Chapter 1

Introduction

1.1 Introduction to Chapter

This chapter starts by describing the problems addressed by the project. The aims and objectives of the research are outlined and novel ideas discovered during the work are listed. A chapter by chapter breakdown of the thesis is also included.

1.2 The Nature of the Problem

The quest for Artificial Intelligence (AI) is one of the most exciting challenges that mankind has ever undertaken. The real promise of AI research is to study intelligent behaviour in humans and animals and attempt to engineer such behaviour in a computer or other machine. Biologically inspired Artificial Neural Networks (ANNs) are one of the tools used to achieve this.

At the present time, most of the research into ANNs which is not focused on Computational Neuroscience, is aimed at engineering applications. Examples of such applications include Pattern Recognition, Control Systems and Signal Processing. These usually involve fairly small networks with fixed topologies, unit functionality and training methods. This has led to the adoption of popular and simple “off the shelf” networks such as Back Propagation trained Multilayer Perceptrons, Radial Basis Networks and others.

This focus contrasts with the early expectations of connectionism, before the publication of “Perceptrons” [Minsky 1969]. Today, only a few researchers carry the flag for large general purpose networks as a route towards genuine intelligence in an unconstrained environment [de Garis 1995]. Most research towards this end has shifted away from neural nets and towards Robotic, Agent or Animat based routes such as Swarm Intelligence [Bonaneau 1999] and Interaction Based Systems [Warwick 1997].
The research presented in this thesis outlines a technique which draws on many of these strands of previous work.

The basis of this project is an evolutionary technique that allows an Artificial Neural Network to evolve in an unconstrained and open-ended manner. The method is demonstrated by using it to develop locomotive gaits for legged robots. The system works by starting with a mechanically simple robot, operating in a primitive environment. It then allows the environment and the robot’s body plan, actuators and sensors to gradually become more sophisticated, while adding modules to the controlling neural network. In this way the controlling network grows in complexity along with the robot. As this development takes place, ANN modules (small networks) are added to the control system. During the process, previously evolved network structures are not retrained but retained. Since both the system and the network grow incrementally in complexity, this may be referred to as ‘Incremental Evolution’. The final intention of the research (beyond this thesis) is that, as the network develops, intelligence will eventually emerge.

A detailed explanation of the technique is given in Chapter 5. The method is based on computer modelling of an approach to biological evolution in an engineering context suggested by MacLeod et al in the PhD thesis of McMinn [McMinn 2002] - a previous researcher in the author’s research group.

1.3 Modularity

The human brain has developed into a very complex structure through million of years of evolution. One of the great scientific challenges of this century will be to understand the code which lies behind its development. It is well known that the structure of the brain is modular [Arbib 1995]; that is, different parts specialize in different tasks (such as vision, taste, sound, touch, smell and language) and groups of neurons interact in complex ways. The modularity of the brain can also be illustrated by another example. When a person loses his vision as a result of brain damage, he is still able to smell, taste, or speak; if the brain were not modular, then all the processing capabilities would be affected when an area was damaged. Another advantage is that, in a modular system, individual functions are broken up into subprocesses that can be executed in separate modules without mutual interference.
[Happ 1994]. One can even see this at a gross level in the human body, where different functions (for example, digestion and circulation) are carried out in different ‘modules’ (in this case the stomach and heart) in order to avoid interference between them.

1.4 Aim and Objectives:

The aim of this research was to develop an Evolutionary Algorithm (EA) to evolve ANNs in an open-ended way, without the need to artificially constrain them, so that they could automatically grow to an arbitrary level of complexity, without the need for human design or intervention. The EA should be able to automatically and naturally evolve a “system”. A system in this context is defined as a group of fully interconnected ANN structures for multiple different, but related, functions; a good example of this is a robot where a “community” of ANNs may be associated with various sensory and motor functions. It is hoped that, by allowing ANN structures to evolve in this modular and incremental fashion, real “intelligence” would emerge.

To accomplish the aims, the following objectives were set out at the beginning of the project.

Background Reading and Appropriate Directed Study

Appropriate directed studies were undertaken at the beginning of the research. These included attending seminars and lectures in the field of study, understanding and reproducing work done by McMinn [McMinn 2002] and understanding the evolutionary method described in the paper “Evolution and Devolved Action” (EDA) [MacLeod 2002].

Literature Search in Field

A literature search into the development of ANN architectures was undertaken. The initial search concentrated on understanding the need for ANN architectures which can grow. Then, the concept of Modularity in ANNs was investigated. The search covered both the fixed and growing Modular ANNs (MANNs).
Later the concept of evolution of the Body-Brain system was studied. This type of evolution is applicable to robotic control systems. The growth of the robot’s body plan and the ANNs controlling it was investigated. Finally, a search on Artificial Life was conducted to understand the effect of environment on the growth of ANNs.

Development of a Basic Central Pattern Generator (CPG) Network in a suitable format for Modular Evolution

The primary aim here was to investigate the development of a CPG which produces movement patterns for Legged Robots using the EA. This involved evolving both the body plan of the robot in terms of its actuators and sensors, and the environment it was interacting with. This was accomplished by allowing the robot’s body plan and environment to start from a simple form and become more complex as it develops, while simultaneously adding ANNs to the structure of the controlling network.

Initial experiments were concerned with finding out whether it is possible to grow a modular neural network to control single functions, such as a simple leg. After evolving the control system for legs with a single degree of freedom, a second degree of mechanical freedom was added to the existing robot structure. In this case the previously evolved network structures are retained and new ANN structures were evolved as separate modules (but connected to existing modules by the EA) to control the new mechanical degree of freedom.

The EA under investigation was used to evolve CPGs for bipedal (walking and jumping) and quadrupedal (trotting) motions. The evolution of the ANNs, robot’s body plan and environment (fitness function) was studied as the system evolved.

The Setting Up of an Experimental Framework for the Evolution of a Sensory System

The purpose of these experiments was to demonstrate the universality of the technique by applying it to a radically different type of network. The work outlined above was based on networks which mainly control outputs (producing walking patterns). On the other hand, a vision system processes inputs. Such a system allows investigations to be carried out to determine whether the technique can be applied more generally. To do this we allowed the sensor and the range of patterns to which it was exposed
started with a 1 by 1 grid (1 pixel) and evolved into a 5 by 5 (25 pixels) sensory system.

The application of the Previous Work to Such a Sensory System
The input sensor and the range of patterns to which it was exposed were allowed to grow from simple to complex as the environment changed and the ANNs controlling the behaviour were grown as described in the previous paragraph.

The Integration of these Techniques into an Overall Algorithm which Random capitalisation Deals with the Evolution of Systems
The issue of systems evolution, integrating both the locomotive and vision networks was considered. This included a consideration of the evolvability of networks in this domain and the neural functionality necessary to integrate these networks. Both the vision and locomotion networks were integrated by growing neural networks to map the different data sets into a single domain. Again, the ANNs have been grown using the method described previously.

Comparison with Previously Published Results from other Researchers
The results obtained in this research were compared with previously published results. Results were presented and discussed in detail to illustrate the technique in operation.

All the objectives mentioned in this section have been met.

1.5 Novel Aspects of this Research
Although researchers have used Evolutionary Algorithms (EAs) and Incremental Growth Algorithms (IGAs) for synthesising neural networks before, there are many unique aspects to the approach presented here. The most important of these are listed below.

- It was shown that, if the system is carefully set up (each module have a minimum number of neurons), the fitness can increase to a maximum as new ANN modules are added to previously evolved structures. This is an important result of the research.
Experiments showed that the neuron model used was critical and should be as flexible as possible as it is required to perform many difficult mappings in both amplitude and time domains. This finding is core to the success of Incremental Growth of MANNs using EAs.

Another significant finding was that the connections between modules as well as their weights have to be chosen by the EA. Fully connected networks are less successful in such Systems.

Networks have been grown to integrate different networks to form a working system. This include the use of “Copy and Paste” methods, permissible connections for a particular module (especially in large networks; modules are added at the end or before of the previously evolved network) and finally network which produce several gaits and can switch between them.

It was also shown that ANN modules can be added incrementally to the controlling network as the robot’s body plan and the environment it interacts with evolves from simple to complex.

Finally, in summary, the research has led to the discovery of a comprehensive method which allows the ANNs to grow incrementally to form a system.

1.6 Thesis Structure

Given below is an overview of each chapter.

Chapter 2: Review of Previous Work within the Department

This chapter describes the work undertaken by previous researchers within the research group and shows the development and context of the current work.

Chapter 3: Evolution by Devolved Action

In this chapter, the original proposal for the research is discussed and the five different practical approaches to the evolution of MANNs it contains are considered. A review of biological evolution and development which led to these approaches is presented.
Chapter 4: Literature Review
This chapter gives a review of other important work that relates to the research. In this chapter a separate section is devoted to describe the differences between the research work with other related investigations. It is hoped that this chapter will give a clear indication of the originality of this research.

Chapter 5: Growth Components for Evolution of Modular Artificial Neural Networks
The different types of simulated neurons and actuator models used in the research are discussed in this chapter. Both the robot’s body plan and vision system framework are also presented. Finally, the growth algorithm is illustrated.

Chapter 6: Results Obtained from Application of Growth Strategies for a Single Function
The results obtained for fully and sparsely connected network modules to control single functions using two different types of neuron models for bipedal and quadrupedal locomotion are presented in this chapter. The result of localising the neural module’s connections are also presented.

Chapter 7: Results Obtained from the Application of Growth Strategies to Multiple Related Functions
In this chapter, the results of network modules used to control further degrees of freedom for bipedal walking and quadruped trotting are presented. Results also illustrate the universality of the growth strategies for “copy and paste” and multiple gait networks.

Chapter 8: Results Obtained from the Application of Growth Strategies to Vision System and Integration of Vision and Locomotive Networks
The responses obtained from the sensory system are given in this section. The outcomes of systems integration the locomotive and vision networks are also demonstrated.
Chapter 9: Further Work

In this chapter suggestions are made for further work. Different application areas for the technique are described. Improvements that can be made with the growth technique are described. Methods to apply the growth technique to achieve the eventual goal of the research, beyond this thesis (emergence of complex and intelligent behaviours) are presented.

Chapter 10: Conclusions

The final chapter revisits the objectives outlined in the first chapter and critically assesses the success of the project.

Published papers and reports produced during the course of the research, and further results are included in appendices.