

## Evolving homeostatic neural controller without depending on initial weight connections

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### Abstract

Adaptation to the initial weight set of a neural network and morphological disruptions is studied in a simple simulated model of phototactic behaviour. To achieve this adaptivity, a homeostatic neural controller is used. A salient feature of the controller is that local plastic adaptive mechanisms work only when neural activations move out of a prescribed region. This idea aims at creating a high dimensional bounded set in phase space that corresponds to neural homeostasis linked to suitable performance. An evolved homeostatic controller shows no dependence on the initial weights and adaptivity to the morphological disruptions. **keywords :** *homeostatic adaptation, learning, plastic neural network, evolutionary robotics*

### 1 Introduction

Homeostatic neural controller has been originally proposed by Di Paolo [1] and is extended to other models in terms of application to a legged robot [2], increasing a sensitivity of the homeostatic neural controller with a different form of a plastic function and variable biases [3], and exploring minimal dynamics of behavioural preference as a model of autonomy [4].

The idea of the homeostatic neural controller is based on an ultrastable system proposed by Ashby [5], which is a system that will tend to change its own configuration plastically whenever stability is lost, until it finds a new internal dynamics which will make the system stable under the new conditions. In the Di Paolo's original work of the homeostatic neural controller inspired by this system, a local plastic adaptive mechanisms that change synaptic weights work only when neural activations move out of a homeostatic region that is defined in advance by a designer. The plasticity keeps working until the activations return to the region. Such a mechanism has been implemented in a neuro-controlled simulated vehicle evolved with a fitness function rewarding phototaxis and the maintenance of neural activations within the homeostatic region. The use of intermittent plasticity in combination

with a selective pressure makes an association between the homeostasis and a desired behaviour. Once the neurocontroller gives rise to behavioural coordination within a given environmental situation that results in internal stability, synaptic weight changes no longer happen. If the situation changes, such as in an inversion of the visual field or some other perturbations, this causes a breakdown of coordination. As this happens, the local adaptive mechanism is activated until it finds a new structure (synaptic weight values) which can sustain the activations within the homeostatic region and re-form the behavioural coordination. As a result, the agent can adapt to perturbations it has never experienced before.

The homeostatic neural controller provides a novel kind of coupling between internal and environmental dynamics. It is not a simple static sensor-motor coupling but rather a dynamical creation of sensor-motor coupling that gives rise to behavioural coordination. However, in the original work, there are several difficulties that should be overcome to shape the notion of dynamical creation view. One is a dependency to the initial weight values which were sensitive parameters as initial configuration of learning. Another is a difficulty of the re-adaptation to environmental situations. The reasons of the difficulties are because a model setting of the plastic rule and the upper- or lower-bound of the weight values tend to make the dynamics converge, and because the homeostasis is not always associated with a desired behaviour. In the original work, only a combination of homeostasis and a desired behaviour is associated using the evolutionary technique. Therefore, some undesired behaviours can also keep homeostasis in neural activations while behaving.

In this paper, we propose an extended homeostatic neural controller and evolutionary ways that can more strongly develop an association between homeostasis and a desired behaviour. As a result, it will be shown that the proposed method can adapt to the various initial weight values and that can re-learn environmental situations.

## 2 Model

Our proposing method is implemented in a simulated mobile agent with a plastic neural controller. The simulated robot is faced with a single light source. The task of the agent is to approach the light source. Different from conventional studies, a set of weights of a neural controller is given randomly at the beginning of a trial. The agent needs to adapt to a new weight set from the experience of a sensory-motor coupling through an interaction with environment.

**Agent.** An agent is modelled as a simulated wheeled robot with a circular body of radius 4 and two diametrically opposed motors. The motors can drive the agent forwards in a 2-D unlimited plane. The agent has four light sensors mounted at angles  $\pm\pi/4, \pm3\pi/4$  radians to the forward direction. Light from point sources impinges on sensors with a local intensity proportional to the source intensity and the inverse of the distance from sensor to source. The model includes the shadows produced by the agent's body.

**Plastic controller.** A fully connected continuous-time recurrent neural network (CTRNN) [6] is used as the agent's controller. The equations are modified from the ordinary form in order to avoid that undesired behaviours, i.e., going away from the light, can generate homeostasis. Therefore, CTRNN needs to have a property that going-away behaviours will cause a same consequence that breaks homeostasis. To realize it, two parameters,  $\alpha$  and  $\beta$ , are added in the equations. The time evolution of the states of neurons is expressed by:

$$\tau_i \dot{y}_i = -y_i + \sum_{j=1}^N \alpha \sin(w_{ji}) z_j(y_j) + \beta + I_i, \quad (1)$$

$$z_i(x) = 1/(1 + e^{-x}), \quad (2)$$

where  $y_i$  represents the cell potential of neuron  $i$ ,  $z_i$  is the firing rate,  $\tau_i$  (range [0.1, 10]) is its time constant,  $I_i$  represents the sensory input, which is given to only sensory neurons, and  $\alpha \sin(w_{ji})$  determines the strength of the connection from the neuron,  $j$ , to  $i$ .  $\alpha$  is a constant given genetically, which decides how much the pre-synaptic neurons can affect post-synaptic neurons.  $\beta$  becomes the equilibrium point unless neither input nor stimulus from the other neurons are given.  $\beta$  is fixed to  $-5$  in this paper. A balance of two parameters,  $\alpha$  and  $\beta$ , become very important, because if  $\alpha$  is too small, the firing rates converge to almost 0, and if it is too big,  $\beta$  does not affect the dynamics so much. Therefore, with appropriate  $\alpha$ , the firing rates converge unless there is enough stimulus from the sensors. and the CTRNN can produce a variety

of behaviours near the light source. The use of this property in combination with an evolutionary technique will prohibit developing the association between going-away behaviours and homeostasis as explained later.

In the previous studies, the firing rate and the synaptic weights tend to converge to a maximum or minimum values where the learning mechanism cannot work anymore or does not cause a qualitative difference. To overcome this problem, the proposed model use the sin function in the effect of weights.

The connection weights between neurons,  $w_{ij}$ , are randomly determined at the beginning of a trial and a plastic mechanism allows for the lifetime modification of the connections. A homeostatic region is described by a plasticity function of the firing rate of the post-synaptic neuron with a parameter,  $\gamma$ . Weights from neuron  $i$  to  $j$  are updated according to :

$$\Delta w_{ij} = \eta_{ij}(1 - z_i)p(z_j), \quad (3)$$

$$p(x) = \begin{cases} 0 & x > \gamma \\ 1 - x/\gamma & \text{else} \end{cases} \quad (4)$$

where  $z_i$  and  $z_j$  are the firing rates of pre- and post-synaptic neurons, respectively,  $\Delta w_{ij}$  is the change per unit of time to  $w_{ij}$ ,  $\eta_{ij}$  is a rate of change (range  $[-1, 1]$ ), which is genetically set for each connection, and  $p(x)$  is the plastic function that defines the homeostatic region. The reason why this is called homeostatic is that if  $z_j$  is more than  $\gamma$ , the weight connection does not change. Otherwise, the plasticity works and the weight connection keeps changing until  $z_j$  is stabilized in the homeostatic region (more than  $\gamma$ ).

## 3 Evolutionary setup

A population of agents is evolved using a rank-based genetic algorithm with elitism. All fixed network parameters,  $\tau_i$ ,  $\eta_{ij}$ ,  $\alpha$ ,  $\gamma$  and the gains are represented by a real-valued vector ([0,1]) which is decoded linearly to the range corresponding to the parameters (with the exception of gain values which are exponentially scaled). Crossover and vector mutation operators, which adds a small random vector to the real-valued genotype, are used [7].

In the evaluation process, half of trials start with the light source and without the light in another half. The light condition consists of the serial presentation of 8 distant light sources which the agent must approach and remain close to. Only one source is presented at a time for a relative long time period, 1000. In the dark condition, there is no light in the arena. It means that no stimulus is given to the network. The agent can freely move in the unlimited

arena for the same time length as the light condition while it is required not to be homeostatic, that is, the network needs to maintain the dynamics outside homeostatic regions. The evaluation under this condition is expected to evolve the networks that have an association between going-away behaviours and non-homeostasis. Therefore, the agents are evaluated by measuring three factors such as the proportion of time that the agent spends near the light source,  $f_s$ , the time-averages of the proportion of neurons that have behaved homeostatically in the light condition,  $f_h$ , and that have *not* behaved homeostatically in the dark condition,  $f_{Nh}$ . The fitness function is given by this,  $F = f_s * f_h + avg.(f_s) * f_{Nh}$ .

## 4 Results

The population can be successfully evolved by 4000 generations. After that, the fitness values does not change so much. We selected one successful agent at the 4000th generation in order to investigate the potential of the adaptivity that the agent has by following experiments.

### 4.1 Creation of sensory-motor coupling

The evolved agent can generate the phototactic behaviour in most cases even if the weight connections are randomly initialized at the beginning of the trial. The evolved agent constructs a new sensory-motor coupling through the experience of interaction with the environment. Examples of the established phototactic behaviour (distances to the light source) and the changes of the weight connections are shown in Fig. 1 and Fig. 2. At the beginning of the trials, the weight connections are randomly given so that the produced behaviour cannot be approaching to the light source. If little light stimulus is provided, the network cannot maintain the neural dynamics in the homeostatic regions. This property is evolved by the fitness function of the dark condition. Following the plastic rules, the network starts changing the network structures that can lead to homeostasis and phototaxis at the same time. As shown in figures, the agent with different initial weight sets can successfully establish the phototactic behaviour and homeostasis in both cases. Interestingly, those converged weight values are very different. It means that the established sensory-motor coupling is dynamically constructed through the interaction.

### 4.2 Adaptation to the sensory inversion

The adaptation to the sensory inversion is examined. Since the agent has 4 sensors in the current

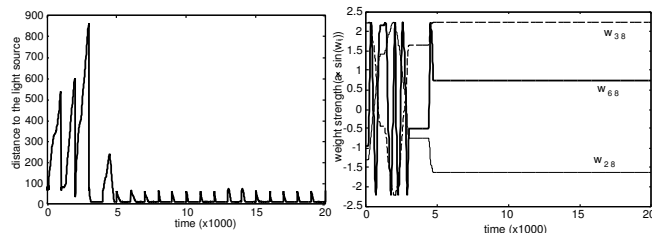


Figure 1: Left: Distance from robot to sources. Each source lasts for 1000 time steps. Right: Change of synaptic weights corresponding to the same run of the left. For the clarity, only three of weights are shown.

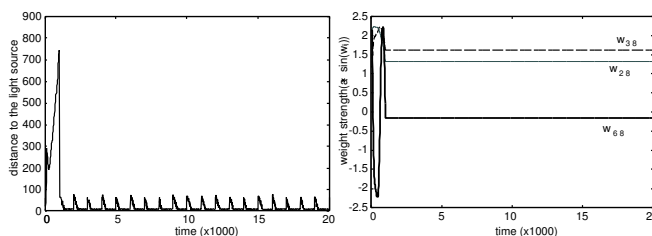


Figure 2: Another result of distances(left) and weight(right) changes starting from a different initial weight set from Fig.1.

setting, each pair of diagonal sensors are swapped ( $\pm\pi/4 \leftrightarrow \mp 3\pi/4$ ) so that the agent “sees” the light source at an opposite direction in terms of back/forth and left/right.

After an initial period with normal positions of sensors, the swapping experiment is tested. Figure 3 shows the distances from the agent to the light sources. The light sources appear at a new place in every 1000 steps and the sensors are swapped when the 13th light source appears. As shown in the previous section, the adaptation to the initial weight set happens before swapping sensors. When the sensors are swapped, the agent moves to an opposite direction by the sensor-motor coupling learned through normal embodiment. However, expected input stimulus cannot be achieved because the agent goes away from the light. That causes breakdown of internal homeostasis and then the synaptic plasticity starts working. After some adaptation processes, the network has been able to find a new homeostatic state that can approach the light. Once the proper new sensor-motor coupling has been established, the synaptic weight becomes stable (Fig. 4).

Re-learning is also tested in the way that the sensors are swapped at 13th light source and their positions are back to the original positions at 30th light. It is observed that the agent can successfully recover the phototaxis to the perturbations through the learning

phase (not shown).

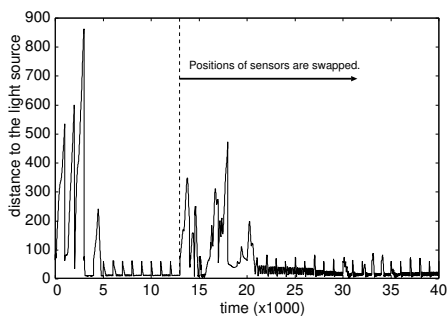


Figure 3: Distance from robot to sources. The vertical dashed line shows onset of swapping diagonal sensors ( $\pm\pi/4 \leftrightarrow \mp 3\pi/4$ ). All initial configurations are same as Fig. 1.

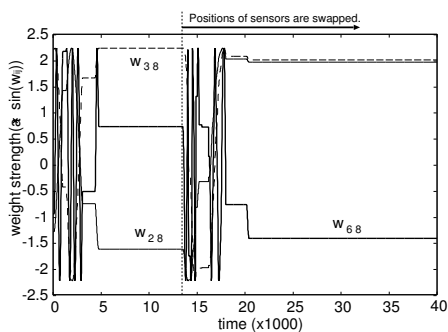


Figure 4: Synaptic changes corresponding to Fig. 3.

## 5 Conclusion

We showed a novel way of adaptation to unexpected perturbations such as sensory inversions and adaptation to the random initial weights. In the conventional neural network modelling in evolutionary robotics, the sensory-motor connections as a low level description are tightly related to the behavioural performances as macro observations. In our model, the sensory-motor connections are randomly determined at the beginning so that the tight connection between low-level dynamics and behavioural performances cannot be created. Instead, the sensory-motor connection is reconfigured to maintain the higher-level homeostasis, which is associated with the desired behaviours. At the same time, the neural network is evolved to make it difficult for undesired behaviours to maintain homeostasis as a network property. Therefore, the bottom-up construction from the sensory-motor dynamics and the top-down regulation from the behavioural performances are mutually coupled and the

structure makes the homeostatic neural network more adaptive.

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