A Multiple Hormone Approach to the Homeostatic Control of Conflicting Behaviours in an Autonomous Mobile Robot

Renan C. Moioli, Patricia A. Vargas and Phil Husbands

***Abstract*— This work proposes a biologically inspired system for the coordination of multiple and possible conflicting behaviours in an autonomous mobile robot, devoted to explore novel scenarios while ensuring its internal variables dynamics. The proposed Evolutionary Artificial Homeostatic System, derived from the study of how an organism would self-regulate in order to keep its essential variables within a limited range (*homeostasis*), is composed of an artificial endocrine system, including two hormones and two hormone receptors, and also three previously evolved NSGasNet artificial neural networks. It is shown that the integration of receptors enhance the system robustness without incorporating to the three evolved NSGasNets more a priori knowledge. The experiments conducted also show that the proposed multi-hormone evolutionary artificial homeostatic system is able to successfully coordinate a multiple and conflicting behaviours task, being also robust enough to cope with internal and external disruptions.**

I. INTRODUCTION

One of the key and most challenging issues when developing autonomous systems which are able to adapt to unforeseen situations and disruptions is how to coordinate conflicting behaviours and to operate and remain adapted within a viability zone.

One possible approach is to modify the weights of an artificial neural network according to a performance criteria at each set of iterations (hence modifying the response of the network), with promising results being reported [1][2][3]. Another proposal, the so-called behaviour-based approach, is to try to coherently coordinate pre-determined behaviours, using some kind of specialist system to switch among them [4][5].

In this work we present a further approach, which derives from the study of how an organism would self-regulate in order to keep essential variables within a limited range. This search for an internal equilibrium, known as *homeostasis* [6][7], has motivated the synthesis of autonomous systems in mobile robotics [2][8][9][10][11]. For instance, Dyke & Harvey [8][12] have pointed out that in order to understand real or artificial life it is necessary to first understand the conceptual framework and basic mechanisms of homeostasis.

The architecture proposed here is an extension of previous work by Vargas *et al.* [9][11] and Moioli *et al.* [10][13]. It is comprised of two main modules, an artificial endocrine system (AES), which is synthesized by means of evolution (under two different performance criteria), and three evolved spatially unconstrained GasNet models, named non-spatial GasNets (NSGasNets) [14]. The AES is responsible for coordinating the output of the network, thus both modules are dedicated to the control of actions in autonomous navigation tasks giving rise to an automatic mechanism of coordination of distinct and possibly conflicting behaviours.

Apart from being concerned with the development of a more biologically plausible model of behaviour coordination [15], we also tackled the reactive and non-reactive behaviour issue [16], considered to be fundamental while devising intelligent systems within the context of embodied cognitive science. According to Arkin (1998) [4], purely reactive systems and purely non-reactive systems have limitations when considered in isolation. There is evidence that hybrid versions, which incorporate both systems, are observed in nature, showing hierarchical organization and action-reaction planning.

The experiments conducted have shown that the proposed multi-hormone evolutionary artificial homeostatic system (EAHS) is able to successfully coordinate multiple and conflicting behaviours, being also robust enough to cope with internal and external disruptions.

This paper is organized as follows: section II presents the basis of the approach adopted in this work, together with the details of our proposal for a multiple hormone evolutionary artificial homeostatic system. Section III describes the experiments undertaken and their implementation procedures. Section IV covers the simulation results of the artificial homeostatic system subject to a novel environment and some degrees of disruption. Section V closes the paper with final remarks and some directions for future investigation.

II. MUTILPE HORMONE APPROACH - THE FRAMEWORK

Similar to previous models of the evolutionary artificial homeostatic system (EAHS) [9][10][11][13], the EAHS proposed in this paper is particularly inspired by neuro-endocrine interactions in biological organisms. The basis for these interactions comes from the production and release by endocrine glands of chemical substances called hormones, that can affect the nervous system, which in turn can transmit nerve impulses affecting the production and secretion of hormones, thus establishing a control loop mechanism. The main objective of this interface is to maintain homeostasis, metabolism and reproduction in the organism.

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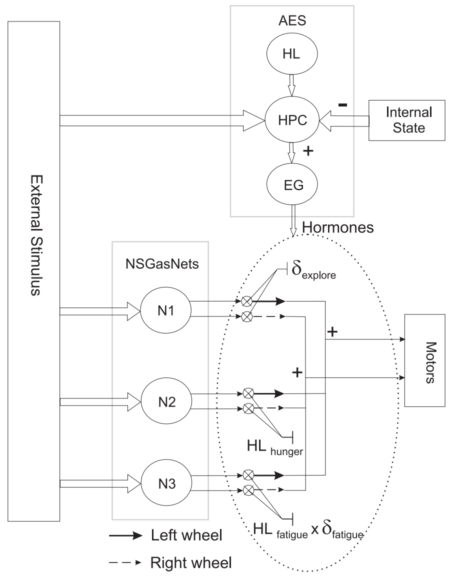


Fig. 1. The basic framework of the Evolutionary Artificial Homeostatic System (EAHS).

Hormones are released in the blood stream and therefore can reach almost any cell in the organism. Each cell in our organism has protein molecules embedded in either the plasma membrane or cytoplasm, named receptors, which will mediate the cell response to specific hormones. The presence of receptors is vital to control these cellular responses to the signalling promoted by assorted types of hormones. Hormones also act as ligand (from the Latin word *ligare* = to bind) while binding to receptors.

Vargas et al. (2008b) [11] was the first to present an EAHS model incorporating hormone receptors. The current paper reports work that extends the approach by increasing the number of ANNs, hormones and receptors and incorporating new rules that govern the interaction between the AES and the ANNs.

Basically, the EAHS is composed of an artificial endocrine system (AES) employing two hormones, three separate NSGasNets (to be described later) and two kinds of hormone receptor. The additional mediation provided by the receptors is intended to enhance the system robustness without explicitly incorporating more *a priori* knowledge into the three evolved NSGasNets. The principal aim is to achieve the control of conflicting behaviours leading to more stable performance of the system as it will be presented on Section IV. Figure 1 shows an overview of the EAHS.

The AES consists of three main modules: hormone level (HL), hormone production controller (HPC), and endocrine gland (EG). HL holds 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 to external stimulation; and the endocrine gland receives inputs from the HPC, being responsible for producing and secreting hormones when required. The hormone production HP_i of the ith hormone is updated as follows:

$$HP_i(t{+}1) = \begin{cases} 0,\ if\ IS_i < \theta_i \\ (100 - \%ES) \times \alpha_i(Max(HL_i) - HL_i(t)), \\ \text{otherwise} \end{cases} \tag{1}$$

where θ is the target threshold of the internal state *IS*; ES is the external stimulus; α is the scaling factor; HL is the hormone level; and t is the discrete time index. If the internal state *IS* is greater than or equal to a target threshold, 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, hormone production will cease. The internal state *IS* is governed by:

$$IS_i(t{+}1) = \begin{cases} 0, if\ (ES \geq \lambda_i)\ and\ (HL_i \geq \omega_i) \\ IS_i(t) + \beta(Max(IS_i) - IS_i(t)), \quad \text{otherwise} \end{cases} \tag{2}$$

where λ and ω are pre-determined thresholds associated with *ES* and *HL*, respectively, and β is a gain value for the rate of change of the internal state. The hormone level *HL* represents the amount of hormone stimulating the artificial neural network (ANN), and is a function of its current value and of the amount of hormone produced:

$$HL_i(t+1) = HL_i(t) \times e^{-1/T_i} + HP_i(t) \tag{3}$$

where T is the half-life variable.

The three NSGasNets (N1, N2 and N3 in Figure 1) are previously and separately evolved to accomplish three distinct and possibly conflicting behaviours. The NSGasNet is a discrete-time artificial recurrent neural network derived from the spatially embedded original GasNet model. The NSGasNet is spatially unconstrained and was shown to present superior performance in terms of evolvability when compared to the original GasNet model on a pattern generation task and on a delayed response robot task [14][17] (the following Section III describes with further details the NSGasNet model).

The outputs of the NSGasNets are modulated by the hormone levels $HL_{fatigue}$ and HL_{hunger} (Eq. 3), mediated when necessary by two hormone receptors sensitivity variables, $\delta_{explore}$ (Eq. 4) and $\delta_{fatigue}$ (Eq. 5), giving rise to the dynamical coordination of behaviours. Basically, the AES is responsible for producing and secreting two types of hormones, each associated to a different internal state of the agent, $IS_{fatigue}$ and IS_{hunger}, respectively. In our model, the $IS_{fatigue}$ of the artificial agent (Eq. 2) stands for the fatigue meter reading and the IS_{hunger} stands for the inverse of the battery meter reading, which implies that the lower the battery level, the higher the IS_{hunger}.

The levels of the two hormones together with the external environmental stimulus are responsible for determining the sensitivity of the receptors. This sensitivity, represented by the δ values, will in the end dictate the real output of three

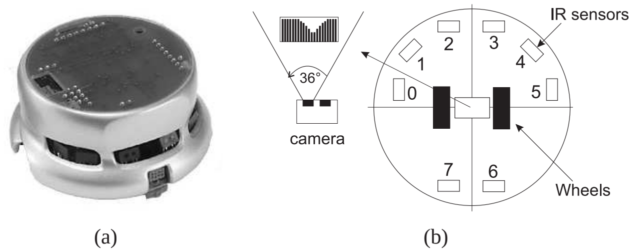


Fig. 2. Real Khepera II robot (a) and its schematic representation, including the IR sensors and the camera (b).

NSGasNets and consequently the coherent coordination of the agent's behaviour.

$$\delta_{explore} = (1 - HL_{fatigue} \times lightSensor) \times (1 - HL_{hunger}) \quad (4)$$

$$\delta_{fatigue} = (1 - lightSensor) \times (1 - HL_{hunger}) \quad (5)$$

$$lightSensor = 1 - \frac{[min(lightSensorReadings) - MinR]^3}{(MaxR - MinR)^3} \quad (6)$$

From Eq. 6 $min(lightSensorReadings)$ is the most stimulated light sensor value. The parameters $MinR$ and $MaxR$ assume the values 65 and 450, respectively. The parameters $MinR$ and $MaxR$ were devised empirically and were specific for the chosen tasks [11].

It is important to highlight that the variables δ, representing the receptor sensitivity, are driven by the light source radiance, thus regulating the agent's response to the presence of the hormones. From a biological perspective, one can understand this sensitivity to the light source as if a fictitious hypothalamus releases a neurotransmitter while sensing the presence of light. This neurotransmitter would then bind to the receptor changing the agent's sensitivity to the hormone level mediated by the proximity of the light source.

III. Methods

A simulated Khepera II robot equipped with an internal battery meter and with an internal fatigue meter has to perform three coupled but distinct tasks: to explore the environment while avoiding obstacles, to search for a light source when its fatigue meter is high (the light source indicates the location of the resting place) and to search for a black stripe in the arena when its battery meter is low (the black stripe indicates the location of the charging area).

The robot has two wheels with independent electric motors, 8 infrared sensors and a camera (see Fig.2). The sensors measure the environmental luminosity (ranging from 65 to 430 - 65 being the highest luminosity that can be sensed) and the obstacle distance (ranging from 0 to 1023 - the latter value represents the closest distance to an object). The camera provides a 36 degrees, 64 pixels gray-scale horizontal vision of an image placed in front of it. These 64 pixels are grouped into 3 mean inputs for the system: the mean value of pixels $0 - 13$ representing the left reading, the mean value of pixels $24 - 39$ representing the central reading and the mean value of pixels $48 - 63$ representing the right reading. The readings range from 50 to 175 - the first value representing the maximum perception of a black stripe. The KiKS Khepera robot simulator was used [18].

The evolution of the entire EAHS was divided in two steps. First, the three NSGasNets are evolved independently employing a distributed genetic algorithm [19][20](one NSGasNet evolved for each task). The AES is evolved thereafter as a coordination module responsible for the swapping of behaviours between the NSGasNets. No crossover is employed. A generation is defined as twenty five breeding events, and the evolutionary algorithm runs for a maximum of 50 generations. The fitness criteria are specific for each task. There are two mutation operators applied to 10% of the genes. The first operator is only for continuous variables. It produces a change at each locus by an amount within the $[-10, +10]$ range. For the second mutation operator, designed to deal with discrete variables, a randomly chosen gene locus is replaced with a new value that can be any value within the $[0, 99]$ range, in a uniform distribution. For further details about the application of the genetic algorithm to the evolution of GasNet models, the reader should refer to [21].

A. Evolving the NSGasNets

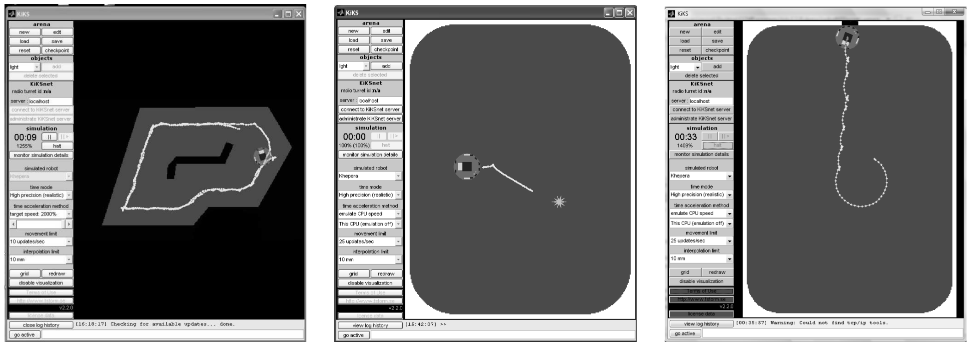
GasNets are a class of artificial neural networks that makes use of an analogue of *volume signaling* in the human brain, whereby neurotransmitters freely diffuse into a relatively large volume around a nerve cell, potentially affecting many other neurons [22]. They are essentially standard discrete-time recurrent artificial neural networks augmented by a chemical signaling system between neurons using diffusing virtual gases which can modulate the response of other neurons.

A number of GasNet variants inspired by different aspects of the real nervous systems have been explored in evolutionary robotics [16] as controllers for autonomous mobile robots. They have been shown to be significantly more evolvable (i.e., in terms of speed of evolution) than other types of artificial neural networks for a variety of robot tasks [21][17][23]. The model used here is the non-spatial GasNet, or NSGasNet [14]. The transfer function of node i in the network is given by Eq. 7:

$$O_i(t) = tanh\left[K_i(t)\left(\sum_{j \in C_i} w_{ji} O_j(t-1) + I_i(t)\right) + b_i\right] \quad (7)$$

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 $K_i(t)$ is a gain whose value is changed by the gases, thus causing modulation of the transfer function.

There are three NSGasNets previously and separately evolved to accomplish each of the three distinct and possibly conflicting behaviours, namely N1, N2 and N3 (Figure 1).



(a) (b) (c)

Fig. 3. Scenarios for the evolution of NSGasNets. Obstacle avoidance (a), phototaxis (b) and black stripe search (c).

The networks 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 [21]. The NSGasNet model has six variables associated with each node plus one modulator bias ($Mbias_{ij}$) for each node, plus task-dependent parameters. The modulator bias is responsible for dictating to what extent the node could be affected by the gases emitted by all the other nodes. Therefore, here, networks N1, N2 and N3 (Figure 1) will have six Mbias for each node. For a more detailed explanation of the mechanisms of GasNets and NSGasNets, the reader should refer to [14][21].

Network N1 (Figure 1), which is responsible for the exploration with obstacle avoidance behaviour, has four inputs: the most stimulated left, right, front and back distance sensors. Two additional neurons were considered to be output neurons, so the network consists of six neurons. The output neurons correspond to the motor neurons. The fitness function (Eq. 8) and the training scenario were inspired by the work of Nolfi & Floreano [16]:

$$\phi = V(1 - \sqrt{\Delta v})(1 - i) \tag{8}$$

where V is the sum of the instantaneous rotation speed of the wheels (stimulating high speeds), Δv the absolute value of the algebraic difference between the speeds of the wheels (stimulating forward movement), and i is the normalized value of the distance sensor of highest activation (stimulating obstacle avoidance). A trial is considered to be 800 iterations of the control algorithm. At the end of each trial, the robot is randomly repositioned in the environment.

The structure of network N2, which is responsible for the phototaxis behaviour, is similar to the obstacle avoidance network. Only the distance sensors were replaced by the light sensors. The training environment consists of a square arena, where the robot has a fixed initial position at the beginning of each trial, and the light sources can appear in different parts of the scenario, close enough for the robot to perceive it. Each trial corresponds to 800 simulation steps. The fitness function is given by Eq. 9:

$$\phi = V(1 - i) \tag{9}$$

where the parameter i (referring to sensory activation) is minimized when the robot is near the light, due to the sensory structure of the robot.

Network N3 is devoted to the search for black-stripe behaviour and has a structure similar to the previous ones, but has three inputs related to the camera sensors. The training scenario (Figure 3(c)) consists of the same previous square arena, with a black stripe on the top side of it. The robot has an initial random position and orientation in relation to the stripe, but always the same distance to it. In each trial, the fitness is scored similarly to the fitness of network N2 (Eq. 9), but now the parameter i (referring to sensory activation) is minimized when the robot is near to the black stripe, and not to the light source anymore.

B. Evolving the Artificial Endocrine System

The genotype of the AES to be evolved is described by 8 parameters (Eqs. 1-3): $\omega_{fatigue}$, $\theta_{fatigue}$, $\alpha_{fatigue}$, $T_{fatigue}$, ω_{hunger}, θ_{hunger}, α_{hunger}, T_{hunger}. The parameters $\beta_{fatigue} = 0.005$, $\beta_{hunger} = 0.008$, $\lambda_{fatigue} = 101.5$ and $\lambda_{hunger} = 56.25$ were pre-defined. $\beta_{fatigue}$ is the internal state (IS) growing rate associate to the behaviour of resting, and β_{hunger} is the IS growing rate associate to the behaviour of charging (Eq. 2). Remember that in our model, the $IS_{fatigue}$ of the artificial agent (Eq. 2) stands for the fatigue meter reading and the IS_{hunger} stands for the inverse of the battery meter reading, which implies that the lower the battery level, the higher the IS_{hunger}. θ is the *IS* level threshold, above which hormone production starts at a rate dictated by α. T is simply the half-life of the hormone.

As the robot is always moving and getting "tired", and the battery is always discharging, $\beta_{fatigue}$ and β_{hunger} both should have predefined values associated with them. Similarly, the minimum camera vision intensity above which the robot could recharge (λ_{hunger}) and the minimum light intensity above which the robot could rest ($\lambda_{fatigue}$) should also be predefined. Remember that the presence of the black stripe here indicates a charging area and the presence of a light source indicates a resting area.

Evolution starts with the robot exploring the arena, controlled by the obstacle avoidance network. The AES is designed to sense the internal states of the robot (e.g. fatigue

	$HL_{fatigue}$, HL_{hunger}			
	high, high	high, low	low, high	low, low
$lightsensor$ high	$\delta_{explore}$ more sensitive, $\delta_{fatigue}$ less sensitive	$\delta_{explore}$ less sensitive, $\delta_{fatigue}$ more sensitive	$\delta_{explore}$ less sensitive, $\delta_{fatigue}$ less sensitive	$\delta_{explore}$ more sensitive, $\delta_{fatigue}$ less sensitive
dominant NSGasNet	N2	N3	N2	N1
$lightsensor$ low	$\delta_{explore}$ less sensitive, $\delta_{fatigue}$ less sensitive	$\delta_{explore}$ more sensitive, $\delta_{fatigue}$ less sensitive	$\delta_{explore}$ less sensitive, $\delta_{fatigue}$ less sensitive	$\delta_{explore}$ more sensitive, $\delta_{fatigue}$ less sensitive
dominant NSGasNet	N2	N1	N2	N1

TABLE I

SUMMARY OF HORMONE/RECEPTOR INTERACTION AND THE CORRESPONDING NETWORK WHICH MAY BE MORE EXPRESSIVE. FOR EACH HORMONAL ($HL_{fatigue}$ OR HL_{hunger}) AND ENVIRONMENTAL (*light sensor*) SITUATION, THE CORRESPONDING RECEPTOR STATE ($\delta_{explore}$ OR $\delta_{fatigue}$) IS PRESENTED.

and hunger). If any of the internal states goes above 95, on a 0 to 100 scale, the robot is considered to be "dead". To obtain a successful performance the robot should be able to efficiently switch between three distinct and conflicting behaviours, i.e., to explore the arena while avoiding collisions, to search a place to rest when its fatigue meter is high and to search for the battery charger when its battery level is low. This switching of behaviour is expected to be due to the production of the hormone related to the decrease of battery level or due to the production of the hormone related to the increase of the fatigue level.

There is a pre-established priority encoded on the AES between the three behaviours which states that the search for a battery charger has the highest priority amongst the other behaviours. In this sense, after charging the battery (associated with being close to the black stripe), which is the mandatory behaviour, and resting (associated with being close to the light), and the consequent decrease in each of the related hormone levels, the robot should switch to its original exploratory behaviour.

As stated previously, the outputs of the NSGasNets are modulated by the hormone levels and mediated by receptors sensitivity variables δ when necessary as follows:

$$Output_{N1} = Output_{N1} \times \delta_{explore} \tag{10}$$

$$Output_{N2} = Output_{N2} \times HL_{hunger} \tag{11}$$

$$Output_{N3} = Output_{N3} \times HL_{fatigue} \times \delta_{fatigue} \tag{12}$$

Table I summarizes the hormone/receptor interaction relatively to the robot position in the scenario and the correspondent network which may be more expressive. For each hormonal ($HL_{fatigue}$ and HL_{hunger}) and environmental (*light sensor*) situation, the correspondent receptor state ($\delta_{explore}$ and $\delta_{fatigue}$) is presented.

Two fitness functions were employed during evolution and thereafter separately investigated, as it will be discussed in Section IV. Eq. 13 shows the first fitness function and Eq. 14 shows the second fitness function, which resembles the fitness function adopted by [24].

$$\phi_1 = V(1-i)t/M \tag{13}$$

where $V \in [0,1]$ is the absolute value of the sum of the instantaneous rotation speed of the wheels (stimulating forward movement), i is the normalized value of the distance sensor of highest activation (stimulating obstacle avoidance), t is the number of iterations in which the robot remains alive and M is the maximum number of iterations a trial can have. Thus, a good performance would consist of adjusting the hormones production thresholds and growth rate in order to allow maximum exploration interspersed with charging and resting steps. Due to the environment set-up, the robot could not stay close to the black stripe when performing exploration of the environment, as the black stripe is itself located close to the wall.

$$\phi_2 = V(1-i) + Bonus_{hunger} + Bonus_{fatigue} \tag{14}$$

where $V \in [0,1]$ is the absolute value of the sum of the instantaneous rotation speed of the wheels (stimulating forward movement), i is the normalized value of the distance sensor of highest activation (stimulating obstacle avoidance); $Bonus_{hunger} = 0$ if the robot dies due to the battery level becoming too low or $Bonus_{hunger} = 10$ if the robot is successful in charging when needed; $Bonus_{fatigue} = 0$ if the robot dies due to a high fatigue level or $Bonus_{fatigue} = 10$ if the robot is successful in resting when needed. Thus, the main difference from the previous equation (Eq. 13) is that now the robot receives a bonus when able to accomplish either of the tasks (charging and resting), presenting an incremental shaping scheme.

IV. RESULTS

The first experiment analyses the resulting behaviour of the system when evolved under different performance criteria, i.e. two distinct fitness functions. The second experiment

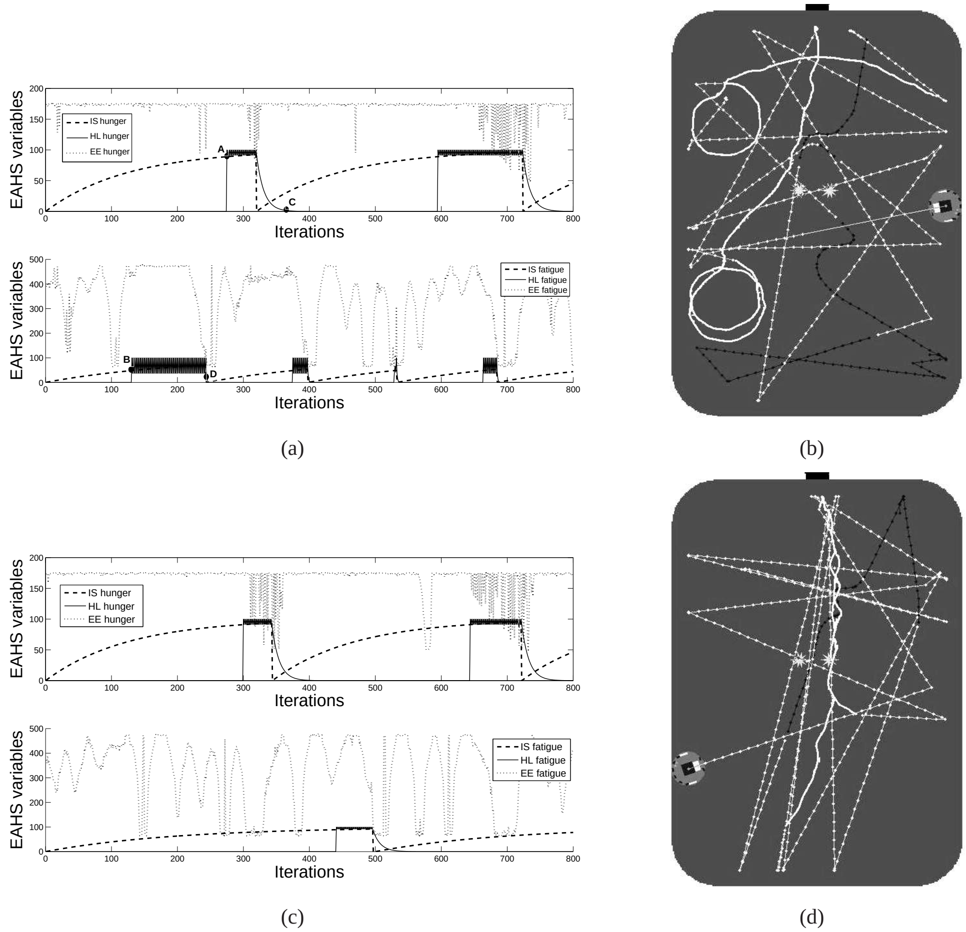


Fig. 4. EAHS variables and robot trajectory for ϕ_1 (a) and ϕ_2 (b). The white doted lines indicate when both hormone levels in the robot are low (exploring behaviour), white lines indicate that HL_{hunger} is high (charging behaviour) and black doted lines indicate that $HL_{fatigue}$ is high (resting behaviour).

investigates the system performance when exposed to internal disruptions, conflicting situations and a changed environment. The experiments are an attempt to verify the performance of the EAHS in terms of the homeostatic regulation process and robustness to changes in environmental conditions. It is expected that such an endeavour will promote the automatic adjustment of variables under regulatory control.

A. Experiment 1

The first experiment is devoted to analyzing the evolution of the multi-hormone EAHS according to fitness functions ϕ_1 and ϕ_2. The main objective is to observe whether or not the system is able to evolve the EAHS parameters in such a way that a reasonable behaviour coordination arises, ensuring the exploration of the scenario while maintaining the internal states of the agent ($IS_{fatigue}$ and IS_{hunger}) within limits. Remember that although the equations that define the sensitivity of the receptors were set by hand, it is the EAHS evolved parameters which will dictate the final global behaviour of the agent, directly modulating the output of the NSGasNets by means of the production of the hormones mediated by hormone receptors.

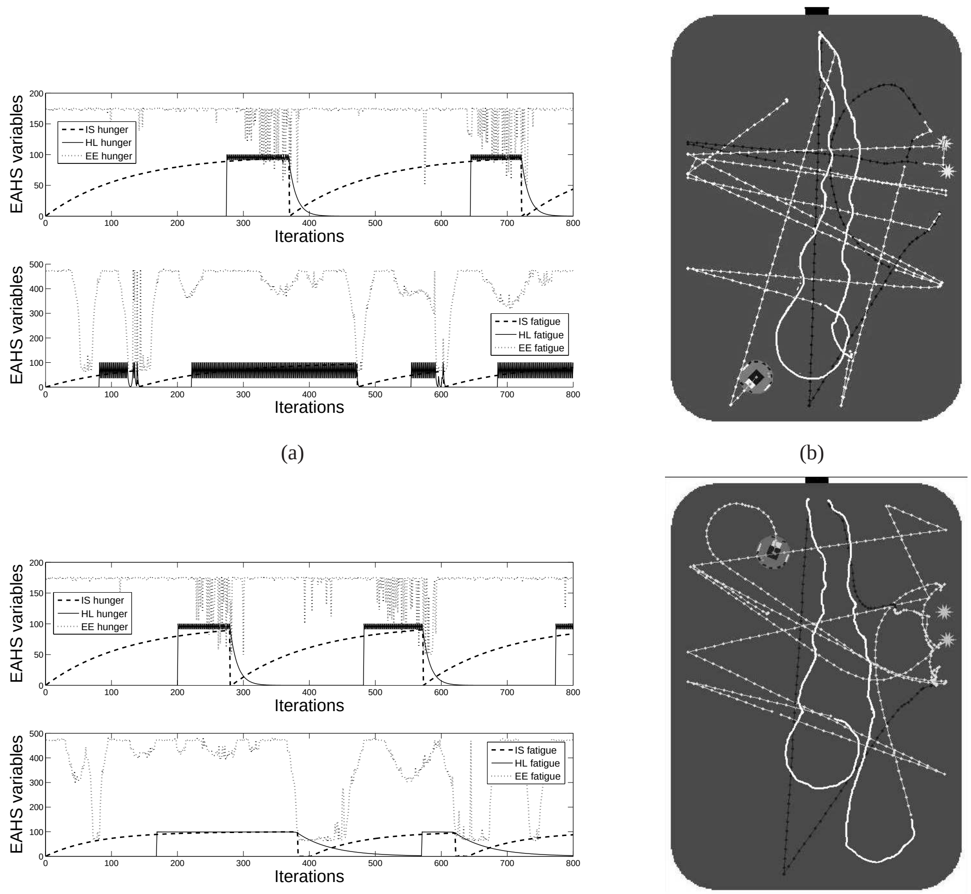
Figures 4(a) and 4(c) present the EAHS variables dynamics and Figure 4(b) and 4(d) show the robot trajectory for each of the fitness functions, ϕ_1 and ϕ_2, respectively. The best evolved individual phenotypes for fitness function ϕ_1 and ϕ_2 are presented on Table II. Notice that in both cases the robot is able to explore the scenario avoiding collisions (white doted lines) while charging (white lines) or resting (black doted lines). The swapping amongst the behaviours could also be spotted by the inferior peaks of the camera and light sensors on Figures 4(a) and 4(c)) which mean the proximity of the robot to each charging and resting area, respectively. Observe that both internal states IS_{hunger} and $IS_{fatigue}$ grow until they overtake the correspondent θ value (points A and B). The hormone production is then started. When the correspondent external stimulus EE is greater than the parameter λ and the hormone level is superior than ω, the internal state tends to 0 (points C and D). Therefore, this results show that the multiple hormone coordination succeeds in combining and switching the influence of each network in the global behaviour for both performance criteria (ϕ_1 and ϕ_2).

Some qualitative differences can be observed, considering the phenotypes for ϕ_1 and ϕ_2. In the former case, the robot approaches the light more times than it approaches the black-stripe, i.e. the hormone related to the *resting* behaviour is

	$\omega_{fatigue}$	$\theta_{fatigue}$	$\alpha_{fatigue}$	$T_{fatigue}$	ω_{hunger}	θ_{hunger}	α_{hunger}	T_{hunger}
ϕ_1	67	48	0.0841	1	54	89	0.0761	11.1
ϕ_2	67.5	89	0.0811	11.1	78.5	91	0.0871	11.1

TABLE II

EAHS EVOLVED PARAMETER VALUES FOR FITNESS FUNCTIONS ϕ_1 AND ϕ_2 IN EXPERIMENT 1.



(a) (b)

(c) (d)

Fig. 5. EAHS variables and robot trajectory for ϕ_1 (a) and ϕ_2 (b), when presented to internal and external disruptions. The white doted lines indicate when both hormone levels in the robot are low (exploring behaviour), white lines indicate that HL_{hunger} is high (charging behaviour) and black doted lines indicate that $HL_{fatigue}$ is high (resting behaviour).

released more frequently than the hormone related to the *charging* behaviour. It is important to highlight that the charging behaviour not only grows faster than the resting behaviour but also is encoded as a priority on the EAHS. Furhermore, even with the charging being prioritized by the system's rules, evolution drove the system towards a new sequence of behaviours, i.e. resting more often than charging. Although more experiments have to be carried out in order to see whether this difference is solely due to the difference on the fitness criteria.

B. Experiment 2

Considering the same evolved genotype of both best individuals, the β parameter (associated with the internal state growing rate) is altered in a way that both hormones are released at the same time, creating a conflicting situtation. According to the pre-defined rules, this new scenario would require the system to prioritize the charging behaviour. Moreover, the environment is changed by repositioning the light source (or resting area) against one of the walls of the arena at the right-hand side, aiming at preventing the robot from facing the light by chance. Therefore, this experiment promotes a disruption in the system thus causing conflicting behaviours to occur in parallel (it changes the value of both β parameters, simulating a faster battery discharge and a faster need for resting) as well as a change in the environment.

The new values for the IS growing factors are defined as follows according to each fitness function:

- ϕ_1 - $\beta_{fatigue} = 0.008$, $\beta_{hunger} = 0.008$;
- ϕ_2 - $\beta_{fatigue} = 0.008$, $\beta_{hunger} = 0.013$.

Figures 5(a) and 5(c) present the EAHS variables dynamics and Figure 5(b) and 5(d) show the robot trajectories for each of the fitness functions, ϕ_1 and ϕ_2, respectively.

Similar to what was observed in the previous experiment (Figures 4(a) and 4(c)), the hormone associated with the resting behaviour is produced before the hormone associated with the charging behaviour (Figures 5(a) and 5(c)). However, However, due to the altered environmental characteristics, the robot needs to explore more (i.e., behaviour associated with network N1) while searching for the resting area (i.e. the light source). Meanwhile, the hormone associated with the recharging behaviour is released as well and starts to grow. As a result, the robot starts searching for the battery charging area. When it finds and approaches it, HL_{hunger} decreases and then the robot is able to continue to seek and approach the resting area, signalled by the decrease of $HL_{fatigue}$.

The experiments have shown that the proposed multi-hormone EAHS is able to successfully coordinate a multiple and conflicting behaviours task, being also robust enough to cope with internal and external disruptions.

V. Discussion and Future Work

Relatively recent findings in neuroscience speculate that the nervous system builds upon coordination of previous, simpler behaviours, incrementally increasing its complexity [25]. In this sense, the present work is a step towards the development of a biologically inspired system for the coordination of multiple and possible conflicting behaviours, employing a multiple hormone and hormone receptors approach to the coherent coordination of three previously evolved NSGasNet artificial neural networks.

Each NSGasNet has a different evolved behaviour, N1 performs exploration and obstacle avoidance, N2 moves the robot towards a black stripe in the arena and N3 performs phototaxis. The artificial endocrine system then affects each network output, based on hormone and hormone receptor levels, which reflect the agent's internal and external state. It is important to stress that the evolutionary process is responsible for setting how hormones are produced as well as their half-lives, allowing the system to self determine the resulting behaviour of the robot.

Two different fitness functions were proposed to evaluate the agent. The results indicate that the system robustly evolved under both functions and was able to perform well after being submitted to internal and external disruptions. It has been shown that the coupling between hormone production and hormone receptors is vital to successfully coordinating the multiple conflicting NSGasNet behaviours, hence driving the robot to charge and rest when necessary.

We are currently investigating whether there is a fitness correlation to the evolved behaviour in an attempt to obtain possible insights on its implications to the diversity of solutions obtained and the global performance of the system.

Future work would include the development of a mechanism to automatically establish the rules of interaction between hormones and receptors, continuing the endeavour for the development of homeostatic robot controllers able to deal with conflicting and unforeseen situations in dynamical environments.

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