A preliminary study on BN-robots' dynamics

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Abstract. Boolean network robotics concerns the use of Boolean networks as robot programs. In this brief contribution, we outline preliminary results on the analysis of the dynamics of BN-robots trained to accomplish a composite task. We find that the successful performing robots, which show the capability of robustly attaining the learned behaviours while adapting to new tasks to perform, are characterised by both number of fixed points and complexity higher than those of unsuccessful ones. These results are in accordance with the conjecture that systems able to balance robustness and evolvability work at the border between order and chaos and may suggest improvements to the automatic design of robot programs.

1 Introduction

Genetic regulatory networks (GRNs) model the interaction and dynamics among genes. From an engineering and computer science perspective, GRNs are extremely interesting because they are capable of producing complex behaviours, notwithstanding the compactness of their description. Cellular systems are also both robust and adaptive, i.e., they can maintain their basic functions in spite of damages and noise, and they are able to adapt to new environmental conditions. Such a complex behaviour can be interpreted from an artificial system design's viewpoint, suggesting the possibility of achieving robust and adaptive behaviours in agents, robots, and group of robots, by exploiting the properties of GRN models. Among the most studied models for GRNs, are Boolean networks (BNs), first introduced by Kauffman [1]. BNs have received considerable attention in the community of complex system science. Works in complex systems biology show that BNs provide powerful model for cellular dynamics [2,3]. In a recent work, it has been shown that BNs can be utilised to control robots [4]. The BN is trained by means of a learning algorithm that manipulates the Boolean functions. The algorithm employs as learning feedback a measure of the performance of the BN-controlled robot (in the following, BN-robot) on the task to perform. The effectiveness of this approach was demonstrated through a simple experiment on both simulated and real robots.

In this short contribution, we outline preliminary results of the analysis of the BN-robot's dynamics. We analysed the trajectories followed by the BN-robot in the space of the BN states. We computed two features along the training process: the number of fixed points [4] and a measure of the complexity of the system, namely the *LMC complexity* [5]. The number of fixed points is an indicator of the generalisation capabilities of the system, as they represent simple functional building blocks of the type `while <condition> do <action>` which compose the overall system dynamics. LMC complexity has been introduced with the aim of quantifying to what extent a system can be said to be 'complex'. LMC complexity is computed as the product of entropy and disequilibrium. A complex system is expected to maximise this quantity, as its dynamics is neither totally disordered (as an ideal gas at equilibrium), nor perfectly ordered (as a crystal). We found that the successful performing BN-robots, which show the capability of attaining the learned behaviours also in spite of noise and perturbations (*robustness*) while adapting to new tasks to perform (*evolvability*), are characterised by both number of fixed points and LMC complexity higher than those of unsuccessful ones.

The structure of the paper is as follows. After a summary of the experimental setting in Section 2, we discuss the main results of the analysis of the the dynamics of the BNs controlling the robot in Section 3. The reader will understand that, due to space constraints and the preliminary status of this work, this paper only provides a succinct overview of the main results, leaving detailed descriptions, in-depth discussions and foundational arguments to further papers. Details on the experimental settings can be found in [4], where the use of BNs to control robots was first introduced, but no analysis on the dynamics was presented.

2 Experimental setting

In this experiment, we control an *e-puck* robot [6] by means of a BN. The values of a set of network nodes (BN input nodes) are imposed by the robot's sensor readings, and the values of another set of nodes (BN output nodes) are observed and used to encode the signals for maneuvering the robot's actuators. The sensors consists of four light sensors and one sound sensor, while the actuators correspond to right and left wheel speed controllers. The robot is placed in a random position in a squared arena, with one light source in a corner. The BN-robot must accomplish the following task: initially, it must perform phototaxis, that is, move towards the light source; upon perceiving a sharp sound, the BN-robot must switch to antiphototaxis, that is, move away from the light source. The robot is trained in simulation by means of an *adaptive walk*: the process starts from a randomly generated BN, it iteratively mutates it and keeps only the changes that either improve the BN-robot's performance or do not decrease

[4] For BNs with inputs, a fixed point is a state repeated as long as the BN inputs do not change.

it. Mutation is implemented by randomly choosing a node and an entry in its Boolean function truth table and flipping it. [5] The BN-robot is trained in two sequential phases. In the first phase, the learning feedback is an evaluation of the robot's performance in achieving only phototaxis. In the second phase, the learning feedback is composed of a performance measure accounting for both phototaxis and antiphototaxis. In this way, we can study the properties of the evolution of the BN-robot when its behaviour must be adapted to a new operational requirement. The entire training process was repeated 100 times, starting from initial BNs generated at random. For each step of the training process, we tested the BN-robot and collected statistics on the BN states traversed.

3 Analysis of BN dynamics

A significant fraction of the training experiments leads to a successful BN-robot (called *good* BN-robots), i.e., a robot able to robustly [6] perform both phototaxis and antiphototaxis and to switch between them depending on the sound signal. The unsuccessful BN-robots are either able to perform phototaxis only or not even that (hereinafter referred to as *bad* and *worst* BN-robots, respectively). In the successful cases, the phototaxis capability acquired by the BN-robot in the first training phase is maintained while also the antiphototaxis behaviour is learned. Whence these systems are able to successfully balance robustness and evolvability. We studied the properties characterising the BNs along the training process in order to find the factors that discriminate between the BNs that attain the best performance with respect to the unsuccessful ones. In this contribution, we show the results concerning two relevant features of the BN-robot trajectories, namely the number of trajectory fixed points and the LMC complexity. An in-depth analysis of the BN trajectories is the subject of ongoing work. First of all, we observe that the successful BNs improve their generalisation capabilities during the learning process, as the overall number of fixed points increases (see Figure 1, left). Fixed points represent micro-behaviours (e.g., "turn right until the light input changes") which are combined to achieve a global behaviour. The emergence of fixed points reveals that the BN is able to extract regularities in the environment and to classify them, thus achieving generalisation. In addition, we also observe a further remarkable property: the complexity of the best performing BNs increases during evolution. In our experiments, the complexity C of a BN is measured as the LMC complexity $C = HD$, where H and D are, respectively, the *entropy* and the *disequilibrium* of the BN states observed in the BN trajectories. A high entropy means that the sequences of states in the BN trajectories are highly diversified. Conversely, a high disequilibrium among the states characterises trajectories mostly composed of the repetition of few states. It is conjectured that a complex system operates in a dynamical regime such that a balance between these two quantities is achieved [5]. As shown in

[5] Details can be found in [4].

[6] i.e., able to perform the task even in the presence of noise and perturbations

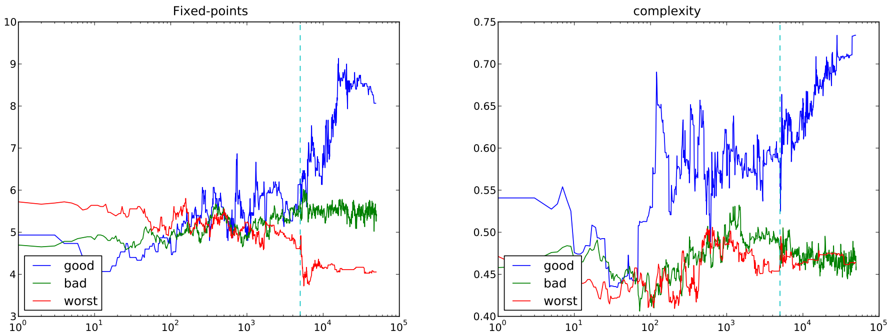

Fig. 1: Average number of fixed points (left) and complexity of the BN controller (right) as a function of the learning algorithm's iteration. The BN-robot is evaluated on phototaxis only till the iteration denoted by the vertical dotted line, then it is evaluated on both phototaxis and antiphototaxis.

Figure 1 (right), the complexity C of the successful BN-robots increases steadily during the training process, whilst it is almost constant for the unsuccessful ones.

In summary, the networks that optimally balance robustness and evolvability are characterised by generalisation capability and high statistical complexity of their trajectories. This result suggests that also artificial systems that must cope with changing environments may have an advantage in enjoying the same properties as living systems, such as cells.

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