The Development of Modular Evolutionary Networks for Quadrupedal Locomotion

Sethuraman Muthuraman, Christopher MacLeod and Grant Maxwell
School of Engineering
The Robert Gordon University
Schoolhill
Aberdeen AB10 1FR, U.K.
email: s.muthuraman-e@rgu.ac.uk

ABSTRACT
Artificial Neural Networks have so far failed to produce a convincing route to Robotic Intelligence. Training and Organizational Algorithms (such as Evolutionary Algorithms) are presently not flexible or sophisticated enough to configure large networks which fuse data from different sensory domains in a complex and changing environment.

The approach outlined here is different in that it allows the neural network to grow, building itself up, piece by piece, from a simple to a complex form. This is accomplished by allowing the robot's body plan and environment to develop while simultaneously adding to the structure of the controlling network. Network structures from previous iterations are retained but are not retrained.

Each time the robot attains a satisfactory performance with its current body plan in its current environment, complexity is increased and new networks are configured on top of the old until this more challenging system is also mastered.

The biological justification for this approach is outlined. Results are presented which demonstrate the operation of the approach in the development of a quadrupedal gait for a simulated robot.

KEY WORDS
Artificial Neural Networks, Modular Networks, Evolutionary Algorithms, Robots, Locomotion

1 Introduction

1.1 Lessons from Life

The complex organisms which surround us today are the result of three billion years of evolutionary development, starting from simple initial life forms.

It is true that at each stage of this process, species have radiated and proliferated in form and function to fill available ecological niches; this happened most famously in the "Cambrian Explosion" [1]. However, these creatures, for all their variety and ingenuity of design, are simpler organisms than those which came later. Perhaps this is because, at any point of evolutionary time, organisms explore their genomic search space through mutation whereas, the addition of truly new genes is a rarer occurrence, opening up new developmental possibilities.

1.2 Biological Development

The argument in the previous section is best illustrated by example. The first fossils evident in Precambrian rocks are those of simple, single-celled organisms.

Early Multicellular Animals, exemplified today by the Sponges, were amorphous creatures lacking the cellular specialization of later animals - for example, recognizable muscles, nervous system, gut and sensory organs. They lived in a simple environment leading a sessile existence, typically attached to a rock.

Jellyfishes and their kin appear next in the fossil record. They can actively move and have simple sensory and nervous systems. Many also live in a more complex environment (the open ocean), all be it simpler than other environments to come (with no need for even basic obstacle avoidance, for example).

We can trace one particular route of development through various worms, Echinoderms and simple Chordates to Fish, Amphibians, Reptiles and Mammals as shown in simplified form in Fig. 1 [2]. As we proceed, four aspects of the organisms develop:

- Their body plan.
- Their sensors and actuators.
- The environment (at least as the organisms perceive it).
- The nervous system.

Only through this process of gradual incremental change from one form to another can such complexity build up. Otherwise the evolutionary search space (like its artificial counterpart mentioned in the first section) would simply be too complex.

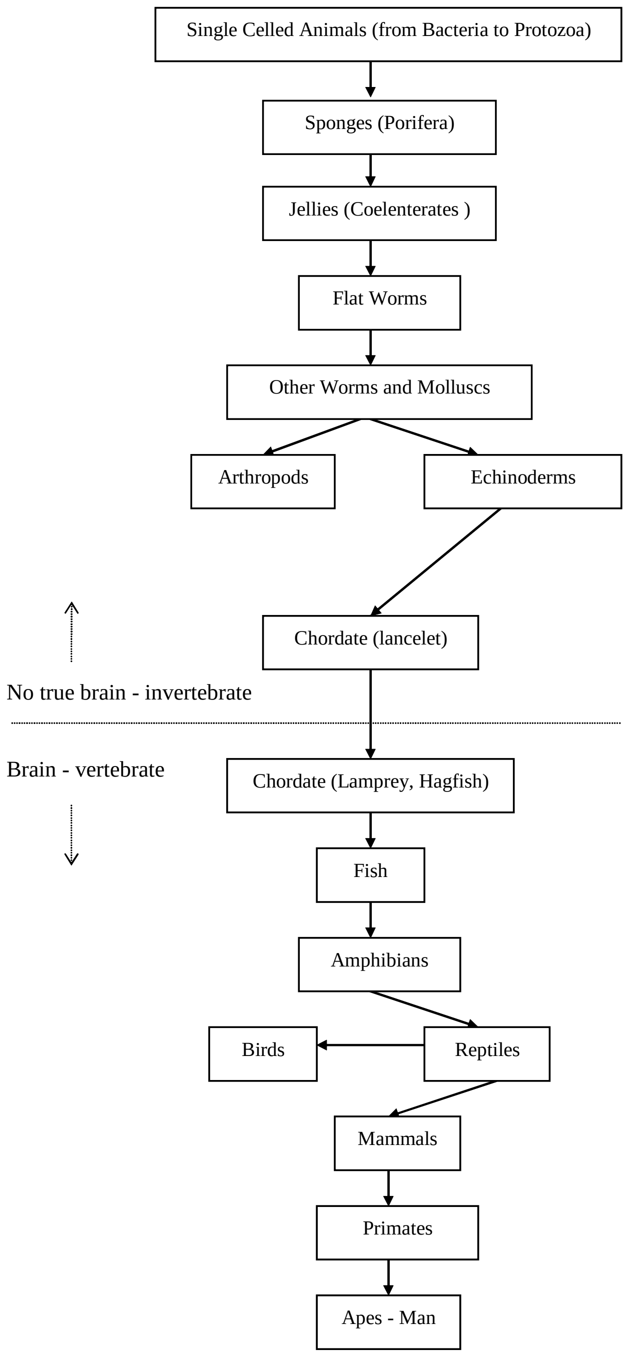

Figure 1. Evolutionary Development

1.3 Lessons for Robots

Given the arguments above, it makes sense to apply these axioms to robots, as suggested by MacLeod and Maxwell [3, 4]. This is the approach which we have adopted with legged robots, starting with a simple body plan - a two legged robot which can drag itself along the ground rather like a mudskipper out of water. This simple model then develops multi-jointed legs and proceeds through intermediate stages to stable quadrupedal locomotion. The actuators used in these robots make use of D.C. motors to control simple legs, as explained in previous work [5, 6, 7]. The work presented here is based on simulation, using a model developed from this previous work. This has been shown to be in good agreement with the physical robot.

2 Robotic Development

The algorithm used in this research proceeds as follows. Initially, the robot's body plan is kept as simple as it is reasonably possible to make it, as mentioned above. The first Neural Network, consisting of a module of four neurons, has its outputs connected to the robot's leg actuators. This network is trained using an Evolutionary Algorithm until the fitness (which is the distance the robot can walk in five hundred time steps) will not get any higher.

Next, a new module is added; connections are allowed to any of the previous neurons and the previous module's weights are retained. The Evolutionary Algorithm optimizes this new module and is able to set both the weights and the connections within the module. Once the structure has stopped increasing in fitness, it is retained and the process repeated with a new module. This process continues until the current maximum possible fitness achievable with the current body plan is attained (e.g. the maximum distance travelled) and then the body form of the robot or its environment is increased in complexity (as shown for a quadruped in Fig. 2).

As the algorithm proceeds, growth occurs in three different stages:

- firstly, when a single function is being evolved - for example, a single degree of freedom leg as described above.
- secondly, when a new function, which depends on those previously created, is being evolved (for example, a second degree of freedom in the legs). The new function takes its inputs from the modules which were evolved previously.
- finally, when two completely different functions (perhaps evolved separately - for example, vision and locomotion) are being interfaced together. It is not clear as yet whether it is more effective to evolve these separately and then link them together or to evolve them as part of the same system from the outset.

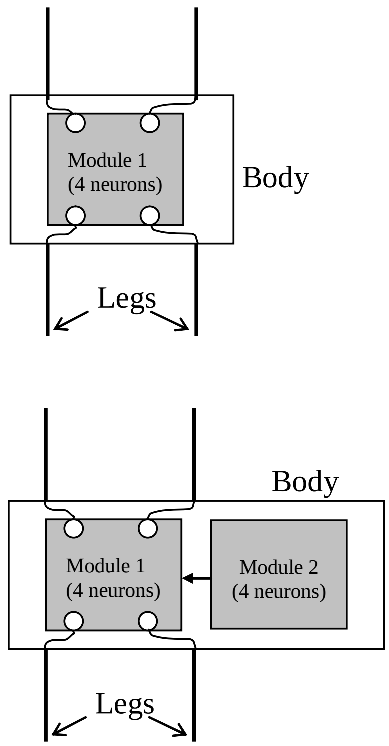

Figure 2. Addition of Network Modules

Previous work in this area has largely been associated with Artificial Life and relied on simulations of population dynamics of simple agents. The development of the body plan and environment has been tackled initially by Sims [8] using block-constructed creatures. Others followed [9, 10], including walking stick figures by Ventrella [11]. The work of these researchers is summarised in [12, 13]. The process outlined here is different, however, in that it is based on the dynamics of a physical robot, uses neural nets for intelligence and is open ended in its aims.

The gradual addition of neurons to a structure as proposed here is a form of incremental evolution [14]. The fact that previously trained modules are retained is often referred to as Incremental Learning [15].

Again, the approach adopted to this here is different from other incremental learning techniques such as Tiling [16], Tower [17] or Cascade Correlation [18]. This is because the network grows in a modular fashion as opposed to the simple addition of neurons within a fixed network topology (for example, a feed-forward structure).

3 Neural Model

It has already been mentioned that the Evolutionary Algorithm allows appropriate connections to be chosen. It was found that fully connected networks often did not allow maximum fitness to be achieved. This was probably because of unwanted interactions between neurons in the modules. This was solved by allowing an Evolutionary Algorithm to choose the connection pattern within a module.

The other factor which proved important in the successful evolution of the system was the Neuron Model used. Initial experiments were carried out using a model proposed by McMinn [5]; this was based on the behaviour of neurons used in motor reflex functions. This proved to be unsatisfactory as, like the connection problem described above, it would not allow full fitness to be achieved. A different neuron model which used a spiky type of behaviour (as described by Shigematsu [19]) was then introduced. This proved to be successful. Our latest model incorporates several of the best features of these previous models and can be described as floows:

For a neuron with n inputs, the input at time t is:

$$S(t) = \sum_{j=1}^{n} i_j w_j \tag{1}$$

The total activity of the neuron also takes previous inputs into account (using a leaky integrator):

$$A(t) = S(t) + S(t-1).d \tag{2}$$

where d is the decay constant; the value of this constant is set by the Evolutionary Algorithm (EA).

The output of the neuron is a square wave with a variable mark to space ratio which has an on-time t_1 and an off-time t_2; the waveform is pulse width modulated by the neuron's activity. If the activity is greater than a threshold value, then:

$$t_1 = c.A(t) \tag{3}$$

where the values of c, the period (t_1 + t_2) and the threshold are set by the EA. The EA can also set a gene switch allowing the neuron to operate as a Perceptron, in which case:

$$output = \frac{1}{1 + e^{-A(t)}} \tag{4}$$

The lesson from this is that the neuron model should be flexible enough to allow the network to increase its fitness - for example, by being able to accommodate both Perceptron and "Spiky" type behaviour.

The Evolutionary Algorithm used was a [$\mu + \lambda$] Evolutionary Strategy with a population of 700 and 100 parents; there were 11 genes per neuron in a two neuron module.

4 Results

The results presented here relate to the first stage in the process described in section 2 - that is, the evolution of a single function using a modular approach. The robots used in the experiments were simulated. However, the simulations used were based on previous modelling work by McMinn [6], which had proved accurate when applied to

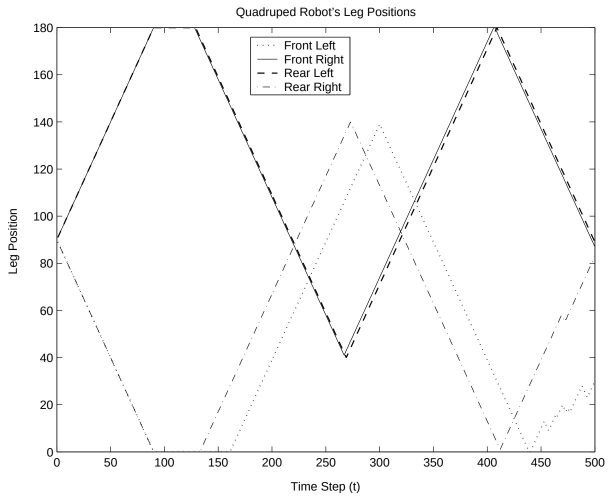

Figure 3. Gait evolution - one module used

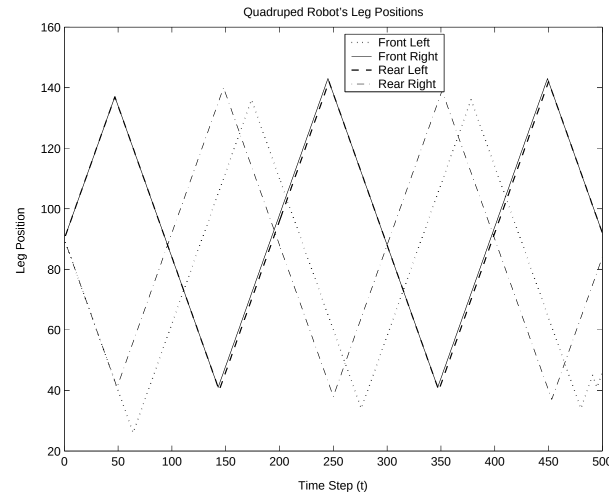

Figure 4. Gait evolution - second module added

real legged robots [7]. The legs were controlled by DC motors.

Figs. 3, 4, 5 and 6, demonstrate the development of a trotting gait in a quadruped using the methods described in the previous sections. In the first stage, shown in Fig. 3, one module of four neurons is attempting to produce the leg patterns necessary.

At this stage the gait is fairly chaotic with only two legs being in phase and two legs having a massively inappropriate amplitude (movement) variation.

In the final graph shown in Fig. 6, the gait pattern is almost perfect with all the legs having the correct phase relationship and also the correct amplitude variation.

The intermediate graphs, Figs. 4 and 5 show the improvement in gait as further modules are added to the network. Each modules consists of four neurons.

Fig. 7 shows the improvement in overall fitness as the three extra modules are added to the initial one. In this case fitness is measured as the distance walked in a straight line within 500 time steps of the simulation.

These results compare well with the results previously published by McMinn as well as those for other legged robots [20, 21]. The main difference is that this system is open ended and flexible enough for continued development over and above these simpler systems.

5 Conclusion

We have shown that an artificial neural network can be evolved in a modular format to create a walking gait for quadruped locomotion. This technique provides a flexible evolutionary alternative to the more rigid structures previously reported. It is novel in that it is based on the incremental addition of modules to a previously evolved structure. The subsequent training only affects the features of the newly added module; the weights and structure of the previous modules are left unchanged.

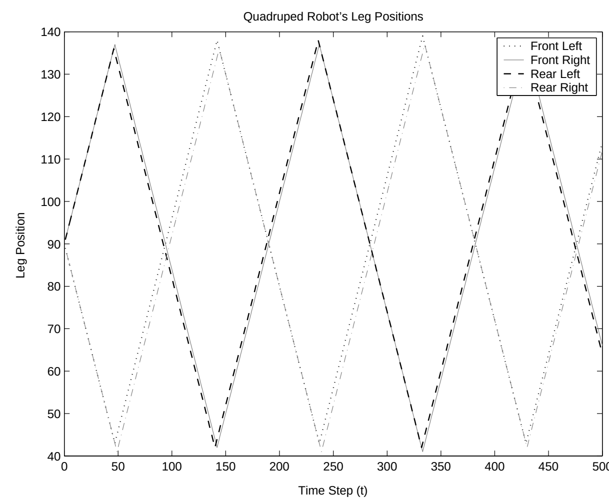

Figure 5. Gait evolution - third module added

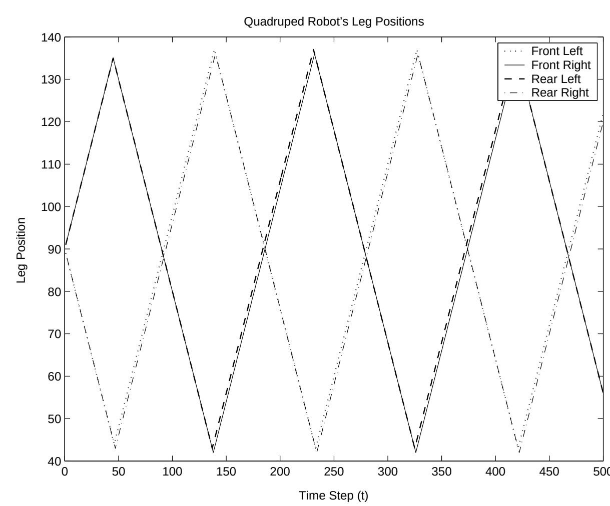

Figure 6. Gait evolution - fourth module added

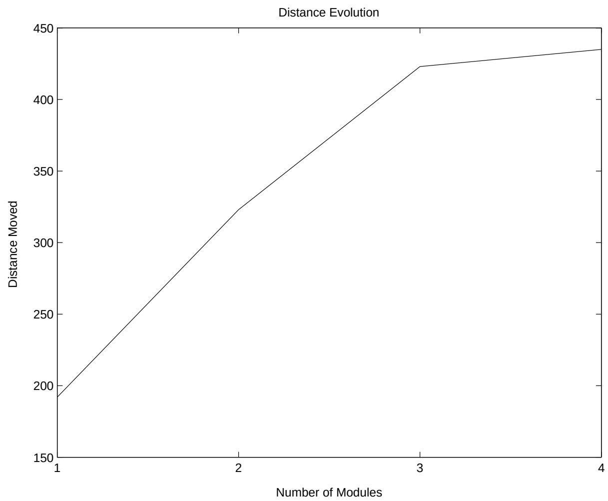

Figure 7. Evolution of distance travelled

Further work is currently being undertaken on the development of a network which can cope with a second degree of freedom in the limbs of the robot.

The next stage is to integrate a sensory network (primarily vision networks) into the scheme and to develop a more general approach (in the form of an algorithm) to control the overall development of the system.

Thought also needs to be given to two other areas. The first of these is the development of the body plan and environment deconstraint in order to avoid forcing the fitness function of the robot down an artificially constrained path. This work will inevitably focus on the nature of the simulated or real environment in which the robot finds itself.

Secondly, further work is needed on the algorithm for adding modules into a large existing network. In particular, this will focus on whether they can be connected locally to only the final layers of the system.

References

[1] S. J. Gould, *Wonderful Life*. (London, England: Vintage, 2000).

[2] R. Buchsbaum, M. Buchsbaum, J. Pearse and V. Pearse, *Animals without Backbones*. (Chicago: University of Chicago Press, 1987).

[3] C. MacLeod, D. McMinn, A. Reddipogu and N. Capanni, Evolution by Devolved Action: Towards the Evolution of Systems. In: Appendix B of D. McMinn, *Using Evolutionary Artificial Neural Networks to Design Hierarchical Animat Nervous Systems*, PhD Thesis, The Robert Gordon University, Aberdeen, UK, 2002.

[4] C. MacLeod and G. Maxwell, *Evolutionary Electronics*. Practical Electronics, August 1999.

[5] D. McMinn, G. Maxwell and C. MacLeod, An Evolutionary Artificial Nervous System for Animat Locomotion. *EANN 2000: Proceedings of the International Conference on Engineering Applications of Neural Networks*, Kingston Upon Thames, UK, 2000, 170–176.

[6] D. McMinn, *Using Evolutionary Artificial Neural Networks to Design Hierarchical Animat Nervous Systems*. PhD Thesis, The Robert Gordon University, Aberdeen, UK, 2002.

[7] D. McMinn, G. Maxwell and C. MacLeod, Evolutionary Artificial Neural Networks for Quadruped Locomotion. *Proceedings of the International Conference on Neural Networks ICANN 2002*, Madrid, 2002, 789–794.

[8] L. Sims, Evolving 3D morphology and behaviour by competition. In: R. Brooks and P. Maes (editors) *Proceedings of the 4th Workshop on the synthesis and simulation of living systems*, MIT Press, 1994, 28–39.

[9] H. Lipson and J. B. Pollock, Automatic design and manufacture of robot lifeforms, *Nature*, 406, 2000, 974–978.

[10] M. Komosinski, The world of framsticks: Simulation evolution, interaction. In: *Virtual worlds 2*, Lecture Notes in Artificial Intelligence, Springer-Verlag, 2000, 214–224.

[11] J. Ventrella, Exploration in the emergence of morphology and locomotion behaviour in animated characters, In: R. Brooks and P. Maes (editors) *Proceedings of the 4th Workshop on the synthesis and simulation of living systems*, MIT Press, 1994, 436–441.

[12] T. Taylor and C. Massey, Recent developments in the evolution of morphologies and controllers for physically simulated creatures, *Artificial Life*, 7(1), 2001, 77–87.

[13] G. S. Hornby and J. B. Pollack, Creating high-level components with a generative representation for body-brain evaluation, *Artificial Life*, 8, 2002, 223–246.

[14] C. MacLeod and G. M. Maxwell, Incremental Evolution in ANNs: Neural Nets which Grow. *Artificial Intelligence Review*. Kluwer, 16, 2001, 201–224.

[15] C. Guo-Jian, *Incremental Learning of Self-organising Variable Topology Neural Networks*. (Aachen: Shaker Verlag, 2001).

[16] M. Mezard and J. P. Nadal, Learning in feedforward networks - the tiling algorithm, *Journal of Physics A*, 22(12), 1989, 2191–2203.

[17] S. I. Gallant, Three constructive algorithms for network learning, *Proceedings of the 8th annual conference of the Cognitive Science Society*, 1986, 652–660.

[18] S. E. Fahlman and C. Lebiere, The cascade-correlation learning architecture, *Advances in neural information processing systems 2*, 1990, 524–532.

[19] Y. Shigematsu, M. Ichikawa, G. Matsumoto, Reconstitution studies on brain computing with the neural network engineering. In: T. Ono, B. McNaughton, S. Molotchnikoff, E. Rolls, H. Nishijo (Eds.), *Perception, memory and emotion: frontiers in neuroscience*. Elsevier, 1996, 581–599.

[20] T. W. Scutt, R. I. Damper, Biologically motivated learning in adaptive mobile robots, *Proceedings of the IEEE international conference on Systems, Man and Cybernetics - Computation Cybernetics and Simulation*, Orlando, USA, October 1997, 475–480.

[21] H. Benbrahim and J. A. Franklin, Biped dynamic walking using reinforcement learning, *Robotics and Autonomous Systems*, 22, 1997, 283–302.