Simultaneous cooperative and conflicting behaviors handled by a Gene Regulatory Network

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***Abstract*—In many current developmental models, artificial Gene Regulatory Networks (GRN) simulate cell behavior. More specifically, GRN can determine and regulate cell behaviors using collected external signals through protein sensors. In this paper, we propose to use the GRN properties to control an agent using external perception. More precisely, we will try to evaluate how a GRN can handle and manage simultaneously four conflicting and cooperative continuous actions to solve a new experiment, the Radbot.**

I. Introduction

Artificial Gene Regulatory Networks are usually used in developmental models to perform cell behavior such as migration, division or differentiation. In such models, a GRN can determine, and regulate, cell behaviors through the production of internal and external proteins. Over the past ten to fifteen years, regulatory networks have been proved efficient as a central system for cell based developmental models such as [1], [2]. Since 2010, new experiments using GRN as a controller have emerged in the literature as in Nicolau, in Joachimczak or in Schramm works [3], [4], [5]. From our past experiences using GRN [6] and from the works of [3], we will try to show that a GRN can make a decent adaptive behavioral controller. More specifically, we think that a GRN can successfully learn how to handle simultaneously several continuous actions or behaviors to fulfill a specific task. By continuous actions, we mean parametrized actions that stay active for a while in the simulation and that only evolves through their parameters changes. To prove this, we have to evaluate how a GRN performs in learning how to keep several competitive and/or cooperative actions active at the same time, and how it can switch from one to another to fulfill its assigned task. To that end, we propose a new experiment, the Radbot. This experiment is designed to evaluate the learning of the management of four continuous actions and, thanks to its easy parametrization, it allows a correct study of how a known GRN [7] converges while learning. If successful, this GRN will be used to produce controllers for agents that need to coordinate several actions, to prioritize one of them or to maintain the best compromise amongst them according to the current situation. Examples of such trained agents can be found in many works related to artificial intelligence in video games as different as car racing [8], first person shooter [9], [10], [11] or real time strategy games [12]. It is however important to note that in most of these works, actions or behaviors are played sequentially and at full intensity while our intend is to obtain, using machine learning, a controller that can play simultaneously different actions and/or mitigate their effects if necessary instead of systematically stopping them. The following section of this paper will present the Radbot experiment. Section III proposes a method based on a gene regulatory network to solve the Radbot problem. Section IV shows the results of three main experiments with two different environments (discrete and continuous) and different complexities. The paper concludes with a discussion of obtained results and many perspectives as well for the benchmark as for regulatory networks.

II. The Radbot problem

The Radbot problem is designed as a benchmark to evaluate performance in learning how to manage and coordinate multiple continuous actions (or behaviors) in a dynamic world. More specifically, we are interested in problems where an agent must maintain and manage more than one action to correctly perform in its environment. These actions share critical resources or/and they benefit from each other influence. In such cases, the agent might need to simultaneously perform at least two tasks or it might need to switch continuously from one task to another. The Radbot problem puts an agent in such a situation: the agent will have to handle accurately four parametrized actions that are either conflicting or cooperative to solve the problem. Obviously, any mistake in the management of the four continuous actions will lead to a more or less quick failure. The problem consists in a robot, the Radbot, which have to go through a linear environment while managing two energy accumulators, A and B, and its internal temperature T. Within this environment, two different radiations, $R1$ and $R2$, increases the temperature of the robot according to their respective intensity. The Radbot can gradually activate two shields, $S1$ and $S2$, to protect itself from respectively radiations $R1$ and $R2$. The more it activates a shield, the more it absorbs corresponding radiation and the more it prevents the robot from heating up. If temperature T reaches its maximum, the Radbot overheats and it is destroyed. The shields share and consume the energy from accumulator B. Each shield converts absorbed radiation in energy stored in accumulator A. The Radbot consumes energy from accumulator A to run through the environment, but it produces energy to fill accumulator B

Level	Activate S1 at δ_{S1}	Activate S2 at δ_{S2}	Cool down at δ_{cool}	Run at δ_{run}
A	$+a_{S1} * \delta_{S1}$	$+a_{S2} * \delta_{S2}$	$-a_{cool} * \delta_{cool}$	$-a_{run} * \delta_{run}$
B	$-b_{S1} * \delta_{S1}$	$-b_{S2} * \delta_d$	NA	$+b_{run} * \delta_{run}$
Temp	$+rad_{S1} * \delta_{S1}$	$+rad_{S2} * \delta_{S2}$	$-S_{cool} * \delta_{cool}$	NA
Speed	NA	NA	NA	$M_{sp} * \delta_{run}$

TABLE I
EFFECT OF THE DIFFERENT BEHAVIORS ON THE STATE PARAMETERS OF THE RADBOT

doing so. The Radbot can cool down its internal temperature T by consuming exclusively energy A. Finally, all behaviors cannot be fully applied. The sum of activation of the actions cannot exceed 100%. In other words, if the Radbot decides to trigger only one action at 100%, all other actions will be disabled. Figure 1 summarizes the possible behaviors of the Radbot. These actions can be formalized by table I. In this table, each column corresponds to the modification of each parameter of the Radbot' state (lines). All the equation are applied at every time step of the simulation. δ_* can take values between 0 and 1. They correspond to the degree of activation of the corresponding action. The sum of δ_* must be equal to one. It means that all the resources are distributed to all the actions. a_*, b_*, S_{cool} and M_{sp} are positive values set up during the definition of the Radbot. According to their values, they will directly influence the complexity of the problem. Finally, rad_{S1} (respectively rad_{S2}) is the quantity of radiation $R1$ (respectively $R2$) emitted by the environment at the considered time step. For example, the activation of shield $S1$ at δ_{S1} will increase $(+)$ the level of energy A of $a_{R1} * \delta_{R1}$, where a_{R1} is a parameter given during the definition of the Radbot. The run behavior will calibrate the speed of the Radbot with the value $M_{sp} * \delta_{run}$ where M_{sp} is a predefined parameter that expresses the maximum possible speed of the Radbot. The difficulty of this problem is to coordinate and manage the four actions (run, cool, activate shield $S1$, activate shield $S2$) to go through the maximum distance in the environment: all the actions cannot be fully applied at the same time; the robot has a total behavioral load and has to share it out among the different actions. For example, the robot can allocate 25% of its load to each action and, if the robot wants to increase the intensity of a specific action, it has to decrease the intensity of another one. Besides, due to the share and production of energetic resources stored in A and in B, the actions to handle cooperate two by two (Activate $S1$ with cool down or Run; Activate $S2$ with cool down or Run) and compete two by two (Activate $S1$ against Activate $S2$; cool down against Run). There are many ways to configure the Radbot: we can configure the gain and the loss of each component for each action; the changes of intensity of both radiations in the environment (discrete values within discrete areas as represented in figure 2, continuous values along the environment (functions, see figure 3) or totally random values) and the maximum behavior load of the Radbot. Playing with these parameters allows to implement very easy to very complex problems. To generate the necessary inputs to make chose an action in reaction to its environment and its internal variables the Radbot can use a maximum of six sensors:

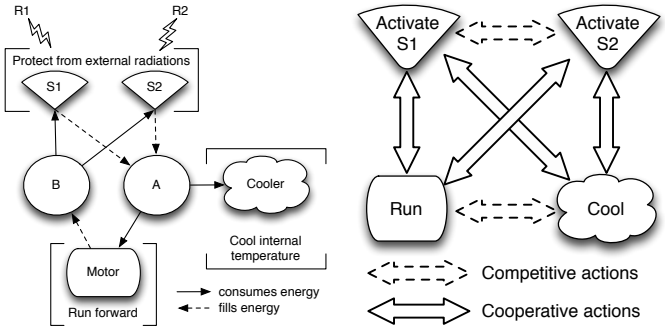


Fig. 1. Behaviors interactions : Activate $S1$ and Activate $S2$ are conflicting because they consume the same energy resource B and the activation of one of them competes directly with the activation of the other (preventing the Radbot to protect itself from one of the two radiations). Cool down and Run are conflicting for they share energy A and cooling down the Radbot prevents to move forward at maximum speed (and vice versa). Activate $S1$ (or $S2$) cooperates with cool down for it fills accumulator A that cooling down needs, and cool down can compensate a partial shielding from activation of $S1$ (or $S2$). At last, Activate $S1$ (or $S2$) cooperates with Run for they produce needed energy of each other and an effective shielding allows a slower run while a faster run allows a more partial shielding.

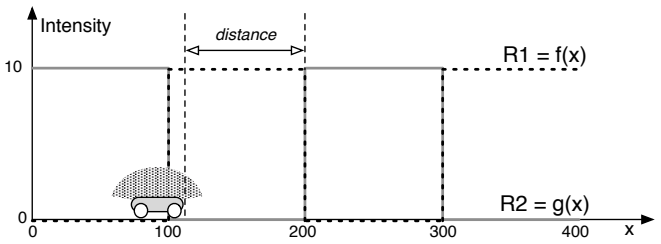


Fig. 2. The Radbot in discrete environment. *distance* is a sensor of the RadBot that represents the distance to the next radiation switch.

- $energy_A$ (0 to 100) that indicates its current energy level stored in A,
- $energy_B$ (0 to 100) that indicates its current energy level stored in B,
- $temp_T$ (0 to 100) that indicates its current internal temperature (0: cold to 100: overheated),
- $rad_R^{norm}1$ (0.0 to 1.0) that indicates the normalized level of radiation $R1$ in current position,
- $rad_R^{norm}2$ (0.0 to 1.0) that indicates the normalized level of radiation $R2$ in current position,
- $distance$ that indicates the distance to the next switch of maximum intensity of radiations $R1$ and $R2$, as represented on figures 2 and 3.

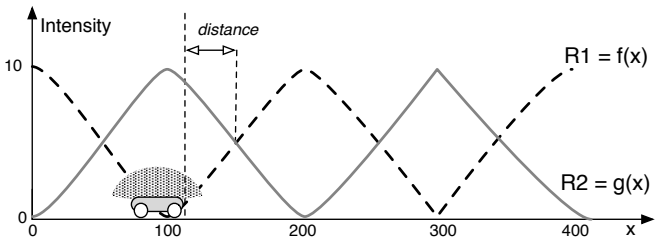


Fig. 3. The Radbot in continuous environment. *distance* is a sensor of the RadBot that represents the distance to the next radiation switch.

In this paper, we propose a first approach to solve the Radbot problem. This approach is based upon an artificial gene regulatory network that regulates the activity of the different continuous actions of the Radbot. This method seems to be well-adapted to this problem. Indeed, the expression of the different genes involved in the regulatory network will represent the expression of the behavior in the Radbot and will be regulated by the network. The next section presents the Banzhaf's regulatory network used in this paper.

III. The gene regulatory network

A. Background on artificial regulatory networks

Many current developmental models rely on an Artificial GRN to simulate cell differentiation. These systems are more or less inspired by gene regulation systems of living systems. In living systems, cells of organisms have several functions. They are described in the organism genome and their expressions are controlled by the regulatory network [13]. Cells use external signals from their environment to activate or inhibit the transcription of genes into mRNA (messenger Ribonucleic Acid), the copy of the daughter cell's DNA (Deoxyribonucleic Acid). Cells collect external signals through protein sensors localized on the cell membrane. Then, gene expression within a cell determines its behavior. Eggenberger [14] was one of the first to use a regulatory network to generate a 3-D organisms able to move in its environment by modifying its morphology. In [15], Reil proposed a biologically plausible model, with a genome defined as a vector of numbers. In this model, each gene starts with a particular sequence (0101), named the "promoter". Then, a graph is used to visualize the gene activations and inhibitions over time with randomly generated networks. Observations revealed the existence of several patterns such as gene activation sequencing, chaotic expressions or cyclic expressions. The author also pointed out that the system was able to display pattern self-repairing after random genome deteriorations. Banzahf also described an artificial GRN model strongly inspired by real-world gene regulation [7]. This model will be detailed in the next section. Starting from these two seminal models, various extensions and variations have been explored, for addressing various concerns and applications. Several works addressed Artificial Embryogeny problems with models of GRN ranging from cellular automaton modeling [16] to stripped-down version of GRN combined with complex developmental systems [2], [1], [17]. Some works have also addressed control problems: using GRN as a control function to map a virtual robot's sensory inputs to its motor actuator values. This has been applied in various setup, from foraging agents [4] to pole balancing [3].

B. The model

In this work, we consider the artificial Gene Regulatory Network (GRN) introduced by [7]. In this model, the network is coded into the genome as a sequence of 32-bit strings (termed *sites*). Each gene in the genome is marked by a particular sequence named the "promoter". When a promoter is detected, the next five sites represent a gene sequence that codes for a protein to be produced. Each site codes for a different molecule of the protein. The concentration of this protein will determine the expression level of the matching gene. To determine the protein's concentration and thus the gene expression level, two sites, coded upstream of the promoter, enhance and inhibit the protein production. The dynamics of enhancer signal e_i and inhibitor signal h_i of a protein i are given by the following equations:

$$e_i = \frac{1}{N} \sum_{j=1}^{N} c_j \exp^{\beta(u_j^+ - u_{max}^+)}$$

$$h_i = \frac{1}{N} \sum_{j=1}^{N} c_j \exp^{\beta(u_j^- - u_{max}^-)}$$

where N is the total number of proteins, c_j is the concentration of the protein j, β is a scaling factor, u_j^+ (resp. u_j^-) is the matching degree of the enhancer (resp. inhibitor) site with the protein j and u_{max}^+ (resp. u_{max}^-) is maximum enhancer's (resp. inhibiter's) matching degree observed in the whole genome. The matching degree u_j^+ (resp. u_j^-) consists in counting the number of "1" resulting from the application of a XOR operation to the protein j and the enhancer (resp. inhibitor) pattern. The exponential function increases the impact of high value of gene expression and filter low values. Finally, the concentration of produced protein p_i follows the differential equation $dc_i/dt = \delta(e_i - h_i)c_i - \Phi(1.0)$, where δ is a scaling factor and $\Phi(1.0)$ constrains the sum of all concentration equals to 1.0.

C. Extension to a computational model

Originally, Banzhaf's artificial GRN is limited to study internal network dynamics. In order to use this model as a control function, [3] proposed an extension by adding inputs and outputs to the regulatory network. This extension is detailed in the following.

1) Inputs: Input values are coded with integers that will correspond to existing proteins. These input proteins can be involved in the regulatory process in two different ways: with their signatures to be considered during the matching process (in equations of e_i and h_i) or with their input value to modify the differential equation dc_i/dt of protein concentrations. Here, the second solution has been chosen as it allows a better resolution with regard to a continuous domain of the problem addressed in this paper.

2) Outputs: In order to produce outputs in the regulatory networks, genes are separated into classes: transcription factors *TF-genes* and product proteins *P-genes*. Whereas TF-genes play the roles of regulatory proteins as in the original Banzhaf's model, P-genes are only regulated but do not regulate other proteins: their expression levels provide the desired output signals. These two kinds of genes are identified by introducing two new promoters, whose signatures are chosen so that their probability of occurrence is equivalent and their matching as low as possible.

D. Evolutionary algorithm

1) Evolution strategy: A classical (250+250) evolution strategy (ES) evolves a population of regulatory networks coded by the binary string previously presented. The (250+250) evolution strategy consists in producing 250 offspring from 250 parents and choosing the 250 best genomes to form the next population. The fitness function that evaluates each genome consists of calculating the distance traveled by the Radbot. The evolution strategy evolves the genome in order to maximize this distance. Genome modifications are only regulated by a common bit-flip mutation operator. The mutation rate is set to 2% at the beginning of the run and adapted by the 1/5 rule of evolution strategies [18]: (1) the mutation rate is doubled when the rate of successful mutation is higher than 20%; (2) the mutation rate is divided by two when the rate of successful mutation is lower than 20%; (3) the mutation rate is doubled when the number of gene mutations in the population is less than 250 by generation. The regulatory network's genome is randomly initialized. It is then duplicated 9 times with a mutation rate of 2% in order to increase the appearance probability of regulation sites.

2) Radbot problem encoding: In this paper, the 6 inputs and 4 outputs are used to control the Radbot. The 4 outputs directly regulate the 4 possible behaviors of the Radbot (Activate S1, Activate S2, Run and cool). Each input is mapped to a sensor: $input_1$ to $energy_A$, $input_2$ to $energy_B$, $input_3$ to $temp_T$, $input_4$ to rad_{R1}, $input_5$ to rad_{R2} and $input_6$ to $distance$. The inputs are normalized then scaled between 0 and 0.05 in order not to overflow the regulatory network with input proteins. Outputs are also normalized. They express the activation level of each behavior. The sum of the four output values is lower or equal to 1 (which is an inherent property of the regulatory network). Because more than 4 output proteins are generally available in the regulatory network, we decide to split the genome in 4 parts, one for each output. The actual value of an output is given by the maximum concentration of proteins in its matching part. At last, to help manage the complexity of the problem, shields $S1$ and $S2$ have an activation threshold θ. The shield outputs follow the equation:

$$Output_{shield} = \begin{cases} \frac{Output_{GRN}}{\theta} & \text{if } Output_{GRN} <= \theta \\ 1 & \text{if } Output_{GRN} > \theta \end{cases}$$

where $Output_{shield}$ is the final value sent to the Radbot to activate shields $S1$ or $S2$ and $Output_{GRN}$ is the value read from the regulatory network. 0.4, 0.5 and 0.6 are the 3 values used as threshold θ in the next experiments. They allow to gradually increase the problem complexity and to stress the Radbot more. Next section presents two experiments we have made using the GRN-based approach to control the Radbot.

IV. Experiments

A. Parameters of the Radbot

In the following experiments, the Radbot is set up with identical parameters. It allows us to study the behavior of the Radbot according to the environment and not according to its setup. This setup has been empirically determined, through a set of tests, to generate a rather complex problem that can be solved with reasonable computation time. The Radbot's maximum speed is 10 units per time step. It means that if the Radbot only activates the running behavior, it will go forward by 10 units at each simulation step. When the Radbot reaches the maximum speed, it consumes 5 units of energy from A and fills B with 12 units of energy. The activation at full intensity of shield $S1$ (or shield $S2$), within an area that receives x units of radiation R1, consumes $\frac{40}{x}$ units of energy from B and fills A with $\frac{50}{x}$ units of energy. Cooling down at full rate consumes 5 units of energy from A to decrease temperature T by 10 units. Finally, the Radbot energy levels A and B and the temperature T can vary from 0 units to 100 units. When T is equal or greater than 100 units, the Radbot overheat and is (virtually) destroyed. This marks the end of the simulation. At the beginning of each simulation, energy levels of A and of B are set up to 100 units and the Radbot is cool (i.e. T set up to 0 unit). Table II summarizes all the parameters and their effect on the equation presented in table I.

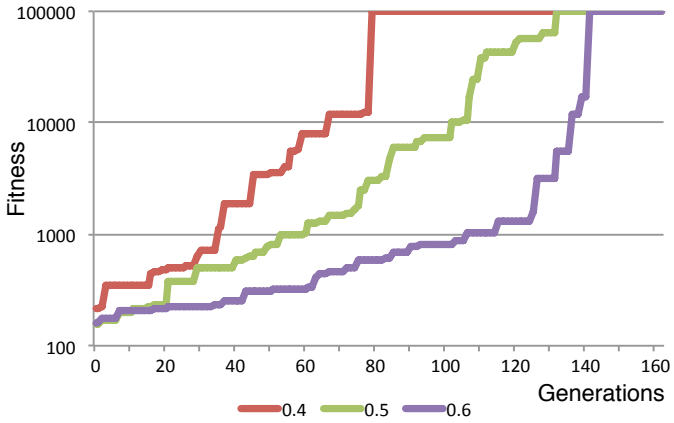


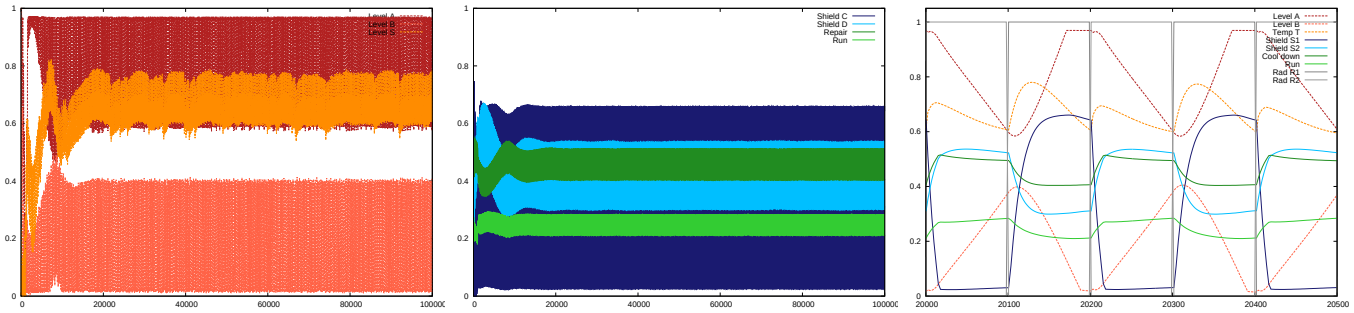
Fig. 4. Influence of the shield's full activation threshold on the convergence of the evolution strategy

Level	Shield S1 at δ_{S1}	Shield S2 at δ_{S2}	Cool down at δ_{cool}	Run at δ_{run}
A	$+5\delta_{S1}$	$+5\delta_{S2}$	$-5\delta_{cool}$	$-5\delta_{run}$
B	$-4\delta_{S1}$	$-4\delta_{S2}$	NA	$+12\delta_{run}$
Temp	$+rad_{R1} * \delta_{S1}$	$+rad_{32} * \delta_{S2}$	$-10\delta_{cool}$	NA
Speed	NA	NA	NA	$10\delta_{run}$

TABLE II
RULES WITH ALL PARAMETERS INCLUDED. rad_c AND rad_d WILL EVOLVE DURING THE SIMULATION ACCORDING TO THE POSITION OF THE RADBOT IN THE ENVIRONMENT. δ_* WILL BE REGULATED BY GRN AND WILL DRIVE THE RADBOT.

B. Discrete mode

In the discrete mode of the Radbot problem, the environment is built as a sequence of areas with different levels of radiations. In this experiment, the environment has 1000 areas. Each area is numbered from 0 to 999 and its size is 100 units. Even areas receive a 10 units of radiation $R1$ and 0 units of radiation $R2$ at each time step and odd areas 10 units of radiation $R2$ and 0 units of radiation $R1$. The 10 units correspond to the temperature T caused at each time step to the Radbot if the shield is activated at 0%. The activation of the shield reduces



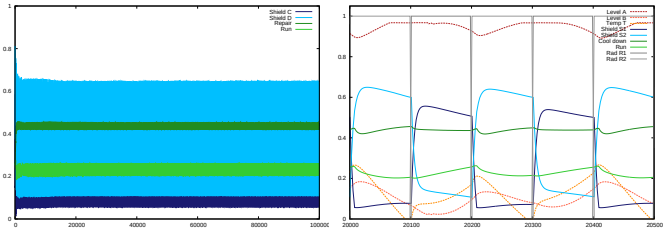
(a) (b) (c)

Fig. 5. (a) Energy and temperature levels during all the simulation; (b) Behavior levels during all the simulation; (c) Zoom on all the levels between time steps 20000 and 20500.

the heat increase according to the equation presented in table II. The regulatory network has been evolved for each value of shield activation threshold previously given (0.4, 0.5 and 0.6). Figure 4 shows the different convergence curves obtained with the three threshold values. The convergence is longer as the threshold increase. As expected, the problem is more complex as the threshold increase.

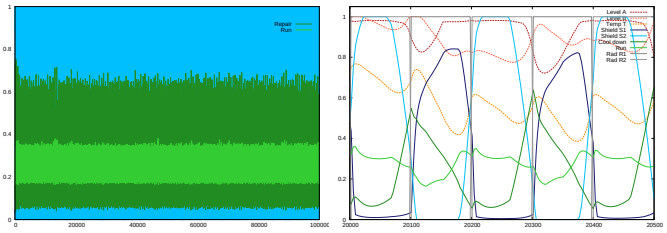
1) Threshold 0.4: Figure 5 represents the data extracted from the simulation with the threshold set up at 0.4. Whereas curves (a) and (b) represents levels of energy, temperature and actions activation through the whole simulation, curves (c) focus on a particular region of the simulation. On curves (a) and (b), a short period of stabilization of the regulatory network before having constant behaviors is observable. This period is about 12000 time steps. After that, all levels remains globally stable, oscillating area after area. Curve (c) focuses on few time steps after the oscillatory stage to detail the behavior of the Radbot. First of all, we can notice that the shields (blue curves) are never activated to their maximums. The regulatory network prefers balance this by pushing up the cooling behavior (dark-green curve). Whereas the shield $S1$ is sufficiently high, the shield $S2$ stays relatively low. In order to protect the Radbot from radiation $R2$, the regulatory network chooses to increase the cooling down and the speed behaviors of the Radbot. However, the dark-orange dotted curve shows the heating of the Radbot that this choice implies. Finally, we can also notice the variety of possible behavior shifts generated by the regulatory network. It can be smooth such as for cooling down and running behavior, very steep such as during the inhibition of the shield $S1$ or between such as for the activation of both shields.

2) Threshold 0.5 and 0.6: Curves on figures 6 and 7 present the data extracted from the simulation using a threshold value of 0.5 (first line) and 0.6 (second line). Curves 6(a) and 7(a) represent the behavior levels during the whole simulation. We can notice that the simulation is more complex through the increase of the threshold and this causes a strong optimization of the regulatory network stabilization stage. Indeed, whereas the stabilization stage takes about 12000 time steps with the threshold at 0.4 (see curves (a) of figure 5), its duration strongly decreases with the increase of the complexity: about 2500 time steps with a 0.5 threshold and 1000 time steps with



(a) (b)

Fig. 6. Threshold=0.5 (a) Behavior levels only during all the simulation; (b) Behavior, energy and temperature levels between time steps 20000 and 20500

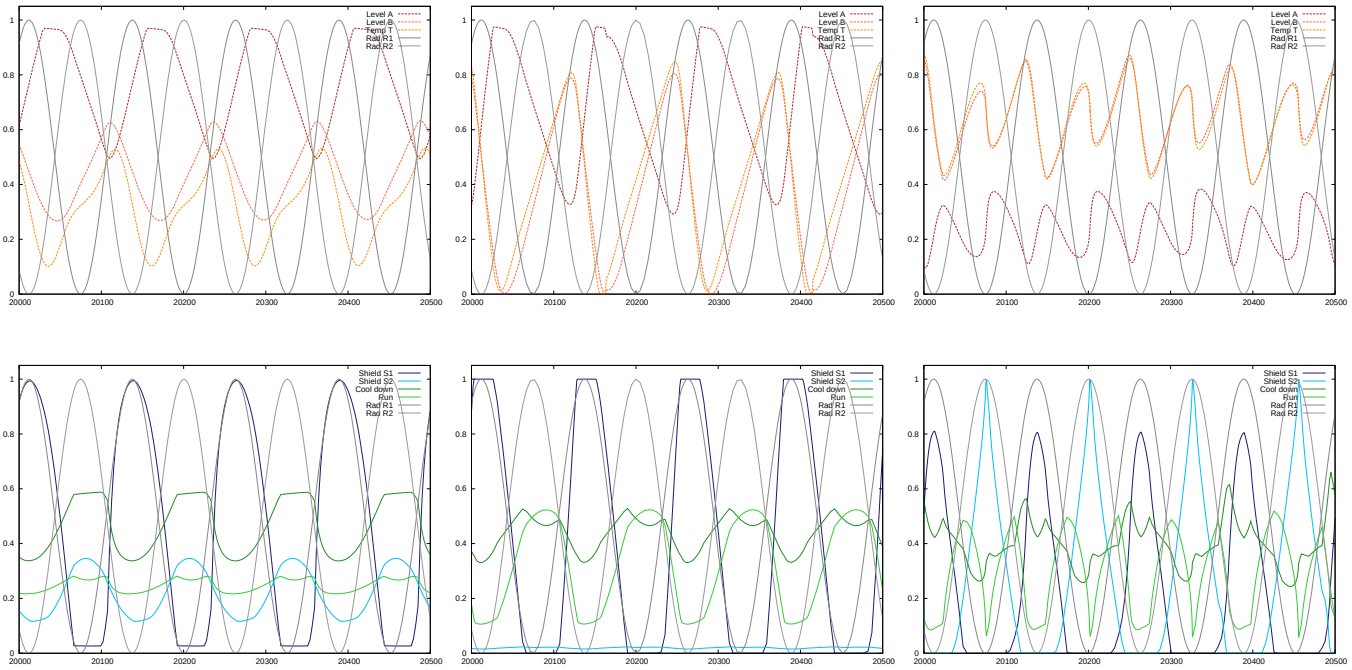


(a) (b)

Fig. 7. Threshold=0.6 (a) Behavior levels only during all the simulation; (b) Behavior, energy and temperature levels between time steps 20000 and 20500

0.6. This optimization is necessary in order to keep the Radbot alive in the first steps of the simulation. Another observation we can make is about the management of different behaviors. Whereas the use of the shield was not very optimal with a threshold value equal to 0.4 (figure 5(c)), a more complex simulation helps a better use of them. First, with threshold equal to 0.5 (figure 6(b)), the transitional stages between shield shifts have been strongly optimized: the regulatory network shift from a shield to the other in very few time steps. When the threshold increase again to 0.6 (figure 7(b)), the shields are really used as expected, the shield $S1$ being used at 80% and the shield $S2$ at 100%. Moreover, even if the transition phases during a shield shift are not so optimized, the regulatory network balances with a strong use of the cool down behavior for a short period.

3) Preliminary conclusion: The more the Radbot problem is complex, the more the convergence time lasts. However,



(a) threshold=0.4 (b) threshold=0.5 (c) threshold=0.6

Fig. 8. Behavior levels of the Radbot in a continuous environment between time steps 20000 and 20500.

this also implies a strong optimization of the transitory phase of the behaviors and a better use of all the system embedded in the Radbot. Whereas this section was treating with discrete shift of radiation in the environment, next section deals with a continuous environment. Areas will be replaced by two opposite sinusoidal variation for the radiations.

C. Continuous: sinusoidal variation of the radiations

In the continuous mode, two functions replace the areas of the discrete mode. These functions give the levels of radiations $R1$ and $R2$ according to the position of the Radbot in the environment. In this particular experiment, the levels of radiations are given by following equations:

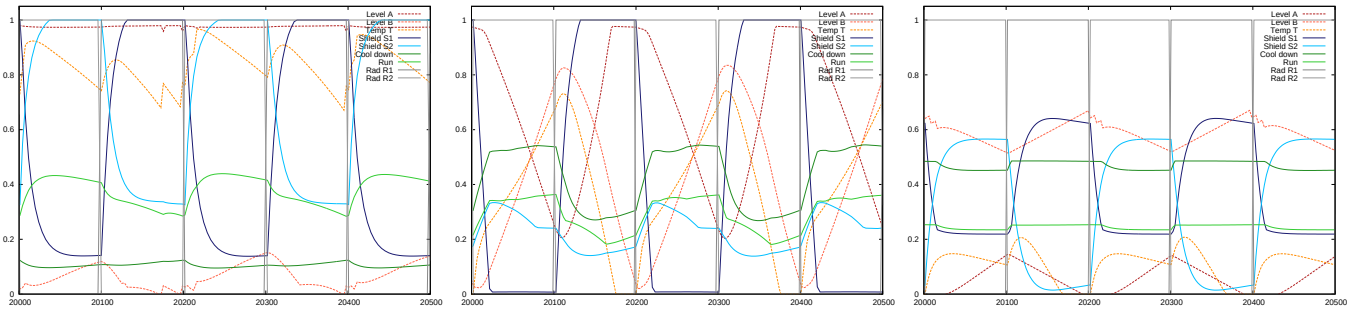
$$radC = 5 * sin(x/20) + 5$$

$$radD = -5 * sin(x/20) + 5$$

where x is the position of the Radbot in the environment. These equations have been made in order to produce sinusoidal radiations in opposite-phases. The size of a phase is equal to $40\pi \cong 125$. In other words, the Radbot will receive exactly the same radiations every time it travels for 125 steps. Figure 8 represents the curves of level of energy and temperature (top) and of the different behavior (bottom) for each possible activation threshold of the shields (from left to right: 0.4, 0.5 and 0.6). We can observe that on every curves, the Radbot compensates the lack of shield $S2$ by a strong amount of reparation. Shield $S1$ is usually sufficiently well-used to protect the Radbot from the corresponding radiation. An interesting behavior has emerged with the threshold 0.5: the Radbot leaves the shield $S2$ and prefers strongly speed-up and cool down in the same time. This behavior is regulated in order to keep all the level in good ranges. Whereas level A strongly decreases and level B and temperature T strongly increase during the fast run, the Radbot strongly slows down and keeps a high level of shield $S1$ in order to regenerate as much as possible all the resources. This behavior was not expected and proposes an interesting alternative to the perfect use of the shields. With a threshold value equal to 0.6, the shields are both globally well managed but transition phases do not match with the radiation curves. Once again, the Radbot compensates this lack of precision by speeding up during the transition phases. The experiment proves the capacity of the regulatory network to answer as well in a discrete environment as in a continuous one. Next section presents the diversity of produced behavior on the discrete problem.

D. Diversity of obtained behaviors

The last experiments present one resolution of the Radbot problem by a gene regulatory network in various cases of environments and complexities. This section focuses on only one of these cases to study the diversity of generated behaviors. To do so, we decide to choose a discrete world with the lower threshold value for the shield activation (i.e. 0.4) so that the convergence of the regulatory network will be as easy as possible. Figure 9 presents 3 different behaviors obtained. Figure 9(a) has the most expected behavior: the Radbot activates the shields at the maximum. It always keeps a small amount of reparation in order to compensate the temperature accumulated during the transitory phases. The strategy allows the Radbot to keep a relatively high speed, that could be optimized if the shields were completely disabled



(a) (b) (c)

Fig. 9. 3 different behaviors generated by 3 evolved regulatory networks in a discrete world with a shield activation threshold at 0.4. (a) Both shield are well managed that allows the Radbot to run faster than usually. (b) The Radbot mainly uses the shield $S1$ and cool down and run faster in an area with radiation $R2$. (c) Shields are not used as expected in both cases but energies and temperature are maintained at good levels.

when there is no corresponding radiation. In figure 9(b), the shield $S1$ is perfectly managed, with a total activation and inhibition consistent with radiation $S1$. Unfortunately, shield $S2$ is almost not used at all. In the areas with radiation $R2$, the Radbot compensates by increasing its speed and cooling more. It implies huge variations of the energy and temperature levels. In figure 9(c), shields are not so well managed. As always, the Radbot uses run and cool not to be destroyed by radiations. Unlike in figure (b), here the Radbot is able to keep the energy and temperature levels very stable, with a very low heating. This strategy was not expected but seems to be also efficient. According to the variety of behaviors and especially according the obtained behavior on figure 9, we can expect the regulatory network to be able to optimize the use of the shields just by giving it one more objective: optimizing the speed of the Radbot. The next experiment shows how adding this parameter to the fitness function optimize each part of the regulatory network.

E. Speed optimization

In this experiment, we decide to optimize the distance covered by the Radbot and its speed. We want the Radbot to run through the environment as fast as possible. The previous experiments were limited to 50000 time steps so that inefficient GRNs would not lock the optimization algorithm. Best GRNs usually reach the end of the environment in about 39000 simulation steps. But this amount of needed steps to perform a successful run do not influence fitness calculation for the fitness of the previous experiments is essentially the distance traveled by the Radbot. To make the Radbot swifter, we decide to penalize the Radbot with the duration of the simulation. The fitness function is now given by $fitness = distance\_traveled - simulation\_duration$. Figure 10 presents the curves of Radbot behavior and levels during the speed optimization phase, after 166, 206, 4429 generations. The graphics are zoomed after the stabilization stage. Whereas figure (a) presents classical patterns already presented in previous experiments, the more the optimization goes, the more the shield activation are optimized. First, they level of activation of the shields (see (a) and (b)), that allows a decrease of the use of the cooling behavior and a first increase of the speed. Then, the transition phases between two areas are optimized (see (b) and (c)). This optimization is slower than the previous one but allows a new increase of the speed during the transition phases because the cooling behavior is lesser and lesser necessary.

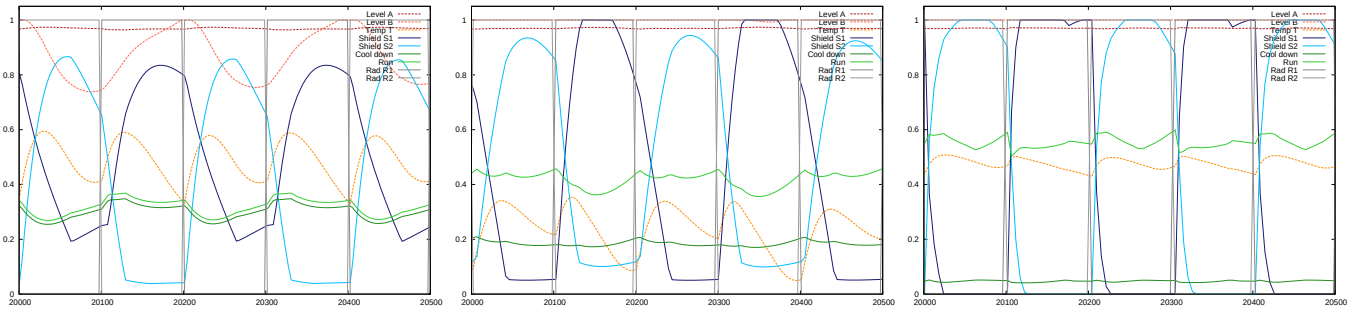
V. Conclusions and Perspectives

This paper presents a new benchmark for behavior simulation: the Radbot. This benchmark consists in a virtual robot, the Radbot that evolves in an one dimensional environment. During its journey, it has to protect itself against two different kinds of radiation with two shields (one for each kind of radiation). The robot can also cool down to reduce its internal temperature that is increased by unstopped radiations. The behavior of the robot consists in managing its different activities: activate shields, cool or run. Each action consumes and/or produces two different kinds of energy, that also has to be managed by the robot. These actions are not binary: the level of activation of each action can be adjusted by the robot between 0% and 100% but their sum can not exceed 100%.

This paper also proposes an original method of resolution of this benchmark. An extended version of Banzhaf's Gene Regulatory Network, already used to solve the pole balancing problem [3] and to generate French flag patterns [6], has here been used to generate the behavior of the Radbot in different situations. The results of these experiences denote the capacity of the regulatory network to generate an adapted behavior to its environment. These results are very encouraging and must be compared with other existing methods such as NEAT [11], Artificial Neural Networks or Learning Classifier Systems.

The regulatory network has been here studied in two particular cases of the Radbot problem: a discrete environment and a continuous environment. These environments do not allow us to study the generalization capacity of regulatory networks. I could be interesting to make the experiment in a random environment. Such an environment could be based on the discrete environment, then the radiations received by the Radbot will be randomly computed areas after areas.

The complexity of the regulatory network is also something we have to work on. Even if the obtained results are promising, the computational cost is still expensive using this method.



(a) Generation 166 (b) Generation 206 (c) Generation 4429

Fig. 10. Behavior optimization to increase the speed of the Radbot. (a) At the beginning of the speed optimization, the Radbot covers the whole environment in 31241 time steps. (b) At the half of its optimization, it takes 24294 time steps to reach the end of the environment. (c) At the end of the optimization, it only takes 18160 time steps.

The evolution strategy has been deployed on 128 CPUs to obtained these results. In our opinion, this complexity comes from two factors: the encoding of the regulatory network as a bit string and the dynamics of the regulatory network itself. The encoding of the GRN, very close to the natural encoding, generates a lot of junk DNA which is good in nature to defend from mutations but not interesting in our computational case. Moreover, only the mutation can be applied, the crossover being too aggressive to the network. The dynamics does not allow the production of non existing proteins. In other words, if the concentration of a protein is null, this protein will never be produced anymore. This is a limitation in the case of the behavior generation because it means that an unused action can not be used anymore. It might be interesting in future works to elaborate a new GRN more specific to behavioral handling problem. A GRN that does not have junk DNA and that allows crossover to perform a better exploration of the solution space.

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