

# **Evolution of Neural Organization in A Hydra-Like Animat**

**Ben Jones, Yaochu Jin, Xin Yao, Bernhard Sendhoff**

**2008**

**Preprint:**

This is an accepted article published in International Conference on Neural Information Processing of the Asia-Pacific Neural Network Assembly (ICONIP-2008). The final authenticated version is available online at: [https://doi.org/\[DOI not available\]](https://doi.org/[DOI not available])

# Evolution of Neural Organization in A Hydra-Like Animat

Ben Jones<sup>1</sup>, Yaochu Jin<sup>2</sup>, Xin Yao<sup>1</sup>, Bernhard Sendhoff<sup>2</sup>

<sup>1</sup> School of Computer Science, University of Birmingham, UK

<sup>2</sup> The Honda Research Institute, Offenbach, Germany

**Abstract.** The role of efficient information processing in organizing nervous systems is investigated. For this purpose, we have developed a computational model termed the *Hydramat Simulation Environment*, so named since it simulates certain structural aspects of fresh water hydra. We compare the evolution of neural organization in architectures that remain static throughout their lifetimes and neural architectures that are perturbed by small random amounts. We find that (a) efficient information processing directly contributes to the structural organization of a model nervous system and (b) lifetime architectural perturbations can facilitate novel architectural features.

## 1 Introduction

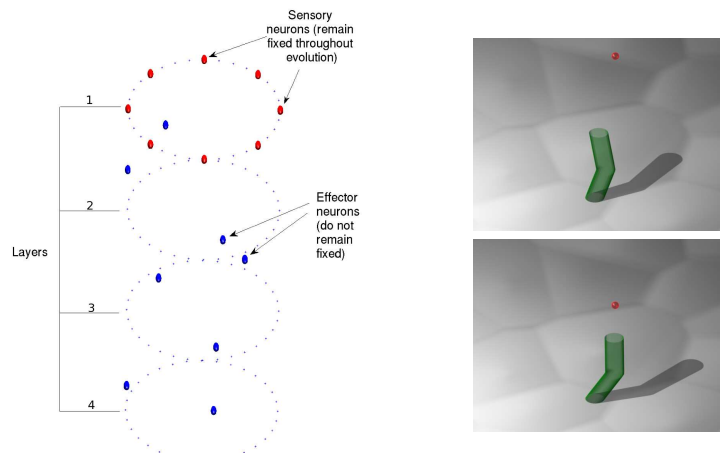
In this paper we explore the influence that energy conservation has on neural organization and the additional effect that *noise* has on this process. In order to do this, we have modeled a radially symmetric organism which loosely resembles the freshwater *Hydra*, which we term ‘hydramat’. We focus on how the nervous system should configure itself around a fixed radially-symmetric body-plan.

Our hypothesis is threefold: the neural architecture of a radially symmetric agent will arrange itself such that (i) the agent is afforded maximal functional benefit and (ii) the agent is afforded the ability to conserve energy and (iii) structural innovations are benefited from lifetime architectural perturbations.

The simulated agent proposed in this work is based on observations of the nervous system of the genus *Hydra*, since crucially, they are phylogenetically the first to have a nervous system that resembles major principles of nervous systems in later organisms [8, 10]. In doing so we make a very high-level abstraction yet we point out the differences as we describe them. Our actual simulation environment to be outlined in Section 2, is heavily inspired by Albert, who devised a simple model for the hydra and its nervous system [1]. From a systems biology approach, we have been further inspired by the work of Niv et al, who looked at the foraging behavior of honey-bees [9] and Florian, who employed biologically inspired neural networks for agent control [4]. We provide the simulation results in Section 3 and conclude the paper in Section 4.

## 2 The Hydramat Simulation Environment

The hydramat is modeled on a tube, and has a nervous system consisting of the following types of cells (also see Fig. 1).



**Fig. 1.** *Left:* A visualization of the hydamat showing a neural cell distribution; *right:* Two snapshots of the simulation environment. The sphere represents a food particle.

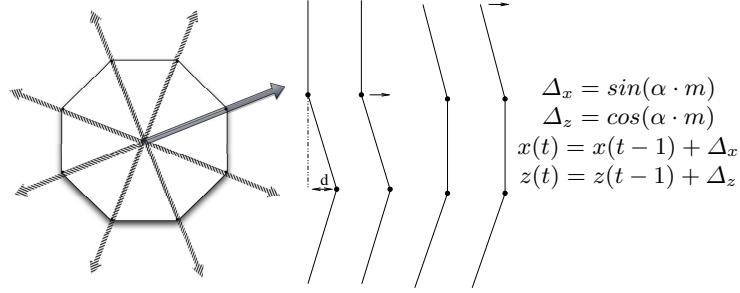
**Sensory neurons** These are computational neuron units that remain fixed at the top of the hydamat tube. They detect falling food particles. When a piece of food is dropped, the sensory cell that the piece of food is closest to is the one that ‘spikes’, providing input to the rest of the spiking neural network. The other sensory cells remain dormant.

**Effector neurons** Each effector neuron, of which there are always 8, is used to ‘wobble’ the animat in one of eight directions, so that a food particle can be ‘caught’, see Fig. 2. Note that a food particle is deemed caught when it comes to within a small distance threshold of the top of the hydamat. The effector cell that ends up firing the most, is the one that brings about movement whilst the others remain dormant. A firing rate is therefore observed within a short time-frame (10 updates to the simulation environment) to decide the behavior.

**General interneurons** Additional neuron units residing within the ‘skin’ of the hydamat. The Euclidean locations of both the interneurons and the effector neurons are evolved throughout a process of simulated evolution and this is the crucial way in which we evolve the architecture of the nervous system. These localities are constrained to reside within the skin of the hydamat, since this is the case in Hydra.

## 2.1 Movement Dynamics

The hydamat ‘wobbles’ to catch a piece of food by moving its third layer, see Figs. 1 and 2 . The other layers passively align themselves to this moving layer.



**Fig. 2.** The movement mechanism of a hydramat layer. A chosen direction of movement has been highlighted. The value  $m$  is a predefined constant and defines movement magnitude. The value  $\alpha$  represents the angle of the directional movement.

The amount by which a contracting layer moves due to a spiking effector neuron is predefined by a movement magnitude ( $m$ ), which we always set to 0.8 (see equations in Fig. 2). The other layers iteratively align themselves in proportion to the amount by which layer 3 changed position during such a movement update, (Eqs. 1, 2 and 3). In this respect the passively updating layers observe very simple spring-like dynamics:

$$f_a = d c_a, \quad (1)$$

$$f_b = -d c_b, \quad (2)$$

$$F = f_a + f_b. \quad (3)$$

Note that we employ,  $f_b$ , as a kind of relaxation ‘force’, causing the tube to resume to a resting upright state. The parameters,  $c_a$  and  $c_b$  are predefined constants set to 0.2 and 0.01 respectively.

## 2.2 Hydramat Nervous System

**An integrate and fire spiking neural network** We use the Neuro Simulation Toolkit NEST [5] to build a simple integrate and fire (iaf) model for the hydramat nervous system. A change in membrane potential of a neuron is given by the following differential equation,

$$\tau_i \frac{du_i}{dt} = -u_i + R I_i(t). \quad (4)$$

where  $I_i$  is input current and  $R$  is resistance. The multiplicative effect is typically equivalent to the accumulated strength of all incoming presynaptic activity i.e. an accumulation of weight values representing the connection strengths multiplied by functions of when presynaptic neurons fired prior to the current ‘time step’ ( $\sum_j^N w_{ji} k(t - F_j)$ ). The value  $\tau_i$ , is the membrane time constant of the neuron.

**Neuron positioning and synaptic efficacy** In our model, the distance between a pair of neurons ( $i$  and  $j$ ) determines the connection strength of the connection between them, if such a connection exists. The formula  $w_{ji} = \frac{\xi}{d_{ji}}$  is used to derive this value, where  $d_{ji}$  is the Euclidean distance between neurons  $i$  and  $j$  and the value  $\xi = 16$  has been set empirically to ensure that  $w_{ji}$  has the potential to be significantly large. The maximum value of  $d_{ji}$  is given by the bounds of the hydramat’s geometrical properties. In our experiments, the length of the cylindrical hydramat and its diameter were always set to 6.0 and  $\sim 1.6$  respectively. Therefore the theoretical ranges of  $d_{ji}$  and  $w_{ji}$  were  $[0, \sim 6.23]$  and  $[\sim 0.64, > \xi]$  respectively; the smaller the distance between a pair of neurons, the larger the weight value between them, if a connection exists between them.

**Neuron positioning and connectivity** A second aspect of our nervous system model, is that the connectivity between any pair of neurons is determined using a Cauchy probability distribution of the form

$$P_{ji} = \frac{1}{\pi \cdot \lambda_i \cdot \left[ \left( \frac{d_{ji}}{\lambda_i} \right)^2 + 1 \right]}. \quad (5)$$

The value of  $\lambda_i$  governs the width and height of the distribution. If the value is small, the shape will be tall and narrow. If it is large, the shape will be short and wide. Each particular neuron-type pair has its own value. Since in the model, there are three neuron types (sensory (S), effector (E) and interneuron (I)), we have six types of connectivity. Given this, the connectivity relation between two neurons is not symmetric. A connection from S to E does not equate to a connection from E to S, i.e.,  $SE \neq ES$ . We actually employ 6+1  $\lambda$  scalars: one for each of the different connectivities, and a further one since we allow interneurons to connect to other interneurons. Except for the interneurons, a particular type of neuron is never connected to a neuron of the same type.

Finally note that we include an artificial constraint that prevents connections bisecting the hydramat cylinder. This is to ensure that connections remain within the ‘skin’ of the hydramat like it is in real hydra. If a pair of neurons are angled more than  $20^\circ$  away from each other, the connection probability is set to zero.

**Lifetime architectural perturbations** In order to assess whether there is an advantage in perturbing the neuronal architecture throughout the lifetime of the hydramat, the neurons are made to move stochastically by small random amounts. We are motivated to do so because in Hydra, the neural cells undergo constant movements (e.g. [3]). At each update of the simulation, a neuron’s position changes with a probability of 0.05, by an amount drawn from a normal distribution having an expectation of zero. For the neuron’s  $y$  coordinate gene, the variance of this distribution is set to 0.1 and for the neuron’s angle, 10.0. If during such a movement, the neuron moves outside of the hydramat’s bounds, it is replaced with a neuron occupying the position of the original neuron before any lifetime movements were undertaken.

### 2.3 Measuring Efficiency

In the hydramat neural model, we consider a single spike as a single unit of information transmission, which is associated with an energy cost,  $e_j$ , of the spiking neuron,

$$e_j = \sum_{i=1}^C \frac{d_{ij}}{d_{max}} S_{loss}, \quad (6)$$

where  $d_{ij}$  is the distance between two neurons and  $S_{loss}$  is the maximum possible energy that will be lost (0.1) when the connection length is  $d_{max}$ . Energy is also accumulated whenever the hydramat catches a food particle. In our simulations, this value was set to  $F_{gain} = 40.0$ .

### 2.4 Evolutionary Process

We employ a simple evolutionary algorithm to evolve the neuron positions and connectivity parameters. Typically we have 8 sensory neurons, 8 effector neurons and 84 interneurons. So we have 92 neuron positions to evolve (since the sensory neurons are fixed) and the 7 lambda connectivity parameters. We employ binary tournament selection, single point discrete recombination and a Gaussian mutation with an adaptive standard deviation ( $\sigma$ ). The adaptation process relies on the setting of two strategy parameters,  $\tau_0 = 1.0/\sqrt{2.0 * D}$  and  $\tau_1 = 1.0/\sqrt{2.0 * \sqrt{D}}$  where  $D$  represents the dimensionality of the vector being evolved. These values have been shown to be optimal in a process of self-adaptation [2]. The  $\sigma$  values are adapted as follows,

$$\sigma_i \leftarrow \sigma_i * \exp(N(0, \tau_0) + N_i(0, \tau_1)). \quad (7)$$

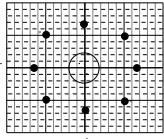
Both genes representing the spatial positioning vectors and those representing the connectivity parameters are evolved by applying the corresponding  $\sigma$  value.

### 2.5 Experiment Overview

We have devised a very simple ‘food catching’ task to explore our hypothesis. In Fig. 3, a birds-eye perspective of the environment is depicted. At the center of the environment resides the hydramat, whose task is to catch each of the eight pieces of food depicted as filled circles (one at a time). The performance (fitness) measure is the amount of energy that can be retained. Each hydramat population member starts with 200 units of energy and units are gained whenever a piece of food is caught and lost whenever a neuron spikes, if energy efficiency is considered. In order to ensure that the spiking neural network truly evolves to react to the food stimuli, the order in which the food pieces are dropped is randomly shuffled at the turn of each population member.

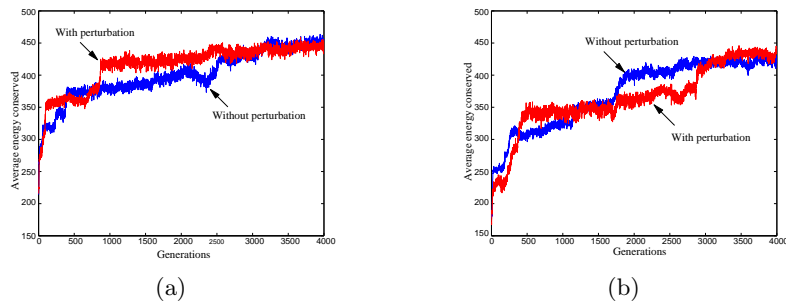
## 3 Summary of Results

Four sets of experiments have been performed to investigate the influence of energy efficiency and lifetime architectural perturbations on neural organization.



**Fig. 3.** The 8-food-task environment from a birds-eye perspective. Each of the 8 pieces of food, represented as an outer filled circle, is equidistant from the center of the hydramat, located at the center of the diagram.

Fig. 4 shows the energy conserved in the four experimental setups. We can see that evolution progresses steadily in all experiments and when energy consumption due to spikes is not taken into account, energy conserved from food caught increases more rapidly. Fig. 5 presents the relationship between energy conserved and connectivity density. From the figure, we can conclude that minimizing energy loss due to spikes effectively reduces the density of neural connectivity, which, however, becomes harder when lifetime architectural perturbations exist. The optimized neural architectures in the four experiments are illustrated in



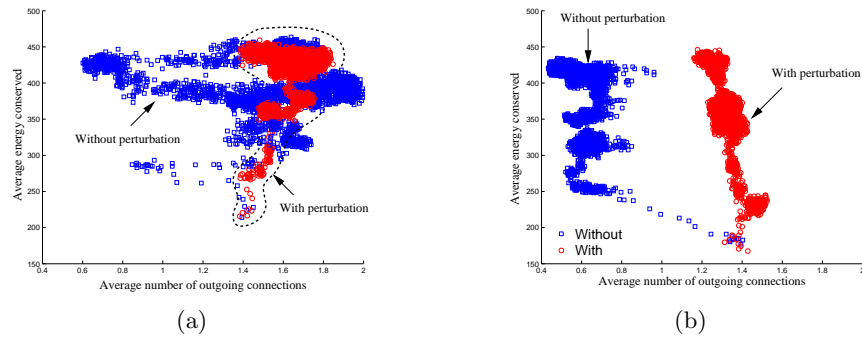
**Fig. 4.** Energy conserved as evolution proceeds (a) without energy efficiency, and (b) with energy efficiency taken into account.

Fig. 6. From these results, we can make the observation that effector neurons (enlarged filled circles) tend to aggregate around the sensory neurons (small filled circles). This suggests that functionally significant neurons have a tendency to become proximal to each other, which might be a functionally useful feature. Moreover, significance tests based on 30 runs when energy efficiency is considered indicate that lifetime perturbations increased the likelihood that effector neurons would move towards the top of the hydramat, to a significance of 0.005.

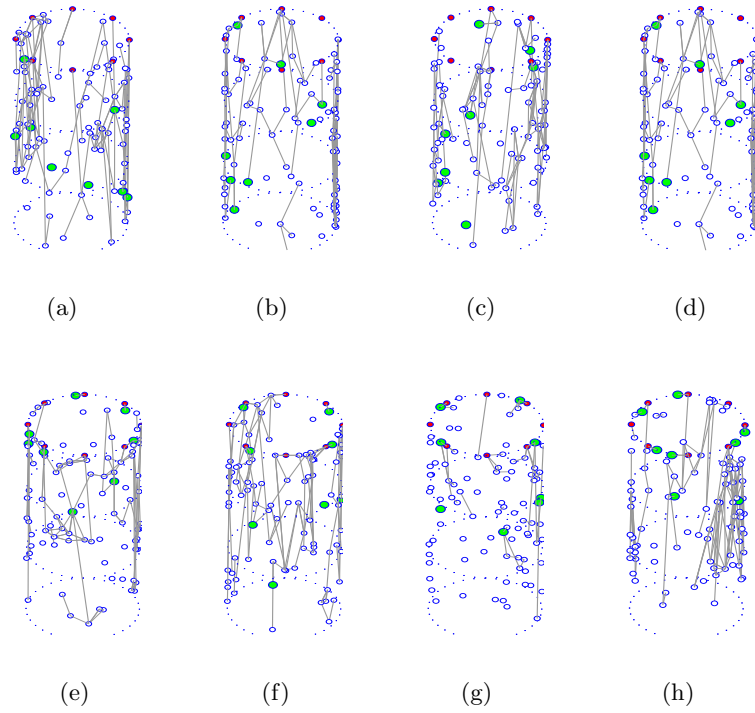
Two main findings seem to have emerged from our simulation results. First, energy has a direct impact on neural organization. Second, lifetime neural perturbations can facilitate the emergence of biologically plausible structures.

## 4 Conclusions

The contributions of this work are as follows. First, we suggest a novel framework that incorporates energy efficiency in organizing nervous systems. This framework allows us to take the first steps in understanding evolutionary transitions of primitive nervous systems, which provides interesting future research direction. Second, our computational results demonstrate how efficiency of information processing and minimization of energy consumption has emerged in



**Fig. 5.** Energy conserved versus the number of outgoing connections (averaged over the whole population) when energy loss due to spikes is (a) not considered and (b) considered.



**Fig. 6.** Initial ((a)-(d)) and optimized ((e)-(h)) neural architectures of the four experiments indicate that effector neurons (enlarged filled circles) tend to move toward to the sensory neurons (small filled circles). (e) energy efficiency not considered, no architectural perturbations; (f) energy efficiency not considered, with architectural perturbations; (g) energy efficiency not considered, no architectural perturbations; and (h) energy efficiency not considered, with architectural perturbations.



evolution through the interactions with the environment. Finally, our results show how random perturbations can facilitate the emergence of novel nervous architectures.

It seems sensible to expect that the same holds for the biological radially symmetric organisms of the genus hydra, i.e., that the formation of ring structures around the hypostomal region, [7], is a result of selection pressure towards minimalistic structures which coupled with their body morphology leads to similar structures. A further view is that the noisy effect of lifetime neural perturbations might increase robustness of the information processing system.

There are two other major extensions of the model presented here. Firstly, we can incorporate simulations of gene regulatory networks and let the neural architectures grow instead of directly encoding spatial information. Secondly, we can allow morphological changes of the hydramat and see how nervous systems depend on and change with body shape; we have begun to approach this in [6].

## Acknowledgements

The authors are grateful to J. Eppler and M.-O. Gewaltig for their assistance in using NEST. We also thank U. Körner for her support in understanding the more detailed spike-based processes in Hydra. The first author is grateful to Honda Research Institute Europe for a PhD studentship that makes this work possible.

## References

1. J. Albert. Computational modeling of an early evolutionary stage of the nervous system. *BioSystems*, 54(1–2):77–90, 1999.
2. T. Bäck and H.-P. Schwefel. An overview of evolutionary algorithms for parameter optimization. *Evolutionary Computation*, 1(1):1–23, 1993.
3. H. R. Bode. Continuous conversion of neuron phenotype in hydra. *Trends in Genetics*, 8(8):279–284, 1992.
4. V. R. Florian. Biologically inspired neural networks for the control of embodied agents. Technical report, The Center for Cognitive and Neural Studies, Cluj-Napoca, Romania, 2003.
5. M.-O. Gewaltig and M. Diesmann. NEST. Scholarpedia, 2007.
6. B. Jones, Y. Jin, B. Sendhoff, and X. Yao. Evolving functional symmetry in a three dimensional model of an elongated organism. In *Proceedings, ALife XI*, pages 305–312, Winchester, UK, 2008.
7. Osamu Koizumi. Developmental neurobiology of hydra, a model animal of cnidarians. *Canadian Journal of Zoology*, 80(10):1678–1689, 2002.
8. H. Meinhardt. The radial-symmetric hydra and the evolution of the bilateral body plan: an old body become a young brain. *BioEssays*, 24:181–191, 2002.
9. Y. Niv, D. Joel, I. Meilijson, and E. Ruppin. Evolution of reinforcement learning in uncertain environments: a simple explanation for complex foraging behaviors. *Adaptive behavior*, 10(1):5–24, 2002.
10. L. W. Swanson. *Brain Architecture: Understanding the Basic Plan*, chapter 2: The Simplest Nervous Systems. Oxford University Press, New York, 2003.