements in Sec. 4.1, for our experiments we use networks with a small number of nodes and links. In particular, we think that 20 nodes are sufficient to fulfill the task. Therefore, we set the number of ingoing arcs $K = 3$. In this way, changing only the homogeneity p (i.e., considering the truth table of a node, the probability to have an entry with 0 as output value is equal to p), it is possible to obtain networks for all the dynamical regimes (ordered, critic and chaotic; see Sec. 2.3). The networks are randomly generated by a software application.

In order to obtain the mapping with sensors and actuators, we need to divide the nodes in three sets (input, hidden and output nodes). If we assign an index for all the 20 nodes of the networks, we can obtain the following mapping:

- nodes from 1 to 9: ground sensors and RAB *(input nodes)*;
- node 10: LEDs *(output node)*;
- nodes from 11 to 20: *hidden nodes.*

Node ID	*Sensor*
1	GS sensing
2,3	RAB sensing from NORTH
4,5	RAB sensing from EAST
6,7	RAB sensing from SOUTH
8,9	RAB sensing from WEST

Table 4.1: Mapping between the robot sensors and the input nodes. We use 1 node for the GS and 8 nodes for the RAB: 2 nodes for direction.

In Tab. 4.1 it is showed the mapping between input nodes and sensors. Here, we use a single node for representing the ground sensor information and 8 nodes to express the information of range and bearing.

If the colour sensed from the floor is white, the state of the node with index 1 is 0 otherwise, if the colour is black, such state is 1. We use 8 nodes for the RAB since we want to group the neighbourhood information by cardinal points (North, South, West and East). As shown in Fig. 4.4, we define a range for each cardinal point. In this way, we associate a direction for each signal received in function of its angle. In Tab. 4.2 we can see that the information is composed by two nodes for cardinal point. Such double information is needed since we consider the hypothesis that there could not be neighbours in a certain direction. Indeed, the node with index i indicates whether a neighbour exists while the other node with index $i + 1$ specifies the kind of information (i.e., the colour of the floor). If we want to give a rational behaviour to the network on the basis of such coding, the node i should inhibit the information of node $i + 1$. In the case that there are more neighbours, we consider only the information from the nearest.

Finally, the state of the node 10 manages the LEDs. In particular, if the state is 1 the LEDs are turned on, otherwise, the LEDs are turned off.

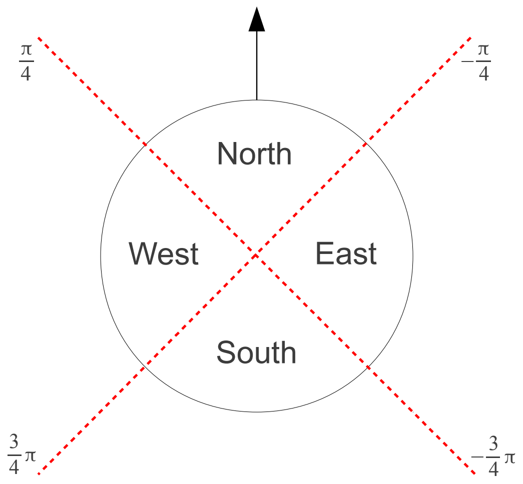


Figure 4.4: E-puck with RAB perceptions by cardinal points. The arrow indicates the front of the E-puck. The dashed lines identify the range for each cardinal points. According to the simulator, the angles are in radians increasing in an anticlockwise direction within the range $[-\pi, \pi]$.

4.2.2 Environment

The environments employed for the task are simple bidimensional textures that define the floors where the robots are placed. As showed in Fig. 4.5, we use two kinds of floor. The former is a black-white tetromino composed of four quadrants of alternating colour (like a simplified chessboard) while the latter is a white floor with a black circle in the centre (like the Japanese flag).

The chessboard texture is axially symmetrical while the Japanese flag is also radially symmetric. The presence of such symmetries combined with a uniform robot distribution prevents the creation of positional bias. Namely, wherever the robots are placed, we always obtain the same quality of spatial information.

x_i	x_{i+1}	*Description*
0	x	no neighbours
1	0	neighbour exists and perceives WHITE
1	1	neighbour exists and perceives BLACK

Table 4.2: Coding of the values for each couple of nodes (x_i, x_{i+1}) driven by the RAB. When the node x_i is 0 there is no neighbours.

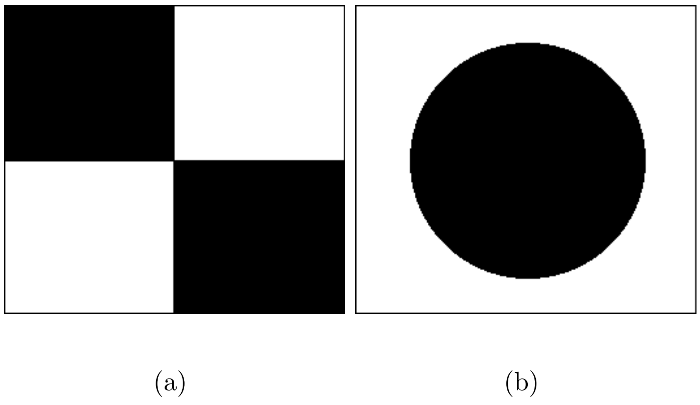


Figure 4.5: The patterns chosen for the recognition task. In (a) is showed the chessboard floor while in (b) the Japanese flag floor.

4.2.3 Initial Conditions

Our goal is to obtain BN controllers that permit to the swarm the recognition of the floors regardless the position and orientation of the robots. To do that, a training process that evaluate the network on multiple initial conditions is necessary. Such initial conditions differ by distribution and orientation. Indeed, if we evaluate the network on a single distribution, we obtain a too specialized behaviour that might not work if robots change position. Thus, the higher the number of initial conditions, the more general the behaviour of the network obtained at the end of the process.

Robot Placement

Both the floors have texture composed by only two colours. In order to avoid bias, we should not prefer an information over the other one i.e., it is important to have the same amount of robots placed on both colours.

In order to uniformly distribute the robots, we use the Diffusion Algorithm. Such algorithm simulates the behaviour of gas molecules which, colliding with each other, moving and uniformly cover the surrounding environment. Thus, we realise a simple secondary task where the swarm moves on a generic arena implementing the diffusion algorithm. The arena has same size as that defined for the original task. After an initial transient, we sample periodically the position of each robot. In this way, we obtain a series of different distributions of robots that we use as different initial conditions for the evaluation.

4.3 Distributed Computation

From this work, thematics emerge such as self-organization and pattern classification. We can easily find studies about them in the literature. However, it does not exist yet a work where such issues are treated for a swarm of BN-controlled robots. Below, we report an overview of two specific research areas that, taken together, slightly approach our issues: the *sensors networks* and *cellular automata*.

4.3.1 Sensors Networks

Sensor Network (SN) consist of a large number of cheap, smart devices with multiple on-board sensors, networked through wireless links and the Internet. SNs provide unprecedented opportunities for instrumenting and controlling homes, cities, and the environment [10]. Sensor networks may have many different types of sensors [1] such as seismic, low sampling rate magnetic, thermal, visual, infrared, acoustic and radar, which are able to monitor a wide variety of ambient conditions that include:

- temperature,
- humidity,
- vehicular,
- movement,
- lighting condition,
- pressure,
- noise levels,
- the presence or absence of certain kinds of objects,
- mechanical stress levels on attached objects, and the current characteristics such as speed, direction, and size of an object.

In this field, the more interesting issue concerns the extension of the autonomy of the sensors constituting the network. To this end, it is important to conserve energy and to give up performance in other aspects of the operation such as QoS and bandwidth utilization [43]. Thus, it is crucial to find a good protocol for exchanging information with a good trade-off among energy saving and QoS.

A remarkable work is [8] where is deeply described how a SN can solve the *distributed classification* problem. They consider the tracking and the classification of a target that crosses the sensor network. Each object in the sensor field generates a time-varying spatial signature field that is sensed using multiple modalities. The classification is obtained by sampling the target's signals over time and analyzing the corresponding time series.

There are two ways to achieve the classification: *fusing data* or *fusing decision*. In both cases, there are some master nodes, different from the others, that collect all data/decision to compute the final result. In general, we can assert that the SN protocols assign *roles* to the network's components. This aspect is further confirmed in [5] and [10] where they sustain that SNs have many similarities with multi-agent systems technology.

4.3.2 Cellular Automata

In the field of sensor networks the main issues concern the processing of signals coming from the real world and the autonomy of the physical devices. Differently, a cellular automaton (CA) is a decentralized computing theoretical model principally studied to provide an excellent platform for performing complex computation with the help of only local information. More precisely, we have a simple model of a spatially extended (in a certain number of dimensions) decentralized system made up of a number of individual components called *cells* [17]. The communication between cells is limited to local interaction. Each individual cell is in a specific state which changes over time depending on the states of its local neighbours. The overall structure can be viewed as a parallel processing device. This simple structure when iterated several times produces complex patterns displaying the potential to simulate different sophisticated natural phenomena. In order to enable the CA to reach a given computational goal, the researchers should be able to predict the global behaviour from the local CA rules. If this was possible, one should be able to design the local rules/initial conditions from a given prescribed global behaviour. The only general method to determine the qualitative (average) dynamics of the system is to run simulations on a computer for various initial global configurations.

The inverse problem of deducing the local rules from a given global behaviour is extremely difficult. There have been some efforts, with limited success, to build the attractor basin according to a given design specifications. However, the most popular methodologies to address the inverse problem of mapping the global behaviour to local CA rules are based on evolutionary computation techniques. One of these attempts is [32] where a genetic algorithm (GA) is used to evolve CAs for two computational tasks: *density classification* and *synchronization*. In both cases, the GA finds rules that give rise to sophisticated emergent computational strategies. For understanding how this individual works, they use a general method for reconstructing the intrinsic computation. This method is called *computational mechanics framework* and decomposes the behaviour in *regular domains*, *particles* and *particle interactions*.

Considering the focus of our work, an interesting study is described in [42] where the main goal is to understand under which conditions a given set of interacting Boolean networks can be found in the same attractor. This work is interesting because each cell is a random Boolean network that shares some nodes with its neighbourhood. The value of these *shared nodes* is determined by *interaction functions* which consider the shared nodes of neighbouring cells. Each cell has the same structure and is driven by the same interaction function. In these conditions, the CA evolves in discrete time. Several experiments are launched with different initial condition, number of shared nodes and different interaction functions. In order to measure the influence of interaction on the degree of order, they define some variables as a function of the presence of attractors into the CAs. In this way, it is possible to classify the CAs in four classes on the basis of their response as a function of the interaction strength. Moreover, analysing the values of the variable called *average attractor period* (AMP) it is possible to understand which class contains a certain CA. Although the phenomena observed are complicated, they can provide insights to determine new ways to study the interaction of random boolean networks.

5. Preliminary Experiments

In this Chapter we report the sequence of preliminary experiments on which we have validated the methodology. Sec. 5.1 describes the initial experimental settings such as the optimisation algorithm, the initial conditions, the number of iterations and the sets of networks. Section 5.2 shows the results using a simple stochastic descent method. Sec. 5.3 and Sec. 5.4 report the experiments using the iterated local search method according two different objective functions. In Section 5.5 we define a more sophisticated objective function and we draw some considerations applying it on two cases of output nodes encoding. Finally, Sec. 5.6 reports the results of experiments setted by the previous considerations.

5.1 Initial Setting

We have launched 90 experiments with the following configuration:

Number of trials: 30

Iterations: 10000

Number of E-pucks: 20

For each experiment we have 20 E-pucks with the same initial Boolean network as controller. The networks are generated at random but according to the following features:

- A total of 20 nodes;
- 9 input nodes: 1 node connected to the ground sensor, 8 nodes connected to the range and bearing sensor;
- 1 output node to set the LEDs ON or OFF;
- Every input node is connected at least to a hidden node;
- Every hidden and output node has 3 ingoing connections ($K = 3$).

The networks used for the experiments can be grouped in three batches with different homogeneity p (i.e., considering the truth table of a node, the probability to have an entry with 0 as output value is equal to p).

- 30 initial networks with $p = 0.5$
- 30 initial networks with $p = 0.788675$
- 30 initial networks with $p = 0.85$

Such homogeneity values statistically correspond to chaotic, critical and ordered regime (see Sec. 2.3). For each experiment, the robots have the same network with identical initial state randomly generated.

We call *trial* a specific initial condition where the swarm of robots will be simulated and evaluated. For each trial, every E-puck has a given position and orientation. The criteria for assigning the positions and orientations are widely described in Sec. 4.2.3. Each step of the training process evaluate the simulation on 30 trials. In the first fifteen, the robots are placed on a black-white tetromino floor while in the other ones we have the Japanese flag floor.

To ensure a correct comparison on the two patterns, we set the same positions and orientations for both sets of trials (i.e., let N the number of trials, the trial 1 has the same robot distribution and orientations of trial $N/2$). The only thing that changes is the floor texture.

For each trial, the optimisation algorithm executes the simulation for 10000 times with these parameters:

Length: 20 (simulated seconds)

Ticks per second: 10

Random seed: 312

For the description of the robots' behaviour during the simulation, you can trace back to the Section 4.2. Let T the number of the simulation time steps and $x(t)_i$ the behaviour of the epuck i at the time t, we consider the performance $P_{n,k}$ of a network n on a certain trial k as the number of correct behaviours at the last time step $t = T$ (Eq. 5.1).

$$P_{n,k} = \begin{cases} \sum_{i=1}^{N} x(t)_i & t = T \\ 0 & \text{otherwise} \end{cases} \quad , \quad x(t)_i = \begin{cases} 1 & \text{led is correct} \\ 0 & \text{otherwise} \end{cases} \tag{5.1}$$

Sorting in descending order all the network performances for K trials, we obtain the distribution D_K

$$D_K = \{P_{n,1}, \quad \dots \quad , P_{n,K}\} \tag{5.2}$$

In this first setting, we define an *evaluation function* $E^{(1)}$ as the median value of the distribution D_K. The *objective function* to maximize $F^{(1)}$ is simply equal to $E^{(1)}$.

$$E^{(1)} = P_{n,\frac{K}{2}+1} \quad , \quad F^{(1)} = \max E^{(1)} \tag{5.3}$$

In the section below, we try to optimize the networks using a simple stochastic descent method (Sec. 3.2.3).

5.2 First Step: Stochastic Descent Results

At first glance, the results are not very satisfactory. In Fig. 5.1 we can see two graphs. The first one (Fig. 5.1(a)) shows the *boxplot* of performance values for each job. Boxplot is a convenient way of graphically depicting groups of numerical data. The spacings between the different parts of the box help indicate the degree of dispersion (spread) and skewness in the data. The bottom and top of the box are always the 25th and 75th percentile (the lower and upper quartiles, respectively), and the band in the middle of the box is always the 50th percentile (the median). The ends of the whiskers can represent several possible alternative values. In our case, the minimum and maximum of all the data. Any data not included between the whiskers are plotted as an outlier with a small circle. In this case, we note that the median value is fairly low (14 on a maximum value of 20) even if some job gets the value 15.

The second graph (Fig. 5.1(b)) is a histogram of the first iteration with the best performance value for each job. Here, we can see that most of the jobs reach the best value before 2000 iterations of the optimisation algorithm. This suggests that an increase in the number of iterations is not necessary, but rather, we need a better algorithm.

Finally, in the boxplot of Fig. 5.2 the values are divided by trial and related to the last iteration with the best value reached. Considering only the median values, we note that the second pattern ("Japanese flag") is better recognized by the swarm and the variance also is smaller.

5.3 Second Step: Iterated Local Search

On the basis of previous results we can conclude that the Stochastic Descent algorithm is too weak to obtain a satisfactory result. We will try with the Iterated Local Search algorithm (Sec. 3.2.3) with the Stochastic Descent

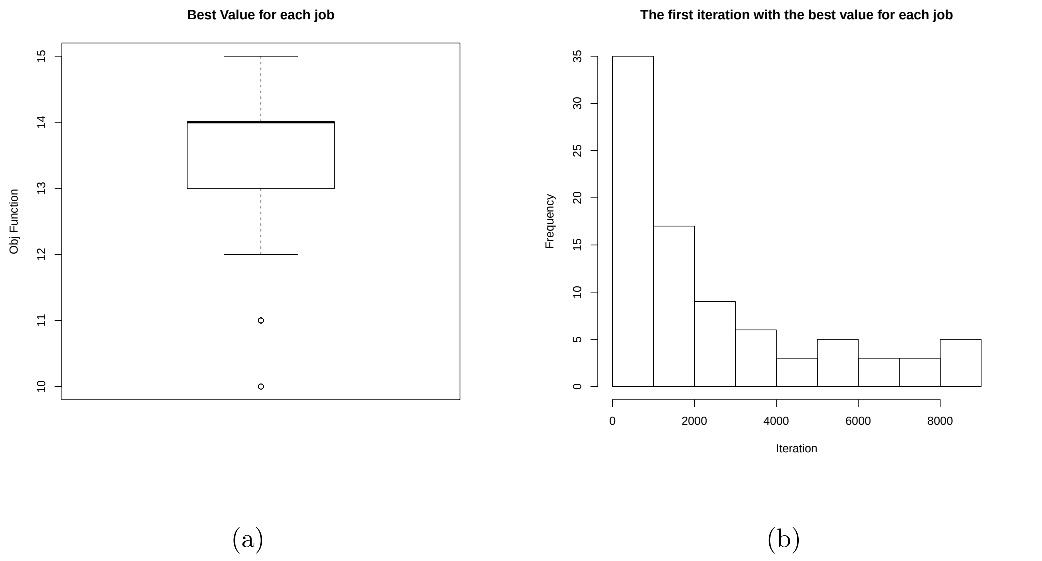


Figure 5.1: (a) shows the boxplot of the best value of each job. (b) is a histogram that indicates the frequency of achieving best value as a function of iterations.

logic wrapped inside. In this scenario, we have two levels of perturbation that we call *ILS perturbation* and *SD perturbation*. The SD perturbation takes place inside the Stochastic Descent algorithm contained within the ILS body. This perturbation flips a bit of a boolean network's node chosen at random. Differently, the ILS perturbation flips a bit chosen at random for each boolean network node (input nodes excluded). Thus, we launch the experiments with the parameters below:

Number of trials: 30

Iterations: 20

SD Iterations: 500

Number of E-pucks: 20

Where *Iterations* and *SD Iterations* are respectively the iterations of the ILS algorithm and the iterations of the Stochastic Descent within it. The total number of SD iterations is 10000; like the previous case.

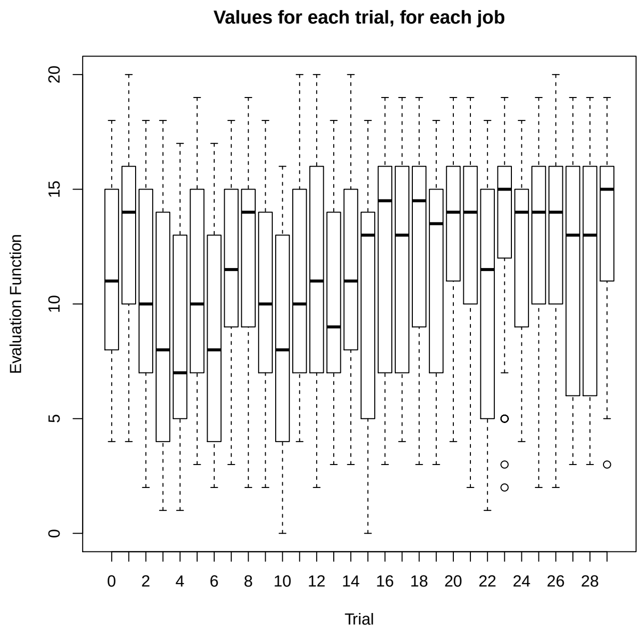


Figure 5.2: In this graph we have the performance distribution for each trial. The first half of boxplot relates to the chessboard, the second half to the Japanese flag.

5.3.1 Results

By looking at Fig. 5.3(a), a slight improvement could be observed with respect to the previous algorithm. The boxplot's shape is the same but we have a outlier in 16. From Fig. 5.3(b) we have almost the same situation seen before (most of the job reaches the best value before 1000 SD iterations, i.e., before the 5th ILS iteration).

The performance values showed in Fig. 5.4 refer to the best SD iteration contained within the best ILS iteration. In this case, the first half of the trials (first pattern) has lower average values than the previous case and the second half values are slightly higher. This is due to the use of a rather myopic objective function. As saw in Eq. 5.3 , we consider only the median value from the performance distribution on 30 trials forcing the evolution to improve only this feature. Since the median provides only discrete values, it

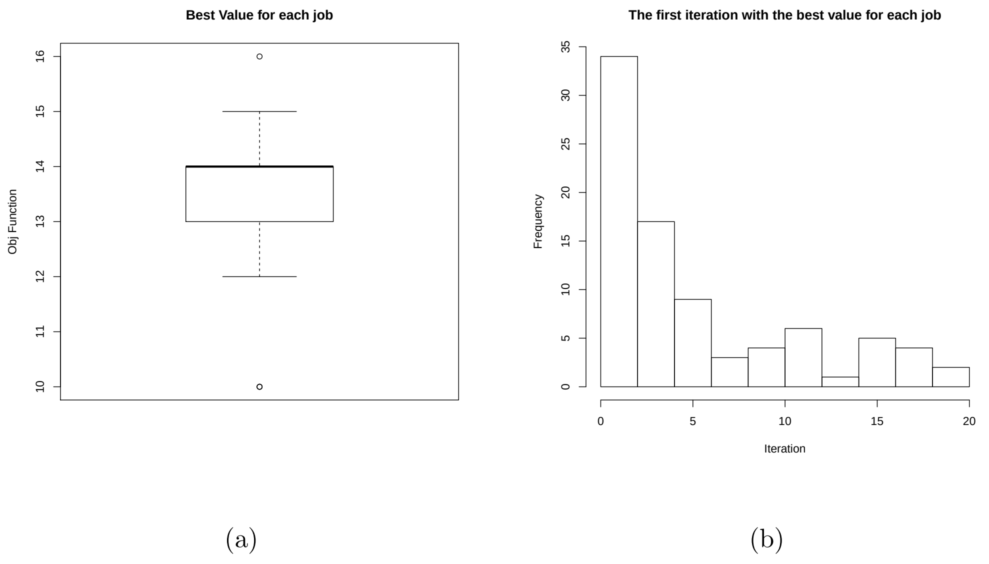


Figure 5.3: (a) shows the boxplot of the best values of each job. (b) shows when the best performance value is reached. The Iterations-axis refers to the ILS iterations.

seems that it is not a good heuristic search for this problem. Thus, we try with the average which is continuous and more sensitive to the bound values.

5.4 Third Step: Iterated Local Search with Average as Objective Function

To face this problem we run another batch of experiments with the same setting seen before:

Number of trials: 30

Iterations: 20

SD Iterations: 500

Number of E-pucks: 20

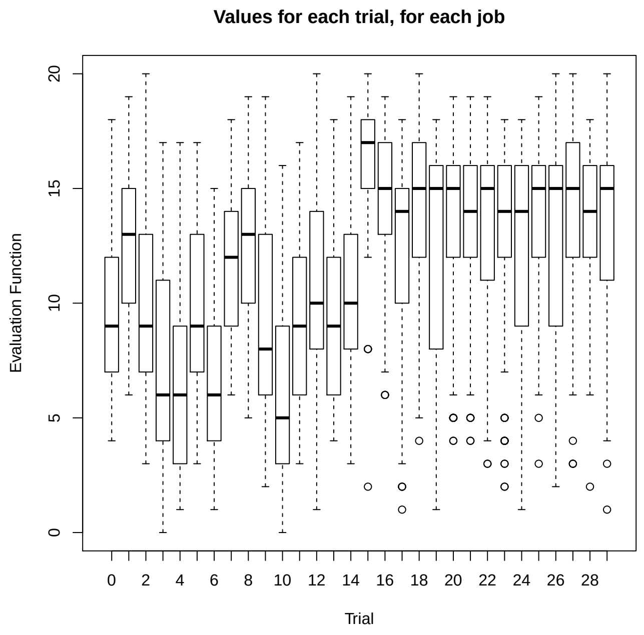


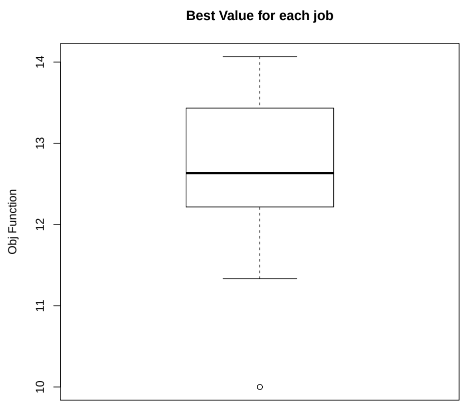
Figure 5.4: In this graph we have the performance distribution for each trial. These values result from the last SD iteration with the best value contained within the last ILS iteration with the best value.

We define a new evaluation function $E^{(2)}$ as the average number of correct behaviours (LEDs on/off) on the trial distribution D_K (Eq. 5.2). In this way, we take into account more of the overall network goodness. The objective function $F^{(2)}$ is the same as in the previous case.

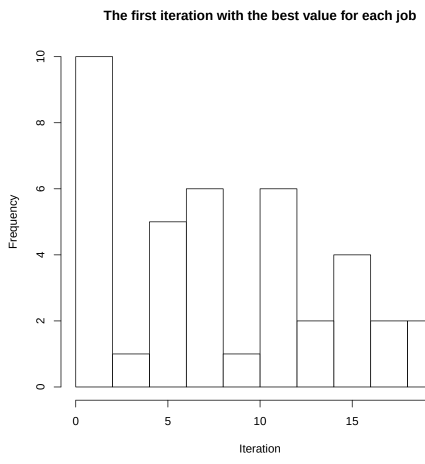
$$E^{(2)} = \frac{1}{K}\sum_{k=1}^{K} P_{n,k} \qquad , \qquad F^{(2)} = \max\ E^{(2)} \tag{5.4}$$

5.4.1 Results

The boxplot in Fig. 5.5(a) shows a distribution of values worse than in the previous results. However, we can observe that the distribution is more



(a)



(b)

Figure 5.5: The boxplot in (a) shows worse results than previous case while in (b) is possible to see a landscape with many flourishing areas.

compact. Also in Fig. 5.6 is showed that.

An interesting observation comes from Fig. 5.5(b).The histogram shows that there is a non negligible fraction of experiments which attain the best value at 10-15 iterations of ILS. ILS exploits most of the available iterations. We could then conclude that the objective function $E^{(2)}$ enables the search process to perform a wider exploration than in the previous cases.

5.5 Fourth Step: Objective Function H

Till this moment, the evaluation has taken place only at the last time step (see Eq. 5.1). By analysing the simulation, we observe that a cyclical LEDs behaviour emerges. This makes us conjecture that an evaluation based on a single time step can be rather noisy. Indeed, the behaviour at the last considered time step can be completely different from the other nearby steps.

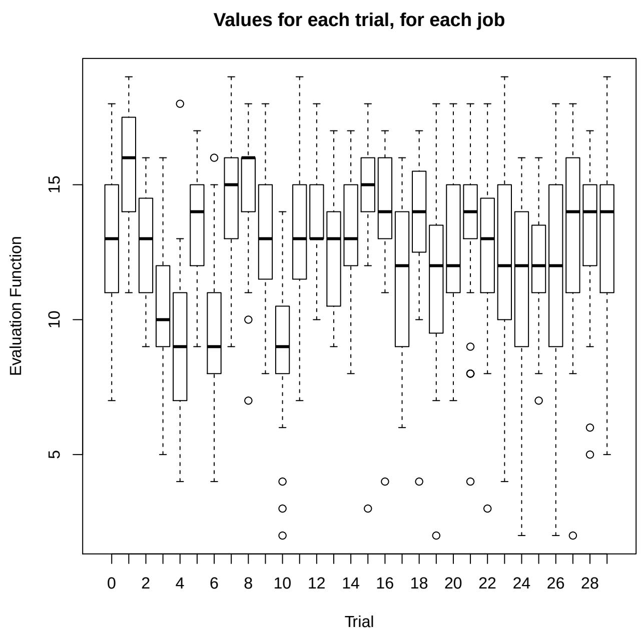


Figure 5.6: Even if the values are lower, we can see the emergence of more compactness among patterns.

More precisely, we could well reward a network which however does not reach a fixed-point attractor.

Thus, we need to direct the network evolution towards a higher stability. As shown in Eq. 5.5, we extend the evaluation x along the last $\bar{t}$ time steps.

$$p(t)_i = \begin{cases} x(t)_i & t > T - \bar{t} \\ 0 & \text{otherwise} \end{cases} , \quad x(t)_i = \begin{cases} 1 & \text{led is correct} \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

Let $p(t)_i$ the performance of the epuck i at step t, we can define $P_{n,k}$ the performance of the network n on the trial k (Eq. 5.6).

$$P_{n,k} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{\bar{t}} \sum_{j=1}^{\bar{t}} p(j)_i \tag{5.6}$$

Where N is the number of robots and $\bar{t}$ is the time window length. The result is normalized according to N. In this way, the networks' score will be as high as the number of correct behaviours maintained over $\bar{t}$ by each robot.

Let D_K the sorted (in descending order) performance distribution seen in Eq. 5.2, we define E the evaluation function on the distribution D_K. In Eq. 5.7, we summarise two possibilities tried in the previous steps.

$$E^{(1)} = P_{n,\frac{K}{2}+1} \qquad , \qquad E^{(2)} = \frac{1}{K}\sum_{k=1}^{K} P_{n,k} \tag{5.7}$$

In this level of evaluation we can add a *compactness function* c to reward the networks with smaller variance on the distribution.

$$c = \frac{1}{K}\sum_{k=1}^{K}\left[\max_{D_K} - P_{n,k}\right] \tag{5.8}$$

Here, we calculate the average distance from the maximum value of the distribution D_K normalised on the number of trials K. In order to combine this function, which is to be maximised, with the previous ones, which is to be minimised, we introduce a variant, called C (Eq. 5.9).

$$C = 1 - \frac{1}{K}\sum_{k=1}^{K}\left[\max_{D_K} - P_{n,k}\right] \tag{5.9}$$

The combined objective function H is defined as follows:

$$H = \max\left(\alpha E + (1-\alpha)C\right) \qquad \alpha \in [0,1] \tag{5.10}$$

The scalar α make it possible to modify the weights of the evaluation during the training process. For instance, in the first half of the process we could prefer the definition of networks with good performance and only in the second half we could tune α in order to increase the importance of compact results.

5.5.1 Two Different Batches of Experiments

This time we launch two new batches of 90 experiments with the Iterated Local Search algorithm. Both batches have $E^{(2)}$ as evaluation function (the average value on the distribution). Furthermore, we try to increase the number of ILS iteration to enable a larger exploration of the landscape. Below the setting in detail:

Number of trials: 30

Iterations: 30

SD Iterations: 500

Number of E-pucks: 20

Objective Function: $H \quad , \quad (E = E^{(2)}, \alpha = 0.8)$

For the moment, we maintain the same value for α in all the ILS iterations. The only difference between the two batches is the epuck's LEDs actuator. In the first batch, like the previous cases, the LEDs are directly controlled by the BN output nodes for each step. In the second one, in order to obtain a binary value for the LEDs state, we compare the *moving average* (MA) of the output node's value over time with a threshold. We consider values inside a time window no larger than 9 time steps (Alg. 2). This method permit us to reduce the network's oscillation and we move further to the stability.

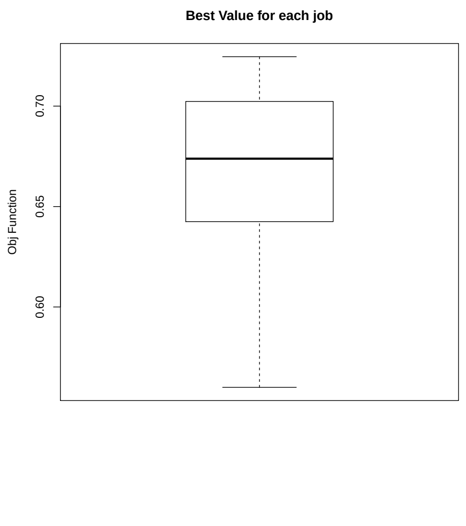
As shown in Alg. 2 the output node's state at step j (s_j) is always 0 or 1. So, when the value of MA is greater than 0.5 it means that the amount of 1-values into the buffer S is greater than the 0-values (vice versa with $MA < 0.5$). When $MA = 0.5$ we have the same amount of 1s and 0s. In this case, we choose at random the value for the LEDs.

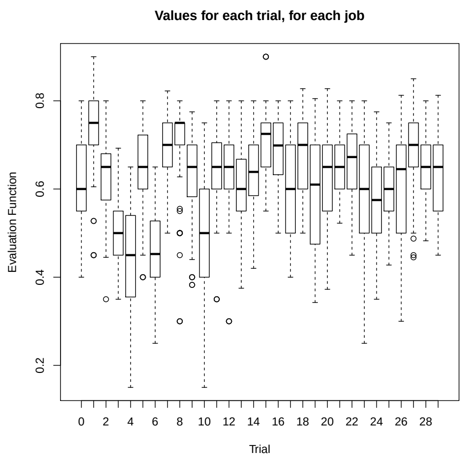
Algorithm 2 Moving Average for Controlling the LEDs actuator

```
1: input: the output node buffer $S$, the current output node $s_j$
2: for all time steps $j$ do
3:   if $dim(S) = 9$ then
4:     $erase\_first\_element(S)$
5:     $push\_back(S, s_j)$
6:   else
7:     $push\_back(S, s_j)$
8:   end if
9:   $MA \leftarrow \frac{1}{dim(S)} \sum_{j=1}^{dim(S)} s_j$
10:  if $MA = 0.5$ then
11:    $LEDs \leftarrow take\_element\_at\_random(S)$
12:  else if $MA > 0.5$ then
13:    $LEDs \leftarrow 1$
14:  else
15:    $LEDs \leftarrow 0$
16:  end if
17:  return $LEDs$
18: end for
```

5.5.2 Results

Since both batches produce almost the same results, we illustrate only the graphs from the MA batch (i.e., the batch where the robots' LEDs are driven by the moving average of at most 9 output elements, Fig. 5.7). Let 1 be the objective function value that corresponds to a perfect network behaviour for all the trials; in Fig. 5.7(a) we obtain a best value greater than 0.7 and a worst value around 0.5. This proves the compactness of the final results even if it is still a bit away from the optimum. An interesting trend emerges from Fig. 5.7(b) where, except for few cases, all the trials have a good median value (over 0.6). Trials with indexes 3,4,6 and 10 seem to be difficult to be recognized while trial 1 is the one which obtains the highest average score.





(a) (b)

Figure 5.7: Two graphs related to the batch with the buffered controllers (MA). In (a) we note a distribution compact with little variance but that never reach the optimum. In (b) some trial deviates from the general trend.

5.6 Fifth Step: Tuning Parameters

From the previous results, we can conclude that the buffered controller MA do not provide relevant improvements. Moreover, since the value of H is the sum of the functions C and E, it is impossible to distinguish the compactness contribution from the performance one. Such aspect is relevant in order to tune the subsequent experimental setting. Finally, analysing the output log of the best jobs, we find best results around the last SD iterations.

For this reasons, we launch other two batches of experiments with the following different setting:

Number of trials: 30

Iterations: 30

SD Iterations: 1000

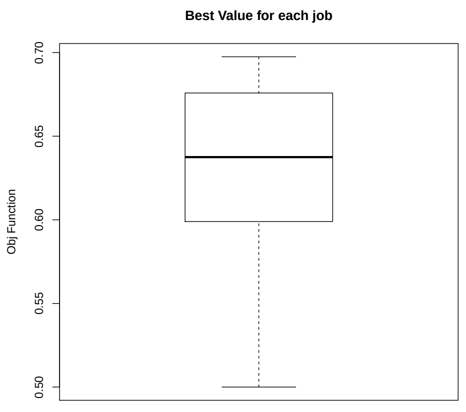
Number of E-pucks: 20

Objective Function: H , $(E = E^{(2)}, \alpha = 1(batch1), \alpha = 0.9(batch2))$

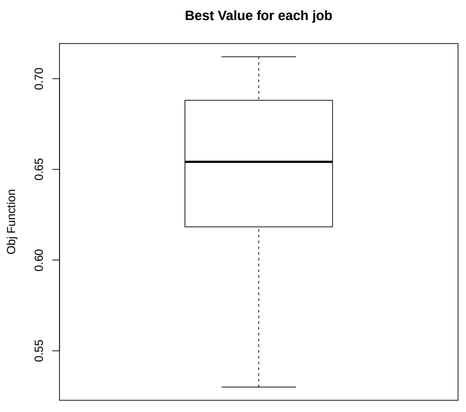
We have increased the number of SD iteration giving more chances to exploitation. The α value changes in relation to the case. In the former batch ($\alpha = 1$) we completely stamp out the C function's effects (see Eq. 5.10) while we have a weakly presence in the latter ($\alpha = 0.9$). In this way, it is possible to prefer the correct behaviour of the robot over the compactness. Therefore, we want to exclude the ordered networks (i.e., since K is always 3, we exclude the networks with $p = 0.85$, see Fig. 2.5) and so we launch only 60 experiments per batch instead of the previous 90. Indeed, because of their strong resistance to perturbations, the ordered networks are harder to change than the other ones. Thus, we can save computational time by focusing only on chaotic and critic networks.

5.6.1 Results

The results are very similar to the previous case. The only difference is shown in Fig. 5.8 where the median value in the case with $\alpha = 1$ is under the threshold of 0.65 while it is slightly above in the other case. We note that the variance is identical. We think that the greater previous best value of H (about 0.7) was pushed up by function C. The only influence of E is not sufficient to improve the results nor with 1000 SD iterations. The other graphs do not provide any additional information.



(a) best values with $\alpha = 1$



(b) best values with $\alpha = 0.9$

Figure 5.8: Boxplots of the best values with different influence of E. In both graphs there are no improvements compared to the previous case.

6. A Simpler Case

In the previous chapter, we tackled the problem trying different approaches. Since the results are not very satisfactory, we simplify the instance of the problem to better investigate the factors that influence the performance. More precisely, we start with a very simple instance of the problem, then, analysing its results, we draw possible hypothesis of improvement. Subsequently, we increase the complexity of the problem taking into account the previous outcomes.

In Sec. 6.1 and Sec. 6.2 we respectively describe the simplest instance of the problem and its results. Sec. 6.3 reports description and results of a slightly more complex instance while in Sec. 6.4 and Sec. 6.5 we define two other instances very similar to the original one (see Cap. 5) and we discuss the results applying the insights derived from the simpler instances.

6.1 Description

The simplified instance of the problem considers two kinds of pattern like the previous cases. However, even if the first pattern remains the chessboard, we replace the second floor (Japanese flag) with a vertical black-white splitted floor (Fig. 6.1). The robots are only 4 and are placed like a grid at the same distance from the centre. Each robot is oriented toward the centre. Due to the specific combination of floor patterns and placements, two kinds of symmetries emerge: *rotational symmetry* and *positional symmetry.*

With the rotational symmetry, each robot has the same kind of neighbourhood i.e., no robots at South and only one robot for the other cardinal points. The positional symmetry is due to the fact that each robot is placed in a different interesting area so that the received information is not redundant for the receiver. As we can see in Fig. 6.1, in order to recognize the floor, it is theoretically sufficient to compare the sensed information from the ground with the received information from North (i.e., if the northern information has the same colour perceived from the floor below, then the swarm is on the first floor, otherwise, on the second floor).

Unlike the previous experiments, we want to exchange different types of information in order to check if a specific one could be able to significantly affect the performance. For this goal, we use two new pieces of information that we call *dialog* and *led* information. The dialog information is given by the value of a generic hidden node while the led information represents the value of the output node that commands the LEDs. Both nodes have ingoing arcs only from hidden nodes. In this way, the information is obtained only by the internal network processing and does not depend directly from inputs.

We define 6 combinations of information to exchange: *ground*, *dialog*, *led*, *ground+dialog*, *ground+led* and *dialog+led.* Then, we launch one batch for each combination. In cases in which we have a single exchanged information (ground, dialog or led) we use a network with 14 nodes where 4 are input nodes while in the cases with double information (ground+dialog, ground+led and dialog+led) the network has 17 nodes with 7 input nodes. We report the mapping between sensors and input nodes in Tab. 6.1 and Tab. 6.2. Since we know a priori the positions of the robots, a single bit is sufficient to encode the information received from each cardinal point.

Now we can define the experimental setting as follows:

Number of trials: 2

Iterations: 30

SD iterations: 10000

Number of E-pucks: 4

Objective Function: $H \quad , \quad (E = E^{(2)}, \alpha = 1)$

Since the experiments have a single placement for the robots, there are only two initial conditions (trials) where only the floors change. The small number

Node ID	*Sensor*
1	GS sensing
2	RAB sensing from NORTH
3	RAB sensing from EAST
4	RAB sensing from WEST

Table 6.1: Mapping between the robot sensors and the input nodes in the simplest case with a single exchanged information. The network has 14 nodes and we use 1 node for the GS and 3 nodes for the RAB. Given the a priori known placement, we need only 1 node for direction.

Node ID	*Sensor*
1	GS sensing
2,3	RAB sensing from NORTH
4,5	RAB sensing from EAST
5,6	RAB sensing from WEST

Table 6.2: Mapping between the robot sensors and the input nodes in the simplest case with two informations. The network has 17 nodes and we use 1 node for the GS and 6 nodes for the RAB.

of trials and robots permits us to achieve a large number of iterations (i.e., $30 \times 10000 = 300,000$ iterations) in a reasonable amount of time. We choose $E = E^{(2)}$ as evaluation function (Eq. 5.4) and we exclude the contribution of the compactness function (with $\alpha = 1$, see Eq. 5.10). In the next section, we discuss the results obtained.

6.2 First Results

In Fig. 6.2 we plot the results of the jobs with the previous setting. We compare the batches using two different methods. In the former, we use boxplots

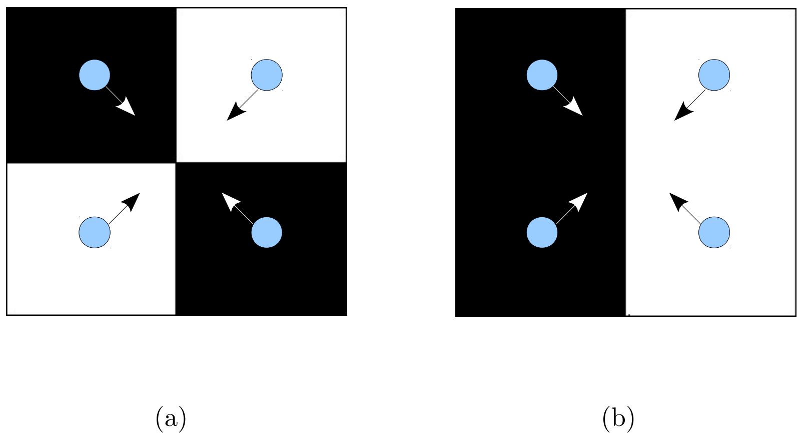
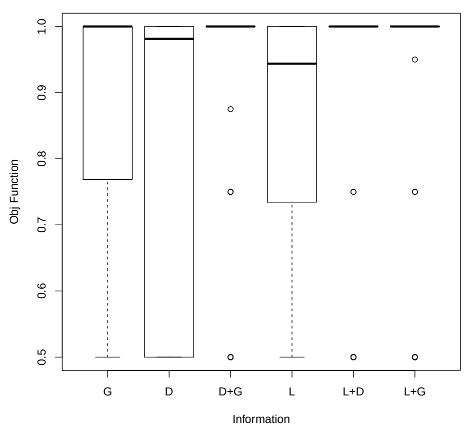


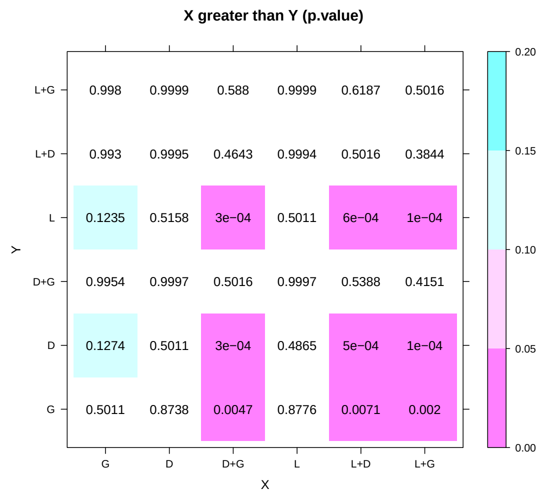
Figure 6.1: The simpler case floors with E-pucks' placement. The circles represent the E-pucks and the arrows indicate the relative Norths.

of the best value distributions (Fig 6.2(a)). Each boxplot refers to the batch where the robots exchange the information indicated on the abscissa (e.g., L+D means *jobs with led+dialog comunication*, G means *jobs with ground comunication*, etc.). We can see that the batches reach the optimum in 4 cases out of 6. Among these, 3 batches exchange double information. With single information, only jobs from the batch G reaches the optimum. Except for some outliers, the jobs of batches with double information always reach the optimum and therefore there is no variance.

The latter method consists of comparing the distributions using the Mann-Whitney test also called the *Mann–Whitney–Wilcoxon* or *Wilcoxon test.* The Wilcoxon test is a non-parametric statistical hypothesis test for assessing whether one of two samples of independent distributions tends to have larger values than the other. Here, we consider two hypotheses: *null hypothesis* and *alternative hypothesis.* At first, the null hypothesis is always accepted while the alternative hypothesis it is the one we try to prove. Under the null hypothesis, the distributions are equal while our alternative hypothesis states that the first distribution (that we call X) exceeds the distribution Y. The probability that the null hypothesis is true is indicated by the *p-value.*



(a)



(b)

Figure 6.2: Information comparison analysing best value distributions. Two methods to compare the distributions. In (a) we have the boxplots of the 6 batches while in (b) it is shown the p-values of Wilcoxon test for each pair of different information exchanged. For simplicity, we colour the cell in function of the level of significance. Darker cells mean high probability that the X information exceeds the Y information. The white cells do not permit evaluation.

Small p-values also mean high probability that the alternative hypothesis is verified. We perform the Wilcoxon test on all the pairs of distributions and we plot the p-values in the grid in Fig. 6.2(b). The smaller the p-value, the higher the probability that the abscissa information is greater than the corresponding one on the ordinate. The p-values distribution confirms the observations made about boxplots in Fig. 6.2(a).

6.3 Results Without Rotational Symmetry

Given the good results achieved before, we slightly increase the difficulty of the task removing the rotational symmetry. Thus, we assign a random

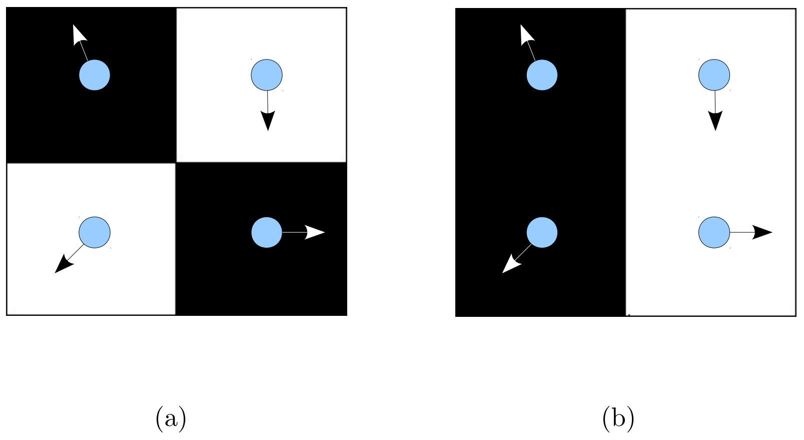


Figure 6.3: The simpler case floors with E-pucks random orientation.

orientation for each E-puck obtaining the placement shown in Fig. 6.3. In this case, the network needs more flexibility since there is a different neighbourhood for each robot. In fact, while in the previous case each robot had a neighbour for each direction except in the South, now the cardinal point without information changes as a function of the robot orientation. In order to understand where the information is absent, we need a different communication coding that involves another bit in the exchanged payload. The networks used to exchange single and double information have respectively 20 and 28 nodes and the input mapping is shown in Tab. 6.3 and in Tab. 6.4.

Like in the previous case, we compare the best value distributions using boxplots and Wilcoxon test. From Fig. 6.4 a general improvement of the performance emerges. All the batches reach the optimum, however, the grid in Fig. 6.4(b) clearly shows the excess of distributions where there is a double information exchanged. The phenomenon is even more accentuate if such information contains spatial data (i.e., the ground information).

Contrarily to expectations, the absence of rotational symmetry has not worsened the performance. Moreover, with the new specific orientation, all batches reach optimum in almost all their cases.

Node ID	*Sensor*
1	GS sensing
2,3	RAB sensing from NORTH
4,5	RAB sensing from EAST
6,7	RAB sensing from SOUTH
8,9	RAB sensing from WEST

Table 6.3: Input mapping in the simpler case without rotational symmetry, single information exchanged. For each direction, we encode the received data with 2 node values. The node with smaller index indicates the presence/absence of the neighbour.

Node ID	*Sensor*
1	GS sensing
2,3,4	RAB sensing from NORTH
5,6,7	RAB sensing from EAST
8,9,10	RAB sensing from SOUTH
11,12,13	RAB sensing from WEST

Table 6.4: Input mapping in the simpler case without rotational symmetry, double information exchanged. For each direction, we encode the received data with 3 node values. The node with smaller index indicates the presence/absence of the neighbour.

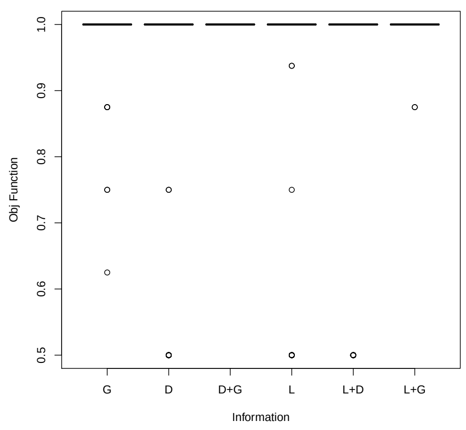
6.4 A New Instance of the Problem

From the previous analysis, it emerges that the ground information boosts the performance in the case of composed information. Now we check whether such information can increase the performance when applied in harder instances of the problem. In particular, we propose the following setting:

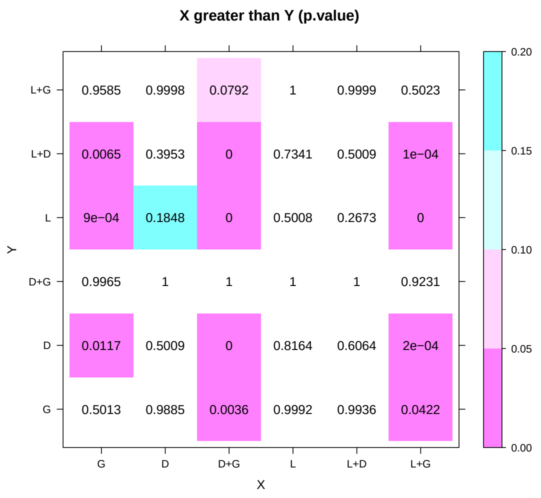
Number of trials: 20

Iterations: 20

SD iterations: 1500



(a)



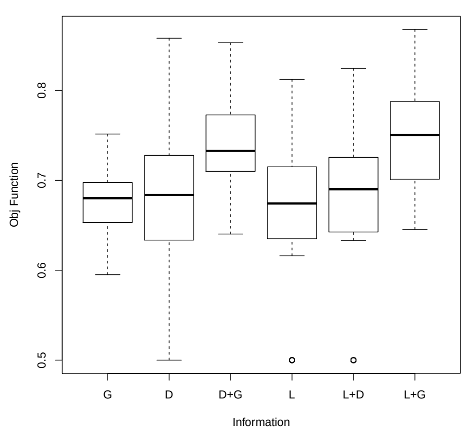
(b)

Figure 6.4: Comparison among best values in the case without rotational symmetry. All the batches reach the optimum and the best combinations contain the ground information.

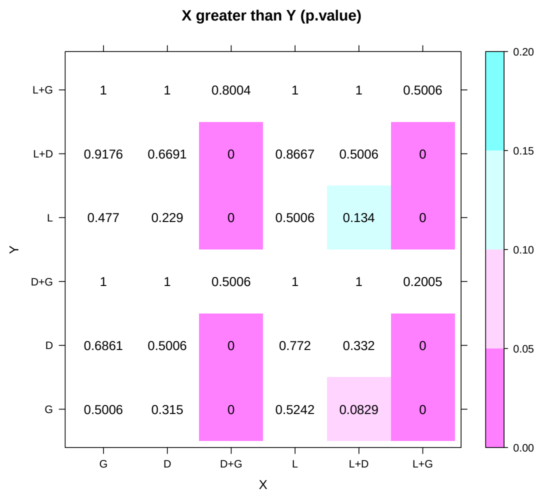
Number of E-pucks: 10

Objective Function: $H \quad , \quad (E = E^{(2)}, \alpha = 1)$

Here, the key change is the increase of initial conditions (trials) and robots. For each trial, we uniformly distribute 10 robots (applying the method described in Sec. 4.2.3) and we choose at random the orientations. For computational load issues, we must strongly decrease the number of stochastic descent iterations (i.e., from 10000 to 1500). The floor patterns remain the same. In Fig. 6.5 we report the comparison. Although no batch reaches the optimum, we mostly get a success rate around 80%. The Wilcoxon grid in Fig. 6.5(b) shows the dominance of "D+G" (dialog+ground) and "L+G" (led+ground) distribution. Such result is consistent with the simpler case, confirming the influence of informations composed with spatial data.



(a)



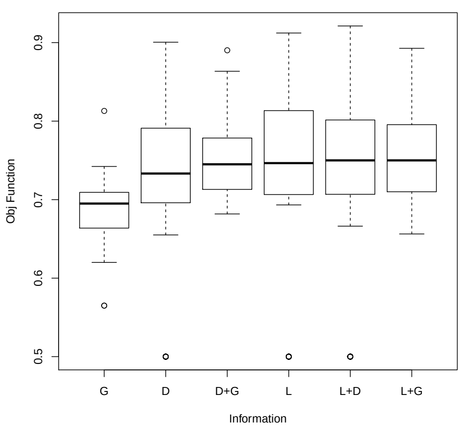
Y \ X	G	D	D+G	L	L+D	L+G
L+G	1	1	0.8004	1	1	0.5006
L+D	0.9176	0.6691	0	0.8667	0.5006	0
L	0.477	0.229	0	0.5006	0.134	0
D+G	1	1	0.5006	1	1	0.2005
D	0.6861	0.5006	0	0.772	0.332	0
G	0.5006	0.315	0	0.5242	0.0829	0

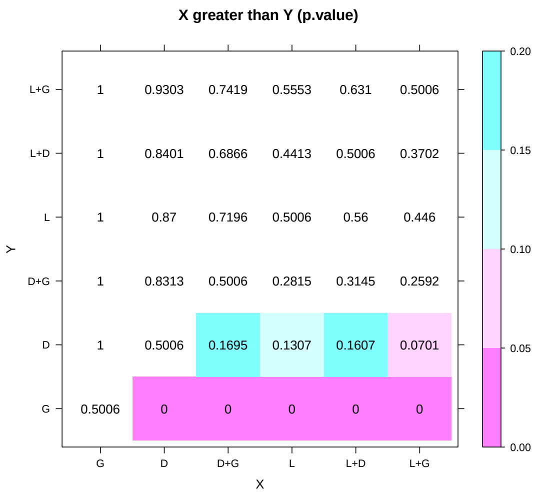
(b)

Figure 6.5: Comparison among best values in a more complex case with 10 robots and 20 trials. The results are consistent with the simpler case.

6.5 Results With Japanese Flag

For approaching further to the original setting described in Chapter 5, we replace the vertical splitted floor (Fig. 6.1(b)) with the Japanese flag pattern shown in Fig. 4.5(b). As we can see from the analysis in Fig. 6.6, the organization of the results are very different from the previous case. However, most of batches reach a better success rate around 90% than the 80% reached before. On the other hand, the only conclusion we can draw from the Wilcoxon grid is that all the combinations predominate the single ground information "G". Perhaps, such phenomena is due to the different level of symmetry among patterns which make it harder the recognition relying on the spatial data.





Y \ X	G	D	D+G	L	L+D	L+G
L+G	1	0.9303	0.7419	0.5553	0.631	0.5006
L+D	1	0.8401	0.6866	0.4413	0.5006	0.3702
L	1	0.87	0.7196	0.5006	0.56	0.446
D+G	1	0.8313	0.5006	0.2815	0.3145	0.2592
D	1	0.5006	0.1695	0.1307	0.1607	0.0701
G	0.5006	0	0	0	0	0

(a) (b)

Figure 6.6: Comparison among best values with 10 robots, 20 trials and Japanese flag pattern. We get higher performance peaks than previous case. Using patterns with different level of symmetry, it seems to lead the ground data to be irrelevant.

7. Conclusion

In this thesis we employed an automatic design methodology in order to develop robotic programs for tasks that require collective computation. Such procedures need two main components that are a model for the robot behaviour and an optimisation algorithm to improve the model characteristics. As model, we used Boolean networks which, although simple, can exhibit complex dynamics. The used optimisation algorithm consists in a methaheuristic technique. In particular, we choose stochastic local search algorithms.

The entire process can be viewed as a constrained combinatorial optimisation problem where the decision variables correspond to the Boolean functions inside the nodes while the objective function guides the tuning of such variables in order to maximise the robots performance.

The methodology has been validated on a well-defined task where the swarm of robots must recognise a certain environment whose characteristics can not be fully collected by perceptions of a single robot. In order to focusing the analysis on the collaborative computation, we equipped robots with simple computational capabilities such as the communication limited to the neighbourhood. In addition, we tried to keep the experiments simple enough to limit the computational resources as much as possible.

In the first part of the experiments we identified a suitable optimisation algorithm as well as a good evaluation criteria for the swarm. Initially, we tried a simple stochastic descent method but such algorithm was too weak to obtain satisfactory results. Thus, we replaced it with an iterated local search algorithm obtaining a slight improvement. We noted that the current objective function (i.e., the median of the performance on different initial conditions) provided only discrete values and it seemed that it was not a good heuristic search for this problem. Then, we changed the objective function with the average number of correct behaviours. With such new objective function we observed more compact performance values across the initial conditions and a wider exploration of the search space. Subsequently, we further improved the objective function by extending the evaluation on a longer time period of the simulation and adding a factor to reward the compactness of the results. Since the obtained performance values were highly compact but lacking improvements, we sharply weakened the contribution of the compactness function. Also in this case, we do not get significant changes.

Since results were still not quite satisfactory, we simplified the instance of the problem to better investigate the factors that influence the performance. In particular, we started with a very simple instance of the problem where a small amount of robots with the same kind of neighbourhood are placed in different relevant areas. We analysed the exchange of different types of information in order to check if a specific one prevails the others. The experiments where robots exchange double information always obtained networks with maximum value of the objective function. In the case of single information, we obtained optimal results only with the exchange of spatial information. Subsequently, we slightly increased the difficulty by assigning a random orientation for each robot and contrary to expectations, general improvements emerged in all kinds of experiments. Moreover, double information that contain spatial data still leads to better performance. After, we checked whether such informations can increase the performance when applied in harder instances of the problem. Although in these cases no experiments reached the optimum, we got a high success rate confirming also the influence of informations composed by spatial data. The predominance of such information disappears if we use patterns with different level of symmetry. However, the success rate remains high proving of the strength of the methodology.

This thesis can provide insights for a wide range of future works. A first possibility concerns the improvement of the evaluation criteria. Indeed, we could add more sophisticated terms inside the objective function as we have partially done for the compactness factor (see Sec. 5.5). We could also focus on the optimisation algorithm, trying new trade-offs between exploration and exploitation as well as we could change the features of the search space (e.g., using a variable neighbourhood search).

The experiments could be repeated with other settings e.g., using Boolean networks with different size, connections and topologies. According to such networks, we could define new couplings between nodes and sensors/actuators, moreover, new communication protocols and codings would be needed.

Regarding swarm robotics, it could be interesting to study the task with hundreds or thousands of robots. For the moment, it is impossible for our simulator to deal with huge swarms of robots that exchange such amount of information. A viable solution could be the development of a simplified simulator that neglects demanding aspects like the physical ones.

Finally, we could conduct studies about dynamics of complex systems consisting of interacting Boolean networks. For instance, in Appendix A we show a preliminary study in which we search correlations between the fixed point achieved by the swarm (which is a network of BNs) and the dynamics of each single node.

A. Interacting Boolean Networks

Interacting BNs are not much studied in the literature, even though the topic would be of great importance for collective intelligence. The main scientific issue concerns the discovery of internal factors that lead to the emergence of a specific behaviour of the complex system where components are complex systems themselves.

In this work, we have a swarm of robots controlled by the same Boolean network. The goal can be only reached with the interactions between these networks. Such robots, communicating among them, must turn on or off the LEDs depending on the floor below. Thus, we can see the swarm as a network (that we call *supernet*) which must reach a fixed point attractor within a specific time window. Its nodes are themselves networks with their own internal dynamics.

As a first attempt to study these dynamics, we consider the Hamming distances of the states of each robot (denoted by vectors of 0s and 1s) between two successive moments in which there is a totally correct swarm behaviour (that we call *unison*). Plotting such values in a single graph (Fig. A.1), we can observe the internal dynamics of the supernet before and during the achievement of a *fixed point unison*.

In Fig. A.1 are shown the Hamming distances of 4 BN-controlled robots from a simulation of 100 time step long. We have a priori checked that the

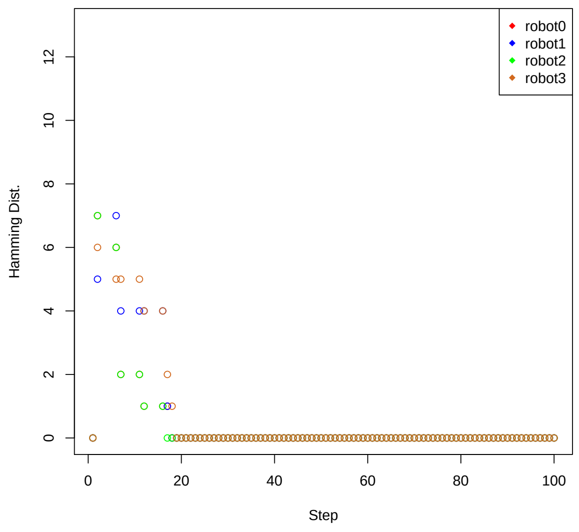


Figure A.1: Interacting BN dynamics. We plot the Hamming distances of 4 interacting BN-controlled robots considering consecutive unison steps. All the BNs reach a fixed point like the supernet.

network has an optimal behaviour, i.e., the swarm keeps consecutively unison at least during the last 20 time steps (see Sec. 5.5). After a first transient phase, all the robots stabilize and reach, in turn, a fixed point.

Thus, only for the BN used in this example, we can assert that the supernet reaches the fixed point unison when all the individual nodes (robots) reach, in turn, an internal fixed point. This is only an example of interaction analysis. In order to generalise the assertion before, we need to perform several tests with different types of networks and initial conditions.

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