Towards the Evolution of an Artificial Homeostatic System

Renan C. Moioli, Patricia A. Vargas, Fernando J. Von Zuben and Phil Husbands

***Abstract*— This paper presents an artificial homeostatic system (AHS) devoted to the autonomous navigation of mobile robots, with emphasis on neuro-endocrine interactions. The AHS is composed of two modules, each one associated with a particular reactive task and both implemented using an extended version of the GasNet neural model, denoted spatially unconstrained GasNet model or simply non-spatial GasNet (NSGasNet). There is a coordination system, which is responsible for the specific role of each NSGasNet at a given operational condition. The switching among the NSGasNets is implemented as an artificial endocrine system (AES), which is based on a system of coupled nonlinear difference equations. The NSGasNets are synthesized by means of an evolutionary algorithm. The obtained neuro-endocrine controller is adopted in simulated and real benchmark applications, and the additional flexibility provided by the use of NSGasNet, together with the existence of an automatic coordination system, guides to convincing levels of performance.**

I. Introduction

Learning and evolution are considered fundamental steps towards the synthesis of complex adaptive systems and the computational modelling of cognitive processes. Due to intrinsic properties of biological systems found in nature, such as decentralization, adaptability, scalability, self-organization and robustness, bio-inspired computational tools have been developed in an attempt to succeed where and when classical problem solving tools produce unacceptable performance. Artificial neural networks [1] and artificial endocrine systems [2][3] are examples of bio-inspired computational tools that have been applied successfully to complex problems.

There is evidence that the immune, nervous and endocrine systems have an intrinsic relation, with coupled stimulations and interdependence, fundamental for cognition and the maintenance of the internal state of an organism [4]. This latter property, known as homeostasis, is considered to be fundamental for the successful adaptation of the individual to dynamic environments, hence, essential for survival. According to Levine [5], the term homeostasis first appeared on the work of Cannon in 1929 [6]. Nonetheless, for Pfeifer & Scheier [7], homeostasis was completely defined by Ashby in 1960 [8]. For Ashby, the ability to adapt to a continuously changing and unpredictable environment, i.e. adaptivity, has a direct relation to intelligence. During the adaptive process, some variables need to be kept within pre-determined boundaries, either by evolutionary changes, physiological reactions, sensory adjustment or by simply learning novel behaviours. Therefore, being within the specified boundaries, a regulatory task that is attributed to the homeostatic system, the organism or the artificial agent can operate and stay alive in a *viability* zone.

The biological inspiration combined with the theory presented by Ashby have motivated applications of homeostasis in the synthesis of autonomous systems in mobile robotics [3][9][10].

Harvey [10] investigated homeostatic adaptation in a simplified model, called Daisyworld model, used to explain the adaptation of daisies to different weather conditions. It is shown that homeostasis can be achieved by the combination of a ”Hat Function” (a function that has a shape similar to a hat) and the use of ”Rein Control”. These ideas were applied to obtain active perception in a simulated robot.

Exploring particular homeostatic properties, Di Paolo [9] evolved a plastic neural controller, where the connections between the neurons were subjected to some plastic rules. The homeostatic processes were implemented by allowing the cells to develop local plasticity, i.e. allowing them to change their connections weights whenever their activity went out of bounds. As the computational power of a neuron is related to its saturation status, this homeostatic approach aimed at avoiding this saturation, thus providing to the system alternatives for maintaining its internal state when confronted by disruptions. In order to study this homeostatic adaptation, the author proposes an experiment related to radical sensory-motor distortions, in particular the problem of adaptation to inversion of the visual field, a neuro-psychological problem investigated both in human and animals [11][12]. It was shown that the controller was able to adapt to this disruption, and the robots maintained certain degree of stability. However, as emphasized by the author, further investigations are necessary to explain why does this happen.

Following some of the ideas of the work of Di Paolo [9], Hoinville & Hnaff [13] presented a preliminary study on the advantages of two bio-inspired homeostatic mechanisms in neural controllers of legged robots. It was shown that the evolvability, stability and ability to reject perturbation of the plastic neural controllers are improved when homeostatic mechanisms are incorporated to them.

The ideas presented by Di Paolo [9] and Hoinville & Hnaff [13] encompass homeostasis within one unique structure, i.e. an artificial neural network capable of dynamically changing their connection plasticity rules. on the other hand, our present work is concerned with the coherent coordination of

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modules of predetermined behaviours, that is, we will employ a behaviour-based approach, and provide the system with the ability to dynamically switch among behaviours, given the current status of the navigation system.

This work is organized as follows: section II presents the inspirations and adaptations towards the development of an artificial homeostatic system, including the approach adopted in this work. In section III the evolutionary robotics paradigm is explored, and the GasNet model is presented as an alternative to the synthesis of the necessary reactive modules. Section IV contains the details of the new artificial homeostatic system developed. Section V illustrates the suggested tasks and its implementation details. Section VI contains the results of the artificial homeostatic system in simulated and real experiments. Finally, section VII presents final remarks and suggests directions for future investigation.

II. Artificial Homeostasis - Previous Work

Apart from the origin of the term, it is a consensus that the homeostatic process is strictly connected to the balance of the system or organism and requires some special sensory receptors skilled in detecting changes. In the human body, these receptors trigger specific responses in the nervous, immune and endocrine systems, which are the main systems directly related with the process of homeostasis. This work is concerned specifically with neuro-endocrine interactions.

The nervous system, among many other functions, has a sensory role in the body, receiving and transmitting nerve impulses as the result of internal or external stimulation [14].

The endocrine system is composed of glands, specialized cells, body tissues and organs [15]. They can produce, secrete and interact with chemical substances, called hormones, which are responsible for the performance of the endocrine system in tasks such as the maintenance of homeostasis, metabolism and reproduction.

The release of hormones can also affect the nervous system, which in turn can transmit nerve impulses affecting the production and secretion of hormones, thus establishing a control loop mechanism.

Timmis & Neal [16] suggested a mathematical modelling for an artificial endocrine system applied to robot autonomous navigation. According to the authors, the idea was to develop a system that could provide the capacity of maintenance of the internal equilibrium of an agent while it interacts with an external environment [2]. In their work, the artificial endocrine system consisted of equations that represented an aggregate of glandular cells that secret hormones in response to external stimuli.

Aiming at designing a more biologically plausible system, Vargas *et al*. [3] suggested an extension to the model of Timmis & Neal [16]. The hormones, which were previously stored in a sort of pool, are designed to be produced and released on demand through artificial glands. There is a positive and negative feedback mechanism (represented by coupled difference equations), which are reminiscent of the biological endocrine system internal regulation.

The artificial homeostatic system proposed by Vargas *et al*. [3] was composed of an artificial endocrine system (AES) and two multi-layer perceptron artificial neural networks. The AES consisted of three main modules: hormone level repository (HL), hormone production controller (HPC), and endocrine gland (G). The hormone level repository has a record of the level of hormone in the organism; the hormone production controller is responsible for controlling the production of hormones in response to variations in the internal state of the organism and external stimulation; and the endocrine gland receives inputs from the HPC, being responsible for producing and secreting hormones when required.

The system dynamics is inspired by some of the main biological mechanisms of homeostasis, particularly positive and negative feedback mechanisms of the endocrine system. The HPC module sends excitatory signals, which work as a positive feedback to the gland G, which in turn starts to produce and release hormone 1, thus increasing the hormone level. The level of hormone will in turn alter the internal state 2 by driving neural network actions upon the environment. By sensing inhibitory signals that promote negative feedback from the internal state, the HPC module ceases the production of excitatory signals (positive feedback) until once again it senses specific changes in the internal state.

$$\begin{array}{ll} If & IS \geq \theta \\ then & (HP(t+1) = (100 - \%ES) \times \alpha(Max(HL) - HL(t)) \\ else & HP = 0 \end{array} \tag{1}$$

where θ is the target threshold of the internal state IS; HP is the hormone production; ES is the external stimulus; α is the scaling factor; HL is the hormone level; and t is the time index. If the internal state IS is greater than or equal to a target threshold θ, then hormone will be produced at a rate that will depend upon the level of the external stimulus received and the level of hormone already present within the artificial organism. Otherwise, if the internal state IS is less than a target threshold θ, then hormone production will cease.

$$\begin{array}{ll} If & (ES \geq \lambda) \ and \ (HL \geq \omega) \ then \ IS = 0 \\ else & IS(t+1) = IS(t) + \beta(Max(IS) - IS(t)) \end{array} \tag{2}$$

where λ and ω are pre-determined thresholds associated with ES and HL, respectively; β is the increasing rate of the internal state.

The hormone level represents the amount of hormone stimulating the artificial neural network (ANN). It is submitted to constant updating in its value due to its internal half-life measure (parameter T) and the amount of hormone produced (Equation 3):

$$HL(t+1) = HL(t) \times e^{-1/T} + HP(t) \tag{3}$$

It is important to stress that any variation in the internal and external states may promote or suppress the activity of the nervous (ANN) and endocrine (AES) systems. For instance, the variation of the internal state of the organism as a result of hormone production may act as a feedback mechanism to the hormone production itself, resulting in the release of inhibitory hormones or in the cessation of hormone production.

III. Evolutionary Robotics and GasNets

Evolutionary Robotics is a particularly novel field of research, which aims to apply evolutionary computation techniques to evolve the physical structure of the robot (its body) and/or the controller, for both real and simulated autonomous robots. In spite of being a well-established research area with many achievements reported in the literature [17], it has some intrinsic difficulties, mainly associated with the time spent while evaluating an individual and the so called "*reality gap*", which is related to the transfer of a simulated evolved controller to the real robot [18].

The synaptic plasticity is considered fundamental to most of the artificial models of the nervous system, from neural networks [1][19][20] to other computational models based on neuroscience [21][22][23]. Inspired by this synaptical plasticity, traditional models of artificial neural networks were extended. An architecture known as GasNet, was developed by Husbands [24] with the aim at reproducing the production and release of nitric oxide (NO) by real neurons, modulating the behaviour of the neurons in its vicinity. This neuro-modulation acts in the neuron transfer function, modifying its behaviour. The GasNet is modelled as a recurrent neural network with a variable number of nodes, which are spatially embedded in a 2D Euclidean space. Each node can produce synaptical stimuli, excitatory or inhibitory, to other neurons to which it is connected, and also chemical stimuli, through artificial gases, to other spatially related nodes.

The output of the network is given by Equation 4. At each time step t, the output is a function of both the electric inputs and the gaseous modulation, determined by the amount of gases at the neuron site.

$$O_i^t = tanh\left[K_i^t\left(\sum_{j\in C_i} w_{ji}O_j^{t-1} + I_i^t\right) + b_i\right] \qquad (4)$$

where C_i is the set of nodes with connections to node i, w_{ji} is the connection weight value (ranging from -1 to 1), O_j^{t-1} is the previous output of neuron j, I_i^t is the external input to neuron i at time t, if the node has external inputs, b_i is the bias of the neuron, and K_i^t represents the modulation of the transfer function caused by the gases.

The K_i^t parameter has its value determined from the set of Equations 5 to 8:

$$K_i^t = P[D_i^t] \qquad (5)$$

$$P = \{-4.0, -2.0, -1.0, -0.5, -0.25, -0.125, 0.0, 0.125, 0.25, 0.5, 1.0, 2.0, 4.0\} \qquad (6)$$

$$D_i^t = f\left(D_i^0 + \frac{C_1^t}{C_0 \times K}(N - D_i^0) - \frac{C_2^t}{C_0 \times K}D_i^0\right) \qquad (7)$$

$$f(x) = \begin{cases} 0, & \text{x} \leq 0 \\ \lfloor x \rfloor, & 0 < \text{x} < \text{N} \\ N-1, & \text{else} \end{cases} \qquad (8)$$

where $P[i]$ is the set of values K_i^t can assume in the N positions array, D_i^0 is the genetically defined value of D_i^t, C_1^t and C_2^t are the concentrations of gases 1 and 2 at time t, respectively. C_0 and K are global constants.

There are two gases, gas 1 and gas 2. The transfer function K is increased by the presence of gas 1 and decreased by the presence of gas 2.

It is believed that all GasNet's combined features, in particular, the spatial relation, provide to the network highly-desired adaptation properties. Nonetheless, recent works have been investigating the effective relevance of this spatial relationship among neurons. For instance, Vargas *et al.* [25] proposed a novel, spatially unconstrained GasNet model, named non-spatial GasNet (NSGasNet). In this model, there is absence of the notion of space, thus any neuron is able to reach any other node of the network, performing the modulation via gases. The degree of stimulation between the neurons is determined by a genetically specified term called Mbias (modulator bias), ranging from 0 to 1. A "0" value means that the neuron is not affected by the specified emitting neuron. A value above "0" means that the neuron will be affected by the specified emitting neuron, at a rate proportional to the stimulation level. Equation 9 defines the concentration of gas at the neuron.

$$C(t) = Mbias \times T(t) \qquad (9)$$

Functions $T(t)$ and $H(x)$ (Equations 10 and 11) model the spread of the gases; t_e and t_s are the last time the neuron started and ceased the emission of gas, respectively; s is a constant related to the build up and decay of the gas emission at each time step t.

$$T(t) = \begin{cases} H(\frac{t-t_e}{s}) & \text{emitting} \\ H(H(\frac{t_s-t_e}{s}) - H(\frac{t-t_s}{s}) & \text{not emitting} \end{cases} \qquad (10)$$

$$H(x) = \begin{cases} 0 & \text{x} \leq 0 \\ x & 0 < \text{x} < 1 \\ 1 & \text{else} \end{cases} \qquad (11)$$

The network genotype consists of an array of integer variables lying in the range [0, 99] (each variable occupies a gene locus). The decoding from genotype to phenotype adopted is the same as the original model [24]. The NS-GasNet model has 6 variables associated with each node plus 1 modulator bias for each node, plus task-dependent parameters (not specified in the genotype below).

$$< genotype >::< rec >< TE >< CE >< D_i^0 > \\ < bias >< s >< Mbias_{i1} > ... < Mbias_{(}ij) >$$

The rec parameter determines if the recurrent connection is excitatory, inhibitory, or inexistent; TE stands for the circumstances under which the neuron will emit a gas: if its electrical activity exceeds a predetermined threshold, if the concentration of gas 1 exceeds a predetermined threshold, if the concentration of gas 2 exceeds a predetermined threshold, or if the neuron does not emit gases under any circumstance; CE specifies which gas the neuron emits, gas 1 or gas 2; D_i^0, $bias$ and s are referred in Equations 7, 4 and 10, respectively, and the $Mbias$ parameter is the modulation bias of the node.

For a more detailed explanation of the mechanisms of the GasNets and NSGasNets, the reader should refer to [24] and [25].

As it will be further described in the next section, the NSGasNet model will be adopted in this work, thus replacing the multi-layer perceptron neural networks used in the original model of the artificial homeostatic system.

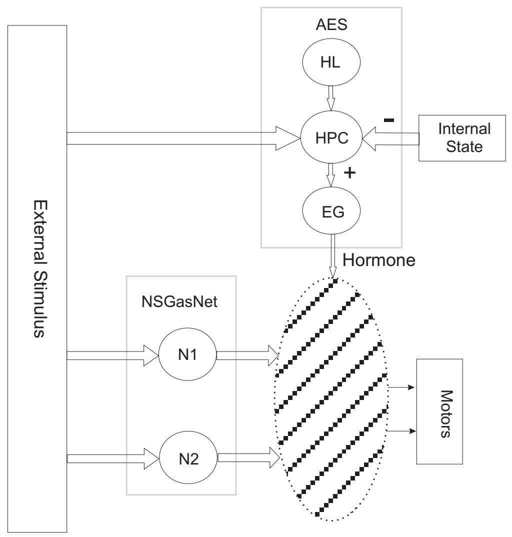


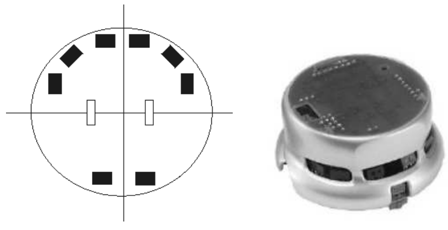
Fig. 1. Artificial Homeostatic System overview

IV. Towards the Evolution of an Artificial Homeostatic System

There is a consensus that the homeostatic process is strictly connected to the balance of the system or organism and requires some specific sensory receptors specially evolved to detect changes. In the human body, these receptors trigger specific responses in the nervous, immune and endocrine systems, which are the main systems directly linked to the process of homeostasis. It is important to highlight that our work is concerned specifically with neuro-endocrine interactions. For interactions with the immune system, the reader should refer to [16].

In the homeostatic system developed here, an artificial endocrine system is employed as a control system to coordinate two evolved artificial neural networks in a robot autonomous navigation task.

Evolutionary theory proposes that the brain has evolved to control behaviour in order to ensure our survival [17]. Additionally, it is agreed that intelligence manifests itself in behaviour. Thus we must understand behaviour before we can completely understand intelligence [17].



(a) (b)

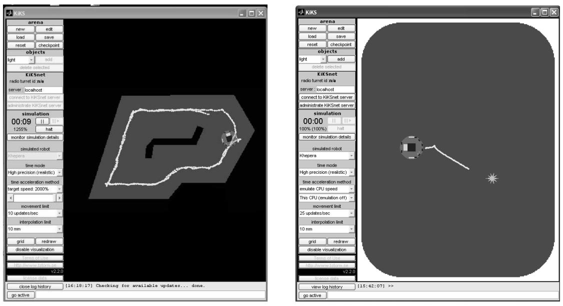
Fig. 2. (a) Displacement of the eight infrared sensors of the Khepera II robot. Six sensors in the front and two sensors in the back; (b) Real Khepera II Robot

The use of evolution in the design of an AHS justifies itself for the advantages of evolving artificial neural networks against previous training, as stated by Yao [26] and others [27][28][29]. The NSGasNet uses evolutionary computation techniques for the adjustment of size, topology and parameters of the network. Moreover, in applications of control of autonomous robotics agents, the original GasNet presents evolution time and performance superior to techniques that employ the classical models of neural networks [24][30][31][32]. It is important to stress that this work presents the first application of the NSGasnet model in robot autonomous navigation. Nonetheless, this model showed to be superior than the original GasNet model in other tasks as stated in the work of Vargas *et al*. [25].

Figure 1 gives the system overview illustrates the interaction of the artificial endocrine system (AES) with the artificial neural networks (N1 and N2), the interactions of both of them with the environment (external stimulus) and the artificial agent. The environment is perceived by the artificial neural system, here represented by two NSGasNets, previously evolved to accomplish specific tasks. The output of the networks are then modulated by the presence or absence of hormones, which are influenced by internal and external stimulus to the AES. The responsibility of the hormones are to coherently coordinate, through its concentration levels, the outputs of the networks by choosing how much influence each of them should have in determining the action performed by the system (here the outputs of the networks are directly connected to the motors of the robot, establishing their velocities), aiming at preserving the internal state of the system. This action may cause the external stimulus to change, hence triggering the whole cycle again.

V. Methods

The first set of experiments consisted of a simulated robotic agent that should learn previously two different tasks: explore the scenario while avoiding collisions and chase a light source (related here to a power source). Both tasks were learned through the evolution of the NSGasNets, independently. These two experiments are designed to assess the competency of the NSGasNet model in the autonomous robotics domain, and will also be used as modules of behaviour within the artificial homeostatic system.



(a) (b)

Fig. 3. Evolving scenarios: (a) obstacle avoidance arena and (b) phototaxis arena

A. Khepera Robot and Simulator

The Khepera II is a mini-robot, shown in Figure 2. It has a diameter of 70 mm and is 30 mm high, weighting around 80g. A robot with this reduced size allows the implementation of experiments in a small-size platform and with a low consumption of energy. The robot gets its energy by wire or by its internal batteries, which have an autonomy of 1 hour, approximately; it is sustained by two wheels, responsible for its motion. The wheels have independent electric motors and, by applying different speeds in the wheel, direction adjustments are obtained. The maximum speed of the robot is 1 m/s, and the minimum is 0.08m/s.

The robot has in its basic structure 8 infrared sensors that incorporate emitters and receptors. The sensors measure the environment luminosity (ranging from 50 to 500, 50 being the highest luminosity that can be sensed) and the obstacle distance (ranging from 0 to 1023, the latter being the closest distance to an object). The range of the sensors, related to obstacles, is 10cm, maximum. The time of data acquisition of each sensor is 2.5ms and, at each 20ms, a complete measure is done. The output of each measure is an analogic value converted to a 10-bit number.

Some external factors, like the presence of incandescent lamps, can cause interference in the measurements of the distance sensors. This is due to the fact that the same sensor is used for both tasks (distance and luminosity detection). For example, the distance sensor emits an infrared ray and calculates the distance to the obstacle based on the time this ray took to left the emitter and return to the receptor. However, if there is an incandescent lamp nearby, its luminosity will cause interference on the received rays, changing the sensorial reading. Though, as the luminosity sensors use the infrared range, we must apply lamps that are on the infrared zone. So, it is important to take care when developing an experiment. This fact appears to have been noted by the manufacturer, and the new Khepera series, Khepera III, have distance sensors based on ultrasound, being immune to light interference [33].

The simulations were carried out using a software named KIKS [34]. It is a robot simulator that reproduces the sensory behaviour of the real robot, which facilitates the migration from the virtual environment to the real environment. It was developed to cope with the KMatLab interface, which was created to control the Khepera Robot from the MatLab environment [33].

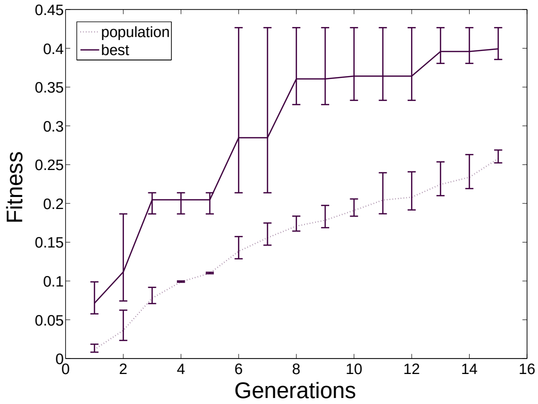


Fig. 4. Obstacle Avoidance: Mean and Best Fitness

B. NSGasNet Evolution

The evolution of the networks used a distributed genetic algorithm [35][36]. Individuals of the population, with random genomes at the beginning, are arranged in a 4x4 toroidal grid, with all fitnesses evaluated. In a breeding event, a random point in the grid is chosen, and a mating pool together with its 8 neighbours is formed. A single parent is then chosen through rank-based roulette selection, and the mutation operators are applied, producing a new individual, which is evaluated and placed back in the mating pool in a position determined by inverse rank-based roulette selection. No crossover is used. A generation is defined as sixteen breeding events, and the evolutionary algorithm runs for a maximum of 50 generations.

There were two mutation operators, each applied in 10% of the gene locus. In the first operator, only for continuous variables, each locus was altered by an amount in a $[-10, 10]$ range. In the second operator, the randomly chosen gene locus is altered to a new value that can be anything belonging to the whole range ([0,99]), in a uniform distribution.

For further details about the genetic algorithm and the mutation operators, the reader should refer to [24].

C. Evolution of an Obstacle Avoidance Behaviuor

For the straight motion with obstacle avoidance behaviour, the network had 4 inputs: the most stimulated left distance sensor, the most stimulated frontal distance sensor, the most stimulated right distance sensor and the most stimulated backward distance sensor. Two different neurons were considered to be output neurons, so the network consisted of 6 neurons. The output neurons corresponded to the motor neurons, responsible for driving the robot. The fitness function (Equation 12) and the training scenario (Figure 3(a)) were inspired by the work of [17]:

$$\phi = V(1 - \sqrt{\Delta v})(1 - i) \tag{12}$$

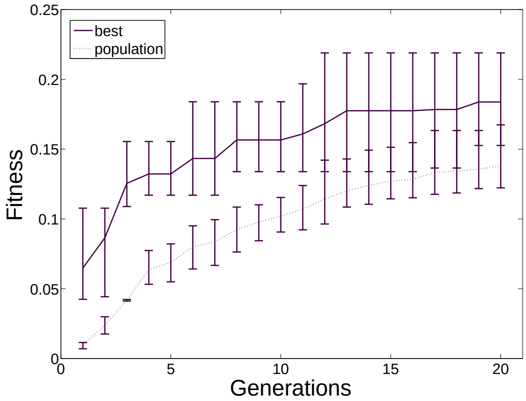


Fig. 5. Phototaxis: Mean and Best Fitness

where V is the sum of the rotation speed of the wheels (stimulating high speeds), Δv the absolute value of the algebraic difference between the value of the speeds of the wheels (stimulating forward movement), and i is the normalized value of the distance sensor of highest activation (stimulating obstacle avoidance).

Figure 3(a) illustrates the behaviour of a higher fitness individual in the training scenario, and Figure 4 shows the evolution of population fitness. Note that, as the robot is always close to an obstacle, and consequently always a distance sensor is stimulated, the fitness value is not close to its maximum. A trial is considered to be 2000 iterations of the control algorithm. At the end of each trial, the robot is randomly replaced in the scenario.

D. Evolution of a Phototaxis Behaviour

The network structure for the phototaxis behaviour was similar to the obstacle avoidance network. Only the distance sensors were replaced by the luminosity sensors. The training scenario consisted of a squared arena, where the robot had an initial, fixed position at the beginning of each trial. The light was randomly positioned relatively far from the robot, but it could perceive it anywhere in the scenario. A trial is restricted to the robot exploring the scenario chasing the light. Whenever it was “captured”, the robot is placed back at the starting point and the light is randomly repositioned. Each trial corresponds to 2000 simulation steps. The fitness function is presented in Equation 13. The i parameter, referred to sensory activation, is maximized when the robot is near to the light (due to the sensory structure of the robot, described in Section V-A). Note that the function is quite similar to the previous one. However, the component that stimulated forward movement is now omitted. This means that the robot could stay turning around the light and yet have a higher fitness. Figure 3(b) illustrates the behaviour of an individual which presents a high fitness in the training scenario, and Figure 5 shows the evolution of population fitness.

$$\phi = V(1 - i) \tag{13}$$

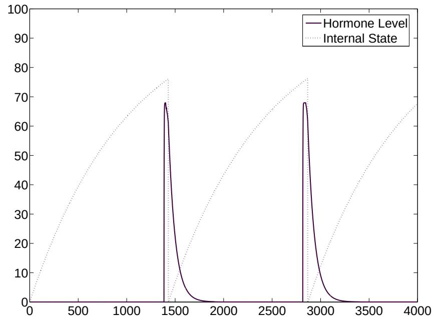


Fig. 6. Hormone and Internal State Levels

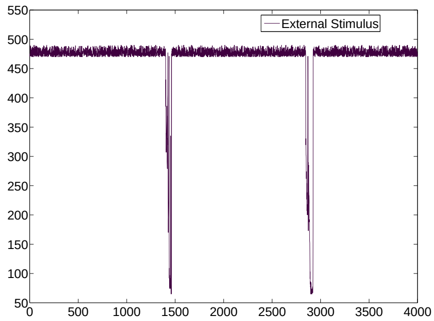


Fig. 7. External Stimulus

VI. Results

A. Experiments with a Simulated Robotic Agent

In the experiment, the robot begins to explore the arena, controlled by the obstacle avoidance network, while its need for recharging its battery remains low. The AES was designed to manage the internal state “desire to recharge” of the robot. As this necessity grows, the production of the hormone related to the decrease of energy causes the switching of the artificial neural network to be employed, gradually replacing the behaviour of exploration by the behaviour of searching the light (phototaxis). After recharging its battery (symbolised by staying closer to the light), and the consequente decrease in the related hormone level, the robot returns to its original behaviour of exploration.

Figure 6 shows the hormone and the internal state levels and Figure 7 shows the external stimuli of the frontal sensor during 4000 iterations or navigation steps. The hormone and internal state values range from 0 to 100 units at most. Note that when the hormone level increases above a predetermined threshold, the robot stops exploring the scenario and starts chasing the light (illustrated by the inferior peaks of light readings in Figure 7). This confirms the influence of the hormone level over the robot’s autonomous behaviour. The parameter values adopted in this simulation are: β = 0.001; α = 0.005; T = 70.0; λ = 100; ω = 65.0; and θ = 75.0, and were defined empirically.

B. Experiments with a Real Robotic Agent

The main idea of this experiment is to use the same control system developed for the simulated robotic agent in a real robotic agent. Due to the robustness of the evolved networks no adjustments were required to cross the reality gap.

Figure 8 shows a complete trajectory in an environment surrounded by walls, with a light source in the corner. The robot starts exploring the scenario while avoiding collisions. When its internal state level exceeds a predetermined limit, the artificial endocrine system stimulates the production of hormone, thus increasing the hormone level. This will cause the robot to follow the light (to recharge its battery). As soon as the robot reaches the light, the hormone level starts to decrease and the robot switches back to the exploration behaviour. The partially evolved AHS was able to keep the internal state of the robot within limits, thus proving its homeostasis.

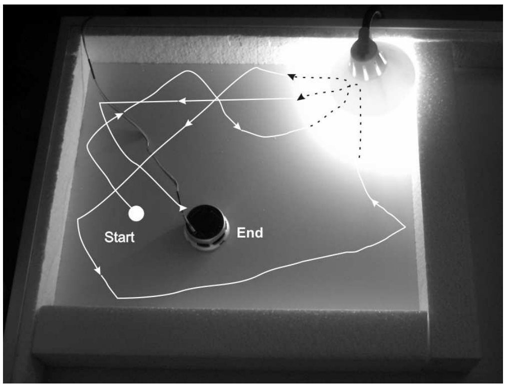


Fig. 8. Complete trajectory of the real robot controlled by the new AHS

VII. Discussion and Future Works

This work is a first step towards the evolution of a previous version of an artificial homeostatic system (AHS), employing an artificial endocrine system (AES) and a more biologically plausible artificial neural network (ANN). The adopted ANN is an extended version of the original GasNet model, named NSGasNet, which has no spatial constraints in its design. The new AHS was applied to solve distinct robot tasks that require coordination of basic reactive behaviours.

The new system explored neuro-endocrine interactions and it was shown that multiple coordination of behaviours could be successfully achieved by the new robot controller. It is important to stress that the coordination is not fully pre-designed, the neuro-endocrine interactions dynamically adapt itself to the environment condition, given the internal state of the robot. The obtained autonomous controller presented good performance both in simulated and real environments and robustness when crossing the frontier between simulation and real application (reality gap) is a mostly desired feature.

The NSGasNet was designed to be evolved. Related works have suggested that the evolution of these networks is considerably faster and more robust than conventional supervised training of recurrent or feedforward multilayer architectures of artificial neural networks. As one of the main difficulties confronted when evolving robot controllers is the time needed to evaluate the individual performance, NSGasNets should be considered in future works within the evolutionary robotics domain.

To achieve higher levels of automation, the parameters of the artificial endocrine system should also be evolved, allowing the agent to self-determine its internal thresholds when interacting with the environment. Moreover, it is believed that this could enable the system to deal with internal and external disruptions. Future work will include this approach.

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