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This is an author produced version of a paper published in

International Conference on Computational Intelligence for Modelling, Control and Automation, 2005 and International Conference on Intelligent Agents , Web Technologies and Internet Commerce (ISBN 0769525040)

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Citation Details

Citation for the version of the work held in 'OpenAIR@RGU':

CAPANNI, N., MACLEOD, C., MAXWELL, G. and CLAYTON, W. 2005. Artificial biochemical networks. Available from OpenAIR@RGU. [online]. Available from: http://openair.rgu.ac.uk

Citation for the publisher's version:

CAPANNI, N., MACLEOD, C., MAXWELL, G. and CLAYTON, W. 2005. Artificial biochemical networks. In: International Conference on Computational Intelligence for Modelling, Control and Automation, 2005 and International Conference on Intelligent Agents , Web Technologies and Internet Commerce, Volume 2. 28-30 November 2005. Vienna, Austria. Pp. 98-102.

Artificial BioChemical Networks

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Abstract

Connectionist approaches to Artificial Intelligence are almost always based on Artificial Neural Networks. However, there is another route towards Parallel Distributed Processing, taking as its inspiration the intelligence displayed by single celled creatures called Protoctists (Protists). This is based on networks of interacting proteins. Such networks may be used in Pattern Recognition and Control tasks and are more flexible than most neuron models. In this paper they are demonstrated in Image Recognition applications and in Legged Robot control. They are trained using a Genetic Algorithm and Back Propagation.

1. Introduction

Protoctists, also called Protists, are singled celled organisms which live in a variety of different environments [1]. Those which display animal-like behaviour are usually called Protozoa and make up a large part of the fauna often disparagingly known as "pond life".

However, despite their primitive reputation, they display remarkable abilities and behaviours [2]. Some have stinging darts with which they disable their prey; others have sensory hairs to feel their way about and sense the vibration of prey approaching and a few even have leg-like appendages for locomotion. They can avoid light with their sensitive eyespots and actively hunt for their food. The variety they display is enormous, with a range of relative sizes greater than that between a rabbit and a blue whale. Some even build shelters - shells with which to protect themselves from predators and the environment. They display many of the traits of intelligence.

2. Natural Biochemical Networks

Protozoa display the behaviours described above by means of interactions between proteins in their cytoplasm. Proteins are the chemical workhorses of the cell [2]. It is the cell proteins which the DNA genetic code specifies, as shown in Figure 1. This scheme is so fundamental that it is sometimes referred to as the "Central Dogma" of biology.
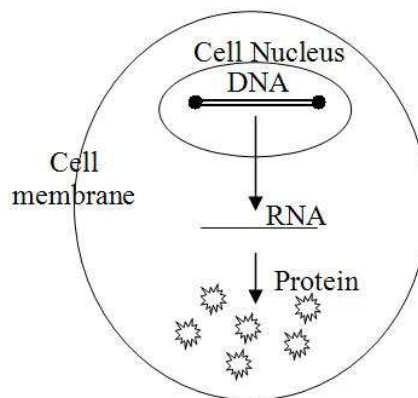

Figure 1. Central Dogma

Proteins perform all the important operations of the cell - making new material, destroying old and sensing and signalling changes in the cell's environment. All proteins bind to other chemicals. Some synthesise new molecules by joining bound component parts together, others break them up - such proteins are called Enzymes. Yet others use their ability to bind by joining to other proteins, changing their behaviour and thereby forming signalling networks within the cell [2]. Such a signalling network is best illustrated by example - see Figure 2.
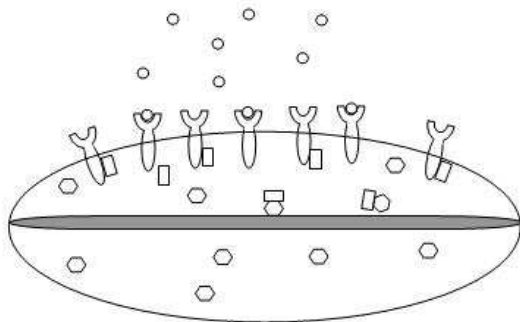

Figure 2. A simplified signalling pathway

Figure 2 is a hypothetical example of a signalling network. Molecules in the cell's external environment A bind to receptor proteins B. This changes the shape of the receptor and causes a protein C, which was bound to the receptor to disassociate from it. This protein then floats freely in the cell's cytoplasm and eventually binds with the protein D (chemicals in the cytoplasm are buffeted around by thermo-dynamic forces which act to mix the constituents). When C and D are bound as shown in E, they can bind further to a motor protein F (a protein which can change its shape by a large amount, allowing it to move large objects). The motor protein is attached to the cell's outer membrane and this causes the cell to move towards or away from the molecules A by changing its shape.

Obviously such a system may be represented by a network in a similar way to a Neural Net [2]. In this case, the nodes would represent the proteins, the connections their interactions and layers represent sequential/hierarchical protein interaction. One can also see that the system allows for intricate control over these functions - for example, by using other proteins generated as a result of other internal or external cellular stimuli, which can stimulate or suppress those shown [4]. An appropriate name for such a network might be an Artificial Biochemical Network (ABN).

3. Artificial Biochemical Networks

Given that in the simplest implementation, the basic network topology can be constructed to be no different in appearance from other connectionist networks, the difference is mainly in the unit functionality and information flow. A typical output is shown in Figure 3. The lag time until the presence of the protein is felt is A; this is set using the Genetic Algorithm which can also train the network weights. Time B is proportional to unit activity, the constant of proportionality being defined by the Genetic Algorithm. Unit activity is calculated using a standard Leaky Integrator [5].
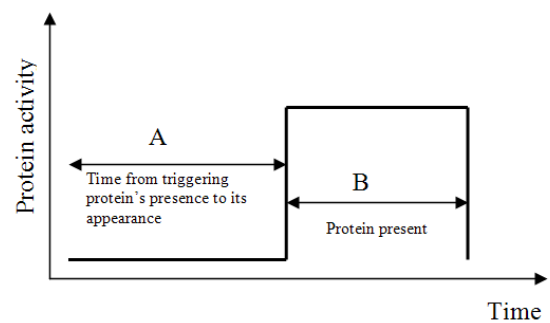

Figure 3. Unit cycle

The Genetic Algorithm has also been implemented to choose which of the time periods A or B is proportional (or inversely proportional) to the unit activity and which is fixed [6]. This additional evolvable parameter [7] has lead to pulse width or frequency modulated units as shown in Figure 4.

This allows for the production of more universal units from this basic type. It has been suggested that such dynamics may lead to new perspectives on intelligence [8].
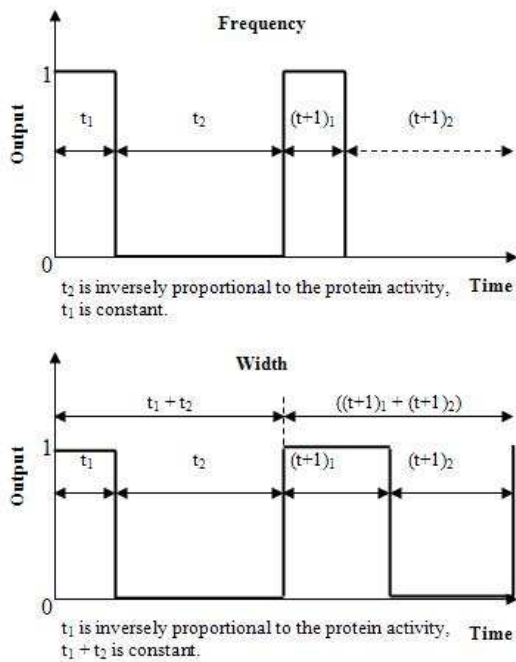
Figure 4. Pulse modulated units

4. Examples in Pattern Recognition

A network based on the units described above (in this case the Pulse Width Modulated variety) was compared with a standard Multilayer Perceptron (MLP) in pattern recognition problems. A 5 by 5 pixel grid was set up with standard roman characters and alternative identifiers as shown in Figure 5.
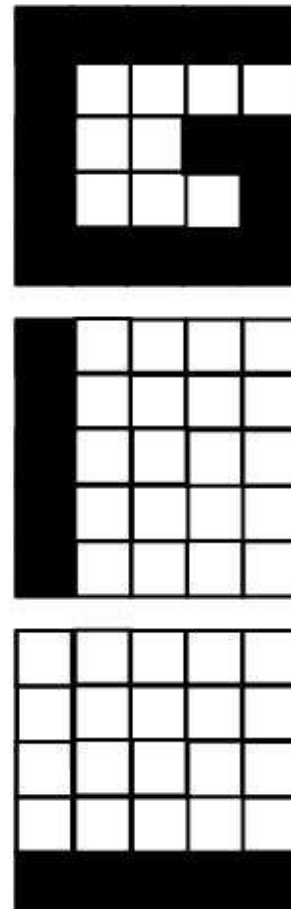

Figure 5. A 5 by 5 grid of letter "G", simple predator and prey identifiers

It was tested first whether the network had the same memory capacity as an equivalent MLP network (one with the same number of units). The networks used had 25 inputs (corresponding to the input pattern pixels) and the same number of output units as patterns. The number of hidden layer units was then increased and the network trained, using a [200, 200] Genetic Algorithm, with one pattern at a time (starting with character .A.) until failure. The results are shown in Figure 6. The solid line shows the MLP and quantised ABN results, the dashed line the initial (un-quantised) ABN.
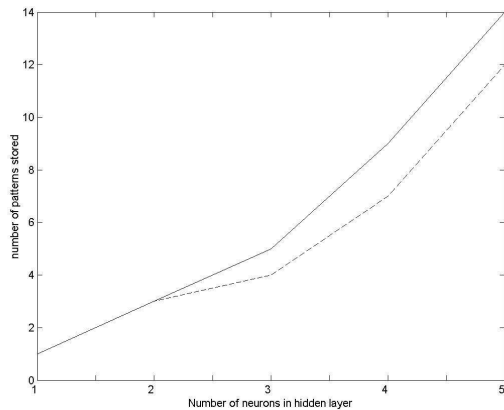
Figure 6. Memory performance of ABN vs. MLP

It may be seen from the figure that the two networks hold a similar number of patterns slight differences at first attributed to different initial values used in the training algorithm were found to be characteristics of the time-domain quantisation of ABNs.

Next the systems were tested to establish their generalisation abilities. Noise was progressively added to the data and the performance measured. Figure 7 shows the results of this (lines are represented as previously). The noise addition procedure is that used in the MATLAB Neural Networks toolbox [9].
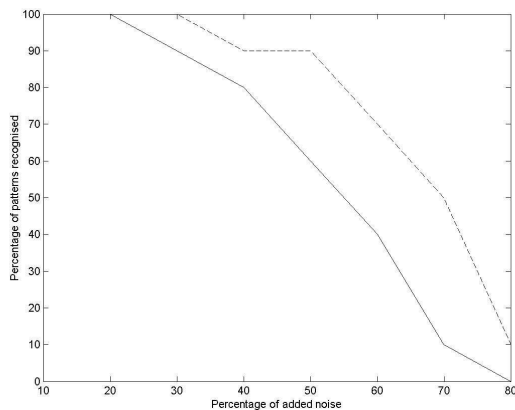

Figure 7. Noise tolerance of ABN vs. MLP

Again, it may be seen that the networks are comparable in performance. Similar results were also obtained for the Frequency Modulated and full versions of the network. The ABN showed better generalisation and an investigation on this is reported [6].

It was also shown that the network could be trained using standard Back Propagation. In these cases, the scalar inputs (in the case of the characters used above, a black pixel was a 1 and a white 0) where coded as

pulses using a sigmoidal transfer function for normalisation as shown in Figure 8. The outputs were similarly normalised.
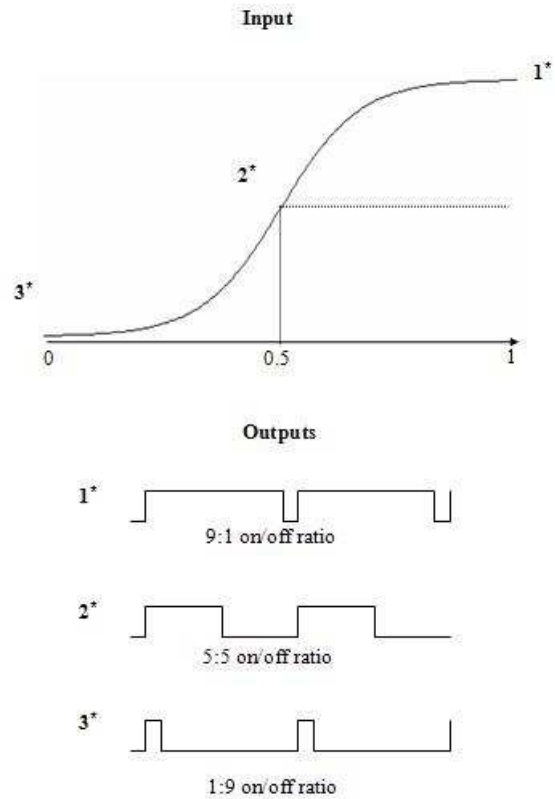

Figure 8. Transfer function

A method of Back Propagation was synthesised for the time domain specifics of the ABN. This resulted in an improved training time over standard Back Propagation from the same initial parameters but as expected no functional improvement in memory or generalisation [6].

5. Examples in control

The results above show that, in pattern recognition problems, the network is similar in performance to a standard MLP type network. There is scarcely any advantage in this in terms of time independent pattern recognition as it is more complex to program (having to keep internal clocks to account for where the units are in their cycles). There are functional advantages which are discussed [6] in the conclusions.

However, MLP networks have difficulty producing suitable outputs to control time domain tasks (for example PWM motor control). The ABN network is inherently time domain and does not have this

disadvantage. It was therefore also trained to control the gaits of a simulated bipedal legged robot. The robot is based on a physical robot, the legs of which are controlled by servo motors as shown in Figure 9. The legs have one active and one passive degree of freedom. The network has four units; two chosen by the GA are designated outputs.
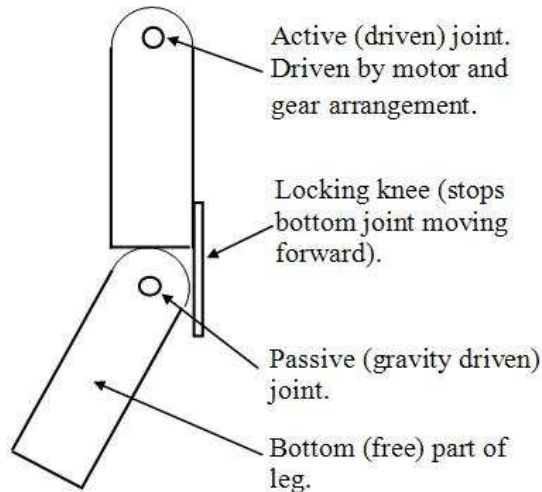

Figure 9. Robot leg layout

Space restrictions here stop us from exploring these dynamics in depth; however, this simulation has been used and reported many times previously and the dynamics of the legs and the robot are fully reported in other papers [10, 11]. Figure 10 shows the leg movements generated when the network was evolved to walk. The result corresponds well with the perfect pattern (a perfect pattern would have a repeat time of 60 time steps and a movement from position 80 to position 100).
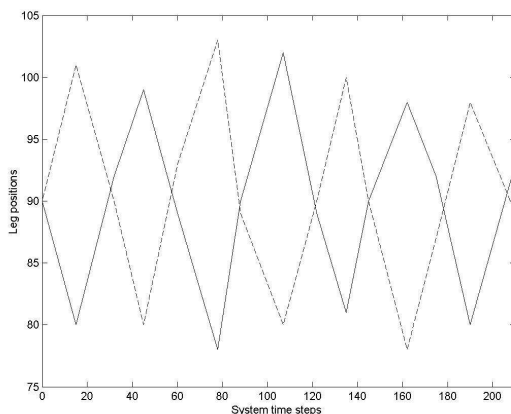

Figure 10. Movement pattern of legs

6. Conclusions

The system discussed in this paper is a new and different approach to connectionist AI. Instead of being based on neural networks, it models the chemical signalling within cells. Of course, such signalling lies at the root of neuron functionality also, as the neuron is itself a cell.

The retention of both generalisation and universality [12] affects the ABN performance in pattern and control, allowing for graceful decay as noise increases. Such "fuzzy" uncertainty is far more stable than a system that performs longer with higher accuracy then undergoes critical failure with little warning.

With regards to mobile robot operation there is a functional advantage of ABN pattern recognition. Most pattern recognition is achieved "in vitro" where time is not a constraining factor, here "snapshot" pattern recognition can be utilised. In an artificial organism that has to adapt to its environment "in vivo" then an ABN information flow pattern system can assimilate information as it appears.

The implementation of ABNs allows a single type of intelligent units to perform all the operations of a modular AI used in robot control and can be encoded as part of the evolutionary algorithm with an operator placing specific units.[6, 13] .

The approach has several advantages. It simplifies the design of time dependant outputs which, in turn, allows the straightforward implementation of Central Pattern Generator networks in robots, Pulse Width Modulation for Motor Control and other similar systems. However, the networks are equally at home in traditional Pattern Recognition tasks. They also allow systems to be developed which behave in many respects like Spiking Neuron models, but without the associated complexity. Finally, they may be trained using traditional methods.

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