Robustness, evolvability and complexity in Boolean network robots

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Abstract. Boolean network robotics concerns the use of Boolean networks, and other models from complex systems science, 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 show that successful BN-robots are endowed with both robustness and adaptiveness and their dynamical complexity is higher than that of unsuccessful ones.

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 [2,3,4]. In a recent work, it has been shown that BNs can be utilised to control robots [5]. 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 present preliminary results of an analysis of the BN-robot's dynamics. We analysed the trajectories followed by the BN-robot in the space of the BN states. We found that the best performing BNs show the capability of maintaining previous learned behaviours (*robustness*), while adapting to new tasks to perform (*evolvability*).[4] This property seems also to be positively correlated with a measure of the complexity of the BN.

The structure of the paper is as follows. After a succinct description of the experimental setting in Section 2, we discuss the main results of the analysis of the symbolic dynamics of the BN controlling the robot in Section 3.

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 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. Robot input sensors consists of four light sensors and one sound sensor, while the actuators correspond to right and left wheel controllers. The robot is put in a random position in a squared arena, with one light source in a corner. The BN-robot has to 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 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.[5]

3 BN symbolic dynamic analysis

A significant fraction of the training experiments leads to a successful BN-robot (called *good* BN-robots), i.e., a robot able to robustly 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).

[4] We use the terms robustness and evolvability with the same meaning as in the work by Aldana et al. [2]

[5] For further details on the experimental setting, we refer the interested reader to the paper by Roli et al. [5].

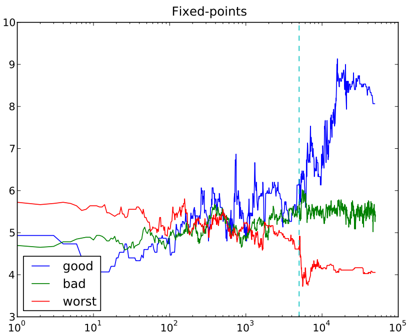

Fig. 1: Average number of fixed points as a function of the learning algorithm's iteration.

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. This result provides evidence to the hypothesis that these systems are able to successfully balance robustness and evolvability.

It is interesting to investigate the reasons for the success of these BNs. To this aim, we study 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 w.r.t. the unsuccessful ones. An in-depth analysis of the BN trajectories in both successful and unsuccessful cases provides very insightful findings. First of all, during the learning process, the successful BNs improve their generalisation capabilities, as the overall number of fixed points increases,[6] (see Figure 1). 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 $C = HD$, 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 [7]. As shown in Figure 2, the complexity C of the successful BN-robots increases steadily during the training process, whilst it is almost constant for the unsuccessful ones.

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

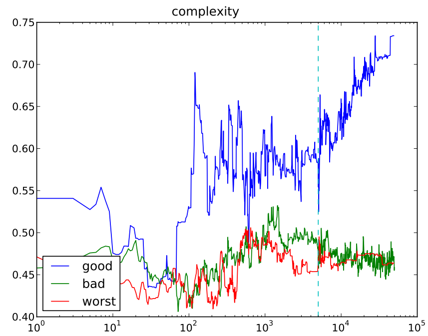

Fig. 2: Complexity of the BN controller as a function of the learning algorithm's iteration.

In summary, the networks which 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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