Three Forgotten Questions about Brain-inspired Computing?

Xin Yao
CERCIA, School of Computer Science
University of Birmingham
UK

Overview

- Introduction
- Evolution
- Environments (tasks)
- Body morphology
- Concluding remarks

Introduction

- **Brain research has been very popular in recent years.**
  - **EU H2020 Human Brain Project (FET Flagship)**
  - **NSF Brain initiative**
  - **IEEE Brain initiative**
  - **Now Chinese initiatives**
- **This talk will *not* offer any solutions to brain research or brain-inspired computing.**
- **Instead, we would like to ask some questions.**

Overview

- Introduction
- Evolution
- Environments (tasks)
- Body morphology
- Concluding remarks

Question 1

- Brains are evolved, not designed.
- Is it possible to understand the brain without understanding the role of evolution?
- Wouldn't it be useful to study the process of arriving at the "product" rather than just study the final "product" alone?
- Let's look at one simple example.

Artificial Neural Networks

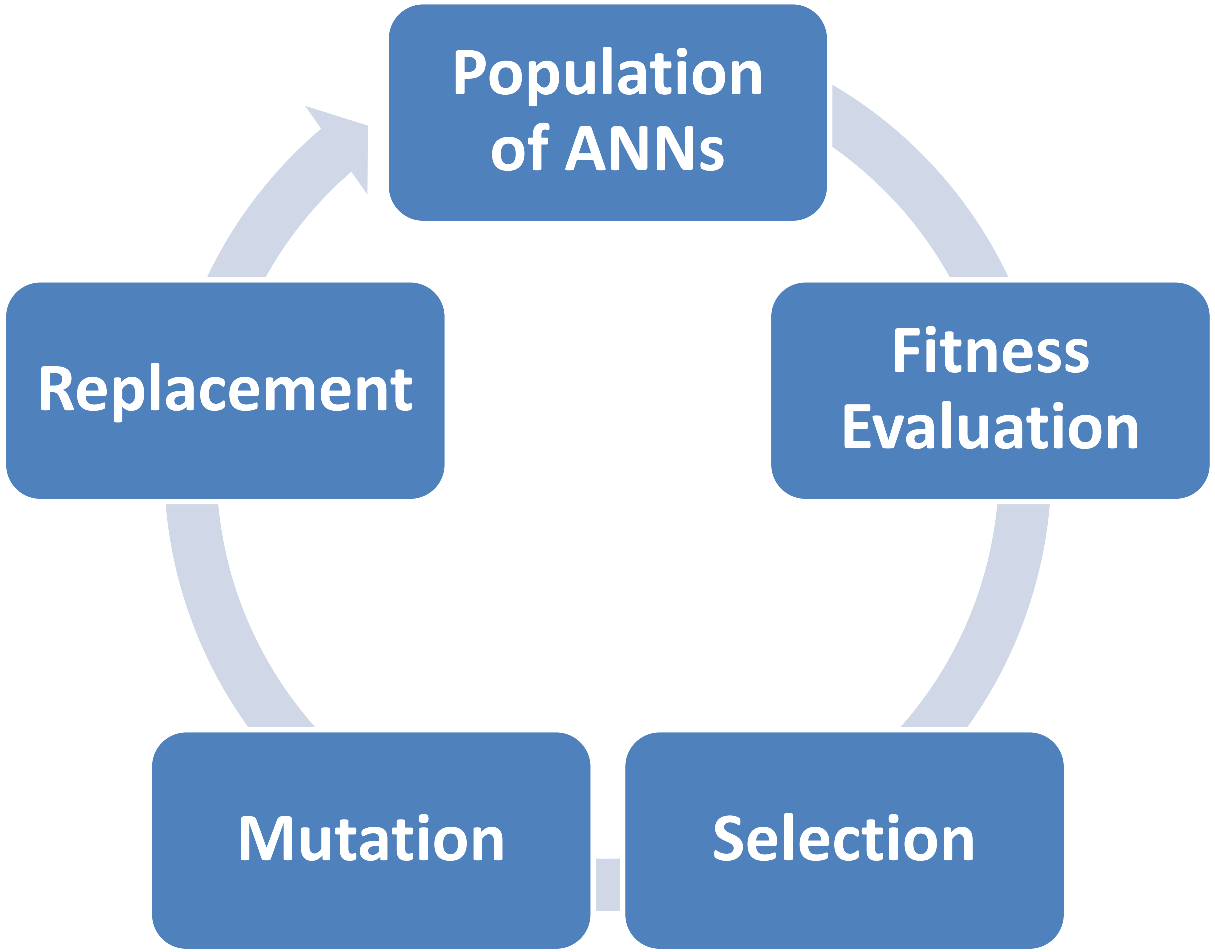
- **Feed-forward neural networks for the *n*-parity problem, e.g.,**
  - **R. Setiono, "On the solution of the parity problem by a single hidden layer feedforward neural network", Neurocomputing, Volume 16, Issue 3, 1 September 1997, Pages 225–235.**
- **What happens if we let evolution to discover the best ANNs for the parity problem?**

Evolutionary Artificial Neural Networks

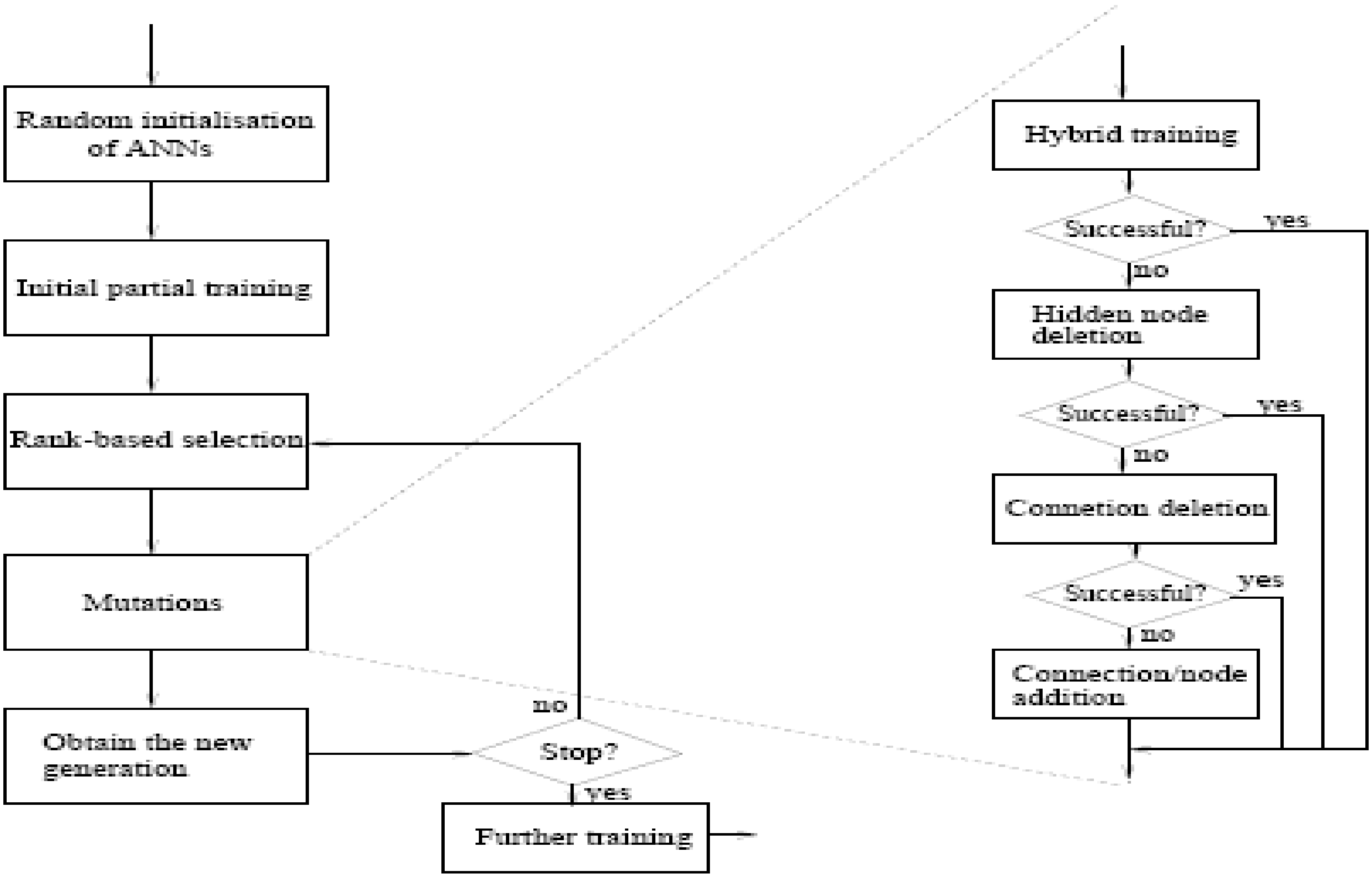
1. Initialise a population of ANNs at random.
2. While the stopping criteria are not met,
    a. Evaluate the fitness of each ANN.
    b. Probabilistically select ANNs based on their fitness.
    c. Mutate the ANNs.
    d. Replace old ANNs by new ones.

- More details about EANNs in general:
    - X. Yao, "Evolving artificial neural networks," *Proceedings of the IEEE*, 87(9):1423-1447, September 1999. (Won the 2001 IEEE Donald G. Fink Prize Paper Award)

EANNs


Population of ANNs
Fitness Evaluation
Selection
Mutation
Replacement

More Specifically, We Used EPNet



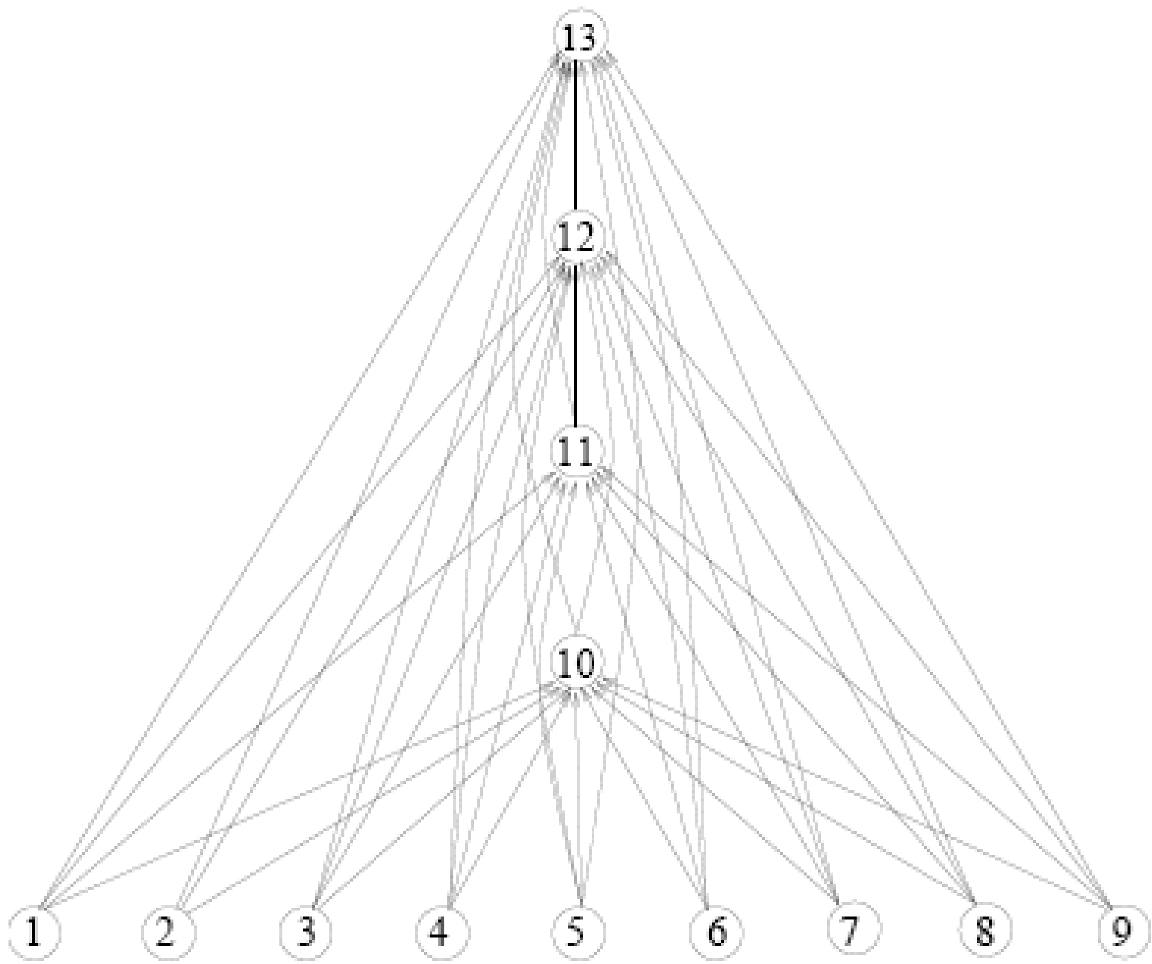
- X. Yao and Y. Liu, “A new evolutionary system for evolving artificial neural networks,” *IEEE Transactions on Neural Networks*, 8(3):694-713, May 1997.

Comparison: Number of Hidden Nodes

N	EPNet	CCA	PCA	TA
4	2	2	2	2
5	2	2	2	2
6	2	3	3	3
7	2	4	3	3
8	3	5	4	4

Table 1: Number of hidden nodes in an ANN for the N-parity problem. EPNet — our algorithm, CCA — Cascade-Correlation Algorithm, PCA — Perceptron Cascade Algorithm, TA — Tower Algorithm.

The 9-Parity Problem — Architectures



The 9-Parity Problem — Weights and Biases

	T	1	2	3	4	5	6
10	-12.35	-12.19	12.38	-12.19	-12.20	12.23	-12.19
11	-4.12	6.04	0	6.04	6.04	-6.34	6.04
12	7.05	6.78	-7.13	6.78	6.79	-6.96	6.79
13	0	7.89	-7.76	7.89	7.89	-8.04	7.89

		7	8	9	10	11	12
10		12.23	-12.12	-12.20	0	0	0
11		-6.34	-26.16	6.05	0	0	0
12		-6.96	-9.59	6.79	26.70	-16.45	0
13		-8.04	-10.71	7.89	30.71	-18.99	-17.02

Observations

- Evolved ANNs are very compact.
- They have more layers than manually designed ANNs.
- They are not as regular as manually designed ANNs.
- The results are interesting because
  - It's very different from human-designed ANNs.
  - It does not seem to match some intuitions that brains have modular structures.

General Observation: ANNs vs BNNs

- **ANNs**: Given a task in a static environment, train an ANN to perform it well, e.g., a CNN for image recognition.
- **BNNs**: The brain performs a huge variety of different tasks in dynamic environments.
- What would happen if we give different tasks to the same ANN?

Overview

- Introduction
- Evolution
- Environments (tasks)
- Body morphology
- Concluding remarks

Benefits of Modularity

- **Although there has not been a unified definition of modularity, there are many studies and discussions on modularity in the brain.**
- **It has been shown that modular ANNs perform better than fully-connected ANNs on *multiple* tasks, given the same number of hidden nodes.**
  - V. Khare, X. Yao and B. Sendhoff, ``Multi-network evolutionary systems and automatic problem decomposition,'' *International Journal of General Systems*, 35(3):259-274, June 2006.
  - V. R. Khare, X. Yao, B. Sendhoff, Y. Jin and H. Wersing, ``Co-evolutionary modular neural networks for automatic problem decomposition,'' *Proc. of the 2005 Congress on Evolutionary Computation (CEC'05)*, Vol.~3, 2-5 September 2005, IEEE Press, Piscataway, NJ, USA, pp.2691-2698.

Evolution Discovers Modularity

- It has also been shown that learning in dynamic environments lead to modular structures, e.g.,
  - V. R. Khare, B. Sendhoff and X. Yao, "Environments Conducive to Evolution of Modularity," *Proc. of the 9th International Conference on Parallel Problem Solving from Nature (PPSN IX)*, T. P. Runarsson, H.-G. Beyer, E. Burke, J. J. Merelo-Guervós, L. D. Whitley and X. Yao (eds.), Lecture Notes in Computer Science, Vol. 4193, Springer, pp.603-612, September 2006.

Question 2

- **In brain-inspired computing, we tend to focus on a specific task, e.g., image or speech recognition, natural language understanding, or playing Go.**
- **Can we understand the brain fully by focusing on individual tasks only?**

Side Remarks

It is important to be clear about research aims in our research:

- Computing vs Understanding.
- Brain-like computing vs brain-inspired computing vs brain modelling.

Overview

- Introduction
- Evolution
- Environments (tasks)
- Body morphology
- Concluding remarks

Brain and Body

- All brains are embedded in bodies.
- Surprisingly, little ANN research considers the roles of bodies, although biologists do.

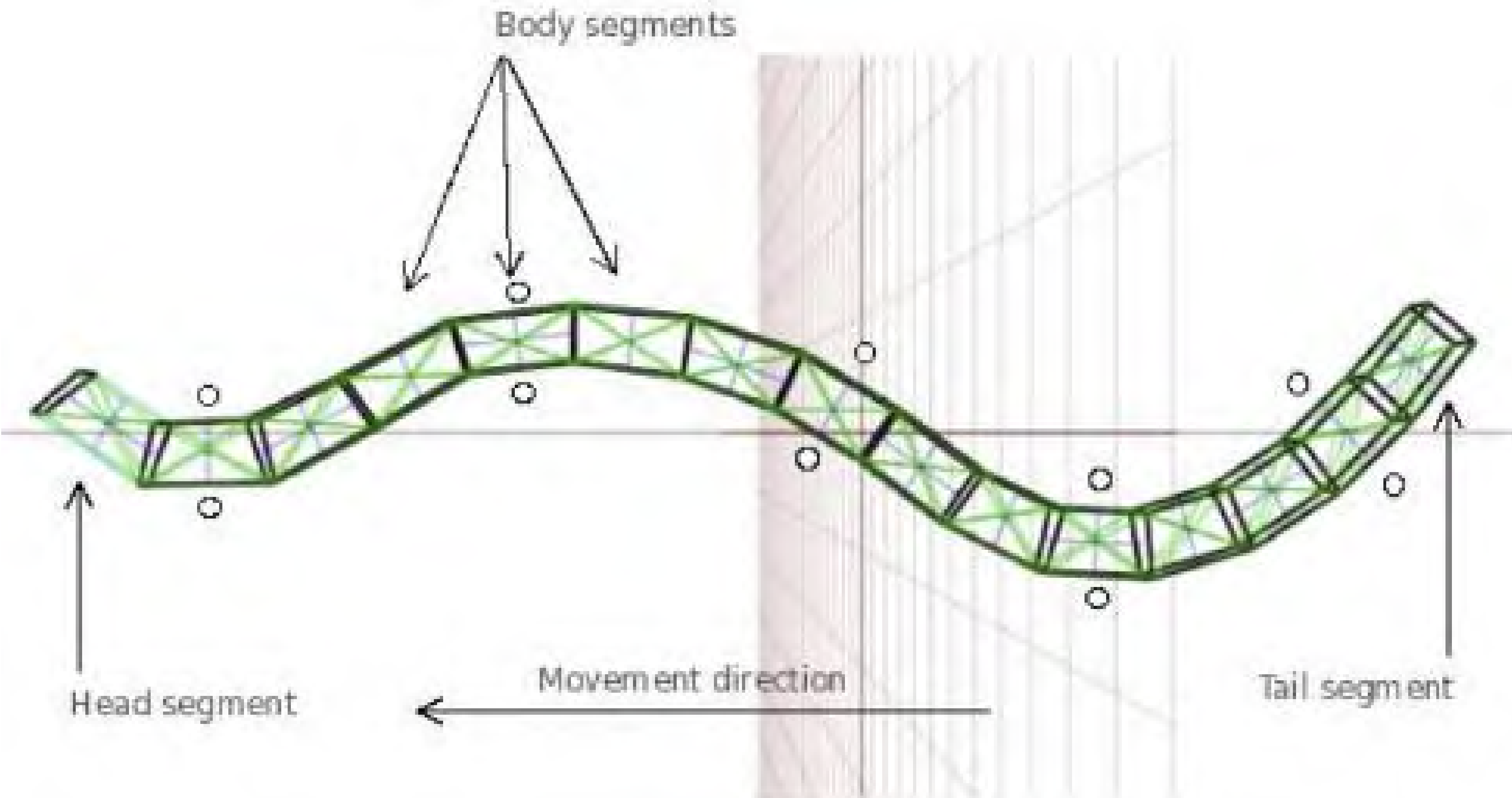
Question 3

- What is the role of body in the evolution of brains?
- Is the body really irrelevant in the research of brain-inspired computing?
- Let’s look at one artificial example.

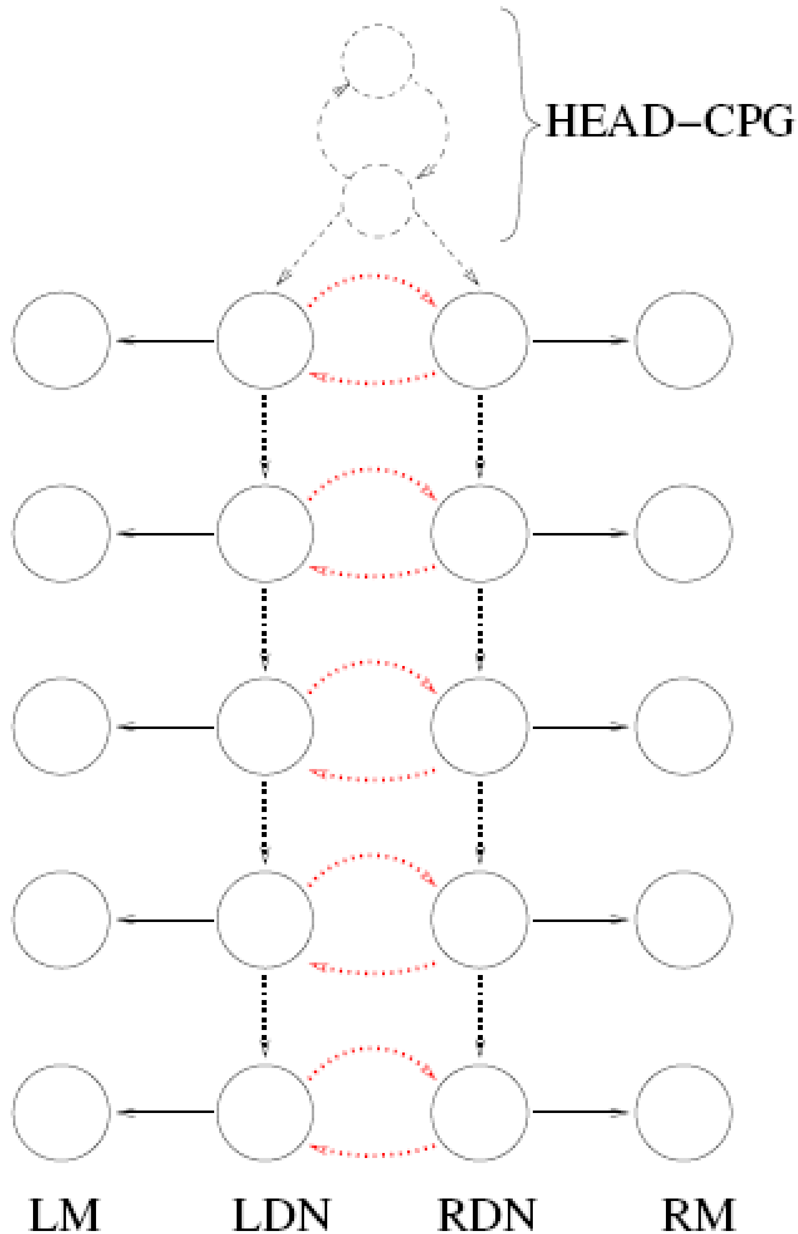
Evolution of a Swimming Animat

- **Research aim:**
  - **to observe the evolution of neural structures in relation to both body morphology and required motor primitives.**
  - **More details:**
    - **B. Jones, A. Soltoggio, B. Sendhoff and X. Yao, "Evolution of neural symmetry and its coupled alignment to body plan morphology."** ***Proc. of the 13th Annual Conference on Genetic and Evolutionary Computation (GECCO 2011)*****, pp.235-242, 12-16 July 2011, Dublin, Ireland, ACM Press, New York, NY, USA.**

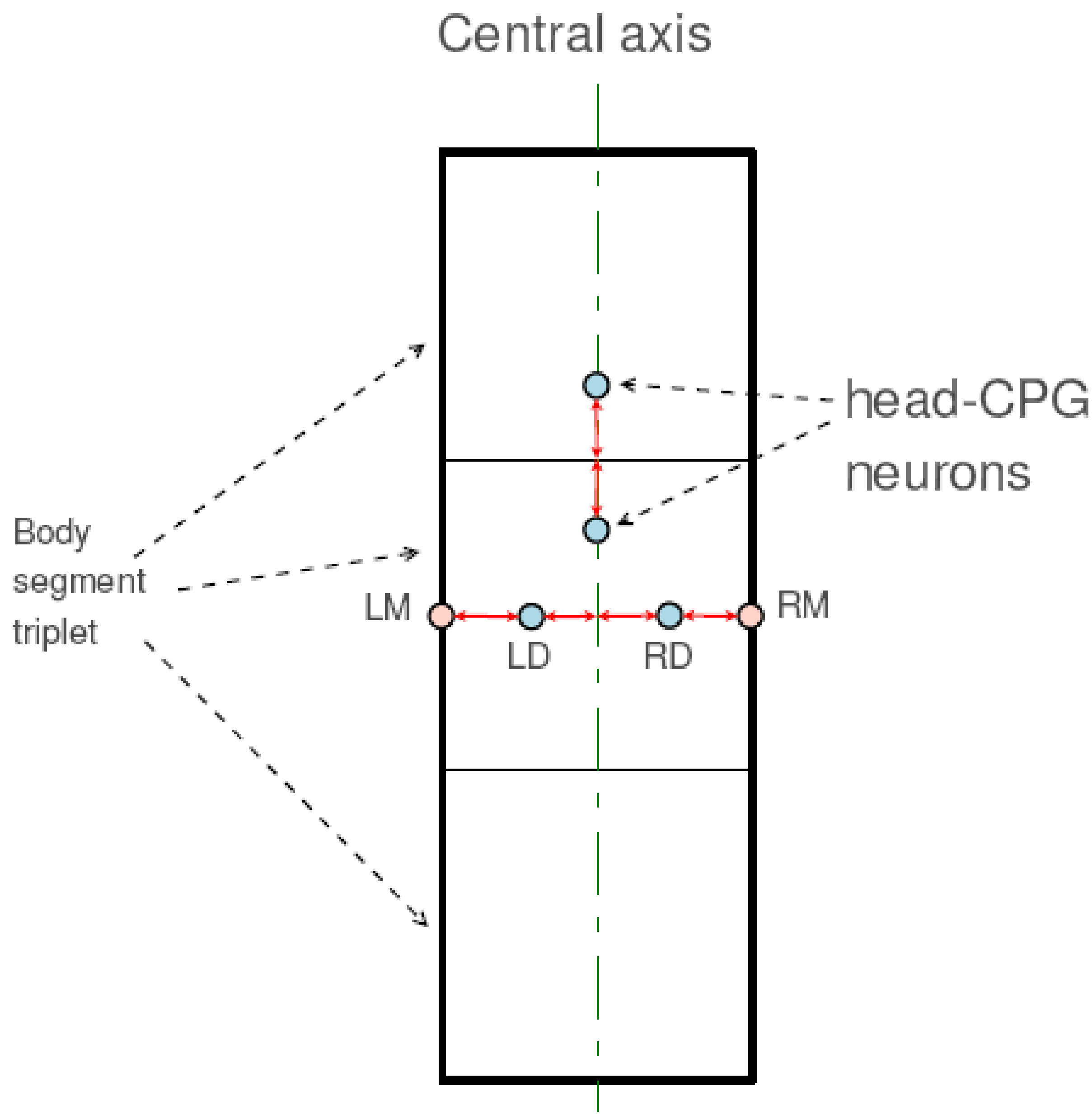
The Swimming Animat



The Neural Control System



Evolvable Neural Positions



Chromosomes

NI	NTC	head–CPG	DCOP	DES	NRAD	HY
10/12	10/12	1	5	8	10	0/2
BOOL	[10, 50]	BOOL	BOOL	BOOL	[0, 0.63]	[0,10.58]

Figure 5: The agent's genotype. Each box holds the following information: gene type (top); gene count (middle); initialisation range or BOOL if boolean valued (lower). The gene types are: NI (neuron is inhibitory); NTC (neuronal time constants); head-CPG (presence of head-CPG structure); DCOP (coupled connections between descending pairs of neurons); DES (presence of descending connections); NRAD (radius position of descending neuron, that is, the distance of the neuron from the central midline of the animat); HY (y-coordinate position of neuron in head-CPG, if head-CPG structure is present). For NI and NTC, it is possible for there to be 10 or 12 genes; 12 if a head-CPG structure exists. For the same reason, it is further possible for there to be 0 or 2 HY genes.

Experimental Studies

- **To study the effect that body morphology has on the evolution of neural structure and moreover, how a requirement for different motor primitives can affect such a structure.**
- **Three sets of experiments were performed:**
  a. **The animat is required to undertake fast, efficient forward locomotion.**
  b. **The animat is *additionally* required to undertake turning behaviour.**
  c. **as in (a) but with an asymmetric body plan.**

Asymmetric Body Plan

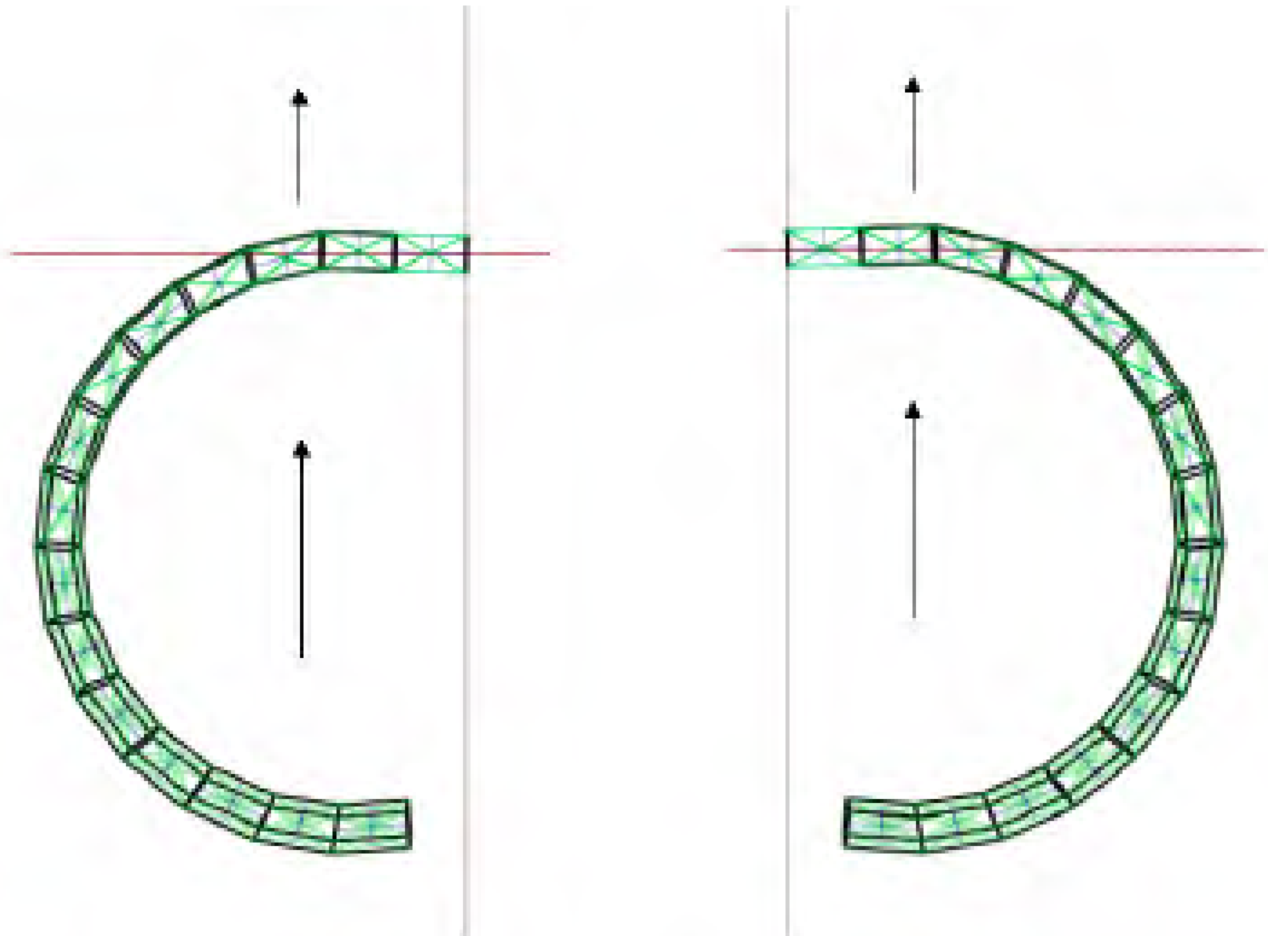
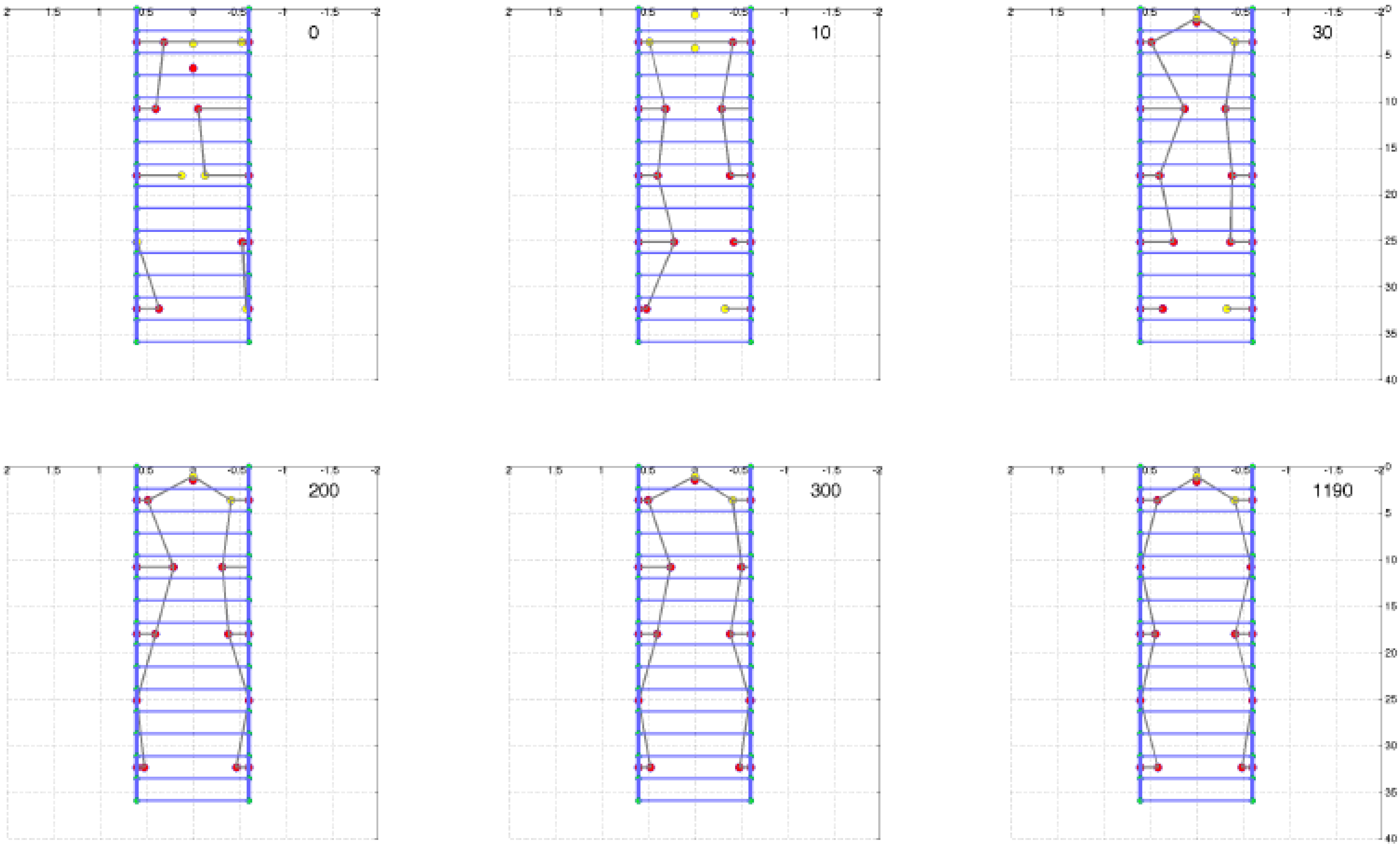


Figure 4: Asymmetric body morphologies: in Scenario (c), the body plan is constrained to adopt one of two body curvatures (*curved right* or *curved left*).

Experimental Results (a)



Experimental Results (b)

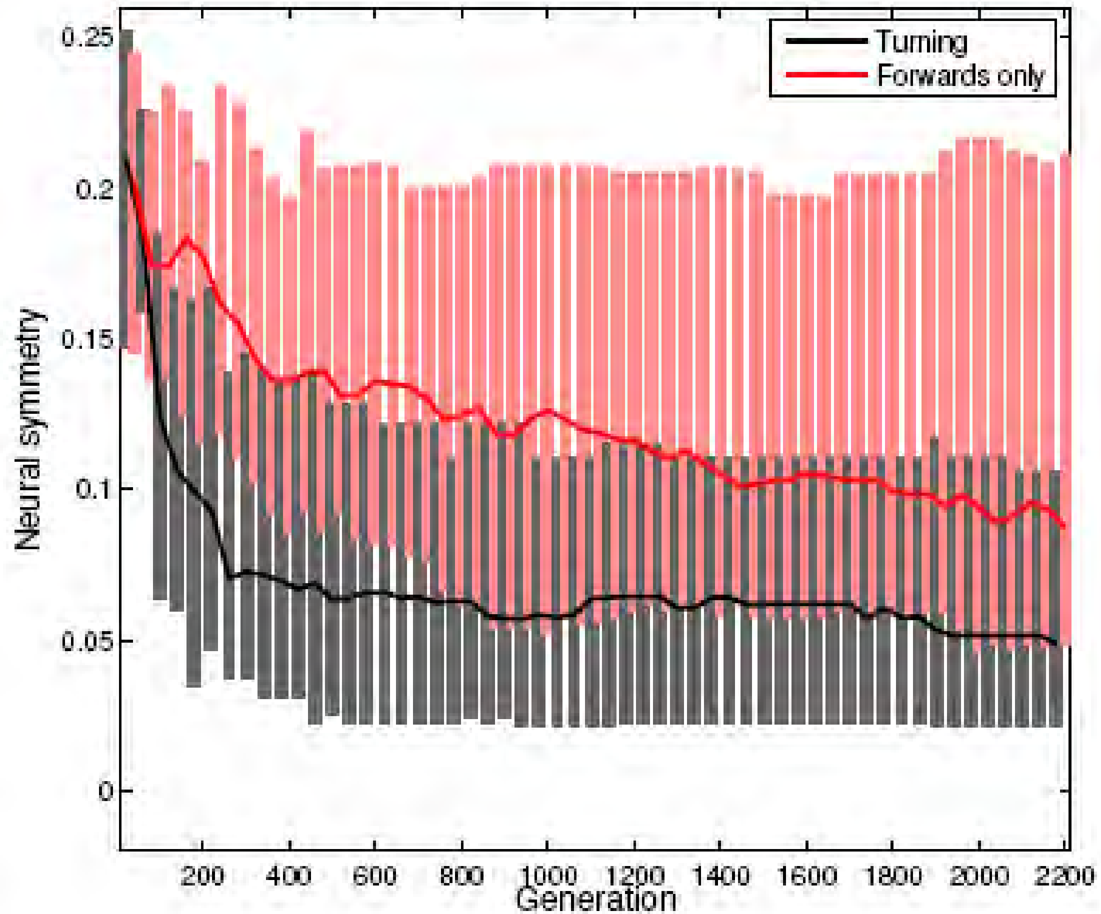


Figure 8: Medians together with upper and lower quartiles of neural symmetry throughout evolution (see Eq. 4 for definition). Symmetry evolves to greater levels (smaller values) in Scenario (b) (forward motion plus turning behaviour) than in Scenario (a) (forward motion only).

Experimental Results (c)

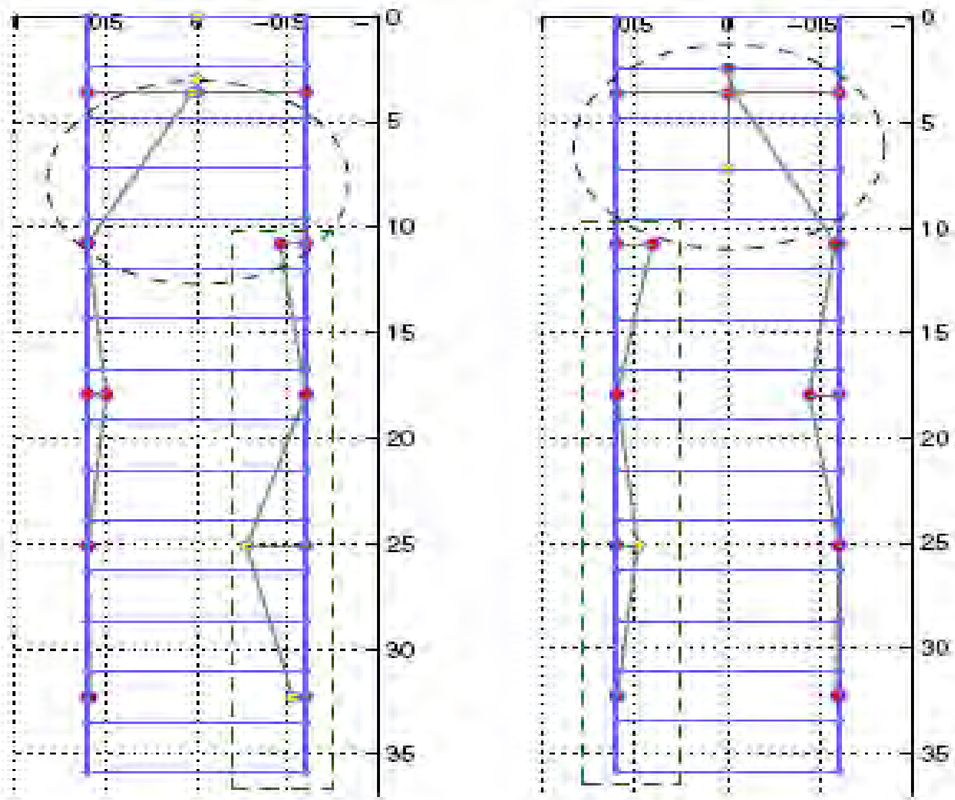


Figure 11: Examples of asymmetrical neural structures for left- and right- biased body asymmetries. The ellipses highlight how descending connectivity from the head-CPG structure is broken on the convex side of the body asymmetry. This largely reflects differences in descending connectivity as plotted in Fig. 10. This results in a lack of oscillatory input current from the head-CPG structure meaning that motor neurons (dashed rectangular regions) yield tonic output. Asymmetrical body morphologies are shown in a straight posture for ease of visualisation.

Experimental Results: Summary

- **The neural geometry becomes aligned to body morphology in order to facilitate the generation of motor primitives.**
  1. **Artificial evolution favours a symmetrical layout in the neural structure, which appears to improve swimming efficiency.**
  2. **The following simulations in which turning behaviour was additionally required interestingly indicate that, as the motor task becomes richer, an even higher level of symmetry becomes advantageous. This is possibly due to the need for better exploitation of muscle synergies during the turning process.**
  3. **The third experiment, in which the body plan was asymmetrical, demonstrated how the nervous system places itself to compensate for the asymmetrical body. By doing so, forward swimming efficiency is maximised.**

What Do They Mean?

- Our results suggest that, at the evolutionary level, the interplay between neural architecture and body morphology is a fundamental driving mechanism, even at the basic level of these simulations.
- The coupling between neural structure and body plan morphology is essential in evolving the neural system.
- The tasks also play an important role.

Overview

- Introduction
- Evolution
- Environments (tasks)
- Body morphology
- Concluding remarks

Concluding Remarks

- Brains are evolved, not designed. It is essential to understand the evolution in order to understand the brain better.
- The brain has to perform a variety of different tasks in complex and dynamic environments. The tasks and environments shape the brain.
- Brains are embodied. The coupling of brain and body plays an important role in brain's evolution.
- Although the above might be commonsense in biology, little research in brain-inspired computing has considered them. Should we?