Parsimonious Modeling of Adaptive Behaviour

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Abstract

The present paper investigates alternative forms of neural modeling for adaptive behaviour in order to determine the potential of minimal cognitive models of adaptive behaviour . Three alternatives are inspected: the CTRNN model proposed by DiPaolo (2000), a mass action model inspired by the experimental selection approach with a simplified form of signal selection (Edelman 1993), and primitive reactive model used for argumentative reference.

Introduction

The complex and divers behaviours of embodied and situated agents are largely underdetermined. Typically more than a single control mechanism will result in equivalent behaviour. This is known as the Bernstein problem (Bernstein 1967). Yet most animals as we do ourselves are able to handle these difficult tasks not only with ease, but with great tolerance to external disturbance. From this, It follows that this ability for behavioural adaptation must also be largely underdetermined. The relevance of adaptive behaviour for an system facing changes in its environment is fundamental for the development of a theory of intelligent behaviour. Early work from cybernetics in the 1950's originally introduced detailed and formal accounts for how systems may accomplish such adaptation (Wiener 1948, Ashby 1957). In the early 90's the regaining popularity of cybernetic ideals via behaviour based robotics, reintroduced the problem of behavioural adaptation (Brooks 1991, Beer 1990, Maes 1994). Contemporary advancements in the area of adaptive behaviour have generally favoured sophisticated neural mechanism based on individually complex functional units (DiPaolo 2000). Although largely successful at exhibiting agent adaptation to a multitude of disruptions, such modeling may in some respect 'over shoot' the Bernstein problem of adaptation by ignoring simpler forms of adaptative mechanisms. In consequence this may result in a biased appreciation of the underlying complexity required to achieve certain tasks by embodied agents. The aim of the current paper is to expose alternate forms of modeling for agent adaptation in the same context as that proposed by DiPaolo, where the agent must perform phototaxis and adapt to disruptions. The first experiment shows that a small number of funcitonal units are still effective for adaptation in a continuous time recurrent neural network (CTRNN) model. The second approach examines the performance of a neural mass model alike Edelman's experimental selection approach with a stabilizing mechanism inspired by stochastic signal selection (Edelman 1993), and the final experiment exposes that non internal stability can result in environment adaptation even in the face of sensory inversion, I call this the minimal reactive approach.

Adaptation, Stability, and Plasticity

In his seminal work which developed a system theoretic approach to describe and understand the essentials of complex agent control, Ross Ashby introduced a number of key concepts still relevant today for the explanation and design of intelligent agents (Ashby 1957, Ashby 1960). One of the principle underlying motivations for this work came from the idea that adaptation may be regarded as a prototypical characteristic of all intelligent creatures. Three core ideas stem from this development: stability, variety and regulation. The notion of stability simply states that given the current configuration of a system, it is stable under transformation T if its variables always return to their original values. We can think for example of the amount of water absorbed , or the body temperature in animals. Stability happens to be a fundamental element in natural organisms (although not exclusive to these), and conforms with the most contemporary definitions of life developed by the autopoietic framework (Maturana and Valera 1980). An agent in the environment must then maintain its system within stable bounds in order to remain the system that it is as a whole, and continue to operate as it can. In order to maintain stability Ashby introduced the notion of variety of a system's configuration. To counteract potential turbulence imposed by the environment, an agent should change its own configuration so as to maintain internal stability. Said differently, the variety of the environment that impacts the agent may be cancelled by it if adequate variety is generated by the agent in return; as Ashby says himself: "variety can destroy variety" which he calls the law of Requisite Variety (1957 p. 207). To do so the third notion of regulation is key. A system must implement a means to apply transformations on its variables so that the adequate counter variety is produced. For instance, the action of grasping a cup of water and drinking so to maintain a good level of water intake constitutes a form of external (or motor) regulation. Yet recourse to bodily extension to keep stability may require the activation of much more complicated processes. Often external regulation will only be employed if internal regulation is insuficient. We can think of the liver as an internal regulator for sugar concentration in the blood. An important element to the Ashbyan contribution is the notion of ultra stability. Traditionally the dynamics in cognitive models of behaviour borrow a pre-designed and limited path intended by the experimenter. The connectionist modeler 'trains' his/her network to learn particular features from a constrained and fixed domain. The evolutionary robotics researcher enforces behaviourally selective criteria on equally limited domains. In fact prescribed dynamics is inherent in the vast majority of cognitive models based on sensory-motor coupling (Braintenberg 1984, Brooks 1991, Scheier and Pfeifer 1995). While these models can contribute significantly to our understanding of diverse and complex behavioural patterns or even higher order cognitive feats such as reasoning and problem solving, some limitations are inevitably imposed by rigid models. Although delimiting the variability of a systems parameters from stringent design criteria may exhibit non linear behaviour, the approach will ultimately lead to rigid dynamics. Hence as it is underpinned in Ashby's framework, there is a strong sense in which simple sensory-motor coupling between an agent and the environment cannot lead to *generative* adaptive behaviour. When stimulated such an agent can only reflexively produce behaviours from an existing repertoire, i.e. those behaviours that are within bounds of the parameters which qualify their dynamics. The motivation behind ultra stability is then to endow a system with a 'meta-regulatory' system that acts on the parameters of the first. This way an agent can not only react to the effects of the environment via a general regulatory system, but it may also generate new behaviours if it encounters disruptions that would otherwise 'max-out' the initial configuration of the system or violate those variables that are essential to the agent's well being.[1] The degree to which a system has mechanisms apt of affecting its own parameters defines the plasticity of the system. Hence plasticity at the parametric level allows an agent to cope with events that would otherwise be impossible using reflexive response. To do so it must generate novel internal and/or external variety. Because of this however, it is possible that some stability may be lost. It is therefor crucial that the agent implements a plastic mechanism that effectively rectifies the stability of the systems variables while ultimately gener-

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[1] The notion of *essential variables* is proper to Ashby's framework and deserves considerable attention. This however, goes beyond the aim of the present paper.

ating new variety. This may de understood as the plasticity/stability dilemma in the context of adaptability.

Modeling Adaptive Behaviour

Since Ashby's foundational framework there have been a number of theoretical contenders advocating effective means to account for plastic change. In the following I introduce some of the main contrasted approaches which should suffice for the sake of argument.

Donald Hebb's seminal work on functional characteristics of the nervous system and individual neurons in particular, constitutes the foundation of modern neural modeling (Hebb 1949). Hebb's rule which dictates the manner in which synaptic potentiation is reinforced or diminished may be held as the archetypical model of functional plasticity. This rule quite simply states that a synaptic connection between two neurons is reinforced if it is repeatedly or consistently active. This simple condition and some variations of it led to the development of a number of neural models geared towards the explanation the nervous system's general functioning. In the realm of neural modeling for behavioural adaptation, two significant approaches have been put forth and are still prevalent today.

In the late 70's Gerald Edelman was motivated by the idea of coming to grips with a framework that would connect psychological phenomena to biological understandings of evolution and development (Edelman 1993). In his work Edelman challenges the information theoretic approach to cognition which makes the problematic assumption that information in the world is unambiguous and predefined. Instead his perspective on the appropriate level of neural modeling consists of admitting the high degree of variability present in the environment and the necessity for an agent to successfully categorize perceptually and conceptually. To do so he proposes the theory of Neural Group Selection. In his view, the nervous system implements a process of selection upon variation. Two fundamental principles guide this process: strongly interconnected and diverse neuronal groups must take place during ontogenetic development, and high variability of synaptic strength which serves to select the most effective neuronal groups to achieve a suitably adaptive behaviour. Although Edelman never makes it explicit, it is clear that his concerns regarding the criteria for adequate cognitive modeling agree quite well with Ashby's developments. In particular the neural group selection approach constitutes a form of plasticity and variety that conforms to Ashby's law of Requisite Variety. The neuronal group theory is particularly appealing in that it not only provides a general guideline for the design of experimental models, but models that follow from it may not only make predictions about adaptive behaviour but also about mechanisms involved in a systems development and how that development may further affect behaviour. Three distinct stages of development in neural group formation are identified by Edelman. The first consists of neural migration and adhesion which under the guidance of morphoregulatory molecules will lead to the formation of a wide variety of neuronal cell groups. Thus constituting what he calls the *primary repertoire.* The following stage involves the process of what he calls 'experimental selection', whereby synaptic changes amongst neurons take place under the influence of the agent's experience and action in the environment, thereby forming what he calls the *second repertoire.* At this stage little anatomical alterations occur. The properties of synaptic reconnection may be best described by statistical signal correlations on a wide number of connections rather than single neuron to neuron activation as usually favoured in more strict Hebbian-exclusive type models. The value of the plastic change is placed less on individual neurons but favours the action en mass of the group instead. Interestingly, the statistical quality of the neural activation patterns in experimental selective models should permit high inner group variety as long as the group coheres to form the adequate signaling. Because of this, complexity of activation at the individual neuron may not be selected for as much as the complexity of activation provided by the whole. The third stage does not follow from the previous chronologically, but is complementary. It involves the coordination of neuronal groups between them and the way they form. Because intelligent agents typically dispose of multiple means of sensing, motor action, and mental activity, complex choreographies between neuronal groups must develop. To account for the way in which neuronal groups form coordinated activation patterns, Edelman introduces the process of signal reentry. This mechanism involves strengthening or weakening of inter-group connections when both groups are simultaneously activated by a particular sensation, thus leading to temporally coordinated activation. Because in this process, no particular direction of the signaling is predefined or dictated in a supervised way, Edelman claims it does not constitute a feedback mechanism. This notion of reentry is crucial for the potential explanation of extended and complex cognitive phenomena. Importantly along with signal selection, it introduces a alternate mechanism of plasticity to Hebb's traditional model. Because processes such as reentry and experimental selection abide by self-organizing principles of plastic change, exploring simple forms of these mechanisms should provide new insights on minimal cognitive approaches to adaptation.

The second important approach to neural modeling for adaptive behaviour consists of dynamical neural networks with hebbian type plasticity (Beer 1990, DiPaolo 2000). This approach takes largely from the minimal neural models inspired by connectionism and sensory motor coupling as shown by Braitenberg (1984), and has been favoured by a large majority of the new ai community. By embodied sensory-motor coupling, Braitenberg showed that a diverse set of sophisticated behaviours can be achieved even with the most basic form of 'wiring'. With additional time dependent non-linear dynamics, as Beer's continuous time recurrent neural networks (CTRNN) exhibit, a much larger variety of sensing and action can be achieved. Scheier and Pfeifer for instance made important findings regarding the ability for highly limited robotic agents[2] to reduce the dimensionality of the input space via active perception using a dozen time recurrent neurons (Scheier and Pfeifer 1995). More recently DiPaolo has shown that sophisticated adaptive behaviour in a simple phototaxis task using minimal robots, is possible in virtue of the integration of Hebbian type plasticity within a time recurrent architecture (DiPaolo 2000). Psychological work on visual inversion in humans has shown that the completion of difficult tasks such as bicycling, skying and others, is possible after a period of adaptation (Kohler 1964). Inspired by this work, DiPaolo designed a neural model implemented in a simulated robot which is evolved via genetic selection to perform reliable phototaxis using only two symmetrically opposed light sensors, and two motors. After the robot successfully approaches a light source a disruption is introduced by inverting the light sensors on the body while maintaining the same internal connectivity. In a standard Braitenberg vehicle this would cause light aversion. DiPaolo illustrates however, that given sufficient plasticity on the synaptic weights, the robot can readjust and perform phototaxis after a period of adaptation.

In the following experiments I intend to illustrate that a simplified form of DiPaolo's implementation can also achieve adaptation to disruption in the phototaxis task. However I also present an alternative approach which takes inspiration from the neural mass action using a form of experimental selection as proposed by neural group selection theory.

Experiment 1

For the first experiment I replicated, with some alterations the model and method described by DiPaolo in his work on homeostatic adaptation (DiPaolo 2000). For his experiments DiPaolo made use of a time recurrent neural network model consisting of 8 neurons with four plastic rules for which effective parameters where set using genetic evolution. His results showed that a simulated Khepera robot with two motors for drive and two light sensors symmetrically opposed by

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[2] Scheier and Pfeifer used 1st generation Khepera robots that posses only two wheels for action and 8 active infrared sensors for perception.

about 120^o can perform phototaxis even after inversinon of the light sensors is applied. Because the aim of the present paper is to illustrate the potential of minimally cognitive models of adaptation, I decided to replicate the model on most details while reducing the number of neurons to 4 and to 2.

Method

The implemented continuous time recurrent neural network was first tested with 4 neurons and later with 2, where each neuron's activation was dictated by:

$$\tau_i \dot{y_i} = -y_i + \sum_j w_{ji} z_j + I_i$$

where τ_i is the rate of activation decay with a range between [0.4, 4], y_i the activation level of the node, w_{ji} the synaptic weight between node j and node i with range [-8, 8], I_i the sensory perturbation on node i, and z_j the the firing rate of the node defined as:

$$z_j = \frac{1}{1 + e^{-(y_j + b_j)}}$$

where b_j is the activation bias ranging between [-3, 3]. Two sensory neurons are perturbed by individual light sensors, and two separate effector neurons are individually used to drive each motor (The same two neurons are used for both sensing and motor control in the 2 neuron case). Input signals from the light sensors are mapped to the real valued range [0, 1] where 0 is darkness and 1 is maximal light. A gain between [0.01, 10] that is exponentially raised is then applied to this transduced signal. Firing rates from two effector neurons are mapped to the range [-1, 1] and a gain between [0.01, 10] also exponentially raised, is used to drive the motors. Each parameter is genetically encoded in ranges from [0, 1] and mapped to the correct range during transcription. Additionally 4 plastic weight update rules are applied to each connection. Two supplementary parameters are genetically encoded for this. The first parameter is an integer in the range [0, 3] indexing the rule of plastic change for that connection, the second is a rate of change η_{ji} in the range [-0.9, 0.9]. The four rules are:

$$\begin{aligned}
&Rule0 : \Delta w_{ji} = \eta_{ji} p_i z_j z_i, \\
&Rule1 : \Delta w_{ji} = \eta_{ji} p_i z_i (z_j - z^o_{ji}), \\
&Rule2 : \Delta w_{ji} = \eta_{ji} p_i z_j (z_i - z^o_{ji}), \\
&Rule3 : \Delta w_{ji} = 0
\end{aligned}$$

where p_i is the degree of local plastic facilitation, and z^o_{ji} is a threshold value corresponding to a projection of the weight w_{ji} in the range [0, 1]. To limit the update of the weights within bounds, their values are imposed a hard limit. Here, p_i is computed as a step function with respect to the sum $y_i + b_i$ where:

$$
\begin{aligned}
p_i &= -1 && for\ y_i + b_i < -4, \\
p_i &= \frac{1}{2}y_i + b_i + 1 && for\ -4 \leq y_i + b_i < -2, \\
p_i &= 0 && for\ -2 \leq y_i + b_i < 2, \\
p_i &= \frac{1}{2}y_i + b_i - 1 && for\ 2 \leq y_i + b_i < 4, \\
p_i &= 1 && for\ y_i + b_i \geq 4,
\end{aligned}
$$

As described by DiPaolo, Rule 0 implements Hebbian/anti-Hebbian change. Rule 1 and Rule 2 strengthen or weaken the weight depending on the activity of the presynaptic (Rule 1) or postsynaptic (Rule 2) activity. Rule 3 simply dictates the weight as being non-plastic. The activation of the each neuron is computed using Euleur integration with a time step $TS = 0.1$.

A genetic algorithm is used to evolve a population of 60 individuals using steady state elite selection. Two individuals are selected randomly amongst the twelve best, an offspring is created by random crossover at each loci with probability 1/2. Mutation as each loci is applied with probability 1/2 using a small gaussian value in the range [-0.01, 0.01]. This individual is then placed in the population by replacing a non-elite individual. Individuals are assigned a fitness score corresponding to the average euclidian distance from the light source over three separate runs. Each run lasting 3000 time steps. Hence no preferential bias is present in the selection process. At the beginning of each of the three runs, the individual is placed randomly in the 800 x 800 space, in which the light source is placed in the center. The space is infinite with wrap around. I used Olivier Michel's Khepera simulator, to handle real robot and world dynamics (5% noise is applied to the light sensors, and noise in the range [0.01%, 0.1%] is applied to the position of the robot) (Michel 1995). No light sensor inversion is performed during evolution.

Results in a 4 Neuron CTRNN

After 500 generations each 60 robot was tested a number of times for an extensive number of time steps (> 10000). More than 80% of the robots performed phototaxis successfully. Individual robots were then tested on light sensor inversion and monitored for performance. After conducting the experiment a number of times, a particular phototaxis strategy tended to dominate. This strategy consisted of rapid 'on-the-spot' spinning in the same direction (although direction could change

Figure 1: To the left, a 4 neuron robot behaviour before disruption. To the right the same robot after light sensor inversion.

amongst robots), followed by intermittent but rapid straight jerks of varying distance. As soon as a robot would be within near distance to the light source it would stop its jerks but continue spinning. although spinning is not visible, straight jerks can be seen in figure 1. After light sensor inversion, the robot is repositioned randomly in the space (similar to DiPaolo). Figure 1 also illustrates a jerky behaviour of the robot, however robots would not typically approach the light source immediately. Hence a period of adaptation as found in DiPaolo's 8 neuron model would seem to have taken place. Here this adaptation required roughly 3000 time steps. Figure 2, shows the distance of the robot to the source before and after sensor inversion. Although the robot never gets as close to the source of light after inversion, is does cease to change position. This suggests that internal stability is regained once the robot reaches the source of light within adequate distance. Arguably it is possible that a confound is present in these results in that the robots where 'pre-adapted' to visual inversion. This is possible if both light sensors are integrated within the network without distinction. I later demonstrate the possibility for this in experiment 3. If adaptation is indeed occurring by exploiting the plastic rules for weight potentiation adjustment, these results show that a simpler CTRNN than that used by DiPaolo can be employed to exhibit adaptive behaviour.

To further explore the possibility of minimal modeling using CTRNN for adaptation, a set of experiments were conducted on 2 neuron networks.

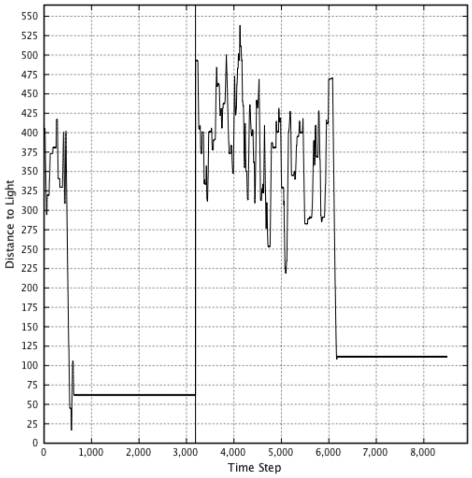

Figure 2: The distance of the 4 neuron robot from figure 1 to the light source with respect to time.The black vertical line indicates the point of inversion and random repositioning.

Results in a 2 Neuron CTRNN

Following the exact same procedure as in the 4 neuron case, the variety of behaviours obtained where much more diverse with robots control by 2 neuron CTRNNs. However, most robots evolved after 500 generations would perform phototaxis successfully. Most behaviours consisted of rapid straight movements in random direction until light was perceived. At this stage robots would alter the angular velocity of their wheels generating circling movements enabling it to maintain close distance to the light source (< 200 distance units). Typical behaviour once near the light source would consists of circling the light continuously as can be seen in figure 3. After light sensor inversion and repositioning, robots would quickly reach the source and recommence circling although not always as close as prior to inversion; this is visible in figure 3. Figure 4. shows that the distance of the robot to the light source after inversion diminishes quickly (< 800 time steps). At first this may indicate that a much shorter period of adaptation seems possible using this behaviour with 2 neurons than in the 4 neuron case seen above. However the required number of time steps for plastic change to take effect should be considerably longer, as shown by DiPaolo. Along with the possibility of pre-adaptation to visual inversion, this may impose further doubt as to the genuine occurrence of adaptive change in the neural controller.

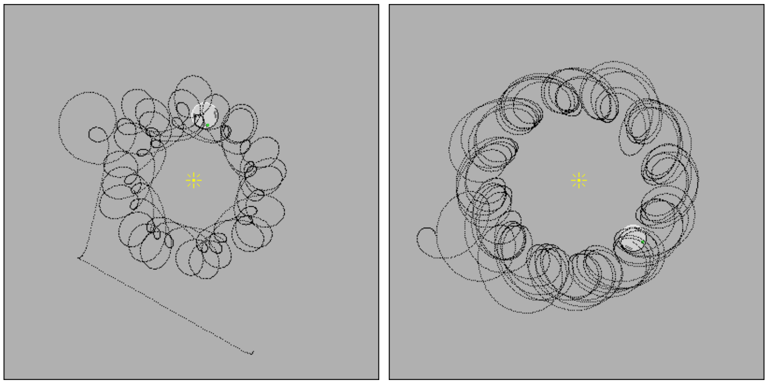

Figure 3: To the left, a 2 neuron robot behaviour before disruption. To the right the same robot after light sensor inversion.

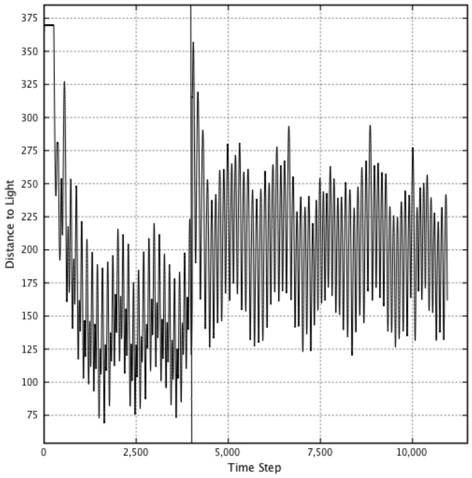

Figure 4: The distance of the 2 neuron robot from figure 3 to the light source with respect to time.The black vertical line indicates the point of inversion and random repositioning.

Experiment 2

As introduced above, an interesting alternative to neural modeling for adaptive behaviour stems from Edelman's neural group theory. Activity in the nervous system is typically the result of massively parallel and temporally orchestrated groups of neurons. Edelman is not alone in this arena. Freeman inspired by work from Katchalsky, has formalized possible mechanism for neuronal mass action based on principles of reaction/diffusion (Freeman 1975, Katchalsky 1971, Turing 1952). The appeal of modeling neural masses is not simply motivated by their biological reality, but also by the degree of simplicity each individual neurons may behave. Complexity using this kind of modeling does not necessarily arise from complex constitutive units, but from the emergence of complex activity via the dynamics of simple interacting parts. This view fits quite nicely with the increasing evidence that synergistic phenomena, such as the individual activity of ants in a colony, may give rise to complex phenomena which in their own contribute effectively to their environment (Forest 1990, Beckers et al. 1994) . Inspired by this I designed a rudimentary model for neural mass action that should allow a robot to perform the same phototaxis task as in the previous experiments while successfully adapting to light sensor inversion.

Method

A network of 80 potentially active neurons is split into 4 neural groups of 20 neurons. One group is assigned to each input light sensor, and one group is assigned to each effector. Sensory groups can potentially connect with either motor group via 400 connections. No inter-sensory or inter-motor group activation is possible. Synaptic activity is either off or on (0 or 1). Similar to a basic Braitenberg vehicle the signal is directly propagated from sensors to motors via this connection scheme. At a single time step the velocity of a motor is integrated using the following equation:

$$E_m = \gamma \frac{\sum c_{s_i m_j} L_s}{N}$$

where E_m is the velocity applied to motor m, γ an input gain in the range [0.01, 10] exponential raised, c_{sm} the connectivity state between neuron i from sensory group s and motor neuron j from effector group m (either 0 or 1), L_s the input value of light sensor for group s projected in the range [0, 1] where 0 is darkness and 1 full brightness, and N the total number of neurons in the network (i.e. 80). Here only γ is genetically encoded. To encourage stability by mimicking neural shedding (cell death) so as to form a primary repertoire the way Edelman describes developmental variation and selection, a decay status value d_{sm} is applied to each connection c_{sm}. This decay doesn't directly affect the potentiation of the connection, but instead dictates the probability that this connection will cease. To restrict and include noise to the chance of shedding a connection, the decay status d_{sm} is scaled to the range [0, 1000] and shed with increasing uniform probability when it is below 100. This ensures a minimal life duration. If shedding occurs reconnection from a random node of the same sensory group to a random node of either motor group is possible if the previous scaled decay value is below an increasing uniform probability below 10. Note that reconnections done this way, may overtake previously existing connections. This decay state of each cell only indicates the 'health status' of a connection between two neurons. The factor that reduces this status is a group-to-group specific decay rate τ_g in the range [0, 1], where g indicates one of the four possible group-to-group mappings: $s_1 \rightarrow m_1$, $s_2 \rightarrow m_1$, $s_1 \rightarrow m_2$, $s_2 \rightarrow m_2$. At every time step every connection decay state is reduced by:

$$d_{sm} = d_{sm} - (TS * \tau_g)$$

where TS is a time step factor of 0.1.

This mechanism of statistical reconnection based on neural cell decay accounts for the criteria of plasticity required in a model of adaptation, and complies to Ashby's law of Requisite Variety. However stability in such a mechanism cannot be attained following this process alone. The preservation of essential variables is necessary so that the agent seeks to alter its behaviour to maintain this essential stability. The phototaxis experiment instantiates these conditions by having a robot strive to maintain a certain level of luminescent input. To implement this stability, a decay damping factor σ is used to compensate the connection decay (range [0, 1]). This damping however, is only applied to a particular connection if that connection contributed in the immediately preceding time step to a higher activation of the neuron in the motor group. In this context because activation increases only when light input increases, this mechanism prevents the shedding of neurons contributing to stability.

The same damping factor is used for all neural groups. It affects the decay state d_{sm} the following way:

$$d_{sm} = d_{sm} + (TS * \sigma * E_{s_i m_{j_{t+1}}} - E_{s_i m_{j_t}}) \; if E_{s_i m_{j_{t+1}}} - E_{s_i m_{j_t}} > 0$$

where $E_{s_i m_{j_t}}$ is the incremental fraction of activity from sensory neuron i to motor neuron j at time t.

To find a suitable set of parameter values for γ, each of the four τ_g, and σ, they were encoded as real values in the range [0, 1] and scaled appropriately during transcription form genotype to phenotype. All connections where initialized to the active state (value 1) during transcription. All decay status values where initialized in the range [0.5, 1] also during transcription. The genetic algorithm employed steady state updating with elitism, recombination and mutation in the same manner as in experiment 1.

Results

In the same fashion as for experiment 1, during evolution each run consists of evaluating the distance of the robot over three separate trials and taking the average for fitness estimation. A population of 60 individuals is evolved over 300 epochs. Less epochs were necessary to obtain individuals that performed phototaxis than in the previous experimental case due to the small number of parameters that need adjustment.

After 300 epochs 95% of the robots performed phototaxis. Most adopted rapid forward motion without spin when the light source did not reach the light sensors, or was not directly incident on them. Increased light exposure would typically induce large circling on the outset and smaller circling as it got closer to the light source or after a period of sustained exposure. Although most robots never tended to approach the light source too closely, their behaviours clearly demonstrated a progressive approach through various circling motions towards the light, as can be seen in figure 5. This implies that the statistical selection model does favour stability via the decay damping factor. Careful inspection of the connectivity rates indicated that persistent connectivity was maintained when the robot what near the light source. Disruption of phototaxis was applied after this stability had been reached. The robot was repositioned, and the light sensors inverted. A clear period of accommodation occurred for the tested robots. The right image in figure 5 shows the extent of exploratory behaviour after inversion for a robot. Figure 6 shows the duration required for adaptation of the same robot. Interestingly a considerable amount of time steps was required for this adaptation to occur (> 25000), much like the results obtained by DiPaolo in his 8 neuron CTRNN model. Also, figure 6 shows how the robot's behaviour is not altered immediately after inversion in the time interval [7450, 8200]. Although repositioned, the robot sustains the same tight circling behaviour as prior to inversion during that interval. This further indicates the role played by the decay damping factor σ which diminishes in effect due to sensory inversion, thus allowing the decay state to decrease which leads to neural death and reconnection. Hence it appears that the connection decay process does confer sufficient neural plasticity for the robot to reconfigure its internal dynamics and gain the ability to perform phototaxis.

Some criticism may question the degree of adaptation that this

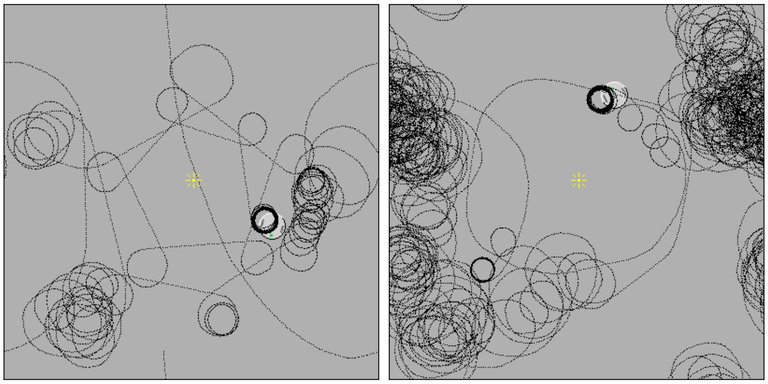

Figure 5: To the left, a statistical selection model robot behaviour before disruption. To the right the same robot after light sensor inversion and random repositioning.

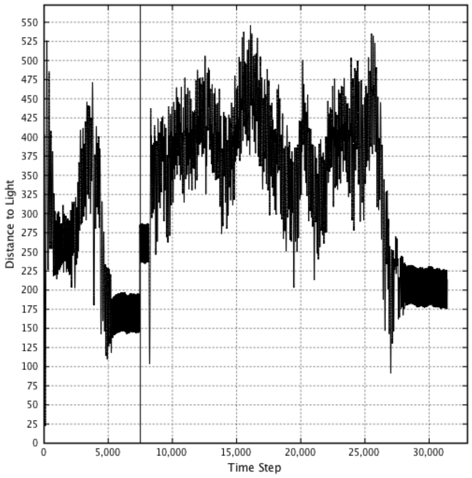

Figure 6: The distance to the light source with respect to time for the same statistical selection model robot as in figure 5. The black vertical line indicates the point of inversion and random repositioning.

model offers. Because the light source is not reached promptly during the normal period of phototaxis, it is difficult to assess the extent to which the period of adaptation is after disruption if not in fact the same process involved in phototaxis prior to disruption. Indeed the present model encourages massive reconnection even when the robot is close to the light after a prolonged period of time. This is because the damping factor is only applied to a synaptic decay state if the connection was more efficacious for phototaxis than it was at the immediate preceding time step. Hence in its current form the model encourage high plasticity continuously, and stability only when the source of light gets closer. Another criticism may stem from the fact that the decay damping factor favours phototaxis in a task specific way, thus invalidating this model as general purpose. This is not true however, since this damping is not suited to this task only, but generally discourages the death of active cells and the creation of new connections. Overall, it is important to realize that without further investigation into the dynamics of such models for adaptation as the one proposed by DiPaolo, and the statistical selection model I propose here, it is possible to mislead the research on dynamics of adaptive behaviour. This is why exploring minimal models can be important to form a solid grounding so as to extend experimentation with more complex models. The following experiment shows how a simple Braintenberg vehicle can give the impression of internal adaptation when facing apparent sensory disruption.

Experiment 3

Method

In order to illustrate how internal adaptation (plastic change) is not always necessary for an adapted behaviour, a simple robot that performs Braitenberg like phototaxis is implemented. In this simulation, each motor is assigned a bias factor b_L for the left motor and b_R for the right motor, both in ranges [-10, 10]. Both motor biases are applied to the same light sensing input I which simply constitutes the sum of both light inputs (each input projected in the range [0, 1] as in experiments above). A gain γ in range [0, 10] and exponentially raised, is finally applied to the sum: $I + b_R$ and $I + b_L$ before effecting the motors, giving:

$$LeftMotor = \gamma(I + b_L)$$
$$RightMotor = \gamma(I + b_R)$$

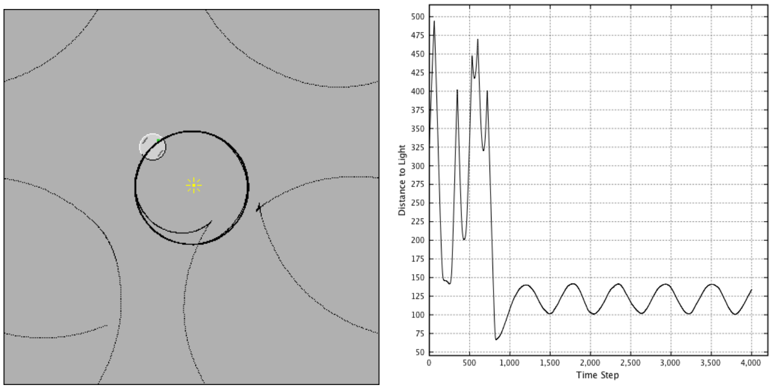

Figure 7: To the left, a simple Braitenberg robot using the same sensory input to drive both motors. To the right, the distance to the light source with respect to time for the same robot. No sensory inversion is necessary since the inputs are combined.

A random set of of parameters for γ, b_L and b_R are generated for 60 individuals in order to find interesting configurations.

Results

Although a wide range of behaviours were generated, we notice from figure 8, that phototaxis is achievable with this sort of control mechanism. Although this particular agent does not get very close to the light source (others got closer), its behaviour showed smooth curved motion while it was distant from the light source. Getting closer however it rapidly changed its behaviour by circling the light continuously. By manually displacing the agent in other positions of the space, the same type of behaviour would appear where eventually it would reach this revolution about the light source. Although sensors in this simulator are subject to noisy input these robots are able to perform adequate phototaxis, under many configurations. Because the sensory inputs are combined and this combination applied to both motors, sensory inversion would not have an impact on behaviour. These simple reactive robots seem then to be pre-adaptive to the experimental conditions. Hence, this suggests that any model which evolves its inner configuration in way that is pre-adaptive to the experimental task may cause misattributions to the performance of an agent. As Bernstein noticed, behaviour is largely underdetermined. It is perhaps of interest to see that this pre-adaptive quality may explain resistance to environmental change that some animals or insects may display.

Conclusion

The importance of exploring potential models for adaptive behaviour is still in its infancy. I believe theoretical development from the cybernetics era has made a significant step in right direction in formulating the foundational implications and principle dynamics for a wide range of adaptive systems. The improved knowledge in the applicability of computation for the testing of models based on these theories has proved to be highly insightful. The modern development of neural simulation and embodied systems allows for the complete implementation of truly scientific models of complex behaviour. Following Ashby's, Kohler's and Beer's footsteps DiPaolo managed to successfully demonstrate the applicability of their work in autonomous robotics. The present paper is an attempt to push this momentum towards genuinely adaptive agents a little further by emphasizing the ability of simple models to accomplish adaptive tasks when presented with disruptions. Although alternative experimentation may be required to agree with the obtained results may be required, it seems possible that simple CTRNN models of plasticity can be effective for adaptive behaviour. Furthermore, inspired by work on neural mass action and particularly Edelman's neural group selection theory, I introduce a preliminary and simplistic neural model of statistical selection which proves to exhibit the ability to self regulate in the face of sensory disruption to continue phototaxis. This approach, indicates that the combined action of simple control units can lead to the emergence of complex behaviour. Finally, I warn of the danger of misattributing sophisticated behaviour such as adaptation to systems that may be pre-adapted to the experimental conditions and their environment. These results, I hope, will motivate further research in the domain of autonomous adaptive agency, while maintaining careful attention to ambiguous conditions.

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