Adaptive Behaviour, Autonomy and Value systems.

Normative function in dynamical adaptive systems

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Only retain... what augments the number of connections.
DELEUZE AND GUATTARI[1]

The beauty of life is not a gift of its inaccesibility to our understanding.
MATURANA AND VARELA[2]

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[1] Deleuze, G. and Guattari, F. (1980) *Mille Plateaux* Minuit. p.634.

[2] Maturana, H. and Varela, F. (1980) *Autopoiesis and Cognition. The realization of the living.* D. Reidel Publishing Company, 1980. p.83.

Declaration

I hereby declare that this dissertation has not been submitted, either in the same or different form, to this or any other university for a degree.

Signature

Abstract

Computational functionalism [5] fails to understand the embodied and situated nature of behaviour by taking steady state functions as theoretical primitives, and by interpreting cognitive behaviour from a language-like, observer dependant framework without a naturalized normativity. Evolutionary functionalism [28, 27], on the other hand, by grounding functional normativity on historical processes fails to give an account of normative functionality based on the present causal mechanism producing behaviour. We propose an alternative *autonomous dynamical framework* where functionality is defined as contribution to self-maintenance [15, 10, 35] and normativity as satisfaction of closure criteria. We develop this framework by a set of formal definitions in the framework of dynamical system theory and propose the hypothesis of an homeostatic-plasticity [31, 40] based general purpose value system as an internalized normative mechanism that selects between internal state trajectories to produce adaptive functionality under different environmental conditions. To test the hypothesis we develop a simulation model where lower level specifications of a control arquitecture (an homeostatic plastic DRNN) give rise (through a simulated evolutionary process) to adaptive behaviour in a foraging task where food sources can be poisonous or profitable. Analysis of the evolved agent show that plastic changes occur when the agent produces salient adaptive interactions, those plastic changes determining the adaptive strategy. The embodied and interactive adaptive functionality is dynamically analysed, illustrating the *autonomous dynamical framework.*

Keywords

Homeostatic adaptation, autonomy, value systems, dynamical systems, adaptive behaviour, emergent autonomous functionality, normativity, simulation models.

Number of Words

13,100

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Contents

Chapter 1

Introduction

Beer's adaptive behaviour program [3] recovered Ashby's pioneering work [1] under the new paradigm of computer simulations, CTRNNs (Continuous Time Recurrent Neural Networks) and the use of Genetic Algorithms to produce complex adaptive systems. The main idea (already present in Ashby's work) was that adaptive behaviour, as the origin of intelligence, should be understood dynamically as the homeostatic maintenance of essential variables under viability constraints through environmental interactions. After a set of criticisms coming from different cognitive scientists and philosophers Randall Beer[1] decided to put aside his program of adaptive behaviour and focus his research on "representation hungry problems" [13] giving rise to the *minimally cognitive behaviour* program. The aim was is to demonstrate that the embodied dynamical approach is able to produce behaviours that could satisfy representationalists' minimal requirements for cognitive behaviour [37, 4]. The new program, although maintaining the emphasis on the embodied, situated and dynamical nature of behaviour does not even mention the central role of the homeostatic maintenance of essential variables under viability constraints.

Similarly almost all the work done in evolutionary robotics and evolutionary simulations [20, 19, 14, 31, 39, 34] is aimed to produce specific cognitive/adaptive behavioural patterns with no reference to autonomy, self-sufficiency and essential variables. The aim of this work is to recover the notion of autonomy (as maintenance of essential variables under viability constraints) as a central notion for adaptive behaviour with special significance on the definition of adaptive function. Under this framework *value systems*, by modulating the state trajectories of some variables of the control architecture according to adaptively significant events, become key mechanisms in the production of adaptive behaviour. Inspired on some recent work on plastic controllers [34, 18] and specially Di Paolo's work [31], we hypothes-

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[1] Personal communication, 15th August 2002 (WGW'02, International Workshop on *Biologically-Inspired Robotics: The legacy of W. Grey Walter.*)

ize that homeostatic plasticity could be a genuine candidate for a general purpose value system. We believe that within an *autonomous dynamical* framework a number of fundamental problems of computational and evolutionary functionalism could also be solved, specially those concerning the notion of normative function.

Chapter 2 introduces the concept of autonomy, defines functionality in terms of contribution to self maintenance and highlights the relevance of value systems for adaptive behaviour. Chapter 3 provides an explicit formalized framework to characterize adaptive behaviour in dynamical system theory. Chapter 4 explains the details of the simulation used to produce a set of autonomous and situated agents. In chapter 5 we analyse two types of evolved agents. Chapter 6 discusses some of the implications of the *autonomous dynamical* framework proposed in chapter 2 with examples taken from the experimental results. Finally chapter 7 briefly recapitulates the work presented in the dissertation.

Chapter 2

Autonomy and Value Systems

The term *autonomy* and *autonomous* has been largely used in cognitive science and robotics [23] to describe an agent embodied and situated in the 'real world', without external energy supply, etc. We consider that a deeper sense of autonomy (as self-maintenance) allows for a richer characterization of cognition and adaptive behaviour. By conceptualizing and modeling autonomy within the dynamical approach to cognitive science [41] and adaptive behaviour [3] a number of important goals could be achieved:

- To provide an normative criteria to interpret and evaluate adaptive and cognitive functionality solving the frame of reference problem (Clancey [11]) of computational functionalist approaches.
- To naturalize the notion of normative function (Millikan [28, 27]) on the dynamical organization of processes giving rise to autonomous behaviour (as proposed by Bickhard, Christensen and Hooker [16, 9, 10]).
- To integrate mechanistic, embodied and interactive explanations without recursion to prespecified functional/behavioural primitives.

The significance of this points will be discussed on chapter 6 with examples and conclusions driven from the experimental results.

We will proceed by defining basic autonomy (as the fundamental process of self-construction and thermodynamic interaction) and analysing its consequences for an autonomous perspective of behaviour. We will then focus on value systems as a fundamental mechanism for adaptive behaviour and finally we will provide a set of formalized definitions in dynamical system notation (with special focus on dynamic normative function and value systems).

2.1 Autonomy: the hermeneutic and normative axis

2.1.1 Basic Autonomy: the root for normative functionality

Living systems are primarily autonomous systems, i.e. their basic organization is that of a self-sustaining, self-constructing entity over time and space. An autonomous systems is a highly recursive network of processes that produces the components that constitute the network itself. When this network is protected by a boundary (membrane) the network becomes a separated self-constructing entity (an autopoietic unity Maturana and Varela [25, 26]). But autonomous systems are far from equilibrium and thermodynamically open systems which adaptively transform their boundary conditions to assure the flow of matter and energy required for their self-maintenance [29], unlike dissipative structures (which hold their organization only under a restricted set of external conditions that the system cannot modify). The key of *basic autonomy*, as developed by Ruiz-Mirazo and Moreno [35], is that of generating internal *and* external constraints. It is the generation of this constraints that defines the function of internal and interactive processes. Functionality is, thus, picked up at the level of their contribution to self-maintenance and not, as evolutionary functionalism proposes, at the level of selective history. For, of course, contribution to self-maintenance is evolutionarily advantageous; but autonomy is to be seen not as a pure outcome of evolutionary processes but as the condition of possibility of such process. That's why autonomy and autopoiesis are taken to be more fundamental processes than evolutionary ones [44], because, although deeply interlinked, for an organism to be selected it must first of all exist as a self-maintaining organized network of processes, i.e. as an autonomous system.

We can, thus, root functionality in autonomy [15], so that the function of a process or structure is determined by its contribution to self-maintenance by means of its constructive nature or of its interactive satisfaction of closure criteria (controll of boundary conditions for self-maintenance). This way functions becomes *normative* [9] by means of its integration in the whole dynamic organization of an autonomous (self-maintaining) system, and not by means of the particular evolutionary history of an isolated trait or structure. A naturalized account of normativity grounded in autonomy provides, at the same time, a way out of an observer dependant semantic description of the processes involved, since the failure to function conditions the very existence of the system. The result is a redefinition of functionality in the grounds of the *biological conditions of possibility* of the dynamical process (autonomous system) it belongs to (*à la* Kantian naturalized transcendentalism).

A *constructive* and an *interactive* closure can be distinguished in the functional organization of an autonomous system:

- The constructive: involving the self-constructing processes and,

- The interactive: involving the thermodynamic flow between the autonomous system and its environment and the controll of boundary conditions.

This second closure condition will become the key for and autonomous characterization of cognition and adaptive behaviour.

2.1.2 Autonomy, Adaptive Behaviour and Cognition

Because metabolic reactions are sometimes too slow to maintain an internal stability under rapidly changing environmental conditions a new subsystem emerges in the history of biological organisms: the nervous system. The nervous system connects sensory-motor surfaces to deal with environmental changes rapidly and without involving change in the metabolic/constructive processes (generally based on slow diffusion processes [30]). The self-maintenance of the system does not exclusively require metabolic processes but interactions with the environment in terms of modulation of interaction to predict and react in complex environmental conditions to keep satisfying its closure conditions. Thus the nervous system, metabolically decoupled but embedded in the organism has to evaluate the results of its body control. Affections and internal sensors become, then, major features to autonomously build a cognitive internal normativity [10]. A second level of functionality (cognitive functionality) can, thus, be described where nervous mechanisms anticipate the effect of environmental interactions for the self-maintenance of the system without having to produce the interaction itself (and subsequently compensate for the produced disequilibrium of essential variables). This way what grounds semantics is not an *absolute* epistemological stand which requires *absolute* observers attributing semantic relations to states of a system but the intrinsic evaluative mechanisms of a cognitive agent. This mechanisms (value systems) have been developed around this self-regulating-sustaining fundamental function in given environmental niches (which are, at the same time, specified by the cognitive capacities of the organism [1]). Christensen and Hooker [10] have developed a theory of *self-directed* agents as those able to anticipate interaction processes and evaluate their performance, as opposed to reactive systems. This capacity of interactive self-structuring is a good candidate for a genuine dynamical and naturalized account of cognition and intelligence which doesn't require the postulation of externally interpreted functional and representational states. Nevertheless further steps into an explicit and workable set of analytic and synthetic tools is required to produce relevant advances in this direction.

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[1] If an organism develops the capacity to recognize or access to new sources of energy, this capacity itself transforms its ecological niche. From the point of view of novelty and interaction is the organism who shapes the the niche and not vice versa

The strength of a dynamical autonomous perspective is given by the shift from:

- viewing cognition as computations between 'representational' automaton states, whose representational normativity is fixed by an heteronomously interpreted functional equivalence with states of affairs in the world

to:

- and interactive dynamical process whose normativity is given by its satisfaction of closure criteria and functionality is grounded on the embodied and situated nature of behavioural dynamics.

2.2 Value Systems as Internal Normativity: regulatory mechanisms

> "All the evaluations are thus *conditional*, each depending on the others. Thus there is no criterion for 'better' that can be given absolutely, i.e. unconditionally. But a neuron must do something. How then do the activities of the neurons become co-ordinated so that the behaviour of the whole becomes better, even though no absolute criterion exists to guide the individual neuron?" W. ROSS ASHBY[2]

Autonomous agents must be able to modulate their responses in varying environments, evaluate their interactions and constraint the space of possible responses to satisfy closure criteria. A number of approaches have tried to address how to solve this essential feature of intelligence. We will briefly introduce the reinforcement learning paradigm and the concept of values systems to end up with the hypothesis that a homeostatic-plastic neural network could be a good candidate for a general purpose value system mechanism.

2.2.1 The Reinforcement Learning Paradigm

A traditional way of dealing with variable environments and a set of possible responses is the reinforcement learning paradigm. Reinforcement learning assumes that the learning task can be specified by a control policy specifying the action (from a set of discrete predefined possible actions) to be taken given the current discrete state of the agent and the environment and a reward or reinforcement signal [21]. The policy takes the form $f(x) = a$, where f is the control policy, x the current state and a the action to be taken. In this context different reinforcement learning algorithms are implemented to find the control policy f that maximizes reward from the taken actions.

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[2] Ashby, W.R. (1952) *Design for a Brain. The origin of adaptive behaviour.* London, Chapman and Hall, 1978. p.7 (1/8)

Q-learning is a well known algorithm to find a good policy. The agent learns a value function $Q(x, a)$ as an expectation of reward so that the decision is taken so as to maximize the expected reward. The learning process is a process of acting and updating the value function.

From a dynamical perspective of adaptive behaviour the reinforcement learning paradigm suffers from a series of problems derived from the set of assumptions it is based on:

- The value of the reward is explicit.
- The environment is decomposed in discrete states.
- Possible actions are given as discrete units.
- Actions and states are given in discrete time units.
- The paradigm provides descriptive and predictive models but does not capture biological mechanistic constraints.

2.2.2 Value systems and hebbian mechanisms

Pfeifer and Scheier [33] introduce the notion of *value systems* as a fundamental design principle for Autonomous Agents: "The value principle states that the agent has to be equipped with a value system and with mechanisms for self-supervised, incremental learning employing principles of self-organization" ([33], p.315).

The central role of value systems is to serve as an evaluative mechanism and to guide learning to modulate adaptive behaviour in changing environments. Pfeifer and Scheier distinguish between *implicit*, innate reactions that select valuable sensory-motor interactions, and *explicit* value systems, those in charge of evaluating performance and modulating learning. Explicit value systems are modelled controlling synaptic hebbian plasticity under the general form:

$$\Delta w_{ij} = V \cdot \eta \cdot z_i \cdot z_j \tag{2.1}$$

where w_{ij} is the synaptic strength between nodes i and j, η is a learning rate constant, z_i and z_j are an averaged memory of pre and post-synaptic activity during the action and V is the value signal. Because the value signals are generated after a particular action is performed a memory of the last activations of neurones is required to reinforce or reduce the connections responsible for that action. Activations of neurones are, thus, averaged over the period of time the relevant action happend and stored in a memory. Other and more complex hebbian learning mechanisms modulated by value systems have been proposed and successfully implemented on robots for categorization tasks and conditioned behaviour [46, 32, 22].

The strength of value systems is that they autonomously guide learning without reference to an external supervision. Plasticity (variation in the synaptic space) produces a constrained variety of interactive patterns which are selected by the value system providing a more complex repertoire of adaptive strategies. As Verschure et al. put it: "According to the theory, evolutionarily selected value systems provide constraints for the selection of adaptive behaviours in somatic time. (. . .) The main characteristic of value systems can be summarized as the generation of a global signal that relates to the occurrence of salient events and that can regulate firing patterns and gate synaptic modification" ([46], p.248). In addition value systems can be associated with existing brain structures. More concretely value signals are taken to be implemented by diffuse ascending systems. Small populations of neurones control the segregation of key neurotrasmitters such as dopamine, noradrenaline, and serotonine affecting the synaptic strength of different brain regions. This way, the value system paradigm integrates biologically plausible lower level mechanisms (hebbian rules with value modulation) with higher level situated behavioural patterns and unsupervised learning.

2.2.3 Homeostatic plasticity value system

One of the problems of the hebbian mechanisms explained above is that they are constrained to prespecified value system modules and that the nervous system must face two opposing requirements: change and need for stability (to guaranty functionality). Different normalization mechanism to avoid uncontrolled growth of synaptic strength have been proposed but more recently homeostatic plasticity has been proposed as a general regulatory mechanism (Turrigiano [40]). Homeostatic plasticity provides, not only a mean for "allowing Hebbian plasticity to modify synaptic strengths selectively"([40], p.221) but the possibility of a general purpose value system. Homeostatic plasticity can also explain how central neurons in the CNS balance the effect of developmental changes. Turrigiano presents a whole set of mechanisms involved in neural homeostasis where the general abstract mechanism works by increasing synaptic strengths when the firing rate is low and scaling down synaptic strengths when firing rates are high. Di Paolo has implemented homeostatic plasticity in a simulation model to study adaptation to inversion of visual field and other sensorimotor disruptions in a phototactic agent [31]. Di Paolo's model regulates synaptic plasticity of the incoming weights to a node according to the node's action potential. If the action potential is maintained between homeostatic bounds, predefined as (-2,2) no plastic change occur, but if action potential is too high (above 2) a hebbian rule is applied to the incoming synaptic connections decreasing the synaptic strength by a local plasticity facilitation parameter p_j. The opposite effect happens when the action potential is too low (below -2). The hebbian rule can expressed as:

$$\Delta w_{ij} = \eta_{ij} \cdot p_j \cdot z_i \cdot z_j \tag{2.2}$$

where w_{ij} is the synaptic strength from neurone i to neurone j, η_{ij} is a learning rate parameter, and z_i and z_j the pre and post-synaptic firing rates. The degree of local facilitation changes according to the equation shown in figure 2.1. Homeostatic plasticity can also be applied to other hebbian variables (e.g. postsynaptic, presynaptic and covariance). In addition we can use evolutionary techniques to select for homeostasis by adding a fitness cost to non-homeostatic behaviour of neurones and let evolution find self-organizing processes that lead to neural homeostasis based in similar rules (see chapter 4 for more details).

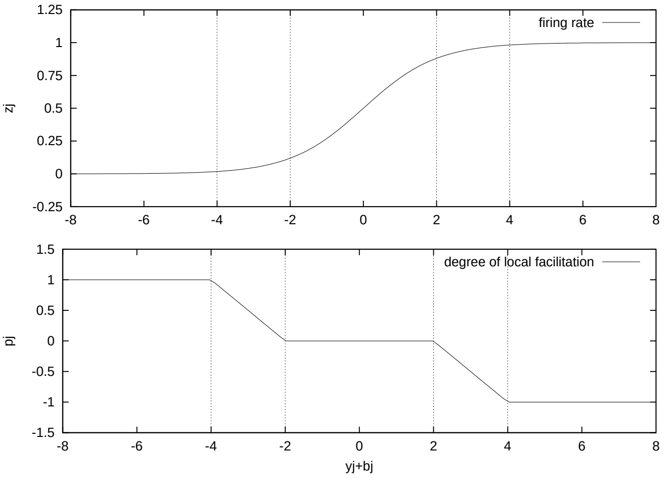

Figure 2.1: *Facilitation of local plasticity as a function of action potential (from [31])*

Our hypothesis is that activity dependant homeostatic plasticity can be considered as a general purpose value system because the agent can generalize weight modulation not only to pre-specified value signals (e.g. dopaminergic neurones) but to any perturbation of the nervous system. But how can homeostatic plasticity act as a value system?

Figure 2.2 illustrates the way in which homeostatic plasticity could lead to value based reorganization of sensorimotor transformations. If neural activity is between homeostatic bounds the weight variables of the system will be stable under equation 2.2. The agent will, thus, be engaged in a series of sensorimotor loops with its environment until a given interaction produces some neurones to get out of homeostatic bounds. At this point synaptic-plasticity is activated until the system founds a new stability point in its weight space reorganizing neural activity and giving rise to a new sensorimotor coupling with its environment.

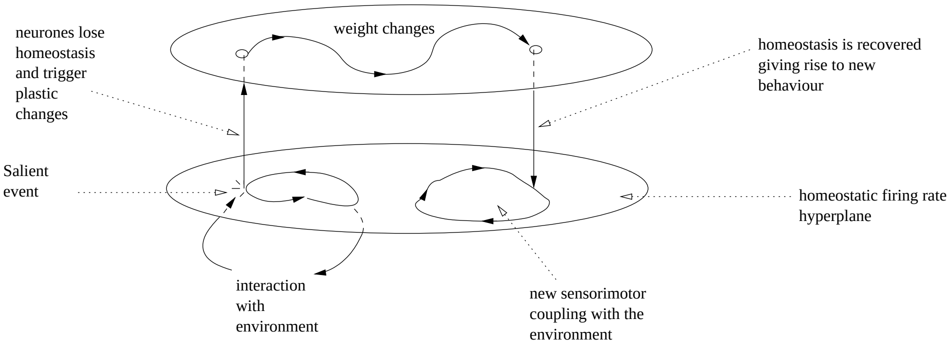

Figure 2.2:

The process can be understood thought the Ashbyan framework of parameters and stability in dynamical systems. Ashby resumes that "in a state-determined system, *a change of stability can be due to change of a parameter*, and *change of value of a parameter causes a change in stability*" ([1], p.78 (6/7), italics in the original). Weights and neural activations can interpreted as two coupled machines, each controlling the stability conditions of the other.

If internalized normativity is understood as the processes that selects/constraints variability we can understand normativity as internalized stability in the weight space i.e. plastic changes (variation in the weight space) is *constrained* by a set of rules and parameters and *regulated* by neural loss of homeostasis. The ongoing process of variation and selection that gives rise to complex adaptive systems in evolutionary timescale can now be expanded to lifetime of an organism allowing for the possibility of functional novelty regulated by evolutionarily selected neural homeostasis.

In contrast with reinforcement learning, no discrete environmental states, nor discrete actions need to be presupposed, homeostatic plasticity based value systems can also be implemented in continuous time. In contrast with the value system literature in robotics the value system is not constrained to act on prespecified situations and it doesn't require averaged values of past activity nor their allocation in a memory function. At the same time homeostatic plasticity provides a synaptic stability mechanism, enables developmetal process stability and allows for an interpretation of internalized normativity.

The viability of the of our hypothesis will be tested in chapter 5.

Chapter 3

An Explicit Formalized Framework for Autonomous Systems

It is time now to make the *autonomous dynamical* framework explicit through a series of formal definitions in the framework of dynamical system theory[1].

Our interest on the dynamical approach [41] is that it allows for a genuine integration and formalization of behavioural, mechanistic, interactive and adaptive aspects of cognition in a state determined, quantitative way. We don't want to rely on an external interpretation of the states of an agent to call it adaptive but, on the contrary, to find the dynamical self-intepreting relations between agent and environment that makes the agent adaptive. In turn, what a dynamical framework provides is a way to avoid taking representations and adaptive functions (categorization, action, inferences etc.) as modeling primitives while allowing for the emergence or self-organization of dynamical processes whose behaviour can be categorized as adaptive or cognitive.

3.1 Agent and Environment

Following Beer's notation and definitions [3] an *agent* can be modeled as a set of state variables $\mathbf{x}_{\mathcal{A}} = \{x^1_{\mathcal{A}}, x^2_{\mathcal{A}}, \ldots, x^n_{\mathcal{A}}\} \in \mathbb{R}^n$ and a set of dynamical laws $\mathcal{A}$ specifying the differential equations gouverning the system: $\dot{\mathbf{x}}_{\mathcal{A}} =$

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[1] This definitions are not to be taken too rigorously, they are all extremely simplified versions of what would require an extensive work far beyond the scopes of this dissertation. Nontheless we believe that the formalization and definitions below provide a good approximation for a 'what is it like to characterize autonomy and adaptive behaviour in dynamical terms'. The definitions given here are an extension of Beer's program [3], integrating fundamental ideas from Ashby's early work [1] and Varela's notion of autonomy [43]. We extended the framework with a definition of adaptive functionality and value systems.

$\mathcal{A}(\mathbf{x}_{\mathcal{A}}; \mathbf{s}(t))$ where $\mathbf{s}(t)$ stands for the set of stimulus the agent receives from its environment at time t. The system has solution $\phi_{\mathcal{A}}(t; \mathbf{x}^0_{\mathcal{A}})$ for initial conditions $\mathbf{x}^0_{\mathcal{A}}$. The *environment* could also be modelled as a dynamical system by a set of variables $\mathbf{x}_{\mathcal{E}} = \{x^1_{\mathcal{E}}, x^2_{\mathcal{E}}, \ldots, x^n_{\mathcal{E}}\}$ with the corresponding set of dynamical laws $\mathcal{E}$ specifying the evolution of the system over time $\dot{\mathbf{x}}_{\mathcal{E}} = \mathcal{E}(\mathbf{x}_{\mathcal{E}}; \mathbf{m}(t))$ being $\mathbf{m}(t)$ the motor actions the agent takes in the environment with solution $\phi_{\mathcal{E}}(t; \mathbf{x}^0_{\mathcal{E}})$. In terms of dynamical systems theory both $\mathcal{A}$ and $\mathcal{E}$ are nonautonomous dynamical systems by receiving inputs from each other. Both systems are thus, dynamically coupled by means of $\mathbf{s}(t)$ and $\mathbf{m}(t)$ and $\mathbf{s}(t) = \mathbf{S}(\phi_{\mathcal{E}}(t; \mathbf{x}^0_{\mathcal{E}}))$, where $\mathbf{S}$ is a function of environmental states to sensory inputs. At the same time the motor output is given by $\mathbf{m}(t) = \mathbf{M}(\phi_{\mathcal{A}}(t; \mathbf{x}^0_{\mathcal{A}}))$, where $\mathbf{M}$ is a function from agent states to motor actions.

3.2 Behaviour

Behaviour happens at a metalevel description of agent-environment interactions. That is because the agent's dynamics alone cannot specify a behaviour. Phototaxis is a relation between agent position and a source of light, swimming is a relation between waterly environment an agents mouvement. Nor phototaxis can happen without light nor swimming without water. Anil Seth [36] has pointed out the category mistake involved on the study of action selection mechanisms, since action is an observer dependant category in an agent-environment level of description, the attribution of actions to selected mechanistic states becomes misleading. It is thus of fundamental importance to define behaviour at the proper dynamical level. We can formalize the coupling between agent and environment (where behaviours are to be described) as an autonomous dynamical system $\mathcal{U}$ composed by $\mathcal{A}$ and $\mathcal{E}$ as follows

$$\dot{\mathbf{x}}_{\mathcal{U}} = \left[\begin{array}{c} \dot{\mathbf{x}}_{\mathcal{A}} \\ \dot{\mathbf{x}}_{\mathcal{E}} \end{array} \right] = \mathcal{U}(\mathbf{x}_{\mathcal{U}}) = \left[\begin{array}{c} \mathcal{A}(\mathbf{x}_{\mathcal{A}}; \mathbf{S}(\mathbf{x}_{\mathcal{E}})) \\ \mathcal{E}(\mathbf{x}_{\mathcal{E}}; \mathbf{M}(\mathbf{x}_{\mathcal{A}})) \end{array} \right].$$

3.3 Autonomy

Be $V \subset \mathbb{R}^n$ the viability constraint space for $\mathbf{x}_{\mathcal{A}}$. Then the agent $\mathcal{A}$ is autonomous iff [2]:

$$\forall \mathbf{x}_{\mathcal{A}}(t) \in V \quad \longrightarrow \quad \phi_{\mathcal{A}}(t + dt; \mathbf{x}_{\mathcal{A}}(t)) \in V \tag{3.1}$$

To make this definition more explicit and applicable we shall introduce Ashby's notion of adaptive behaviour as maintenance of essential variables within physiological limits ([1], p.58). Consider the subset $\mathbf{e}_{\mathcal{A}} = \{e^1_{\mathcal{A}}, e^2_{\mathcal{A}}, \ldots, e^i_{\mathcal{A}}, \ldots, e^m_{\mathcal{A}}\} \in \mathbb{R}^m \subset \mathbb{R}^n$ where all $e^i_{\mathcal{A}}$ is a non-controlled essential variable and often tend to decay through time (energy, temperature,

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[2] Adapted from [43]

etc.). We say that $e^i_{\mathcal{A}}$ is a non-controlled variable if the change on the agents variables cannot directly (without the mediation of an environmental interaction) modulate $e^i_{\mathcal{A}}$ to keep it under viability range. The laws gouverning some essential variables could be simplified to the form: $\dot{e}^i_{\mathcal{A}} = i(t) - k$; where k is a decay constant and $i(t)$ an input from the environment where $i(t) \in \mathbf{i}$ and $\mathbf{i}(t) = \mathbf{I}(\phi_{\mathcal{E}}(t; \mathbf{x}^0_{\mathcal{E}}))$. $\mathbf{I}(\phi_{\mathcal{E}}(t; \mathbf{x}^0_{\mathcal{E}}))$, in this simplified form, is a function of the environment determining the input to essential variables, e.g. position and energy of food, temperature and position of a shadow, etc.

We shall then expand Beer's definition of $\mathcal{A}$'s laws above as $\dot{\mathbf{x}}_{\mathcal{A}} = \mathcal{A}(\mathbf{x}_{\mathcal{A}}; \mathbf{s}(t), \mathbf{i}(t))$ where $\mathbf{i}(t)$ is the set of inputs to the set of non-controlled essential variables.

When that is the case a system must *interactively* maintain its essential variables under viability range. Lets take the example of body temperature. When the body temperature approaches the viability boundary some organism can display sweating mechanism, which, under certain environmetal conditions, directly decrease body temperature by hot dissipation through the segregated sweat evaporation. This mechanism allows the system to directly regulate body temperature to maintain it under viability range. But it might be the case that external temperature is too high and sweating is not sufficiently effective or that the system need to acquire more water. Being under a shadow or acquiring water input from the environment is not a directly controlled variable (as producing sweat). Formalized this makes that for $\dot{e}^i_{\mathcal{A}} = i(t) - k$:

$$e^i_{\mathcal{A}} \in V \iff V^{max}_{e^i_{\mathcal{A}}} < \quad i(\mathbf{M}(\mathbf{x}_{\mathcal{A}}), \mathbf{x}_{\mathcal{E}}) - k \quad > V^{min}_{e^i_{\mathcal{A}}} \tag{3.2}$$

where $V^{min}_{e^i_{\mathcal{A}}}$ is the low boundary of $e^i_{\mathcal{A}}$'s viability constraint and $V^{max}_{e^i_{\mathcal{A}}}$ its upper boundary.

If equation 3.2 is not satisfied $e^i_{\mathcal{A}}$ will decay until it gets outside $V_{e^i_{\mathcal{A}}}$. It is then when the control of behaviour in terms of agent environment interaction becomes an essential autonomous process to maintain the essential variables under viability constraints and the system acquires its agency. We will term, following Collier [15], this necessary interactions *satisfaction of closure criteria.*

3.4 Adaptive Function

A function $F(\mathbf{x}_{\mathcal{U}})$ is an adaptive function for $\mathcal{A}$ iff: $F(\mathbf{x}_{\mathcal{U}})$ satisfies $\mathbf{e}_{\mathcal{A}} \in V$. Lets call the most abstract and general adaptive function F that satisfies $\mathbf{e}_{\mathcal{A}} \in V$: $F_{e_{\mathcal{A}}}(\mathbf{x}_{\mathcal{U}})$. And the more specific adaptive function that satisfies the maintenance of one or more essential variables under viability constraint through a particular behaviour: $f_{e_{\mathcal{A}}}(x_{\mathcal{U}1}, x_{\mathcal{U}2}, \ldots, x_{\mathcal{U}n})$.

To clarify this point lets imagine the scenario where an agent needs to move to a lower temperature space to prevent the essential variable $e^T_{\mathcal{A}} >$

40^oC, e.g. to cover itself under a shadow. In this case the environment is completely passive (in any relevant sense to the performance of the function) and the agent must actively change its relative position to an specific space of the environment (shadowed area). In the given environmental conditions the general adaptive function $F_{e^T_{\mathcal{A}}}(\mathbf{x}_{\mathcal{U}})$ to satisfy $e^{T^o}_{\mathcal{A}} < 40^oC$ can be specified as:

$$f_{e^T_{\mathcal{A}}}(x_{\mathcal{U}}) = \frac{dD_{a-s}}{dt} < 0 \ \ until \ \ D_{a-s} = 0,$$

where D_{a-s} is the distance between the agent and the shadow. Note that the distance between the agent and the shadow is not a controlled variable $\in \mathbf{x}_{\mathcal{A}}$, so that the function must be *enacted* by $\mathcal{A}$ through $\mathbf{M}(\mathbf{x}_{\mathcal{A}})$ [3]. How does $\mathcal{A}$ modulate $\mathbf{x}_{\mathcal{A}}$ by coupling $\mathbf{S}(\mathbf{x}_{\mathcal{E}})$ and $\mathbf{M}(\mathbf{x}_{\mathcal{A}})$ to perform $F_{e^T_{\mathcal{A}}}(\mathbf{x}_{\mathcal{U}})$ becomes the object of study of the observer interested in the adaptive behaviour of $\mathcal{A}$. More generally we can abstract that Adaptive Behaviour, as a discipline, is concerned with how $\mathcal{A}$ systems perform adaptive functions $F_{e_{\mathcal{A}}}(\mathbf{x}_{\mathcal{U}})$. But we must be careful at this point. What embodied and situated approaches have shown is that (alike computational functionalist approaches will defend) $F_{e_{\mathcal{A}}}(\mathbf{x}_{\mathcal{U}})$ is not always performed by an "input – change of state – output" sequence [4] but is enacted by a interactive process in which the agent exploits multiple sensory-motor loops through its body-environment dynamics.

3.5 Embodiment and Situatedness

Embodied and situated approaches [8, 7, 13, 45] have highlighted the importance of body and environment interactions from the situated perspective of the cognitive/adaptive agent for cognitive/adaptive functionality. In our set of definitions embodiment and situatedness are introduced by the functions $\mathbf{M}(\mathbf{x}_{\mathcal{A}})$ and $\mathbf{S}(\mathbf{x}_{\mathcal{E}})$. Both sensory and motor functions represent the body as constraining the interaction between the agent and the environment. $\mathbf{S}(\mathbf{x}_{\mathcal{E}})$ makes the agent's perception of its world situated in its relation with the environment and not given from the point of view of an absolute observer (dislike some GOFAI models where absolute relations: distance between objects, properties of objects etc. are given to the agent).

The consequence of embodiment and situatedness is that at least some (and probably most) adaptive functions are not instantiated by a decomposable structure $\mathbf{r} \subset \mathbf{x}_{\mathcal{A}}$ that controlls the variables defining the specific

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[3] An adaptive function could also be performed even if the agent is passive. A mother could perform an adaptive function for her daughter by feeding her. In such a case the component $\mathcal{A}(\mathbf{x}_{\mathcal{A}}; \mathbf{S}(\mathbf{x}_{\mathcal{E}}))$ of equation **??** remains passive and is $\mathcal{E}(\mathbf{x}_{\mathcal{E}}; \mathbf{M}(\mathbf{x}_{\mathcal{A}}))$ that performs the function. We could also imagine the case where the daughter cries to draw the attention of her mother to be feed. In this case the adaptive function emerges from the mother-daughter behavioural coupling. In general the higher the causal role of $\mathcal{A}$ is on the realization of an adaptive function, the more autonomous $\mathcal{A}$ becomes.

[4] On which a given input specifies some "information" to the agent, which subsequently changes its state and outcomes and "action"

adaptive function but is interactively *enacted* by the coupling between $\mathcal{A}$ and $\mathcal{E}$. This coupling does not happen in the trivial sense that the agent need an input to the essential variables to maintain them under viability constraints. Nor we are making the obvious claim that the agent must interact in its world to achieve this. What embodiment and situatedness illustrates is that the way the specific adaptive function is achieved involves a dynamic coupling between agent and environment where no structure of the agent can be pointed to be sufficient for the function to happen. We can contrast this embodied and situated functionality, what Luc Steels has called *emergent functionality* [38], as opposed to *hierarchical systems.* Hierarchical systems are those where the system can be decomposed into different components which perform isolated functions by directly controlling the variables defining the function, i.e. the structure of the mechanism and the function it performs are codefined. An example of a hierarchical system is a motor engine where, for example, a valve that controls the flow of oil to an engine performs it function by directly manipulating the size of the gap through which the oil flows.

Bonabeau and Theraulaz [6] show how the manipulation of boundary conditions[5] not defining the function itself play a fundamental role in the performance of that function. Given an environment $E = \{x_1, x_2, \ldots, x_n, \ldots, x_m\}$ and the subset of environmental variables defining a function $E_n = \{x_1, x_2, \ldots, x_n\}$ a function is defined as $F(E_n) = dx_1/dt, \ldots, dx_n/dt$. An structure S performs the function F iff: $S(E) = F(E_n)$. What reductionists presuppose is that $\{x_{n+1}, \ldots, x_m\}$ remains constant, i.e. $\delta S/\delta x_i = 0$ for $i = \{n+1, \ldots, m\}$. In short: reductionists believe that the external variables of those defining a function do not affect how a structure performs that function. Embodiment and situatedness shows how agents exploit many features of their body and environment (boundary conditions) to perform functions which are not defined by those body/environment features.

Clark [12, 13] has pointed out how the nature of what he calls *interactive emergence* seriously compromises the classical computationalist definition of function by:

- The dissolution of functional structures in highly interactive loops between agent and environment.
- The dissolution of functional structures in distributed causal networks

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[5] According to Bonabeau and Theraulaz [6] *boundary* conditions are those constraining lower-level processes to give rise to the "proper" emergent behavioural pattern. The internal local rules of a system (the neural network in an agent) are generally unspecific on their functionality. Extreme reductionism only considers internal explanations (logical/causal relationship defining functionality by means of their correspondance relation with the environmental variables defining the function) of the performance of a function. Alife synthetic computational methods, on the contrary, are better suited to study how systems generate their own boundary conditions and perform functions interacting with them.

on the side of the agent's behavioural mechanism (neural networks).

We believe that the incapacity of classical functionalist approaches to integrate the interactive and embodied nature of natural processes should not invalid all kind of functional accounts. Alife techniques (such as genetic algorithms [20]) and dynamical system theory can help us on the synthesis and analysis of the interactive functional processes (as defined above) involved in adaptive behaviour.

3.6 Value systems

In our notation a value system could be described as a set of variables of the agent which change according to relevant input to essential variables. This change of value system variables can be given by being directly influenced by essential variables through internal sensors (e.g. satiation and hunger, measuring the level of glucose in the blood) or evolved/associated to correlate with environmental features which are relevant to the maintenance of essential variables (such as taste of poisonous food, pain, etc.). But that is not enough for a value system to be so, at the same time value system states must be connected with (must modulate) directly or indirectly motor functions; i.e must be integrated in the overall behaviour control architecture. This way the agent can evaluate its interactions with the environment, affecting the internal states and adjusting sensory-motor transformations in relation to adaptively relevant experience. When the environment is changing or new situations are encountered, value systems help modulating adaptive behaviour by evaluating the consequences of certain interactions and accordingly restructuring internal dynamics.

Figure 3.1 shows the basic structure of a value system. By being directly connected or correlated with input to essential variables the value system can evaluate an interaction in terms of its satisfaction of closure criteria and modulate neural dynamics accordingly.

A simplified formal definition of value systems can be given as: $\mathbf{v}_{\mathcal{A}} \subset \mathbf{x}_{\mathcal{A}}$ so that:

$$\exists f_1 \wedge \exists f_2 \wedge \exists f_3 \longrightarrow \dot{\mathbf{v}}_{\mathcal{A}} = f_1(\mathbf{I}(\mathbf{x}_{\mathcal{E}})) \ \wedge \ \exists x^i_{\mathcal{A}} \in \mathbf{x}_{\mathcal{A}} \ \longrightarrow \dot{x}^i_{\mathcal{A}} = f_2(\mathbf{v}_{\mathcal{A}}) \ \wedge \ \mathbf{M}(f_3(x))$$

But we want the value system to be relevant in the production of adaptive function so we should add to the definition above:

$$\exists f_{e_{\mathcal{A}}} \quad \wedge \quad \exists \quad e^i_{\mathcal{A}} \in \mathbf{e}_{\mathcal{A}} \quad \longrightarrow \quad f_{e_{\mathcal{A}}}(\mathbf{M}(f_3(x^i_{\mathcal{A}})), \mathbf{x}_{\mathcal{E}}).$$

Putting both equations together we get that $\mathbf{v}_{\mathcal{A}} \subset \mathbf{x}_{\mathcal{A}}$ is a value system iff:

$$\exists f_1 \quad \wedge \quad \exists f_2 \quad \wedge \quad \exists f_3 \quad \wedge \quad \exists f_{e_{\mathcal{A}}} \quad \wedge$$

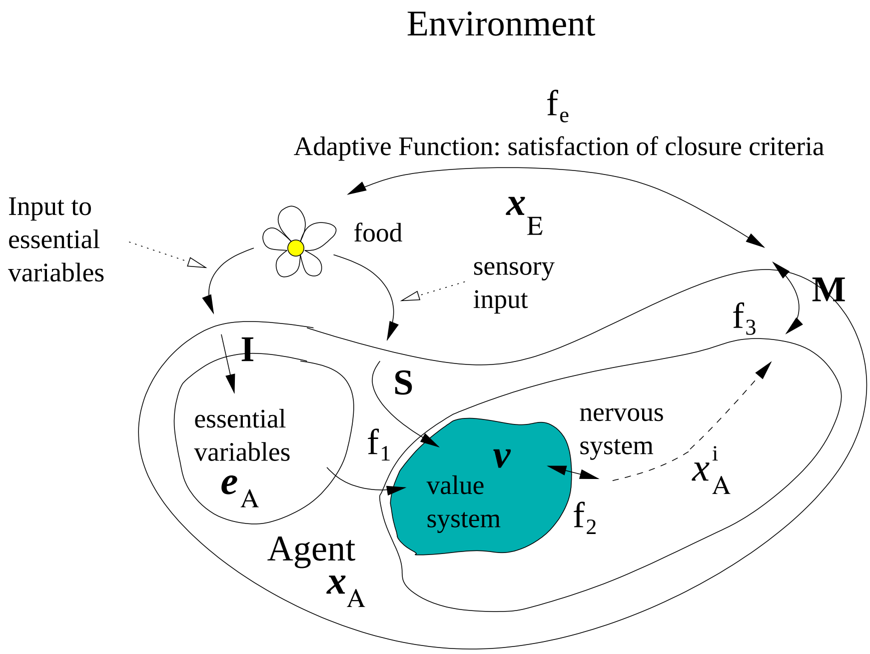

Figure 3.1: *Agent and environment state variables and their interactions. Value system (colored)is defined by its interaction between the nervous system and input to essential variables. See text for more details.*

$$\exists\ e^i_{\mathcal{A}} \in \mathbf{e}_{\mathcal{A}} \ \wedge\ \exists\ x^i_{\mathcal{A}} \in \mathbf{x}_{\mathcal{A}} \longrightarrow$$
$$\dot{\mathbf{v}}_{\mathcal{A}} = f_1(\mathbf{I}(\mathbf{x}_{\mathcal{E}})) \ \wedge\ \dot{x}^i_{\mathcal{A}} = f_2(\mathbf{v}_{\mathcal{A}}) \ \wedge\ f_{e_{\mathcal{A}}}(\mathbf{M}(f_3(x^i_{\mathcal{A}})), \mathbf{x}_{\mathcal{E}}). \qquad (3.3)$$

In other words, for a value system to exist there must be at at least:

- a function (f_1) of the input to essential variables that affects the value system variables,
- a function (f_2) of the value system variables that affects the control architecture (which could be the value system variables themselves) and
- a function (f_3) of the control architecture variables (affected by the value system variables) which produces a motor interaction

so that:

- the motor function and some environmental variables produce an adaptive function ($f_{e_{\mathcal{A}}}$) for the agent: i.e. maintains the essential variables under viability constraints.

The reader can now localize the functions and variables involved in the formal definition inside figure 3.1.

Chapter 4

Simulation Design

To test the viability of the hypothesized mechanism (homeostatic-plasticity based value system) and to illustrate the autonomous dynamical framework formalized above we choose a minimally adaptive task. An agent (defined as a set of dynamical laws gouverning a control architecture, a body and a set of sensors) will have to maintain an essential variable (energy) under viability constraints (above zero) in an environment composed of poisonous and profitable food. Each of the food sources will provide a smell gradient and a quality signal (taste). The aim of the simulation is to evolve the parameters of the controll architecture in order to produce autonomous adaptive behaviour in a changing environment where the quality of the food varies between trials or during the trial. By evolving adaptive architectures without predefined functional structures we will study how the internal dynamics of the agent and the agent-environment dynamical coupling gives rise to adaptive behaviour. The task requires behavioural plasticity to satisfy closure conditions in different environmental conditions providing a minimal paradigm to study how internal structural variation produces autonomous behaviour in changing environments.

This chapter provides a detailed exposition of the simulation design and chapter 5 analyses the evolved mechanisms.

4.1 The environment

The agent's environment consists of a two dimensional infinite plane with two food sources (A and B) located between 20 and 27 su (space units) of the agent's initial position at an angle of $\pm(\frac{\pi}{12}, \frac{3\pi}{12})$ from the agent's initial position (see figure 4.1). Each food source is defined by a quality parameter, a quantity parameter and size. The quality parameter defines the amount of energy the agent loses or acquires when the agent enters into the radius defined by the size of the food (2 space units – su). The quantity parameter states how much food the source contains. When the quantity of food is

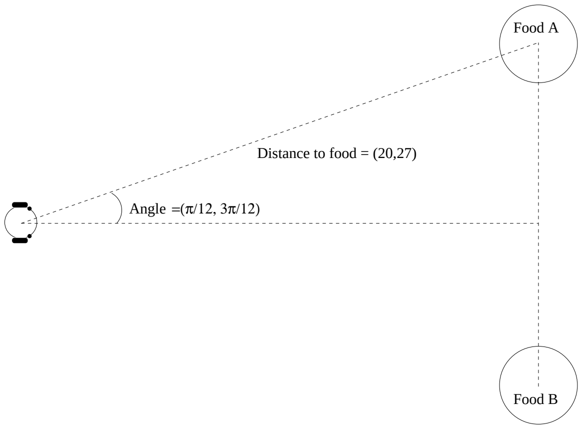

Figure 4.1: Environment of the simulation. Two food sources appear a variable distance from the agent (between 20 and 27 su) at $\pm(\frac{\pi}{12}, \frac{3\pi}{12})$ degrees.

finished both food sources disapear and a new pair of food appears again at variable distance between 20 and 27 su from the last food position and at a $\pm(\frac{\pi}{12}, \frac{3\pi}{12})$ angle from the last position's center. When the new food sources appear there is a 50% probability of swapping the angle of food sources so that if food A was situated between an angle of $+\frac{\pi}{12}$ and $+\frac{3\pi}{12}$ is now located between $-\frac{\pi}{12}$ and $-\frac{3\pi}{12}$ of the x axis.

4.2 The agent

Our agent is composed of an energy variable, an homeostatic plastic CTRNN (Continuous Time Recurrent Neural Network), two motors connected to the network and five sensors, as shown in figure 4.2, the diameter of the two dimensional round body being of unit length one.

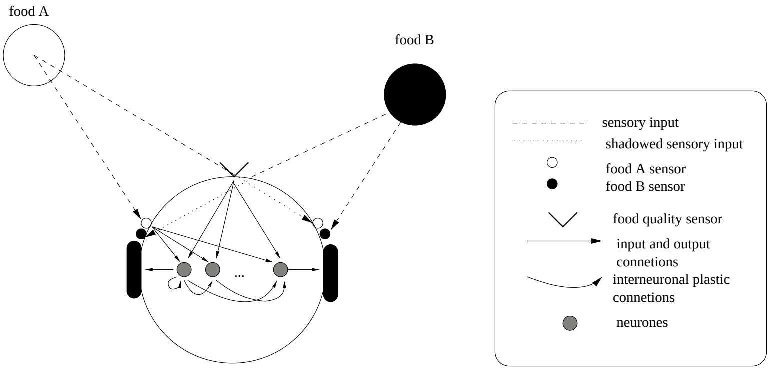

Figure 4.2: *Simulated Minimally Autonomous Agent*

Energy Variable

The energy variable is initialized at 100 units and decays linearly by one energy unit for time unit. When an agent enters the eating radius of a food source the energy increases or decreases according to the quality of the food (±5 energy units per time unit depending on the food being poisonous or not). The agent has a satiation limit of 100 energy units, above which the agent's energy variable does not increase. The agent's energy variable represents the essential variable of the agent as an autonomous system. It is a representation of the conditions of possibility of the agent's self-maintenance (closure) conditions which decays over time so that the agent has to interact with the environment to maintain the essential variable under viability constraints (bottom boundary at 0 energy units). The agent has an energy cost function for loss of homeostasis of the neurons, given by the equation:

$$\Delta E = -0.15 \cdot \sum_{i=0}^{n} \frac{p_i}{n} \Delta t \tag{4.1}$$

Where p_i is the degree of local plastic facilitation (explained below in section 4.2 page 27).

Sensors

The food sensors are situated in the perimeter of the agent, separated by 120^o as successfully tested by [31] for a similar task.

The input to the sensor is calculate according to the following equation:

$$I = e^{\frac{-d^2}{D^2}} \; ; \tag{4.2}$$

where d is the distance from the sensor to the source and D the maximum initial distance of the agent from the source (27 su). The sensory input is divided by 2 when the body shadows the source of light (as shown in figure 4.2). Sensors are connected to all the neurons of the controll architecture and modulated by a fixed weight value for each neuron whose value (-5,5) was subjected to evolution (see genetic encoding below); each neuron has a gain value parameter (genetically determined) to modulate all the inputs from sensors, value (-5,5).

A food quality sensor connecte to all the nodes is situated in the center of the agent's body. When the agent is at eating distance (2 su) from the food source the sensor takes an input 1 if the food is non-poisonous and -1 if poisonous. Note that positive-negative value of the signal is, in principle, neutral to the agent, it is given negative when the food is poisonous for clarity to the observer but it could have been otherwise. The positive or negative value of the signal is interpreted by the agents dynamics and does not have any a priori value.

Motors and motion

Two neurons of the CTRNN are connected to right and left motors respectively. The motor output is a linear mapping (-1,1) of the firing rate of the neuron (a sigmoid function of its activation) multiplied by a gain (subject to evolution) ranging (-2,2). The motion of the agent is calculated by a 0.2 timestep Euler approximation, the velocity being directly proportional to the motor outputs.

Controll architecture: CTRNN

The agent's behaviour is controlled by a continuous-time recurrent neural network (or DRNN, Dynamic Recurrent Neural Network, generally used in autonomous robotics and animats [2, 14, 31, 37]) gouverned by the the following state equation :

$$\begin{aligned} \tau_i \dot{y}_i &= -y_i + \sum_{j=1}^{n} (w_{ij} z_j) + g_i \sum_{k=0}^{5} s_{ki} I_k \ ; \\ \text{where} \quad z_j &= \frac{1}{1 + exp(-(y_j + b_j))} \end{aligned} \tag{4.3}$$

where y is the state of each neuron, τ is the time constant, w_{ij} is the connection weight between neuron i and j, z_j is the activation of neuron j, y_j is j's state and b_j a bias term; g_i is a gain (-5,5) applied to the overall sensory input to the neuron, s_{ki} (-5,5) is the input weight from sensor k to neuron i and I_k is the input value of sensor k. States where initialized at 0 and the CTRNN was integrated using forward Euler method with an integration step size of 0.2. All neurons are connected to each other and to themselves; w_{ij} can take values from $(-n, n)$, i.e. from minus the number of neurons to the number of neurons. The bias term b_j takes values from $(-\frac{n}{2}, \frac{n}{2})$. Neurons activity decays according to the time constant τ_i values between 1 and 2 or 4 (depending on the experiments, see section 5). Figure 4.3 (top right) shows the dynamic of a neuron with input 3 during the first 30 time units. The same input was give to a neuron in a 3 node network during 70 time steps, the state space of the network is shown in figure 4.3.

Plasticity

Four plastic rules gouverning the weight change where implemented in the CTRNN:

0: No plasticity: $\Delta w_{ij} = 0$,

1: Plain Hebbian: $\Delta w_{ij} \ = \ \delta_{ij} \ \eta_{ij} \ p_j \ z_i \ z_j$,

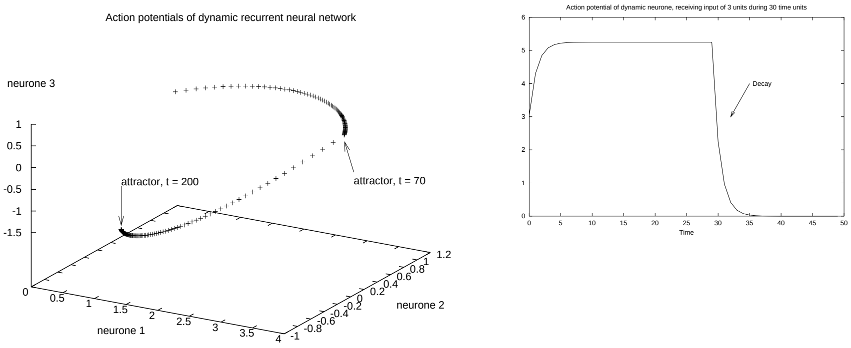

Figure 4.3: *Neural dynamics*

2: Presynaptic Hebbian: $\Delta w_{ij} \;=\; \delta_{ij}\ \eta_{ij}\ p_j\ (z_i \;-\; \mu_{ij})\ z_j,$

3: Postsynaptic Hebbian: $\Delta w_{ij} \;=\; \delta_{ij}\ \eta_{ij}\ p_j\ z_i\ (z_j \;-\; \mu_{ij}),$

where p_j is the degree of plastic local facilitation explained below, μ_{ij} depends linearly on the value of w_{ij} so that $\mu_{ij} = 0$ if $w_{ij} = max$ and $\mu_{ij} = 1$ if $w_{ij} = min$, η_{ij} is the genetically specified learning rate and δ_{ij} is a linear normalization value that constraints changes within allowed weight values $(-n, n)$.

Figure 4.4 shows the Δw_{ij} for plain hebbian and presynaptic hebbian rules. The effect of the postsynaptic rule can be easily figured out by inverting the x and y axis on the postsynaptic graph. The effect of the degree of local facilitation parameter p_i is not included in the graph, but the effect of how the normalization parameter works can be observed: as the weight increases (or decreases) the Δw decreases as well.

Plastic changes are triggered when postsynaptic neurons lose their homeostasis by determining the degree of local plastic facilitation p_j mentioned above. The relation between action potential, firing rate, and p_j is shown in figure 4.5. Note that the equation gouverning the degree of local facilitation is the inverse of the one shown in figure 2.1 but by allowing the learning rate η_{ij} to have negative sign, evolution can find the appropriated homeostatic arrangement.

The initialization of weights depends on the experiments.

Noise

Noise was added to motor output, sensory input and nodes. Noise to sensory input and motor output was introduced by adding a noise factor (-0.25,0.25) multiplied by a genetically determined parameter for sensory noise. Motor output noise was implemented in the same way. Noise to activation values

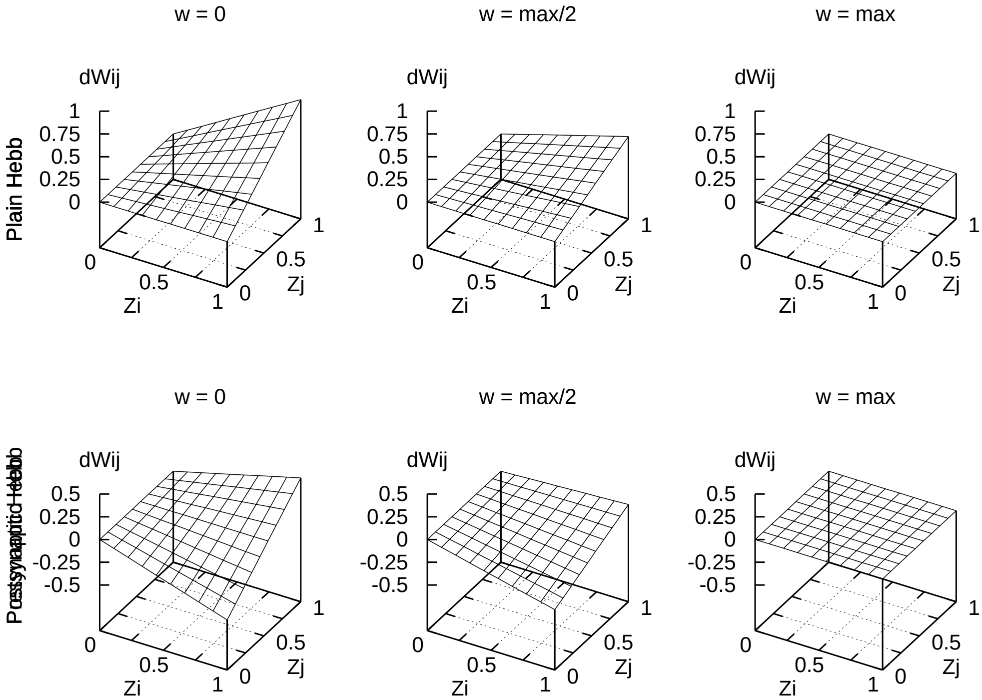

Figure 4.4: *Plain and Pretsynaptic Hebbian plastic rules*

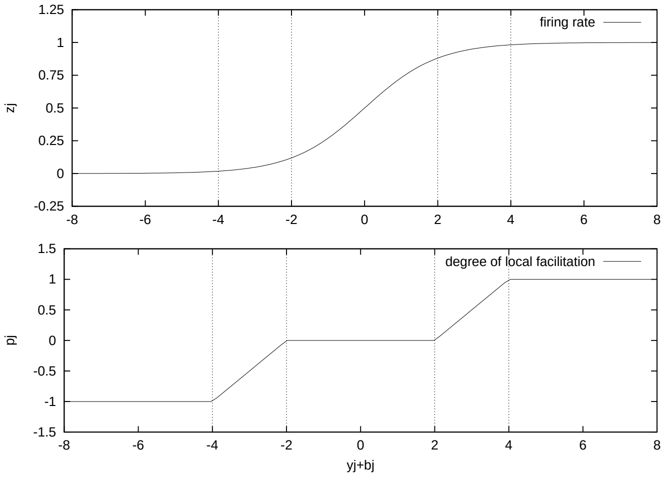

Figure 4.5: *Facilitation of local plasticity as a function of action potential*

was implemented through the following equation: $\Delta y_i = 0.25 \cdot y_i \cdot \rho \cdot \mu$, where ρ is a random value (-1,1) and μ is an evolved parameter $(0, 1)$ controlling activation noise.

4.3 Genetic encoding

The genotype is composed of a string of L double precision real numbers (-1,1) for different parameters of the architecture and a string of n^2 integers [0,3] encoding a rule for each of the synaptic connections. Where $L = (n \times k) + (n \times n) + (2 \times n^2) + 5$, being n the number of neurons (different for both experiments) and k the number of inputs (5); 3 locus are for the noise parameters (μ), 2 for the motor output gains, n^2 for the learning rates of the weights (η_{ij}), n^2 for the initial weight values, n for the time constants τ_i, n for the input gains (g_i), n for the bias terms (b_i), and $n \times k$ for the input weights to the nodes (s_{ki}). The genotype-phenotype mapping is a linear mapping between the value of the gene and the range of the parameter it encodes (see subsections above for specifications).

4.4 Fitness Function

Agents where evaluated on 4 trials (2 for condition A and 2 for condition B). Each trial is a lifetime of 800 tu (4000 ts) or 500 tu (depending on experiments). The fitness is averaged over the 4 trials and is given by the following equation:

$$\text{Fitness} = \int_0^{t_{max}} \frac{e(t)}{e_0} dt. \tag{4.4}$$

where $e(t)$ is the state of the agent's energy variable at time t and e_0 the agent's initial (and satiation) energy level.

The fitness function is meant to be a representation of the agent's autonomy in terms of its essential variable. This way selection acts upon the agents autonomy and not on particular behaviour (as it is very often implemented in evolutionary robotics, and specially conventional optimization).

4.5 Genetic Algorithm

A rank based Genetic Algorithm (GA) was used to evolve an adaptive architecture. The population (see chapter 5 for details of each experiment) was evaluated on four tests (two for condition A and two for condition B) and ranked from fittest to less fit. The probability of being selected for reproduction was calculated with the following equation:

$$P(i) = \left(\frac{i}{N_{pop}} \right)^{\alpha} - \sum_{n=1}^{i-1} P(n) \ ; \tag{4.5}$$

where α is the selective pressure (2), N_{pop} the size of the population and agents are ranked from $i = 0$ to $i = N_{pop}$ according to their fitness.

A roulette *selection* mechanism was used to select two parents to mate. Point *crossover* with 50% probability for each locus was used to create an offspring. A *mutation* probability of 0.1 per locus was applied to the offspring; the mutation size being a Gaussian random variable with 0 mean and variance (σ^2) of 0.02 (a simplified version of mutation vectors proposed in [2] and [37]).

Elitism was implemented by copying the four best genotypes to the next generation without mutation nor crossover.

Chapter 5

Experimental Results: Multilevel Analysis of Evolved Agents

After a series of experiments with the evolutionary scenario and the control architecture explained in the last section two main types of agents were produced. In the first case network architectures where evolved which showed a developmental process where early interaction with adaptively significant events (encounters with food) shaped the weight space trajectories to produce robust adaptive strategies. This first type of results showed their limitation on their sensitivity to initial interactions with the environment, once the initial critical period was finished agent's couldn't readapt to change on food quality.

The second type of results showed highly adaptive agents robust to an indefinite number of food profitability changes. Nevertheless this agents were reactive, in the sense that no long term variable state variation was correlated with their behaviour. In particular synaptic plasticity didn't seem to play any significant role on the observed adaptive behaviour.

In this chapter we will analyse an agent from each of the evolved types described above. Both analysis (experiments one and two below) focus on different aspects of the dynamical properties shown by the agents of each type. Experimental results and operational tests will illustrate the autonomous dynamical framework developed in the preceding chapters with special attention to 1) value systems, 2) and homeostatic plasticity and 3) the concept of adaptive function.

5.1 Experiment 1

In the first experiment we the agent was tested on 4 trials for 4000 ts where the poisonous food source remained constant during the trial but changed

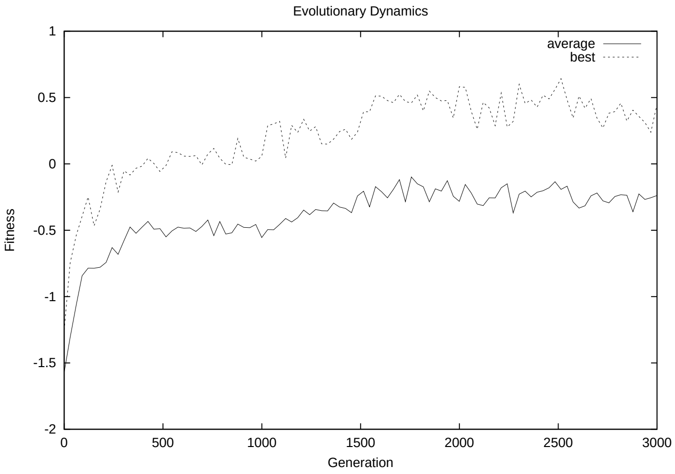

Figure 5.1: *Evolutionary dynamics for experiment 1. Dashed line top shows best fitness and solid line average fitness of the population*

between trials. Network consists of 10 nodes. Synaptic weights with plastic rules (1,2,3) where initialized at zero and those with rule 0 (no plasticity) where initialized with a genetically specified value. Agents where evolved for 3000 generations. Figure 5.1 shows the evolutionary dynamics. The phenotype of the evolved agent can be found in Appendix A.

5.1.1 Behavioural Analysis

Average behaviour over 10 trials

Our first behavioural test attempts to test the evolved agent's adaptive behaviour over 10 different trials. The agent is tested over 2500 ts (500 tu) in two different conditions:

- **Condition A**: Food A begins being profitable and remains profitable.
- **Condition B**: Food B begins being profitable and remains so for the rest of the trial.

Figure 5.2 shows agent's food preferences over time; amount of food A and B consumed over time (averaged for 100 ts and over 10 trials). It can be seen that the agent adapts to both conditions. The peak of eaten A food on condition B (left of figure 5.2), represent the first interaction with food, where the agent always goes to food A, after that early interaction the agent shows a distinctive 'preference' for food B.

Figure 5.3 shows the quantity of poisonous and non-poisonous food eaten during the trial. The amount of poisonous food eaten is significantly reduced

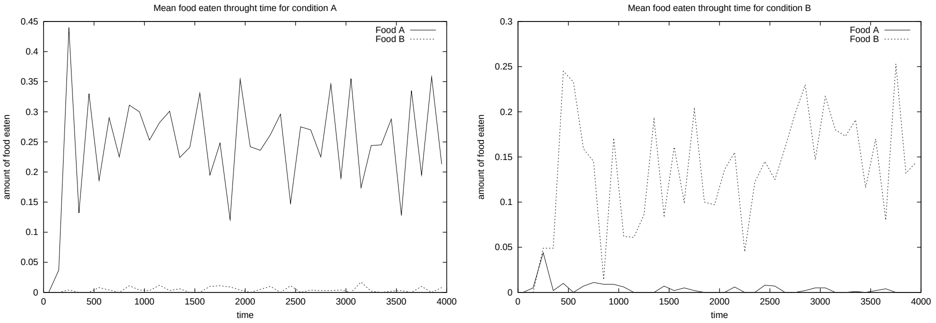

Figure 5.2: *Mean eaten food thought time for a sample of 10 agents. The left figure corresponds to condition A (food A profitable). Figure on the right shows agents food choice for condition B. Values have been average for 100 ts over 10 trials for each condition.*

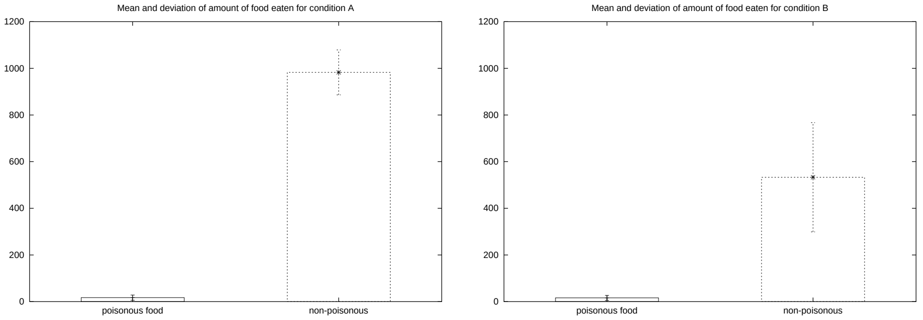

Figure 5.3: *Mean eaten poisonous or non-poisonous food per time step for a sample of 10 tests. The on the left shows data for condition A, and the figure on the right for condition B*

in comparison with the non-poisonous one and condition B shows a poorer adaptive performance than condition A.

Single trial behaviour

We proceed by analysing single trial behaviour for both conditions. Figure 5.4 shows the agent's trajectory on the two dimensional world (first and third graphs starting from the top) and the distance to each food sources through time. Behaviour in condition A shows a clear preference for food A. Condition B gives rise to not such a clear behaviour in the two dimensional world but distance to food in the graph below illustrates the tendency towards food B after an initial period of 'confusion', during the interval (0,1000).

The behaviour is clearly different in both conditions: there a clear tendency to approach (and 'eat') profitable food after and early stage of 'exploration', both in a single trial and in an averaged test of ten trial per each condition. But how does this behaviour arise? The hypothesis is that

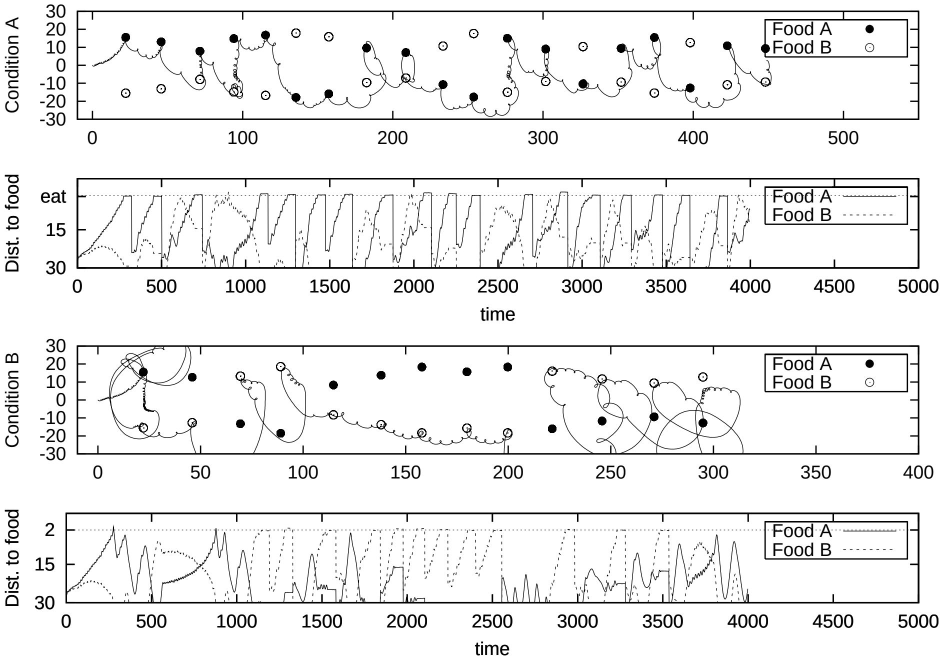

Figure 5.4: *Behaviour on a single trial for both conditions. First and third figures starting from the top show the agent's behaviour on the two dimensional world. The second and fourth graphs show the distance from the agents position to the food sources thought time.*

homeostatic plasticity allows for a different configuration of the weights on each condition which determines a particular dynamical coupling with the environment that leads to the observed behaviour. The following section will try to demonstrate the hypothesis, through a series of operational tests and observations on the agent-environment dynamics with special attention on the weight dynamics.

Long term stability test

When long term dynamics (in our case weight plasticity or long time constants) are implemented in a simulation it is necessary to make a long term stability test how robust over time is the behaviour produced by the evolved parameters. The agent was tested 10 times for long term stability in a 25000 ts (time step) trial, 10 times longer than evolutionary tests. Results, in figure 5.5, show that after 15000 ts adaptive behaviour degenerates for both conditions.

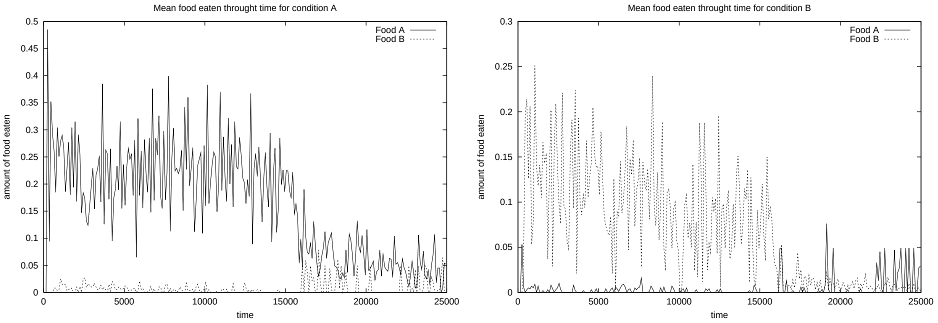

Figure 5.5: *Long term stability test for both conditions. The plots show average eaten food per ts over 10 trials. Behaviour degenerates after* $t = 15000$*, i.e. after 6 times the length of an evolutionary lifetime.*

5.1.2 Dynamical Analysis: weight states determine adaptive strategy after developmental process

Because the time constants are reduced to low values (1,4), we believe that a change on the weight space trajectory is the responsible for the observed differences on behaviour for both conditions. As a first approximation we will initialize the weight values of the agent with the weight values developend under condition A and test the agent on condition B.

Figure 5.6 illustrates the agent's behaviour after the test is carried out. The agent, whose weights have been developed under condition A, systematically goes to food A, although in the new condition food A is poisonous. Unlike the agent's behaviour in condition A, when food A is approached the agent shows a repulsive behaviour but gets attracted to it afterwards, the effect can be observed on the punctuated repulsion-attraction to food A (see figure 5.6, the behaviour around the food, top graph, and the oscillation on distance from food source on the bottom graph). The cycle is repeated until the food is consumed and a new pair of food sources appears. The reaction looks like an innate repulsive reaction in response to negative food quality signal. A similar effect is observed when the agent is put on condition A with the synaptic weight values developed on condition B: the agent systematically approaches food B and the attraction-repulsion dynamics can also be observed.

We can conclude that the weight state determines the agent's behaviour and that a particular weight state is achieved during a developmental stage on every condition, after which, the agent's preference for food is fixed. We shall now look more closely to the weight dynamics for both conditions.

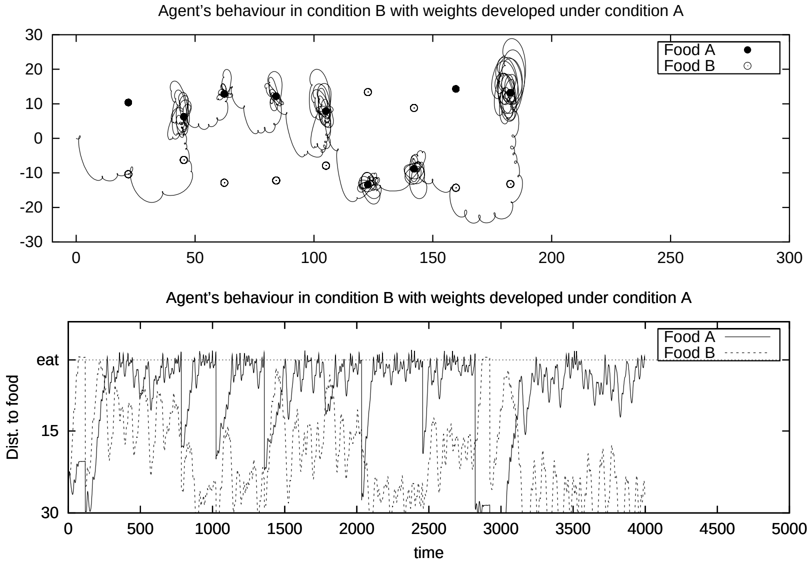

Figure 5.6: *Synaptic weight values developed under condition A are tested on condition B. The operational test shows that the agent's behaviour is conditioned by its weight state.*

Comparison of weight trajectories for both conditions

The first operation to discriminate a set of observable weight values (of a total of 100 connections in the network) is to observe variation of weight values through time on both conditions. From the variation analysis we plot the weight trajectories for those weights showing a higher change between the two conditions.

Figure 5.7 shows the trajectories of the synapses with highest variance between the two conditions (values correspond to the single trial behaviour shown in figure 5.4). After a common trajectory during the first 300 ts the trajectories diverge. The bifurcation point corresponds to the first encounter with food A (see figure 5.4). After this first encounter the weight values take different trajectories until they stabilize.

Figure 5.1.2 show the trajectories of the three synapses with higher variance. It can be noticed that different runs on both conditions produce a very similar trajectories. The values of the shown weights being crucial for the behavioural patterns observed. An operational test not allowing synaptic plasticity on $w_{9,0}$, $w_{9,9}$ and $w_{9,2}$ shows that they are crucial to give rise to the behavioural patterns displayed under both conditions. By a further test we discovered that not allowing plasticity on $w_{9,0}$ completely disrupts adaptive behaviour under condition B.

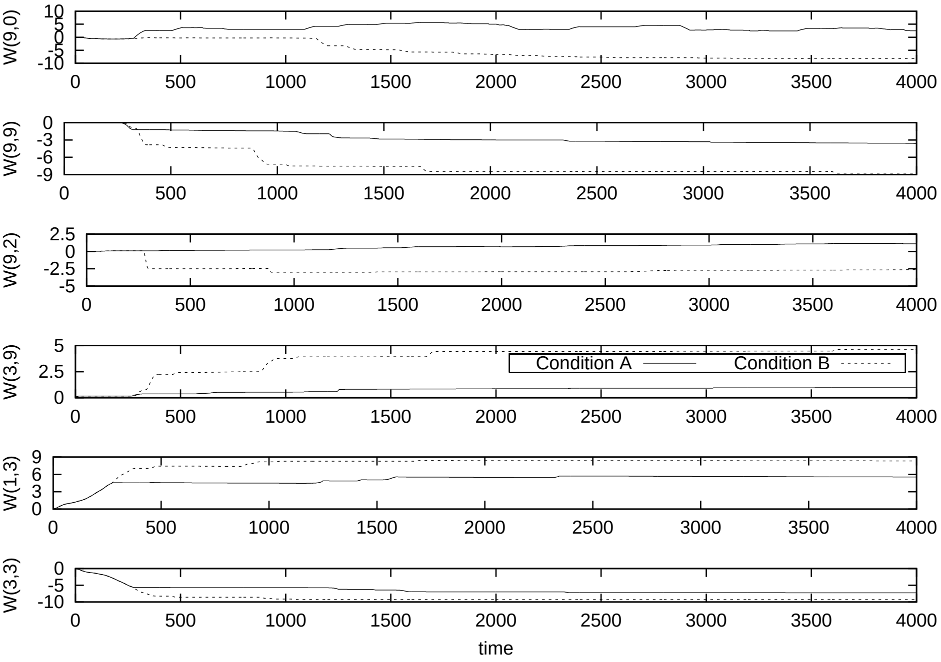

Figure 5.7: *Synaptic weight value trajectories for conditions A and B for the weights with higher deviation between the conditions. After a common trajectory during the first 300 ts, the trajectories bifurcate significantly and stabilize. Weight trajectories for condition A are plotted with solid lines and for condition B with dashed lines.*

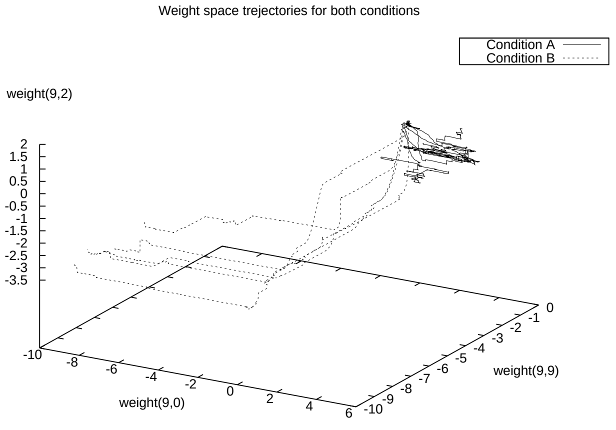

Figure 5.8: *Attractors in the weight space of the three synapses with highest variation between both conditions. 5 different trials has been plotted, starting from (0,0,0). Dashed line shows the trajectories for condition B, solid line for condition A. The trajectories show that weights systematically tend to two different regions of the weight space.*

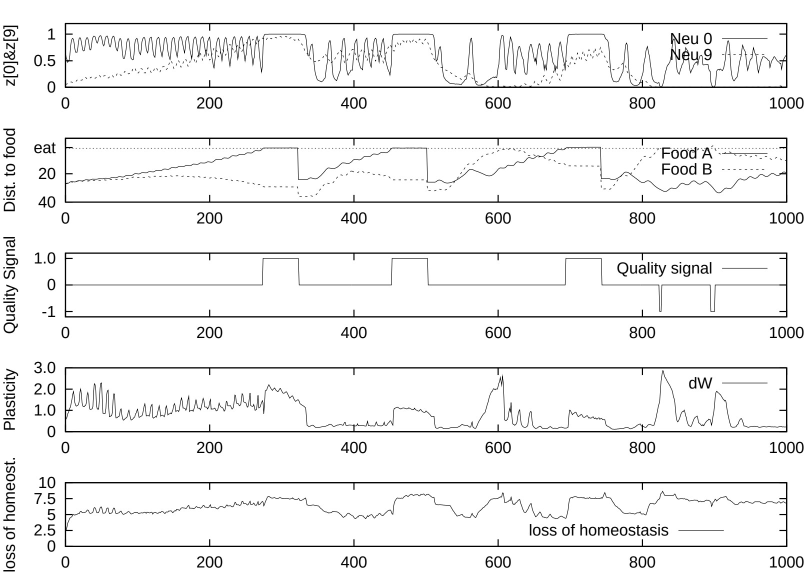

Figure 5.9: *Values of different state variables for the first 1000ts of a trial on condition A. Starting from the top: firing rate of nodes 0 and 9, distance to food A and B, quality signal, plasticity (amount of weight change in the network per time step), and loss of homeostasis (summation of the local degree of plastic facilitation, for details see section 4.2, page 27)*

Homeostatic Plasticity

We will now have a closer look at the early developmental stage where the first encounters with food happens, in order to analyse the way in which homeostatic plasticity and environmental interaction shapes the trajectory of the weight space.

Figure 5.1.2 shows the activities of nodes 0 (right motor) and 9 (first graph on top), distance to food (second graph), food quality signal (middle graph), the amount of plasticity[1] produced (next graph) and the loss of homeostasis of the network ($\sum_{i=0}^{n} p_i$), thought the first 1000 ts of a trial in condition A. During the first 250ts a big amount of plastic change can be observed, weight values (initialized at 0) are been developed thought the early sensory-motor interactions. When the first food source (A) is encountered (and in the following food encounters) large plastic changes occur due to the food quality signal and the high food sensor activities (not shown in the graph but correlated with distance). That the quality signal is not the only responsible of plastic changes on food encounter can be illustrated by the first approach to food source B (at $t = 600$) where the plasticity graph shows a great peak although no quality signal is triggered (i.e. the agent does not enter the 'eating' radius of food source B).

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[1] The amount of plasticity is calculated as $\sum_{i=0}^{n}\sum_{j=0}^{n}\Delta w_{ij}$.

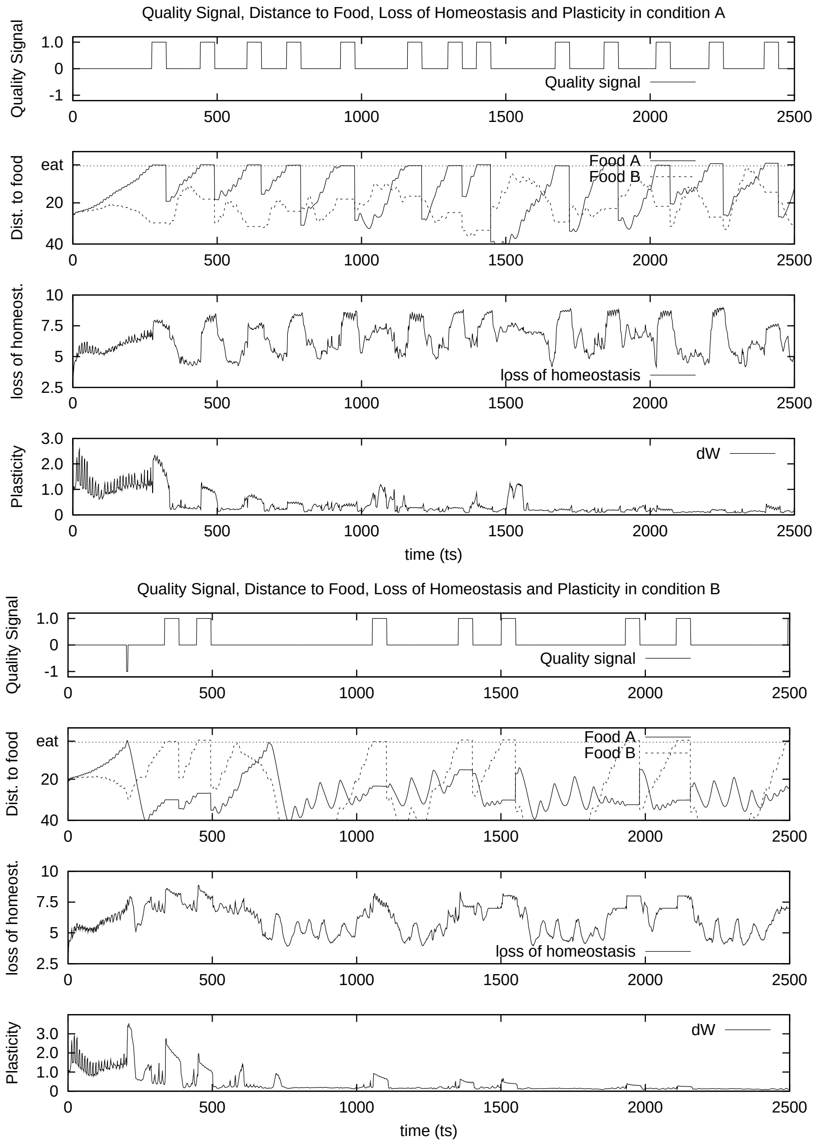

Figure 5.10: *Relation between quality signal, distance to food, loss of homeostasis and plastic changes for both conditions. The graphs illustrates how plastic changes occur during the first 300ts and with the first encounters/approaches to food, specially with quality signal.*

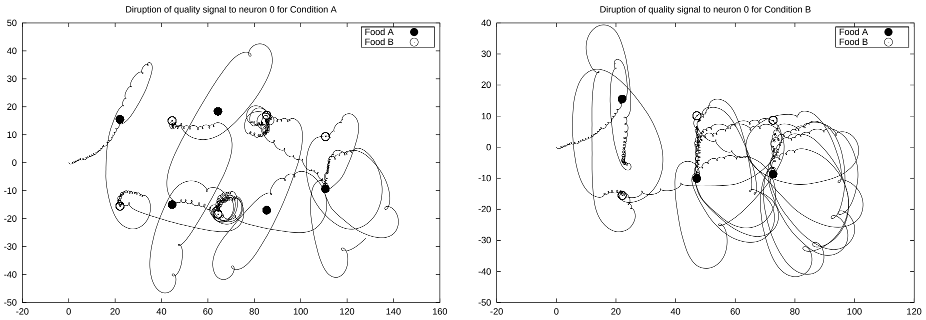

Figure 5.11: *Agent's behaviour in the two dimensional world with disruption of food quality signal to neuron 0 (right motor).*

Further analysis of the relation between food encounters and plasticity shows that the highest peaks on plasticity occur precisely when the first adaptively significant events (encounters with food sources) occur as well as on the first 300 ts. Figure 5.1.2 illustrates the claim.

5.1.3 Homeostatic Plasticity and Value System

A further analysis on different operations on the network variables showed that the quality signal to neuron 0 (left motor neuron) is crucial for the adequate developmental process of weight values. Disruption of the quality signal to neuron 0 destroys adaptive behaviour in both conditions as shown in figure 5.1.3.

According to our definition of value system (equation 3.3, page 23) neuron 0 can be interpreted as a value system: its change of state when adaptively significant interactions occur (specially when the first encounter with food happens) produces a loss of homeostasis and a subsequent modulation of weight trajectories leading to a particular adaptive function in the given environmental conditions.

5.1.4 Conclusions from experiment 1

When early encounters with food happen, weight trajectories are affected until stability is reached around the areas shown in figure 5.1.2. The food quality signal to the left motor node makes the activity of the neuron go out of homeostatic bounds thus allowing for $w_{9,0}$ to take the characteristic trajectories of conditions A or B. But after the initial encounters with food the weight values stabilize and no further accumulation of adaptation is possible.

The simulation of this first experiment showed how homeostatic plasticity can give rise to a value system: a developmental process sensitive to adaptively significant events modulates different trajectories in the weight space which produce different adaptive behavioural patterns for different environmental conditions. Evolved parameters for a homeostatic-plastic CTRNN allow, at least, for a developmental value system to arise without functional prespecification of a value system module or mechanisms.

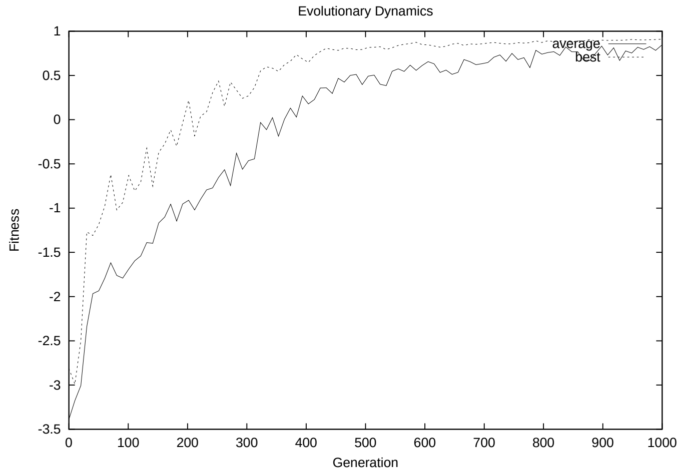

Figure 5.12: *Evolutionary dynamics for experiment 2. Dashed line top shows best fitness and solid line average fitness of the population*

5.2 Experiment 2

In this second experiment size of the population was 40 and network size 8 nodes. Agents where tested over 4 trials (duration 4000 ts) where food quality (poisonous, non-poisonous) was changed during the interval (1500, 3000). This time weights where initialized to genetically pre-specified values, plastic changes where then applied during the trial to synaptic connections. Figure 5.2 shows the evolutionary dynamics of experiment 2. The phenotipic details of the evolved agent can be found in Appendix B (details will be given when relevant to explanations).

5.2.1 Behavioural Analysis

Average behaviour over 10 trials

Our first behavioural test attempts to test the evolved agent's adaptive behaviour over 10 different trials. The agent is tested over 4000 time steps (ts) in two different conditions:

- **Condition A**: Food A begins being profitable and changes to poisonous after $t = 2000$ and *vice versa* for Food B.
- **Condition B**: Food B begins being profitable and changes to poisonous after $t = 2000$ and *vice versa* for Food A.

Figure 5.13 shows agents average eaten food through time. Although some poisonous food is always being eaten agents behaviour shows a robust

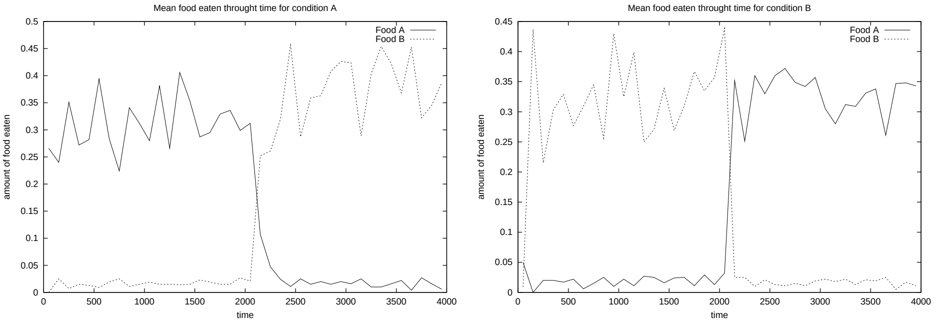

Figure 5.13: *Mean eaten food thought time for a sample of 10 agents. The right figure corresponds to condition A (food A profitable). Left figure shows agents food choice for condition B.*

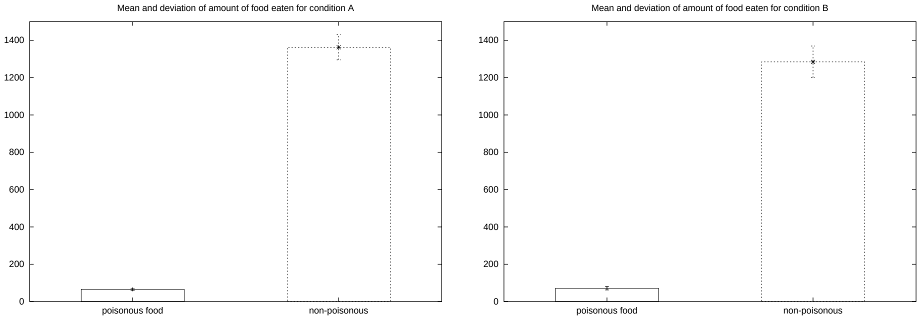

Figure 5.14: *Mean eaten poisonous or non-poisonous food for a sample of 10 tests. The right figure shows data for condition A, and left figure for condition B*

adaptive behaviour illustrated by the behavioural transition when poisonous food in changed.

Figure 5.14 shows the quantity of poisonous and non-poisonous food eaten during the trial averaged every 100 ts and over 10 trials. The amount of poisonous food eaten is significantly reduced in comparison with the non-poisonous one.

Single trial behaviour

We proceed by analysing single trial behaviour for both conditions (beginning with food A being poisonous and beginning with food B being poisonous). Trial duration is reduced to 1600 ts and food is changed at $t = 1000$. Figure 5.15 shows agent's behaviour for both conditions.

Second and third graphs in figure 5.15 show distance between agent and both food sources. Graphs show that the agent stays around the food when profitable (non-poisonous) and withdraws from it when poisonous.

The agent approaches poisonous food even after having 'eaten' it before

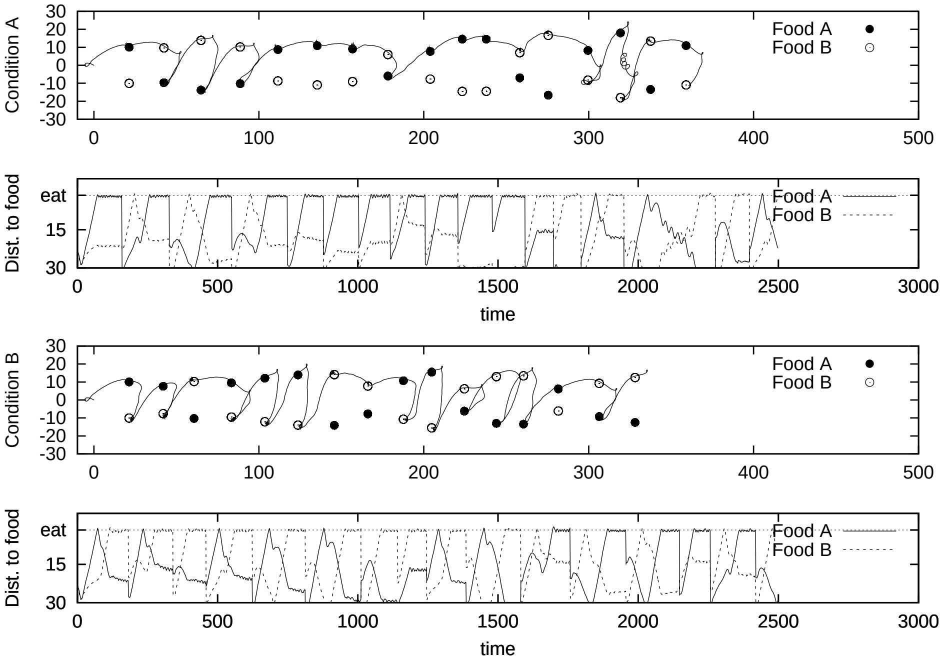

Figure 5.15: *Behaviour of evolved agent. First two figures on top show agent's behaviour when Food A starts being profitable and changes to poisonous after $t = 1500$. The two last figures show behaviour when Food B starts being profitable and changes after $t = 1500$.*

(see punctuated approach to poisonous food in figure 5.15), which shows that agent's approach to food is not completely determined by food quality. The agent does not 'eat' only the non-poisonous food, it approaches both foods but remains on the profitable one. When encountering poisonous food withdraws from it and approaches the other source, 5.16 shows a close view of this perspective. The oscillatory behaviour in 5.16, between $t = 100$ and $t = 160$, shows how the agent repeatedly enters the 'eating' ratio of the food source when profitable and only enters the 'eating' radius once when poisonous.

Autonomous Adaptation

That the agent is autonomous (satisfies closure criteria maintaining essential variables under viability range) could be deduced from the behavioural tests above. Nontheless we shall illustrate its internal energy variable to demonstrate that the agent is, effectively, autonomous in the given environmental conditions.

Figure 5.17 illustrates the trajectory of the essential variable Energy and shows how the evolved agent is autonomous (according to equation

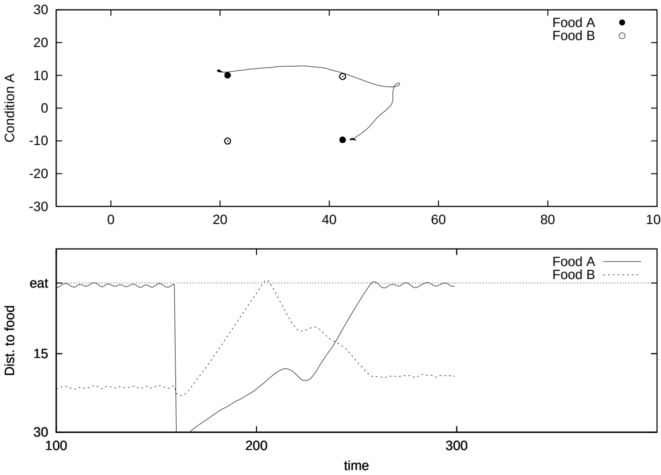

Figure 5.16: *Closer illustration of 'eating' behaviour in condition A*

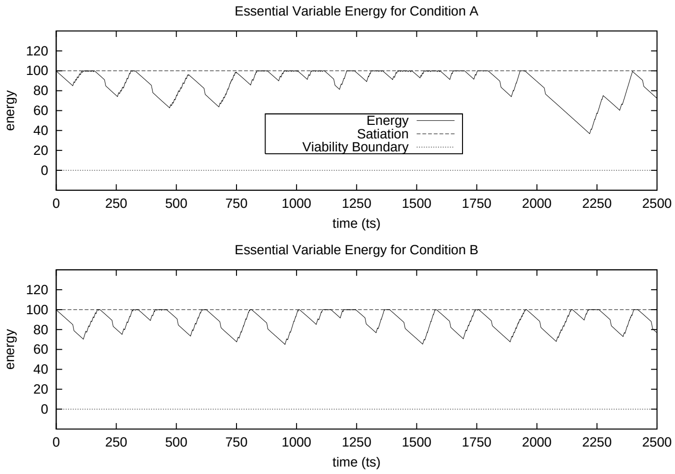

Figure 5.17: *Essential variable energy for both conditions. The agent is autonomous according to the definitiongiven in equation 3.1 in section 3*

3.1 in section 3) under the given environmetal conditions. It is now time to analyse how is its autonomy ($e_{\mathcal{A}} > 0$) realized through the observed adaptive function:

$$f_e = \begin{cases} dD_a/dt < 0 \quad \text{until} \quad D_a < 2 \quad \text{if } a = \text{profitable} \\ dD_b/dt < 0 \quad \text{until} \quad D_b < 2 \quad \text{if } b = \text{profitable} \end{cases} \tag{5.1}$$

where D_a and D_b are the distance between the agent and the A and B food sources respectively.

5.2.2 Dynamical Analysis

Weight Dynamics

Although the network had the possibility to exploit plasticity a comparative analysis of the difference on weight dynamics for both conditions showed little variation. The network was tested without plasticity and no significant change occurred on fitness nor behaviour. We thus conclude that synaptic plasticity didn't play any role on the adaptive behaviour this agent. We will thus ignore weight dynamics in what follows.

A close look to brain-body-environment dynamics

We proceed by having a closer look to the brain-body-environment dynamics. Figure 5.22 shows the state of all the relevant dynamics of the brain-body-environment coupled system for condition A, interval (0,300) ts. Nodes 6, 7 and 8 where omited because their activity remains near 0 for the whole trial (an operational test forcing nodes 6,7 and 8 to zero showed no significant difference on behaviour).

The coupled dynamics show that significant neural dynamics can be divided on two behavioural interactions: when the agent is near the profitable food where fast oscillations can be observed — intervals (70, 160) and (260, 300) — and the rest. Note that no significant neural activity change happens when the agent encounters poisonous food at interval (200, 210) — the peak on the right motor neuron at $t = 220$ is due to B food right sensor[2]. We will thus proceed by analysing the dynamics on three different processes: a) approaching behaviour, b) when the agent encounters profitable food and c) when the agent encounter poisonous food.

Approaching Behaviour

To analyse the approaching behaviour we record agent's behaviour during the first hundred ts. Figure 5.19 shows how the right sensory input oscillates producing a similar oscillation on both motor nodes and motor output. The sensory oscillation is due to the agent's body shadowing. As explained in section 4.2 (page 26) if the body is between the food source and the sensors, sensory input is divided by two. The effect is exploited by the agent's nervous system to *enact* the approaching behaviour. Figure 5.20 shows agent's behaviour in the same environmental conditions but not implementing body shadowing, the approaching behaviour is completely disrupted.

But how does the agent exploit its body shadowing to approach the food source? A close look at the circuit composed of the two motor neurons and

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[2] And operational test stopping quality sensory input when the agent approaches poisonous food shows that the behaviour does not change significantly. The question will be addressed later on more detail.

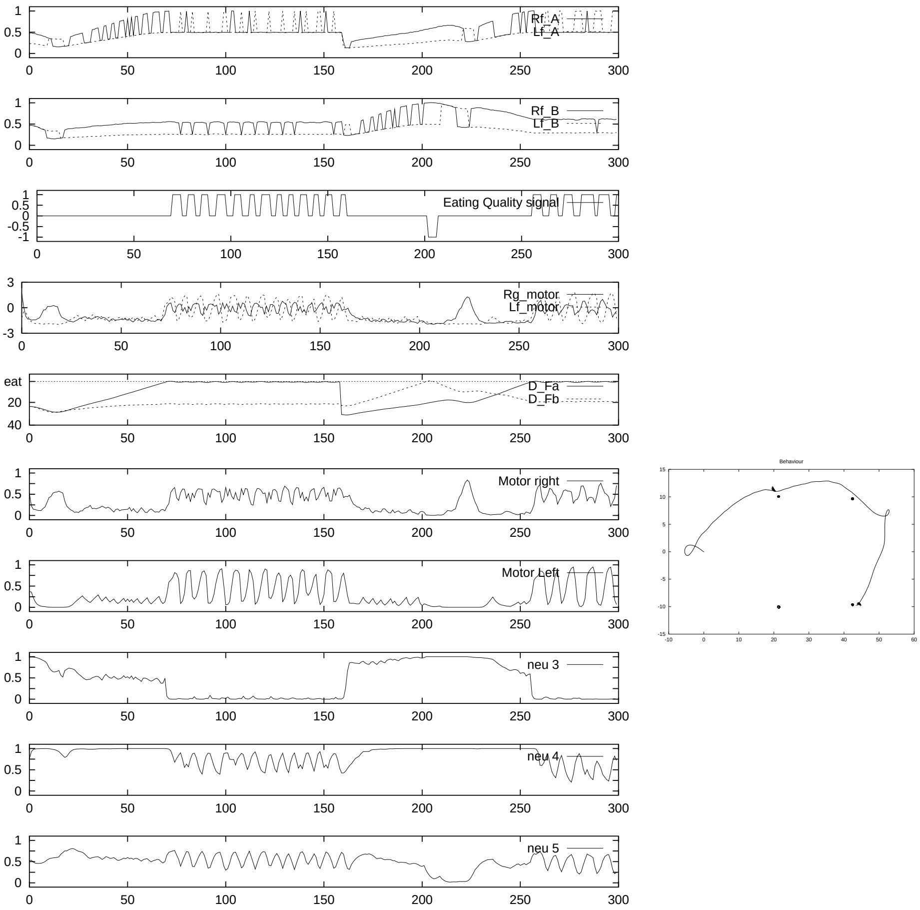

Figure 5.18: *Agent's behaviour with both food sources being poisonous*

the food A sensors can give us some clue about what happens when only the left sensor is shadowed. Figure 5.21 shows the connections of the isolated circuit. By the values of the motor output (figure 5.19) we know that the agent moves backwards, moving in relation to the food source by shadowing only the left sensor or both. Looking to the simplified circuit (figure 5.21 left) we deduce that when only the left sensor is shadowed the input from the right sensor to the right motor neuron inhibits its activity stronger than the inhibitory connection between left sensor and left motor neuron. Because the motor activities are negative (by the linear mapping from motor nodes (0,1) to motor activity (-2,2)) this situation makes the agent move so that both sensors are shadowed. When both sensors are shadowed the inhibitory connections compensate each other. In this case dynamics of the whole network must be considered, because the circuit shown in figure 5.21 will produce the wrong movement.

Figure 5.21 shows an simplified version of the effect of sensor shadowing

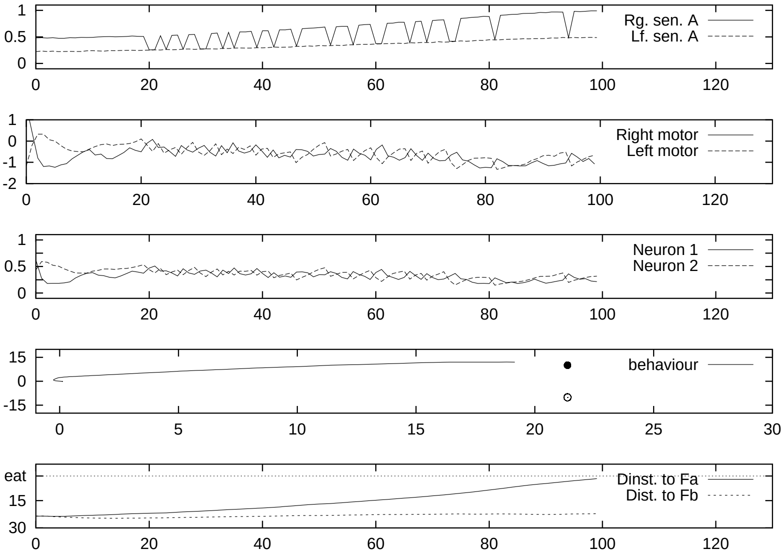

Figure 5.19: *Agent's approaching dynamics. The series of plots on the leftshow: right and left food A sensors (top), right and left motor outputs, firing rates of nodes 1 and 2 (motor nodes), agent's behaviour in the 2 dimensional world and distance to food.*

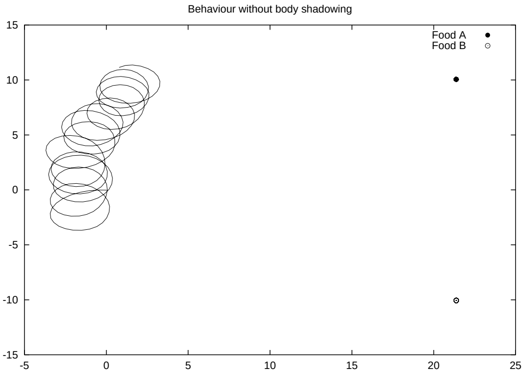

Figure 5.20: *Agent's behaviour not allowing body shadowing to sensors.*

on the behaviour of the agent. The detailed analysis of the network show a much more complex behaviour, but the significance of the sensor shadowing has been shown. The approaching behaviour (a the main component of the adaptive function specified in equation 5.1 —page 46) is not performed by an internal representation of the food's position and subsequent plan-action sequence but is carried out by a complex interplay (active perception-action), involving, at least, control of body shadowing.

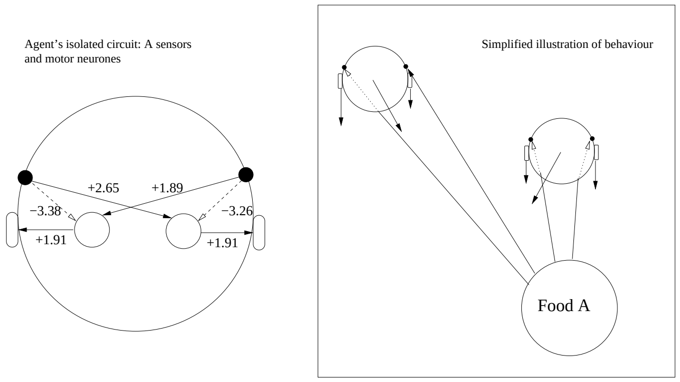

Figure 5.21: *Agent's approaching mechanism*

Encounter with Profitable food

We move now to analyse the dynamics of the system when the agent encounters profitable food. Figure 5.22 shows the dynamics of sensors, motors and neural activity when the agent encounters profitable food. The left motor node oscillates strongly between (0,1) producing oscillatory positive and negative motor output which produces the agent to move forward and backward. When the agent enters the eating radius of the profitable food, the positive food quality signal triggers a complex repulsion-attraction dynamic shown in figure 5.23.

At a first view it looks like the food quality signal to the network causes the moving back of the agent. An operational test not allowing shadowing didn't produce the repulsion-attraction dynamic shown in figure 5.23. Another operational test forcing both (left and right sensor) shadowing showed that the shadowing is required for the food quality signal to produce a repulsive reaction. Figure 5.24 shows the agent's behaviour on that test. It can be observed that only the left motor is significantly excited by the food quality signal which produces a twisting behaviour around the food. We can conclude thus that both body shadowing of the food source sensory input and the food quality signal interplay to produce the behaviour shown in figure 5.23.

Encounter with non profitable food source

We have analysed the agent's interaction with the environment on two dynamically distinguishable situations, where agent's internal dynamics and its interaction with the food source changed significantly: the approaching strategy to food source A and the encounter with food A. Both situations are adaptively significant but something else is required so achieve autonomy: some kind of behavioural discrimination between poisonous and profitable

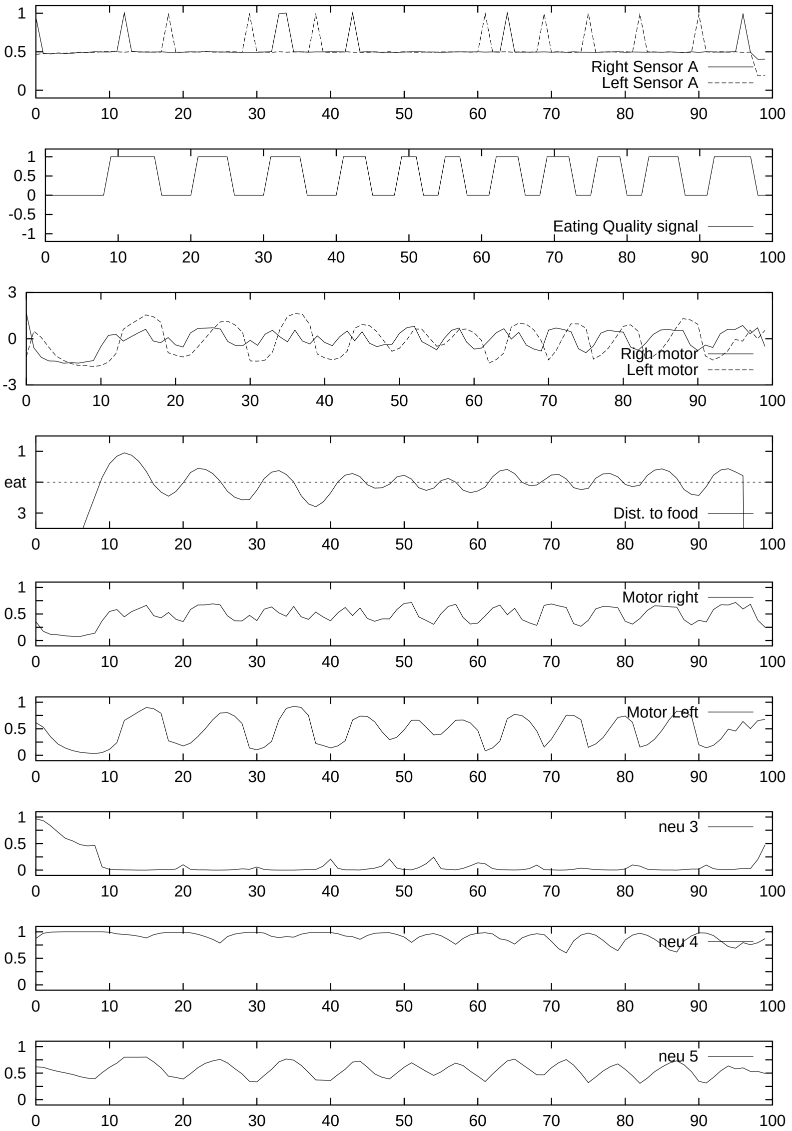

Figure 5.22: *Agent's behaviour during encounter with profitable food*

food. What happens when the agent encounter poisonous food? It looks, a-priori, that this encounter should be dynamically significant since its effect on the agents autonomy is of great importance. But figure 5.16 in section 5.2.2 (page 46) showed no significant perturbation on the neural dynamics when the agent encounters poisonous food. How could this lead to adaptive behaviour? What would happen if the agent's environment only contained poisonous food? Figure 5.25 shows agent's behaviour when both foods are poisonous (food quality signal for both food sources in -1). By not falling

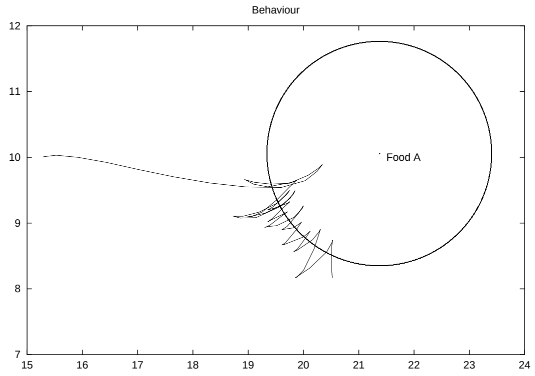

Figure 5.23: *Agent's behaviour during encounter with profitable food but shadowing disrupted*

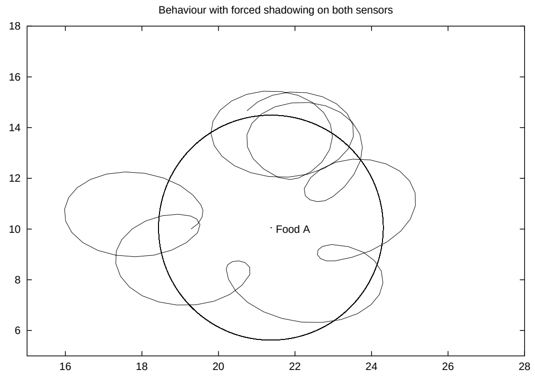

Figure 5.24: *Agent's behaviour with both food sources being poisonous*

into the attraction-repulsion dynamics of profitable food shown in above, the agent passes thought the food and gets attracted to the other food source. The resulting behaviour is a quasi periodic cyclic attractor.

5.2.3 Emergent Adaptive Function and Value System

The adaptive function f_e, described in equation 5.1 (page 46) cannot be understood as state of the agent's state space, not even as a series of states. The function is distributed not only among the states of the agent but among the agent-environment relationships. The agent exploits its sensory boundary conditions (by going thought the poisonous food, for example) and its body-environment interaction (by shadowing its sensors) to *enact* an adaptive functionality that leads to autonomy. In fact how the adaptive function is realized is by engaging in the cyclic quasi periodic attractor shown in figure 5.25 until the agent finds a profitable food, where the food quality

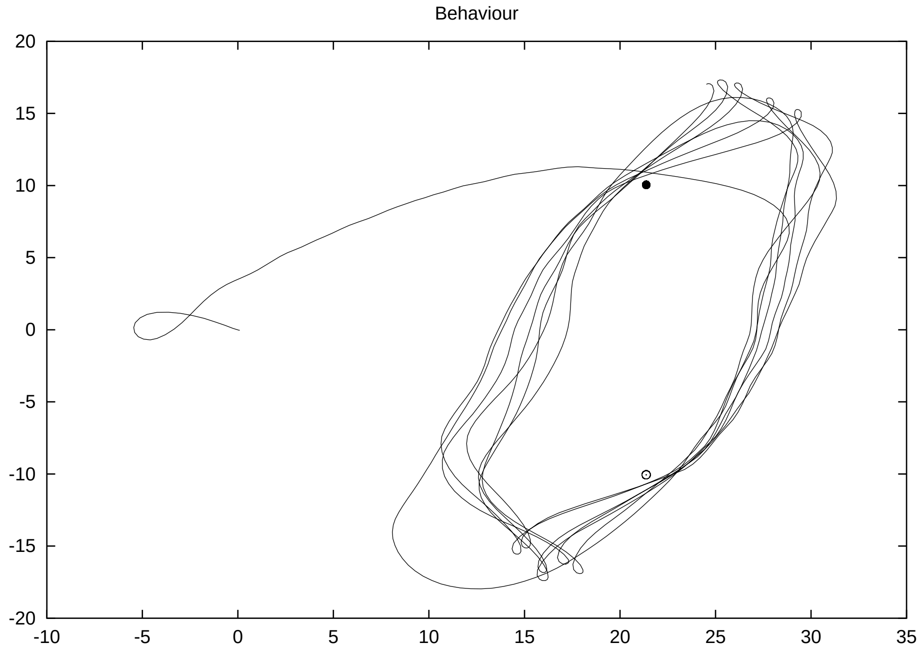

Figure 5.25: *Agent's behaviour with both food sources being poisonous*

signal triggers an attraction-repulsion dynamic until the food is finished an two new food sources appear. Is there any value system involved? The food quality signal for profitable food has shown to be of major importance in the agents adaptive functionality, in fact it can be considered to be a *value* signal in its own right according to the definition 3.3:

- the food quality signal is correlated with a positive change in the essential variable Energy,
- it produces a change in the network (specially in the left motor neuron),
- which produces an interactive pattern that gives rise to consuming the food and
- breaking the quasi periodic cyclic behaviour around the two food, selects the profitable one.

5.2.4 Conclusion for experiment 2

If autonomous adaptation is taken as the normative criteria no interpret adaptive functionality and behaviour a detailed explanation of the agent's adaptive functionality. The simulation, as a simplified abstraction, allows for such interpretation in clear and dynamically analyzable ways and without any prespecified functional lower level functional pre-specification.

5.3 Limitations and possible improvements

Homeostatic-plasticity in experiment 1 produced a stable adaptive behaviour for a period of time 6 times longer that the evolutionary lifetime on which the autonomous agent was evolved. But the mechanism showed a limited robustness to longer periods of time. Internal homeostasis was probably not sufficiently enforced, the energy cost of loss of homeostasis (a maximum of 0.15 energy units per time unit) could be incremented. Different cost parameters where tested during a set of experimental evolutionary runs and finding an appropriate value was a difficult task, high cost values didn't allow any kind of evolution (agent's remained stationary to avoid loss of homeostasis) while lower values didn't produce any significant homeostatic behaviour of nodes.

Another severe limitation of the implemented plastic rules was that the linear normalization parameter tended to push weight values to the maximum or minimum bounds. It was very rarely found that weight values oscillated which made readaptation to change of food quality almost impossible. More work on normalization of synaptic plasticity should be carried out. At the same time a covariance hebbian rule and other kinds of plastic rules could be used in future experiments.

The amount of evolutionary runs which produced agents where plasticity didn't play any significant role and the highly adaptive functionality of the agent in experiment two suggests that the ecological parameters could be improved to force a selective behaviour where approaching both kinds of food does not result evolutionarily advantageous. The difficulty of such ecological valance was bigger than expected. If the ecological parameters (distance to food, energy decay, food quality, etc.) constrained too much the exploratory behaviour of the agents during evolutionary trials adaptive behaviour couldn't be evolved. If they didn't constraint enough the evolutionary pressure was too weak to improve purely reactive behaviour. This difficulties point to the use of essential-variable based fitness function. Despite the difficulties involved we believe that such implicit fitness functions are important to for the study of adaptive behaviour (the question is analyzed in more detail in the next chapter).

Homeostatic-plasticity showed some success to produce a value system. A comparative analysis between the evolution of other value system mechanism (such as dopaminergic models) and the proposed one could should be carried out.

Chapter 6

Discussion

6.1 Autonomy, fitness function and evolutionary simulations

Floreano and Urzelai [34] categorize fitness functions over a three dimensional fitness space:

1. **Functional-Behavioural:** where the functional extreme evaluates the *causes* of behaviour while the behavioural extreme evaluates the *effects* of a behaviour.
2. **External-Internal:** where internal-external refers to the availability for the agent of the variables defining the fitness function.
3. **Explicit-Implicit:** refers to the quantity of constraints imposed by the fitness function over the agent's behaviour.

Floreano and Urzelai defend a behavioural, internal and implicit fitness functions as giving rise to *autonomous self-organizing* processes while the opposite extreme is more closer to *conventional optimization.* We believe that the study of adaptive behaviour as an autonomous self-organizing process (and not as optimization to environmental absolutes) will be significantly enriched by essential variable based fitness functions.

Essential variable based fitness functions are easy to design but difficult to implement because the ecological parameters in relation to the essential variables must be chosen very carefully. In our evolutionary simulation food's quality and quantity, distance to food, and energy decay constants were carefully valanced so that autonomy (as maintenance of essential variables under viability range) did not become trivial nor too difficult to evolve.

If the aim of an evolutionary simulations is to study the relation between mechanism and behaviour, for example the capacity of homeostatic plasticity to adapt to visual inversion [31] or the capacity of a CTRNN to integrate reactive and learned behaviours [39], there is no necessity nor benefit on autonomy based fitness functions. But not all behaviours are adaptive behaviour. If the scientific object of study is the emergence of adaptive functionality and its relations to mechanisms, essential variable based fitness functions provide the means for:

1. Evolving adaptive behaviour without prespecified adaptive strategies.
2. Allowing for the internalized normativity of closure conditions
3. Allowing for a codefinition of niche (relevant environmental features to achieve closure conditions) and adaptive behaviour

The contrast between autonomy based and more explicit fitness functions will become more evident in more complex simulated environments. Explicit fitness functions, by selecting for particular behaviours, could miss an important feature of adaptation in complex environments. With a rich set of environmental opportunities to satisfy closure conditions the selective pressure will push the evolving systems to redefine their autonomy through novel interactions with their environments. The complex process of codefinition between an organism and its ecological niche (as the set of environmental variables contributing to its adaptive functionality) could be lost if explicit fitness functions are used. We believe that as evolutionary modeling techniques develop the use of autonomy based fitness functions will become more and more significant to the study of the evolution and nature of adaptive behaviour as defined by Ashby.

6.2 Computational and evolutionary functionalism revisited

Computational functionalism (Block [5]), as a theory of what cognition *is about*, has conceptualized Cognitive Science and established a research paradigm based on a set of assumptions. The main idea is that a mental state can be defined by its causal role in the whole system, which can be specified in a look-up table of states and input-output correspondences. Cognition, for functionalist theories, is about the “right” computation (state transition rules) of representational states, the content of those states being the relation between them and “states of affairs” in the world. The definition of function in terms of input-output relations and its *independency* from the mechanisms involved introduces an hermeneutic (interpretative) problem when having to fix what counts as the input-output relationship that specifies a function; and, in cognitive terms what counts as the representation ‘in the mind’ and the entity (or “state of affairs” in the world) it represents. William Clancey [11] has conceptualized the problem under the label ‘the frame of reference problem’ as a lack of clarity on differentiating between: “a robots designer’s ontological preconceptions, the dynamics of a robot's interaction with an environment, and an observer's descriptive theories of patterns in the robot's behavior" (p.107). In most functionalist accounts the observer's descriptive theories and design preconceptions have been taken to be an explanation of the causes driving the cognitive agent's behaviour avoiding references to the robot's dynamic interactions.

On the other hand evolutionary functionalism (Millikan [28, 27]) claims to provide a naturalized and normative account of functionality. It is a *naturalized* account because having a function is not dependant on a given interpretation by an observer but on the 'natural' (selectionist) history of the *system itself.* And it is *normative* because it gives an account of what is the *proper* function of trait or structure even if the structure does not perform the function. Normativity introduces a solution to hermeneutic adequacy (mentioned above) because, although an indefinite number of functional interpretations can be made of any behaviour, evolutionary history provides the "right" one.

But a number of problems remains unsolved in both evolutionary and computational functionalism:

Functionalism or evolutionary history does no catch the causally effective mechanisms that produce cognitive behavior

Maturana and Varela's [24, 25, 26] *structural determinism* thesis criticises computational/representational functionalism as a rather misleading metaphor which doesn't appeal to any causally present mechanism/organization to explain cognition. They consider functional/representational descriptions to be semantic projections of an observer which pertain to the linguistic consensual domain of the observer rather than to the cognitive system under study. If fact, any claim about internal representational states is completely undetermined. As Verschure et al. put it [46]: "Any stimulus response relationship can be described by multiple functional models and a selection between these alternative models cannot be made by sole reference to the observed response" (p.247-8). Bickhard, Christensen and Hooker [16, 9, 10] have developed a similar critique to evolutionary functionalism. Millikan's recursion to history to ground functional normativity make functions to be ontologically separable form the system in which they are performed, functional explanations stand in the history of the mechanism and not the present causal mechanisms. Functions then become epiphenomena [9] since adaptive systems do not have access to their evolutionary history. The question, then, becomes how to ground functionality and normativity to be ontologically tied to the system it belongs to while still maintaining a normative hermeneutic (interpretative) criteria to justify functional explanations.

No dynamical nor interactive factors are considered in the production of adaptive behaviour

Formally, functionally, equivalent systems can be absolutely non equivalent in real life where time and energy can be essential for adaptation, and cognition [17]. Real organisms must survive in dynamical environments, in real time, coping with very complex interactions which might not be explicitly 'represented' in behavioural mechanisms. This critique was strongly defended by Brooks approach to situated robotics [8, 7], where the attention is focused on non-representational sensory-motor transformations without any sens-plan-action architecture. Both internal (structural and organizational) and interactive dynamics are essential to explain cognitive behaviour and neither computational nor evolutionary functionalism integrate dynamical explanations in the picture.

Our simulation experiments showed that lower level specifications bearing dynamical resemblance with biological mechanisms, do not allow for an interpretation of internal states representing, in any computationally relevant way, states of affairs in the world. We showed that no such functional decomposition is possible when agents are designed and analysed as dynamical systems whose functionality emerges from the internal and agent-environment dynamic interactions. The case of approaching a food source (section 5.2.2, page 47) is a good example where body (shadowing) and sensorimotor dynamics give rise to an active-perception loop where no computational decomposition of perception-plan-action structure can be localised. But a dynamical approach to adaptive behaviour does not rule out the notion of normative function, we have illustrated how normative function could be grounded in dynamical interactive nature of autonomous systems by evaluating and interpreting adaptive behaviour as maintenance of essential variables under viability constraints. Even more, we showed that value systems can act as internal normative mechanisms. In particular the first experiment showed an agent whose homeostatic plasticity, through environmental interactions, selected between different weight trajectories giving rise to different dynamical couplings with its environment depending on the food quality conditions. The internalized normativity of the value system comes form the effect it has on the agents autonomy, i.e. on its essential variable (energy) that represents the condition of possibility of the system.

Apart from the problems exposed above evolutionary functionalism cannot explain functional novelty. Di Paolo [31] evolved an agent able to adapt to visual inversion and other sensorimotor disruptions. Under evolutionary functionalism the agent's re-adaptation cannot be considered to be functional because the agent was never selected for adaptation to visual inversion. This is a great deficit of evolutionary functionalism. If simulated autonomous agents are able to evaluate their interactions with the environment they might show new adaptive strategies when faced with environmental conditions never encountered during their evolutionary histories, in such cases we will still require a normative and naturalized account of functionality to evaluate and interpret adaptive behaviour. The notion of adaptive functionality based on autonomy can provide such account.

6.3 Towards a definition of biological cognition

If representational functionalism is rejected to characterize cognition and a dynamical perspective is embrace.. how do we characterize cognition in dynamical terms? Which are the necessary and sufficient dynamical conditions for cognition? On one hand van Gelder's dynamical hypothesis bypasses the problem by claiming that: "This paper simply takes an intuitive grasp of the issue for granted. Crudely put, the question here in not what makes something cognitive, but how cognitive agents *work*" ([41], p.619). On the other hand theoretical biologists such as Maturana and Varela [25, 26], take the very act of living as a cognitive activity. "A cognitive system is a system whose organization defines a domain of interactions in which it can act with relevance to the maintenance of itself, and the process of cognition is the actual (inductive) acting or behaving in this domain." ([25], p.13). An autopoietic system creates its own phenomenological world (different from the environment) and its autopoietic activity in that domain is the very essence of cognition. In more recent articles Varela has constrained a use of the term *cognitive self* as specified in the behavioural domain (as a subdomain of the general autopoietic domain) and to the operational closure of the nervous system: "The operational closure of the nervous system then brings forth a specific *mode* of coherence, which is embedded in the organism. This coherence is a *cognitive* self: a unit of perception/motion in space, sensory-motor invariances mediated through the interneuron network. The passage to cognition happens at the level of a behavioural entity, and not, as in the basic cellular self, as a spatially bounded entity." ([42], p.10). Following a very similar perspective Beer [3] equates cognition with adaptive behaviour. But the problem remains that of distinguishing from coordinate walking, optimal foraging, and mathematical reasoning in purely dynamical terms. Cognition is a subset of adaptive behaviour but it is difficult to specify how the boundaries of this subset should be distinguished without reference to representations. A step forward in this direction has been made by Christensen and Hooker [16, 10]. Their notion of *self-directedness* allows for a gradual classification of adaptive behaviour from less to more cognitive on the basis of three criteria: a) capacity to adaptive the effect of environmental interactions, b) reduction of local-context dependency and d) modulation of interaction over larger timescales.

The difference between the first and second types of agents evolved in our simulation illustrates two different positions under this criteria. Experiment two (page 43) analysed an agent whose adaptive behaviour was based on very closely coupled environmental interaction where no discrimination between profitable and non profitable food occurred until the agent encountered a food source. The first experiment, on the contrary, showed an agent where the effect of early interactions on weight trajectories allowed for a discrimination between poisonous and profitable food decoupled from continuous interactive engagement with both food sources. The study of value systems controlling long term internal dynamics seems to us an important object of study for a gradual understanding of the mechanism involved in biological cognition.

Chapter 7

Conclusion

By modeling lower level neural mechanisms with no prespecified functional structures we produced autonomous agents that showed adaptive behaviour under changing environments. The analysis of the evolved agents and their interactive dynamics showed that computational functionalist approaches fail to give and adequate account of the dynamical nature of adaptive behaviour. We showed how adaptive functionality emerges from a complex interplay between internal dynamics and body-environment interactions. At the same time value systems where found to be essential components on the production of adaptive behaviour. In particular homeostatic plasticity proved to be able to generate a developmental value system capable of modulating weight space trajectories giving rise to different behavioural patterns under different environmental conditions. By defining adaptive function as homeostatic maintenance of essential variables under viability constraint through environmental interactions, normative function can be reconceptualize under the notion of autonomy. This way we can solve the frame of reference problem while avoiding recursion evolutionary history to define adaptive functionality.

If we are to take the continuity between life and mind seriously (Wheeler [47]) an autonomous dynamical framework seems to be the natural way to study how cognition arises through the increasing complexity of adaptive strategies. But the scientific understanding of a naturalized and dynamical characterization of cognition is still in need of a workable theoretical foundation and methodological tools. We hope to have contributed something in this direction.

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Appendix A

Phenotype Agent Experiment 1

```
================================ NEURON PARAMETERS =====================================

 Phe/Neu  Neu[0]  Neu[1]  Neu[2]  Neu[3]  Neu[4]  Neu[5]  Neu[6]  Neu[7]  Neu[8]  Neu[9]
  Bias    +0.91   -0.60   -3.32   +2.30   -1.17   -3.66   -0.71   +0.08   -2.63   -2.78
  Timec   +2.08   +3.77   +3.02   +3.74   +1.31   +2.66   +2.74   +2.97   +2.78   +3.93
  Gains   -3.99   +3.96   +2.94   -3.32   +4.80   -0.52   +0.13   +3.60   +0.83   -1.93
========================================================================================


============================== INPUT WEIGHTS ===========================================

 Sen/Neu  Neu[0]  Neu[1]  Neu[2]  Neu[3]  Neu[4]  Neu[5]  Neu[6]  Neu[7]  Neu[8]  Neu[9]
 Sens[0]  -3.35   -2.69   -4.83   +3.67   +0.24   -4.98   -1.27   +0.45   -2.85   -1.02
 Sens[1]  -4.98   -1.27   +0.45   -2.85   -1.02   +4.19   -3.53   +2.18   -2.78   +0.24
 Sens[2]  +4.19   -3.53   +2.18   -2.78   +0.24   -2.95   -3.55   -3.02   +0.78   -4.62
 Sens[3]  -2.95   -3.55   -3.02   +0.78   -4.62   +2.29   -2.10   +2.36   +3.82   -1.47
 Sens[4]  +2.29   -2.10   +2.36   +3.82   -1.47   +0.16   +3.50   +1.44   -2.91   +4.41
========================================================================================

================================== OUTPUT ==============================================
                     Right Motor = 1.969   Left Motor = 1.969
========================================================================================

========================================================================================
         NOISE: Input= 0.022375, Output= -0.040201, Activation=-0.019814
========================================================================================
```

```
==================================== DRNN ==============================================
 rules
 learn    Neu[0]  Neu[1]  Neu[2]  Neu[3]  Neu[4]  Neu[5]  Neu[6]  Neu[7]  Neu[8]  Neu[9]
 iweig
           1       3       3       3       3       1       1       0       1       1
 Neu[0]  -0.82   -0.77   -0.52   -0.29   -0.90   +0.49   +0.05   -0.48   -0.71   -0.03
         -2.45   -9.20   -5.44   +5.92   +4.24   +0.93   -5.19   -9.78   +0.86   +7.89

           2       3       2       2       2       1       1       0       1       0
 Neu[1]  -0.61   +0.44   -0.06   -0.46   -0.44   +0.98   -0.02   -0.05   -0.07   +0.36
         -4.28   +1.98   +7.63   +5.26   -0.53   +9.45   -3.33   -7.98   -4.72   -3.77

           2       3       3       0       0       1       3       1       3       3
 Neu[2]  -0.71   +0.84   -0.63   +0.02   +0.61   +0.63   +0.39   +0.78   -0.88   +0.87
         +1.12   -7.00   -3.14   -2.15   +8.74   -9.78   -4.30   +8.10   -6.78   -4.36

           2       2       2       3       2       3       3       2       2       3
 Neu[3]  -0.05   -0.50   +0.45   -0.65   -0.68   +0.03   -0.30   +0.50   -0.26   +0.61
         -0.70   -4.21   +8.24   +4.10   -0.98   +4.69   -5.78   -9.85   +1.51   +3.07

           0       3       0       1       2       2       0       2       2       3
 Neu[4]  -0.11   +0.15   -0.47   -0.45   -0.22   -0.79   -0.04   +0.85   -0.68   +0.82
         +8.62   -1.52   -0.60   +2.59   -4.53   -4.21   -0.75   +7.52   +2.60   +9.94

           2       2       2       3       3       0       3       3       3       3
 Neu[5]  -0.07   -0.26   -0.95   +0.40   -0.07   +0.41   -0.80   -0.46   +0.06   +0.40
         +5.97   +7.45   -4.00   -2.87   -6.03   +1.18   -6.56   +7.44   -6.43   +0.83

           3       1       0       2       2       3       3       3       0       0
 Neu[6]  -0.72   +0.55   +0.09   +0.74   -0.13   +0.88   +0.63   +0.01   +0.51   -0.05
         +4.70   +4.00   -5.09   -2.24   +1.12   +6.39   -5.56   -1.49   -6.64   +2.17

           3       2       1       3       1       1       0       2       1       0
 Neu[7]  +0.84   -0.60   +0.04   -0.46   -0.75   -0.59   -0.55   -0.57   -0.89   +0.97
         -1.80   -9.31   -2.93   +1.00   +5.03   +4.29   -9.72   +6.59   +5.08   -1.09

           0       3       3       2       0       0       3       2       1       1
 Neu[8]  -0.31   -0.82   -0.13   +0.79   +0.86   -0.08   +0.77   -0.30   -0.82   -0.26
         -6.42   -8.04   +5.69   +9.94   -9.78   -9.11   +6.22   -7.95   -3.08   +4.58

           2       2       1       2       1       2       0       2       1       2
 Neu[9]  +0.86   +0.08   -1.00   +0.06   -0.74   +0.01   +0.48   -0.55   +0.16   -0.91
         +3.45   +1.33   +5.24   +8.20   -5.67   -0.96   -4.47   +8.37   +6.49   -3.08
=======================================================================================
```

Appendix B

Phenotype Agent Experiment 2

```
================================ NEURON PARAMETERS =====================================

 Phe/Neu  Neu[0]  Neu[1]  Neu[2]  Neu[3]  Neu[4]  Neu[5]  Neu[6]  Neu[7]  Neu[8]  Neu[9]
  Bias    +2.98   -1.49   +2.27   -0.23   -0.28   -2.20   +0.37   -3.74
  Timec   +1.08   +1.00   +1.24   +1.13   +2.00   +2.36   +2.99   +1.05
  Gains   +2.02   +4.88   +4.73   -3.23   +3.69   -0.20   -0.57   -3.89
========================================================================================


============================== INPUT WEIGHTS ===========================================

 Sen/Neu  Neu[0]  Neu[1]  Neu[2]  Neu[3]  Neu[4]  Neu[5]  Neu[6]  Neu[7]  Neu[8]  Neu[9]
 Sens[0]  +2.66   +0.73   -3.43   +1.97   +1.38   -3.38   +1.89   +0.76
 Sens[1]  -3.38   +1.89   +0.76   -2.46   +1.12   +2.65   -3.26   -2.99
 Sens[2]  +2.65   -3.26   -2.99   -1.56   -1.27   -4.71   +2.74   +1.69
 Sens[3]  -4.71   +2.74   +1.69   -1.91   +0.33   +2.57   -3.29   +3.69
 Sens[4]  +2.57   -3.29   +3.69   -1.42   -3.91   -4.77   -0.86   -0.92
========================================================================================

================================== OUTPUT ==============================================
                     Right Motor = 1.911   Left Motor = 1.911
========================================================================================

========================================================================================
         NOISE: Input= -0.006422, Output= -0.029760, Activation=0.102917
========================================================================================
```

```
============================================= DRNN =========================================================
 rules
 learn      Neu[0]    Neu[1]    Neu[2]    Neu[3]    Neu[4]    Neu[5]    Neu[6]    Neu[7]    Neu[8]    Neu[9]
 iweig
              3         1         1         3         0         2         2         0
 Neu[0]    -0.85     +0.61     +0.90     -0.66     -0.19     +0.50     -0.76     +0.86
           -6.82     +4.32     +6.55     -4.93     +7.37     -7.01     +0.25     -0.21

              3         3         2         2         0         0         0         1
 Neu[1]    +0.08     -0.85     -0.95     +0.91     +0.33     +0.97     -0.76     -0.94
           +3.33     -0.80     -4.38     +4.22     -3.18     +1.56     +3.12     -1.02

              0         2         2         2         0         2         0         2
 Neu[2]    +0.69     +0.17     -0.87     +0.63     +0.87     +0.96     +0.60     +0.85
           -1.11     -1.68     -6.92     +4.23     +4.85     -1.11     +0.43     +1.63

              1         1         0         2         0         1         0         3
 Neu[3]    -0.04     -0.71     -0.74     -0.79     +0.12     +0.31     +0.37     +0.24
           +5.41     -6.01     -6.71     -4.65     +0.98     -7.25     -6.57     -7.12

              2         1         0         0         3         2         2         3
 Neu[4]    +0.65     +0.80     -0.89     -0.51     -0.65     +0.25     +0.43     -0.63
           -6.21     +6.32     +4.68     +0.69     -2.29     +7.36     -0.81     -4.65

              3         1         2         1         3         2         3         1
 Neu[5]    +0.13     -0.56     +0.01     -0.10     +0.24     -0.71     +0.80     +0.66
           -2.29     +6.92     +1.63     +1.80     -6.74     -2.90     -5.46     +1.42

              3         1         2         0         3         2         3         2
 Neu[6]    +0.73     -0.62     +0.78     -0.35     -0.17     +0.59     +0.51     -0.77
           -6.44     +3.43     +3.61     -1.14     -1.17     +2.91     -7.67     +1.81

              1         1         1         0         0         2         0         3
 Neu[7]    +0.85     +0.94     +0.50     +0.46     +0.78     +0.33     +0.14     -0.51
           -0.77     +3.47     +6.60     +2.92     +6.55     -1.74     +0.71     -1.30
============================================================================================================
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6th April 2004

> *Finally, a set may be created by the* fiat *of a theoretician who, not knowing which state a particular machine is at, wants to trace out the consequences of* all *the possibilities. The set now is not the set of what* does *exist, but the set of what* may *exist (so far as the theoretician is concerned). This method is typically cybernetic, for it considers the actual in relation to the wider set of the possible or the conceivable.*
> W. ROSS ASHBY[1]

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[1] Ashby, R.W. (1957) *An introduction to cybernetics.* Chapman & Hall, London, 1956. p.136. of the online version (1999): http://pcp.vub.ac.be/books/IntroCyb.pdf