Chapter 2

Review of Previous work within the Research Group

2.1 Introduction to Chapter

The Artificial Neural Networks group in the School of Engineering at The Robert Gordon University was formed in 1994. Since then it has built up a considerable amount of knowledge and practical experience with Evolutionary Artificial Neural Networks. This work started with the PhD project of MacLeod [MacLeod 1999] and was continued by McMinn [McMinn 2002], Reddipogu [Reddipogu 2002] and others. The current research has evolved from work undertaken by researchers within this group. In this chapter, the previous research of the group and its development into the project work presented here is discussed.

2.2 Single String Evolutionary Techniques

During the early stages of research into Evolutionary Artificial Neural Networks (EANNs), the architecture of each network was predefined and fixed for a given task (the architecture of an EANN includes its topological structure and the connectivity of each node in the network). This has a significant impact on the network’s information processing abilities. Unfortunately, the architectural design was heavily dependent on a human expert and involved much trial and error.

The group’s first project [MacLeod 1999], concentrated on the optimisation of ANN topologies using Incremental Evolution (IE) - that is, allowing the network to expand by adding to its structure. This method allows the network to grow from a simple to a complex form, until it is capable of fulfilling its intended function. The approach is sometimes thought of as being somewhat analogous to the growth of an embryo and is therefore also called Incremental Growth or occasionally Embryology or an Embryological Algorithm (EA).
To illustrate the technique, let us first consider a fully connected, three layer standard network, as shown in Figure 1.

![Fully connected network diagram](image)

**Figure 1 A fully connected network**

This network will be used as a reference when describing the growth strategies. There are six different growth strategies which can be considered. These are:

1. **Change the number of neurons**
   - The number of neurons in a layer may be increased or decreased while maintaining a fully connected network.

2. **Change the connectivity**
   - The number of connections (active weights) in the network may be reduced or increased.

3. **Asymmetry**
   - Asymmetry may be introduced by providing more connectivity in part of the network

4. **Horizontal connection**
   - In synchronous networks (those which operate with a clock signal) horizontal connections may be introduced between neurons in the same layer.

5. **Skipping layers**
   - Rather than connecting to the layer directly below, a connection may skip a layer.
6. Feedback

- Feedback may be added to the network. A connection is allowed to any previous layers.

To illustrate the operation of incremental growth, MacLeod applied the growth strategies to a simple two layer network designed for a character recognition problem. A basic example of the technique’s operation is a network which adds neurons to its hidden layer, one by one, until the network is capable of fulfilling its intended functionality. The idea of the growth strategy is that the network changes in a predictable way and grows by adding incrementally to its structure [MacLeod 1999]. Figure 2 shows how the network’s performance changes as neurons are added to its hidden layer.

![Network performance changes as hidden layer neurons are added to a pattern recognition network](Reproduced by permission of MacLeod)

The performance measure used was the number of training cycles required to train to a Sum Squared Error (SSE) of 0.1. Notice from Figure 2, that the network cannot solve the problem with fewer than six neurons but the performance increases as the number of neurons increases. 16 neurons is the optimal number for fastest training and by 20 neurons the network starts over-fitting.

MacLeod successfully used these growth strategies together with an encoding scheme, in a unified algorithmic framework to illustrate network growth for simple pattern recognition problems.
We may summarize MacLeod’s work by noting that, although the network expands as the algorithm runs, the system is limited in that:

1) It is applied only to simple tasks.
2) It uses only the basic McCulloch-Pitts neuron model.
3) The whole network must be retrained after each alteration to its topology.
4) The network architectures used are essentially structured (layered) and simple.

At the end of this initial stage of research, a model of an Artificial Nervous System [MacLeod 1999] (ANS) was proposed by MacLeod as a suitable test-bed for further research into more complex network problems and, in particular, those involved in defining complex ANNs in a system context. It was suggested that this model could be used to construct a control system for an animal-like robot (an animat).

2.3 Evolution of Functions within the Animat Nervous System (ANS) – Lower Layers

The ANS model suggested by MacLeod is both hierarchical and modular; it consists of smaller individual networks operating together. The model allows us to understand the working principles of the nervous system’s component modules, their interaction, connectivity and organisation. McMinn and Reddipogu implemented some aspects of the nervous system and insights into their work are described in the following sections. The ANS model enabled them to create a community of networks for a particular task. The networks were evolved based on a simulated robot.

It is necessary to first consider the ANS model as this forms the basis for the structure of later work and for a comparison of the results, as well as being an inspiration for the current research. The ANS is shown in Figure 3. Multiple modules can exist in certain layers marked with an asterisk.
Intelligent processing systems. Biological brains are not completely understood.

Prioritises what to do depending on the situation of the animat.

Sensory systems, e.g. sound, vision, smell, etc.

Behaviours (both innate and learned) for performing sequences of movements

Examples include walking, running, swimming, flying, respiration, chewing.

One reflex for each controllable actuator.

Figure 3 Animat Nervous System (ANS) (Reproduced by permission of McMinn)
The highest layer, labelled “higher functions”, in Figure 3, represents the intelligence layer, where higher levels of brain activity (like reasoned thought) reside. This is connected to the priority layer; here behaviours or actions are given a priority depending on the condition of the system. The sensory processing layer gathers information from the system environment using, for example, vision, sound and/or other sensors. This then triggers the appropriate behavioural modules for the current state. In turn, these initiate a sequence of actions from the action layer. The action layer uses the reflex layer to produce repetitive or rhythmic actions such as running or walking and corresponds to the Central Pattern Generator (CPG) in animals. Reflexes are used to control the physical movements of the system. Feedback from the actuators and sensors is fed to the reflex layer in order to make any movements precise and efficient in the form of a feedback control system.

The original ANS [MacLeod 1999] represented the flow of information in one direction, from the upper layer to the bottom layer. In later versions of the ANS structure [McMinn 2002], there were interactions among modules starting from the action module moving upwards on the ANS, as shown. If the system senses a change in its environment, it uses the higher functions to evaluate and prioritise the conditions before initiating any behaviour to produce a sequence of actions.

McMinn used this structure successfully as a basis to develop Evolutionary ANNs implementing Central Pattern Generators (Action Layer) and Reflexes (Reflex Layer) for robot locomotion [McMinn 2002]. Figure 4 shows the block diagram of the functionality of McMinn’s artificial reflex. The reflex ANN circuitry controls the position of the actuator. The actuator sensor in turn provides an additional input to the reflex on the status of the actuator. The artificial reflexes were created using a simulation of a DC electric motor as the system actuators.
Simple feed-forward and recurrent networks were used. The type of neuron was limited to a McCulloch-Pitts model with a sigmoid transfer function. The three main EAs (GA, EP, and ES) were used to train the reflex ANNs and their performance was compared. The ANN weights were trained until a good solution was found.

After creating the lowest layer of the ANS (the reflex), McMinn constructed the action layer. This layer was built on the functions provided by the modules in the reflex layer. The neural circuits responsible for generating rhythmic patterns (for locomotion) in the biological nervous system are called Central Pattern Generators (CPGs). McMinn successfully evolved CPGs for biped and quadruped gaits.

A new neuron model was developed specifically to simulate the timings required for the CPGs. The simple McCulloch-Pitts neuron does not produce time varying outputs and therefore the synapse model used in the artificial CPG networks was designed to include features which made it more suitable for simple implementation of time dependant parameters. More information about the neuron and synapse model can be found in [McMinn 2002].

The neurons in the network were randomly connected; there was no imposed layered structure in the network. The artificial CPG networks were created using an Evolutionary Strategy (ES). Again, the entire network’s connections were retrained until a good solution was found.
Finally, McMinn combined the evolved CPGs with the reflexes as shown in Figure 5. Since the CPG neurons produce pulsed outputs in the time domain and the reflexes require a continuous input value, a “leaky integrator” was added to convert from discrete pulses to an average firing frequency. For further information on leaky integrators refer to [McMinn 2002].

![Figure 5 Chain of connections from CPG to robot actuator](Reproduced by permission of McMinn)

An alternate strategy for structuring the network was also investigated. The CPG evolved for the biped walking pattern was used as an oscillator. The pattern generator took the oscillating inputs from this and produced the appropriate gait patterns as outputs. The connection between the two units is shown in Figure 6.

![Figure 6 Connectivity of the functional units in alternate CPG strategy](Reproduced by permission of McMinn)

Quadruped Gallop, Trot, Pronk, and walking gaits were successfully evolved using this alternative method. An example result for a quadruped gallop is shown in Figure 7. The conclusion of these experiments was that by making the structure of the CPGs as modular as possible, they can be evolved more easily.
2.4 Evolution of Functions within the Animat Nervous System (ANS) – Upper Layers

Reddipogu looked at the upper layers of the ANS. The work mainly concentrated on the sensory layer and particularly the processing of visual information. A careful search of the various options was undertaken to find a suitable neural network which combined simplicity and functionality. Eventually, it was found that the visual system of toads was interesting since their brains are structurally simpler than the human brain, and this offered a good model to build a novel visual system upon.

A biologically inspired vision system, based on the toad’s ability to differentiate between prey and predator, was then developed. This work is described below.

Firstly, the visual field was split into a grid (for example, 10 x 10), which forms the front view of the toad, as shown in Figure 8. The various patterns that best represent the prey and predator configuration are presented within the visual field at various locations. For example, if a worm configuration (a long horizontal line) is presented in the snapping region, the expected behavior would be for the toad to snap.
A modified biological neural circuit based on a toad’s vision system, proposed by Ewert [Ewert 1987], was used for testing the system’s suitability for simple pattern recognition tasks, as shown in Figure 9 (the network has been reduced in size for simplicity). All the neurons in the network are McCulloch-Pitts type with a sigmoid logistic. An Evolutionary Algorithm, using Reinforcement Learning (EARL) was used to train the network. The network connection weights are trained until a good solution is found, incorporating all different input patterns.
The network was then tested with new patterns to check its ability to generalize. A typical output of the network is shown in Figure 10. The horizontal axis represents the classes of outputs and the vertical axis corresponds to activation level of each predator and prey output neurons.

![Figure 10 Output for Prey and Orient input pattern](Reproduced by permission of Reddipogu)

The artificial vision system was trained using inputs that best represented prey and predator patterns in various positions in space. Later, the network successfully recognised the combination of patterns which were not part of the training set and developed into a Robotic Vision System. The capabilities of the network are thought to arise from its modularity. Further detailed analysis of this network can be found in [Reddipogu 2002].

McMinn and Reddipogu’s work was aimed at investigating the effect of modularity on the network and its evolution. However, it should be noted that the arrangements of the modules within the system is fixed and that the structured growth aspect introduced by MacLeod had been lost.

### 2.5 Conclusions Drawn from the Group’s Previous Work

Although interesting conclusions were drawn from the work described in the previous sections, it became apparent, over the course of these projects, that a network which can evolve into a modular structure without the need for designed partitioning would be the next stage in the research. This would represent the most general Evolutionary Networks. The EA should allow the network to develop naturally and in an open-ended way without the need to artificially constrain or design it. Such an approach needed an EA that could automatically and naturally evolve a “system” - that is, a
modular network which could operate in different sensory domains rather than a fully interconnected homogenous structure. No existing Genetic Algorithms or EAs were available to do this. Therefore the group looked to nature to discover the reasons why natural systems allowed such modularity to evolve and how it might be exploited. This search for a more general and sophisticated algorithm resulted in the paper “Evolution and devolved action” which is discussed in Chapter 3. The paper concluded that the growth aspect of evolution in MacLeod’s work needed to be integrated with the modular networks of McMinn and Reddipogu to produce a more general system.

2.6 Summary

Initial research within the RGU group focused on the growth of simple networks to fulfil relatively straightforward functions, using simple neurons. From this an interest in “Communities” of networks working together as a system developed. Research in this area was undertaken using an ‘Artificial Nervous System’ as an experimental framework with particular reference to robotics.

It became apparent, during this research, that the most general system would be a combination of the two techniques above (growth and modularity), resulting in a system which could evolve or grow modular neural networks. However, suitable theoretical frameworks and algorithms for this purpose were lacking and this forced the group to look back to biology for inspiration. This resulted in the paper “Evolution and devolved action” which is the foundation stone upon which this current research is built. The next chapter gives a review of the paper, its conclusions and developments into the current work.