DIVISION OF COMPUTER SCIENCE

Developmental Artificial Neural Networks for Shape Recognition: A Model of the Retina

Alistair G Rust
Stella George
Hamid Bolouri
Rod Adams

Technical Report No.243

May 1996

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Alistair G Rust
Division of Computer Science

Stella George
Division of Computer Science

Hamid Bolouri
Engineering Research and Development Centre

Rod Adams
Division of Computer Science

University of Hertfordshire, AL10 9AB, UK
Tel : +44 1707 284661 Fax : +44 1707 284185
E-mail : a.g.rust, s.j.george, h.bolouri, r.g.adams@herts.ac.uk
WWW : http://sparky.herts.ac.uk

Computer Science Technical Report No.243
ERDC Technical Report ERDC/1996/0011

May 17, 1996

Abstract

There has been recent interest in mimicking the self-organising processes of biological development to design artificial neural networks. An *a priori* decision must however be made as to the degree of biological detail modelled (ie neuron vs molecule). This report therefore presents a theoretical framework aimed at investigating biological self-organisation. A model of self-organisation of structure is proposed in terms of development across different levels of scale and the division of self-organising processes into phases. This initial study focuses on the design of a Developmental Artificial Neural Network (DANN) to investigate the growth of neuron-neuron connections. A model of a biological retina is used as the *target* structure for the self-organising process. The development of general 2D and 3D retina-like structures are reported. This is believed to be the first report of a 3D DANN.

1 Introduction

The recognition of an image which has undergone some transformation and/or translation is an extremely difficult task. So-called invariant shape recognition is however seamlessly performed by biological vision systems which incorporate 3D vision, selective attention, colour processing, texture analysis and so forth. Replicating a complete biological system simply is not feasible due to its sheer complexity. This may be overcome in by part choosing to model the structure and functionality of individual, co-operating neural circuits.

The biological visual system is a complex, hierarchy of inter-communicating neural units [Van Essen and Anderson, 1995]. It is believed that the development of the precise and intricate form of the brain and therefore the visual system, is governed by simple developmental rules [Stryker, 1994, von der Malsburg, 1995, Udin and Fawcett, 1988]. These rules encompass the genetic encoding of structure and the modulation of structure by neural activity. The rules are not rigidly defined allowing some degree of freedom in the placement and routing of neural 'components' [Cherniak, 1995, Hilgetag et al., 1996]. The interactions of these simple rules represents biological self-organisation. The inspiration to investigate the emergence of structure and behaviour using simple rules has been demonstrated in other disciplines [Reynolds, 1987, Theraulaz and Bonabeau, 1995].

Self-organisation of structure within biological systems occurs at several levels of scale. One such division of structure self-organisation is illustrated in Figure 1. Here there are 3 levels: self-organisation of neuron structure, self-organisation of neuron connectivity, and self-organisation of neural modules. The complexity of the structures created increases across the levels, together with the timescales required for the self-organisation processes to occur.

This document is only concerned with the last 2 stages illustrated in Figure 1. It is postulated that the same rules of self-organisation are applicable to both neuron connectivity and the grouping of neural modules. This suggests that there is self-similarity across scales. The programme of work of which this study forms a part, considers this self-organising paradigm within the context of developing artificial neural networks to perform shape recognition. The primate biological visual system is the

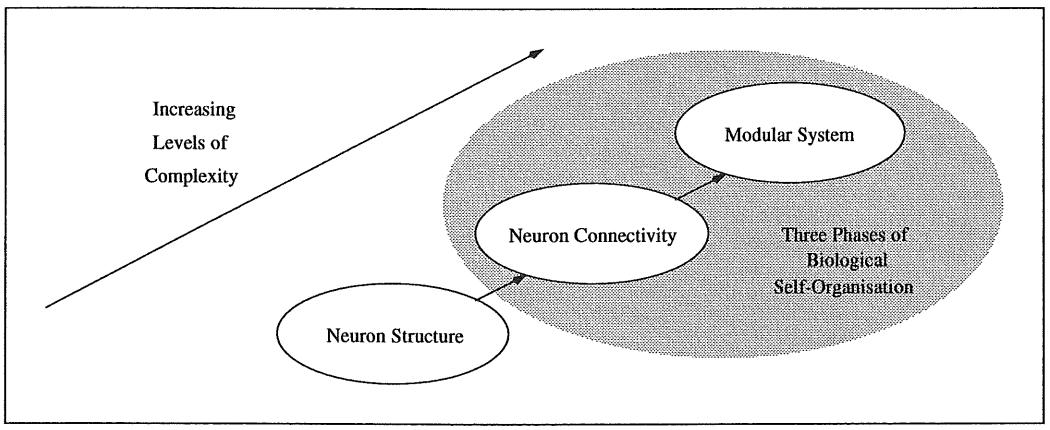


Figure 1: Self Organisation Across Scales

primary source of information. A model is presented to test a set of development rules which incorporate sufficient biological information to provide a detailed analysis of self-organisation without proving to be unwieldy and computationally expensive.

The *three phases of biological self-organisation* is proposed as the framework to this model. The framework encompasses the last 2 levels in Figure 1, being sequentially applied to each level. Each phase is the collection of abstract, biological processes and mechanisms which result in the self-organisation of structure. To date some simple development rules have been designed to model the first of these phases: neural growth. A simulator has been created to model both 2D and 3D systems, enabling retina-like neural connectivity to be grown from given neuron structures.

The document is organised as follows. The second section presents brief summaries of neural development and biological retinas. Developmental artificial neural networks are summarised in section 3. Section 4 introduces the *the three phases of biological self-organisation* along with starting assumptions. The modelling environment and growth rules are discussed in section 5 followed by a description of the implementation. Section 7 presents the results of modelling an artificial retina, which are discussed in section 8 before conclusions are drawn.

2 Biological reviews

The following section presents overviews of neural development and biological retinas. More detailed reviews may be found in [Rust and Bolouri, 1996].

2.1 A brief review of neural development

2.1.1 Neural growth

During neural development [Stryker, 1994]:

> *Neurons are generated in appropriate numbers at appropriate times; they migrate to appropriate positions; they send out axons that find appropriate paths to their target structures; and the axon terminals recognise the correct cell types and even the right general region in the target structures.*

These processes occur without neural activity and appear to be driven by chemical events [Gazzaniga, 1992, Purves, 1994, Stryker, 1994, Udin and Fawcett, 1988]. It is argued that genes alone cannot provide the 'blueprint' for the final structure as this process can only create highly regular architectures [von der Malsburg, 1995, Wolfram, 1984] and that the chemical environmental has a critical role in the development process.

Cells which differentiate into neurons are developed from very distinct areas [Alberts et al., 1994]. These cells then migrate along a framework of glial cells to assume their final positions [Gazzaniga, 1992, Alberts et al., 1994]. Gazzaniga [Gazzaniga, 1992] believes that chemical gradients exist which guide these processes, dictating when and where the neurons stop migrating.

The time at which the cells are generated is important since it determines the distance travelled by a cell within the brain (younger cells migrate further towards the periphery [Alberts et al., 1994]), and is believed to determine the chemical labelling of individual cells [Goodman et al., 1984]. It is further suggested that it is this chemical labelling, in the form of recognition molecules on the surface of embryonic axons, that guide neurons to their target axons [Goodman et al., 1984].

Once a neuron has reached its final position, it sends out axons and dendrites, collectively termed neurites [Alberts et al., 1994]. A neurite extends with a growth cone on the end of its fibre, which is covered in microscopic hairs called filopodia [Alberts et al., 1994, Goodman et al., 1984]. Filopodia are extremely chemically sensitive and guide the growth cone to specific chemical targets by probing the immediate environment [Goodman et al., 1984].

As a growth cone nears the point of termination it is influenced by neurotrophic factors produced from the target neurons [Alberts et al., 1994]. Not only may these factors provide the chemical recognition [Alberts et al., 1994] but they also control the survival of the subsequent axon connection and ultimately the neurons themselves [Purves and Lichtman, 1985].

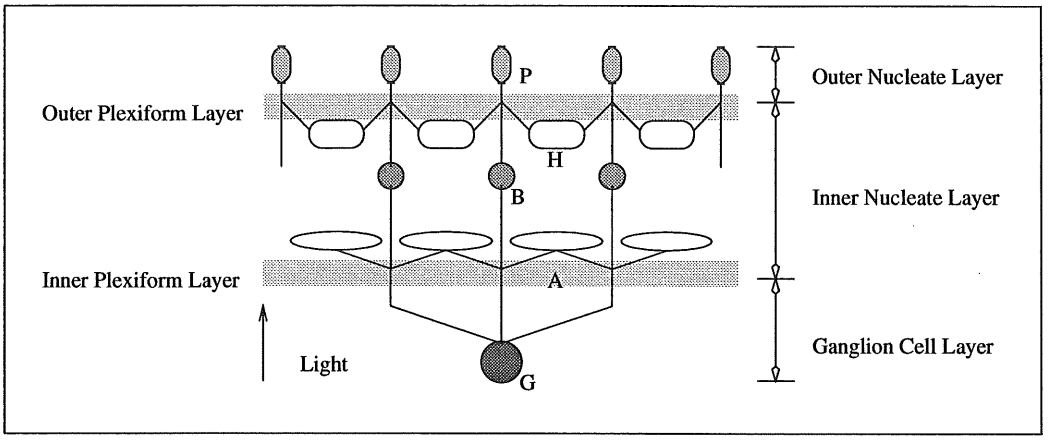


Figure 2: A simplified diagram of the retinal architecture. Key : P-photoreceptor, B-bipolar, H-horizontal, A-amacrine and G-ganglion Cells

2.1.2 Neural activity

The processes of genetic encoding and chemical gradients are able to create a skeletal framework but it is patterns of neural activity which subsequently produce the final, complex and optimised circuitry [Kandel, 1981, Galli and Lamberto, 1988, Purves, 1994]. For example, it is found that basic receptive field structures are present at birth and it is subsequent post-natal experience which modifies or tunes the final visual connections [Purves and Lichtman, 1985]. In principle this may be considered to be self-organisation [von der Malsburg, 1995].

The development of the visual system is said to pass through a critical period, which starts before birth and continues into post-natal life [Purves and Lichtman, 1985]. It is suggested that this critical period represents the time when neurons and their connections are competing to shape the final visual system. These activity-driven processes occur randomly pre-natally [Galli and Lamberto, 1988] and under the influence of post-natal 'experience', when sensory information is present [Purves, 1994]. However, as stated previously, visual experience is not a prerequisite in determining the initial feature detecting structures [Purves and Lichtman, 1985].

2.2 An overview of the retina.

The retina is an outgrowth of the central nervous system (CNS) and because of its location, it is one of the most studied organs in vertebrates [Dowling, 1992]. The retina is described as having a 'stereotyped architecture' [Van Essen and Anderson, 1995] which is 'highly ordered anatomically' [Dowling, 1992].

Five major cell types are found in the retina - photoreceptor, bipolar, horizontal, amacrine and ganglion cells. Each cell type may be further divided into subclasses, for example there are two types of photoreceptors; rods and cones. These cells are arranged into three cellular layers - the Outer Nucleate Layer (ONL), the Inner Nucleate Layer (INL)and the Ganglion Cell Layer (GCL). Synaptic connections between cells occur in two distinct plexiform layers (Inner and Outer). The architecture of the retina is shown in Figure 2. In terms of information processing, experimental evidence has shown that the OPL processes static, spatial elements of images whilst the IPL deals with transient or temporal aspects [Dowling, 1992].

The topology of the retina is governed by simple interconnection rules :

- There is a distinct vertical arrangement : Photoreceptors $\rightarrow$ Bipolar $\rightarrow$ Ganglion cells. Therefore, receptors cannot directly contact ganglion cells, with the bipolar cells acting as inter-layer links.
- Lateral interactions are transmitted by horizontal and amacrine cells but within the respective plexiform layers.
- At each plexiform layer, the synapses from three cell types interact; photoreceptors, bipolar and horizontal cells in the outer layer, and bipolar, ganglion and amacrine cells in the inner layer.

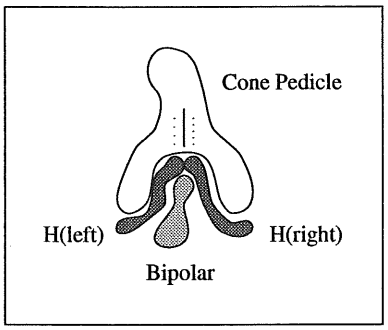


Figure 3: A triad junction.

The highest visual resolution is found at the centre of the retina, the fovea in primates. From the fovea to the periphery of the retina there is a linear decrease in resolution with angular distance [Van Essen and Anderson, 1995]. Studies on one class of ganglion cell in cats, has shown that as the density of cells decreases with increasing eccentricity, the dendritic field size increases at the same rate. With varying eccentricity the product of cell density and dendritic field size therefore remains constant. Other cell types within the cat retina exhibit the same inverse relationship. Hence in cats, it seems that in the centre and periphery of the retina 'there are identical functional circuits differing only in spatial scale and number of cells [Wässle and Boycott, 1991].'

The two classes of photoreceptors, rods and cones, both convert light into electrical signals but have different functions. Cones respond to bright light and are responsible for colour vision. Rods function at low light levels needed for nocturnal vision [Van Essen and Anderson, 1995]. The highest density of cones is found in fovea, and it is the cones and not the rods which dictate visual resolution. Cones form a regular hexagonal mosaic within the primate fovea [Wässle and Boycott, 1991]. Outside the fovea the mosaic becomes more irregular.

Horizontal cells mediate the lateral connections in the outer plexiform layer. Horizontal cells synapse into cone terminals (pedicles) at junctions called triads, which are observed in many retinas [Dowling, 1992]. The two outer postsynaptic contacts come from dendrites of horizontal cells, with a dendrite from a bipolar cell forming the central connection. A triad is illustrated in Figure 3. Each cone pedicle has between 20-30 such triad synapse connections [Wässle and Boycott, 1991].

Bipolar cells form the vertical connections between the two plexiform layers. Bipolar cells have circular receptive fields, areas of input information which are sensitive to particular areas on the surface of the retina. A bipolar cell's receptive field consists of a central area encircled by another area, termed the surround. Receptive fields can be either On-Centre (centre-excitatory, surround-inhibitory) or Off-Centre (centre-inhibitory, surround-excitatory). In structural terms the centre response is mediated by cones and the surround by horizontal cells.

3 Developmental artificial neural networks (DANNs)

3.1 The current state of DANNs

There has been recent interest in incorporating biological development in the design and construction of artificial neural networks [Kodjabachian and Meyer, 1994]. There is however a great degree of variation in the detail with which biological processes are modelled in such developmental artificial neural networks [Rust and Bolouri, 1996]. For example, Dellaert and Beer proposed a model for the development of autonomous agents which included a number of biologically plausible developmental mechanisms [Dellaert and Beer, 1994a]. The complexity of the model however increased the difficulty of determining optimal parameter values. A simpler model has subsequently been proposed [Dellaert and Beer, 1996]. Hence there is a trade-off between the degree of biological plausibility and the success with which complex networks are evolved [Rust and Bolouri, 1996].

Key attributes and findings of DANNs are:

- Developmental rules can be efficiently encoded [Gruau, 1994b,Dellaert and Beer, 1994a,Boers et al.,

1993].

- Directly mapping from a cell genotype to a phenotype is a limited process [Kitano, 1990, Nolfi and Parisi, 1991].
- Cells or neurons can be modelled as self-contained elements which may be influenced both by internal and/or external factors [Vaario, 1994, Fleischer and Barr, 1994, Jakobi, 1995].
- Developmental rules can successfully model individual neural growth but an artificial environment is required to allow cell-cell and cell-substrate interactions [Vaario, 1994, Dellaert and Beer, 1994a, Fleischer and Barr, 1994, Nolfi and Parisi, 1995].
- Cell division, differentiation and migration are non-trivial processes to model [Cangelosi et al., 1994, Dellaert and Beer, 1994a, Jakobi, 1995].
- Modularity, symmetry breaking and scalability may need to be incorporated in the development process [Kitano, 1990, Gruau, 1994b, Dellaert and Beer, 1994a, Fleischer and Barr, 1994].
- In a number of DANNs no learning occurs as function is encoded in the development process [Nolfi and Parisi, 1991, Gruau, 1994b, deGaris, 1993, Jakobi, 1995].
- Identifying optimal parameter values requires large problem spaces to be searched. This is computationally expensive [Gruau and Whitley, 1993, deGaris, 1995] and may ultimately be intractable [Dellaert and Beer, 1996].
- The search for optimal parameters primarily uses function as the fitness measure. Parameter searches are generally initiated without any pre-conception of the final DANN's architecture. Incorporating structure can direct the search [Gruau, 1994a] reducing the size of the problem space to be traversed.

3.2 A DANN to investigate self-organisation

The DANN presented in this document incorporates the desirable features of existing DANNs, whilst aiming to achieve a balance between the level of biological detail modelled and the ease with which the model can be manipulated. It is hoped that the model will occupy a mid-point along the *the spectrum of developmental neural networks* [Rust and Bolouri, 1996].

A minimal set of developmental rules is used that is intentionally simple and informal. The rules are inspired by the belief that biological neural development uses simple rules [Stryker, 1994] and by Reynolds' informal *boids* rules [Reynolds, 1987]. The key feature of the rules are that they are an abstraction of biological self-organisation. To explicitly model biological development rules requires detailed knowledge of molecular and chemical processes, which vastly increases the complexity of modelling. It is thought that an informal approach will create more robust and adaptable developmental rules. A restricted number of rules is used such that the size of the problem space is minimised when searching for optimal parameters.

Development can occur in simulated 2D and 3D chemical environments. Neurons are modelled as discrete elements which interact with each other and the environment. The simulated environment allows more complex cell-cell interactions than previously proposed [Nolfi and Parisi, 1991, Vaario, 1994] but within a framework that is less complex than that modelled by Fleischer [Fleischer, 1995].

The model further extends DANN research by providing a framework within which it is proposed that learning can be investigated.

4 A model of biological self-organisation

4.1 Starting assumptions

A model of biological self-organisation is proposed based on the following assumptions:

- The development process occurs within a simulated chemical environment. This model is intended to be a simplified version of the environment in which biological development occurs (see 2.1.1).

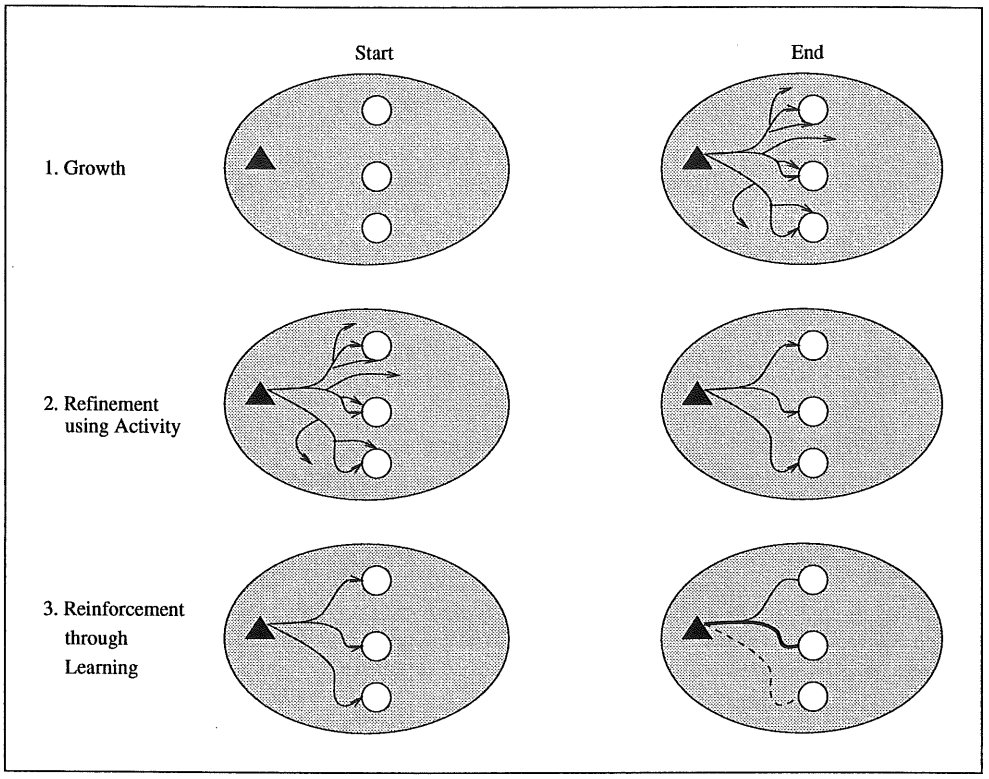


Figure 4: The three phases of biological self-organisation.

- Cell division, differentiation and migration have previously occurred.
- The genetic encoding provides a system which consists of layers of neurons. For example, this layering is found in the visual tract [Kandel, 1981, Hubel and Wiesel, 1979].
- The distribution of neurons within layers is inherently regular.
- The orientation and direction of both axon and dendrite growth is specified. In biological systems the nature of connection growth is determined by the orientation of the neuron in its final position [Purves and Lichtman, 1985].
- Development is determined by simple, local rules. As stated previously these rules are abstract versions of those governing biological development.

4.2 The three phases of biological self-organisation

Having established the starting conditions, the development process can be considered as three phases (see Figure 4). Each phase is a specific set of self-organising mechanisms and processes.

- **Phase 1 - Growth.** The creation of inter-layer and inter-neuron connections.
- **Phase 2 - Spontaneous Activity.** Refinement of the initial skeletal structure by spontaneous activity.
- **Phase 3 - Learning.** Further refinement of structure and initial pattern learning based upon external stimuli. It is proposed that pattern learning and identification will be achieved through the use of a hierarchy of further neural networks.

The specification of the model enables it to be applied at different levels of self-organisation as shown in Figure 1. Individual components may either be neurons, leading to the development of neuron-neuron connectivity, or networks of neurons, creating modular systems.

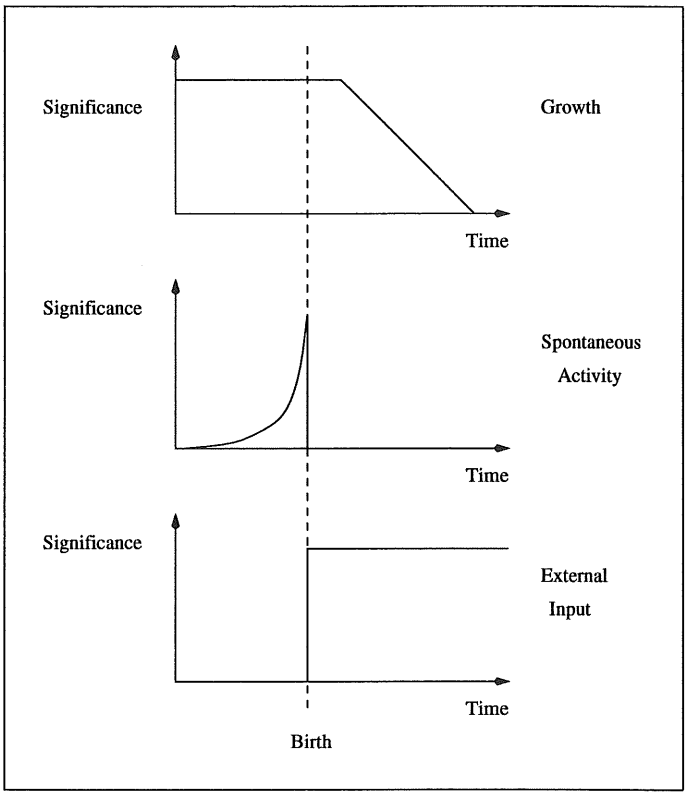


Figure 5: Overlap of the three phases of biological self-organisation.

Although there is a distinct transition between the spontaneous activity and learning phases [Goodman and Shatz, 1993], the three phases of biological self-organisation overlap to varying degrees. In biological systems for example the growth phase and the spontaneous activity phase are interdependent [Shatz, 1994, Cabelli et al., 1995]. An interpretation of the overlap and significance of the three stages is shown in Figure 5.

This definition of self-organisation emphasises the relationship between function and structure [Rust and Bolouri, 1996]. Underlying neural structure places boundary conditions and restrictions on learning and the resulting functionality.

4.3 Methodology

Function and structure are intertwined in a number of DANNs [Nolfi and Parisi, 1991, deGaris, 1993, Gruau, 1994b, Dellaert and Beer, 1994b, Jakobi, 1995]. For instance, neuron function and connection strengths can be specified in the development process. Therefore, modifications to structure may have a significant affect on the resulting function. Function is widely used as the fitness measure to search for optimal parameters in DANNs. This search is, however, generally initiated with no a priori expectation of underlying architecture. This may result in several networks with similar fitness values but with different morphologies: number of neurons, number of layers, connectivity and so forth. It is suggested that network optimisation, based on function alone, can result in multiple structural solutions.

The methodology adopted in this model explicitly emphasises the relationship between function and structure [Rust and Bolouri, 1996]. It is believed that if the 'right' architecture can be grown then function will follow. By examining biological neural systems 'target' structures can be defined which can be used to measure the fitness of grown structures. Having a single desired architecture constrains and directs the search for optimal developmental parameters thereby reducing development time and computational cost. It is hoped that there will be no unique set of developmental parameters for each target structure. If the developmental growth rules are robust and adaptable then multiple sets of parameter values will result in closely matching structures.

The retina is used as the 'target' architecture in this document, since it has a stereo-typed architecture

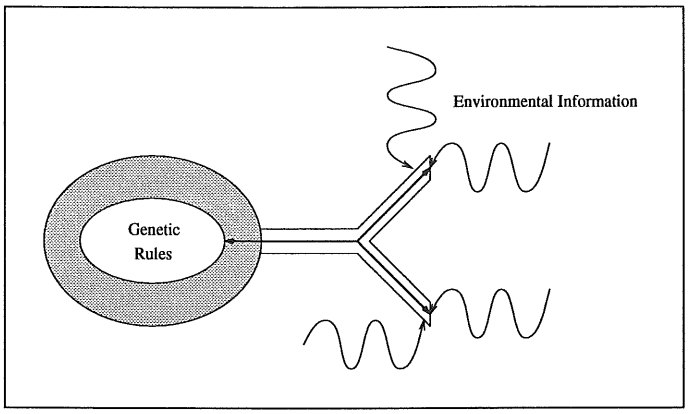


Figure 6: The neuron model.

[Van Essen and Anderson, 1995] and may be assumed to be reasonably 'hard-wired'. Hence since learning (synapse modification) is not considered to be important in the retina this allows the experimental work to concentrate on the first two phases of biological self-organisation. Once the developmental rules and parameters have been characterised for the retina, learning can be incorporated when modelling higher levels in the visual cortex.

The remainder of the document discusses Phase 1: the growth phase.

5 Phase 1: The modelling environment

5.1 Chemical environment

Networks develop within a virtual chemical environment, which can be either modelled as a plane (2D) or as a box (3D). An underlying gradient is imposed on the substrate of the environment to encourage neurites to move in predefined directions. The substrate chemical gradient is maximum in one direction and zero in perpendicular directions. The change in gradient is small compared to the chemical gradients emitted by the neurites (see 5.2). Axon growing neurons are positioned at the bottom of the gradient whilst dendrite growing neurons are found at the top.

5.2 Neuron model

Neurons are fixed within the environment and contain a set of internal genetic rules which dictate growth (Figure 6). The rules enable neurons to extend both axons and dendrites (neurites) though not simultaneously. The same rules are used for both axon and dendrite processes.

Neurites emit chemicals from every point along their length, which produce local gradients in the environment. This process is inspired by the production of neurotrophins in biological systems (see 2.1.1). The gradient fronts are spherical in 3D and circular in 2D. Axon producing neurons emit negative chemicals whilst dendritic neurons emit positive chemicals. The characteristics of a neurite's emitted gradient are determined by the parameters; strength, range and diffusion law ($1/\text{distance}^n$). Gradients are assumed to be additive.

The tips of extending neurites actively sense the local chemical environment, analogous to biological growth cones. The internal rules determine the response of the neurite: extend, split(branch) or terminate if a target neurite is contacted. Hence although the behaviour of a neurite is determined globally at the neuron level, the response is local to the tip of the neurite. Neurites are restricted in the directions of movement: in 2D a neurite can move in one of 8 directions and in one of 26 in 3D.

5.3 Growth rules

Neurite growth is governed by the following informal developmental rules:

- Follow the path of the steepest gradient of the opposite polarity to that emitted. Therefore, axons perform hill-climbing and dendrites gradient-descent.
- Maintain the same path unless attracted by a larger gradient. This allows neurites to be guided initially by the underlying substrate gradient and then to search out local target neurites over time.
- Split if genetically programmed or if there are two strong local gradients.

It is proposed that no one rule will account for all neurite growth and that it is a combination of these rules which will generate the final, complex structures.

6 Phase 1: Implementation

6.1 Growth initialisation

Neurons are arranged into layers separated by pre-defined distances. All neurons in the same layer possess the same set of genetic rules but the range and strength of the chemical emitted by each neuron may vary.

6.2 Growth sequence

Growth occurs between two layers at a time forming connections when axons and dendrites meet. An extension to this process allows connections made in a previous growth sequence to become the targets for neurites from another layer; the connections become static targets and do not grow neurites themselves. Growth is halted after a pre-defined period, after which the resulting chemical gradients are removed and the underlying substrate gradient replaced, before subsequent layers are processed.

Although this is much simplified in terms of biological development, each layer may be considered as one class of neuron which is sensitive to the chemical labelling of only one other class of neuron. Layers can therefore be considered in pairs, in isolation from the rest of the system.

6.3 Neurite splitting

A neurite may split into two separate paths moderated by two rules. Environmental splitting is a stochastic process regulated by the local chemical gradients, whilst genetic splitting is deterministic being regulated by the neuron itself. This mixture of deterministic and non-deterministic behaviour is believed to have greater flexibility and to be capable of generating more complex structures.

Splitting is not a limitless procedure. A *recovery period* is incorporated such that once a neurite has split it is inhibited from splitting for a predetermined time. It is proposed that a neurite expends resources in splitting which must be replaced before splitting can occur again. Split inhibition prevents a neurite splitting profusely once it is close to a target neurite. Upon splitting the strength of the chemical gradient emitted is halved, whilst the range and diffusion law remain the same.

6.3.1 Environmental splitting

Environmental splitting uses the two largest local gradients to calculate a probability of splitting. Neurites are more likely to split if any 2 gradients are large and approximately equal. The split occurs in the directions of the two largest gradients. The probability of splitting is currently given by the equation below and is shown graphically in Figure 7:

$$Probability\_of\_splitting = \frac{max1 * max2}{X + (max1)^2} \tag{1}$$

where max1 is the highest gradient and max2 is the second highest. By varying the X parameter the shape of the rising ridge can be varied.

When split inhibition is enforced it will prevent an environmental split from occurring. Hence although environmental information is the stimulus for splitting, environmental branching is regulated by the internal genetic rules.

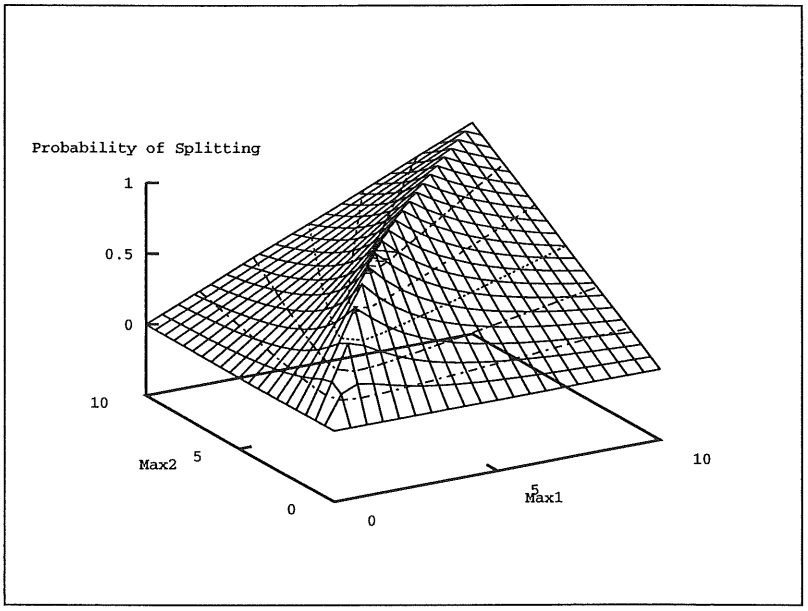


Figure 7: Environmental probability splitting function for X = 1.

Method	Description
1	Split *opposite* sides of current direction
2	Split *opposite* sides of substrate gradient
3	Split *opposite* sides of max gradient
4	Initially Method 1 and then split along 2 max gradients
5	Initially Method 2 and then split along 2 max gradients
6	Initially Method 3 and then split along 2 max gradients
7	Always split along 2 max gradients
8	Never do genetic split

Table 1: Summary of implemented genetic splitting methods.

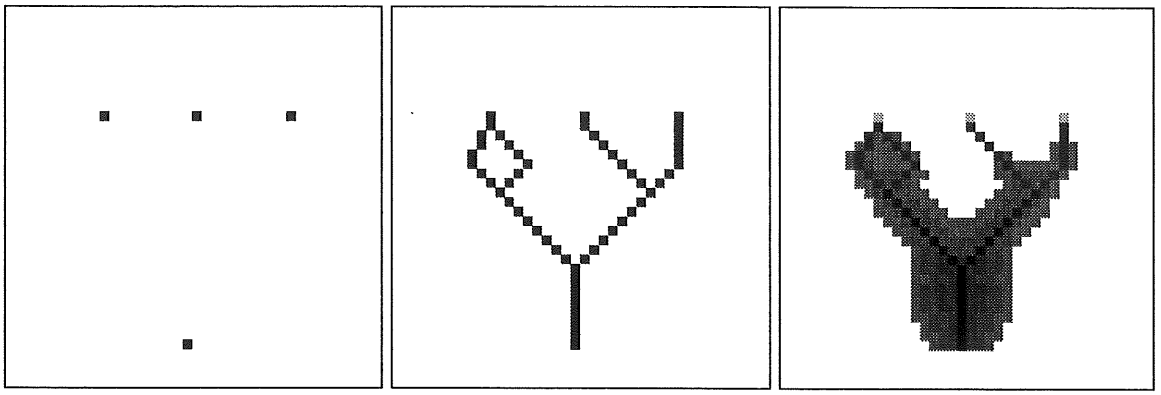
6.3.2 Genetic splitting

Unlike environmental splitting this branching occurs at pre-determined time intervals. A modified Fibonacci series is used to generate the time duration between branching. This method was chosen since it permits multiple branching at early stages of growth but 'cools' down as the sequence increases.

As with environmental splitting, there is an interaction between the genetic split signal and the direction of split. Once a genetic split has been signalled the direction of the split is determined by the gradients at the tips of neurites. A number of genetic splitting methods have been implemented and are summarised in Table 1. In 3D the pair of directions branched along is chosen at random with the branches being in the same plane.

6.4 Connection formation

When a growth cone collides with either a trail, tip or cell body of a target neuron a connection is formed. The neurite which makes contact stops growing. Further connections can be made on existing connections.



(a) (b) (c)

Figure 8: An example of 2D neuron growth (a) Neuron positions. (b) Axon trail. (c) Resultant chemical environment.

7 Phase 1: Results

7.1 Simple examples

Figures 8, 9 and 10 show a 2D example of neuron growth. Three static neurons are the targets for a single, axon growing neuron. The target neurons are equally spaced whilst the growing neuron is offset to the left of the central target neuron. The growing neurites maintain their current paths over the underlying substrate gradient until attracted by the local gradients of the target cells. The neurite splits are genetically determined and are either side of the local gradient.

Figure 11 is an example of a 3D neuron system containing two dendrite growing neurons and one axon emitting neuron. Cell bodies are represented as spheres. This example highlights some of the primitive structures which can be grown using the developmental rules.

Figure 12 is a 3D snapshot of a neurite splitting in response to two local target neurites. The central, black neurite splits and makes connections (polygons) with two different neurites. The left hand, grey neurite splits in response to the black neurite and forms two, identical connections. The 'random walk' of the right hand grey neurite is due to the point of connection made by the black neurite. The black neurite has terminated along the body of the grey neurite, away from the active tips. Once the left tip has sensed the black neurite it doubles back upon itself, whilst the right is attracted to an unpictured source.

7.2 Retina Models

The retina structures grown so far are modelled on the cells that make connections in the outer plexiform layer: cones, horizontal and bipolar cells. Exact connections and cell numbers have not yet been specified. The target structure in this case is general, aimed at evolving triad-type connections between the three cell types.

7.2.1 A 2D Model

The layer by layer development of a 2D retina model is shown in Figures 13 and 14. The final structure is illustrated in 15. A layer of cone neurons is specified at the bottom of the environment, with a central layer of horizontal cells and upper layer of bipolar neurons. The first cycle of growth occurs between the cones and the horizontal cells. The second cycle defines bipolar cell neurite growth to the connections made during the cone to horizontal cycle. The connections in this case are static targets for bipolar neurites. These are shown as the dark central points in Figures 13(b) and 15, and are shown as the darker areas in Figure 14(a). This example demonstrates the implementation of neurite growth onto existing connections.

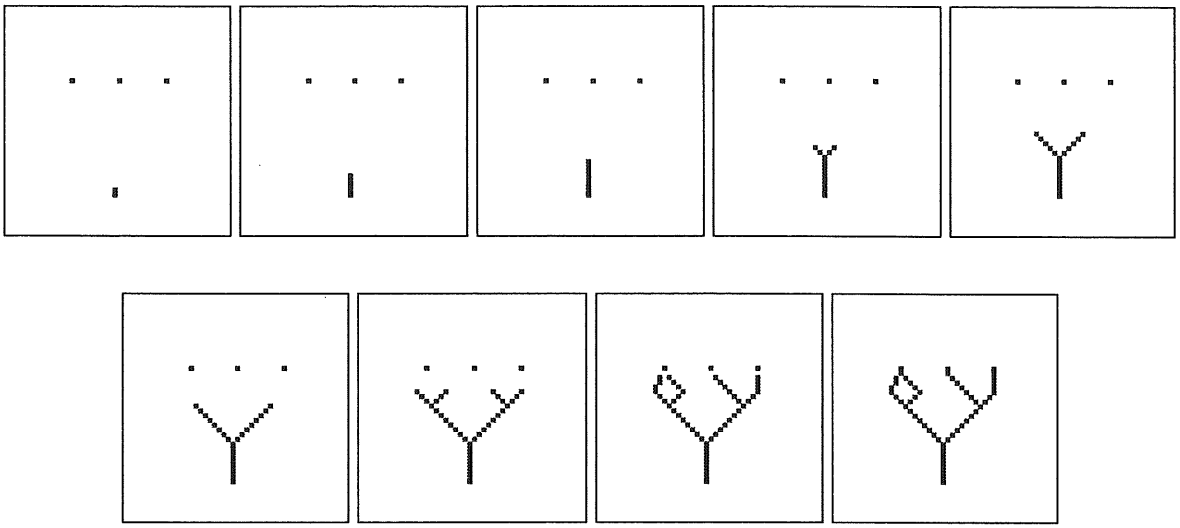


Figure 9: An example of 2D neuron growth: Sequential steps of development.

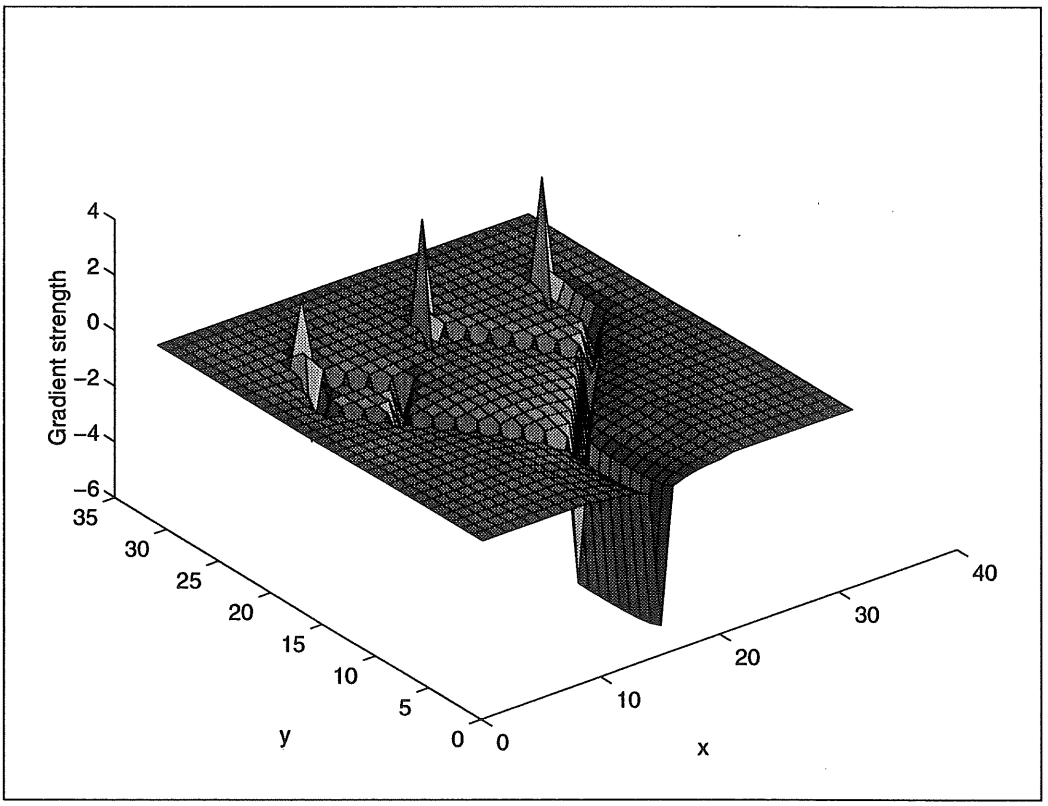


Figure 10: An example of 2D neuron growth: A 3D representation of the resultant chemical environment.

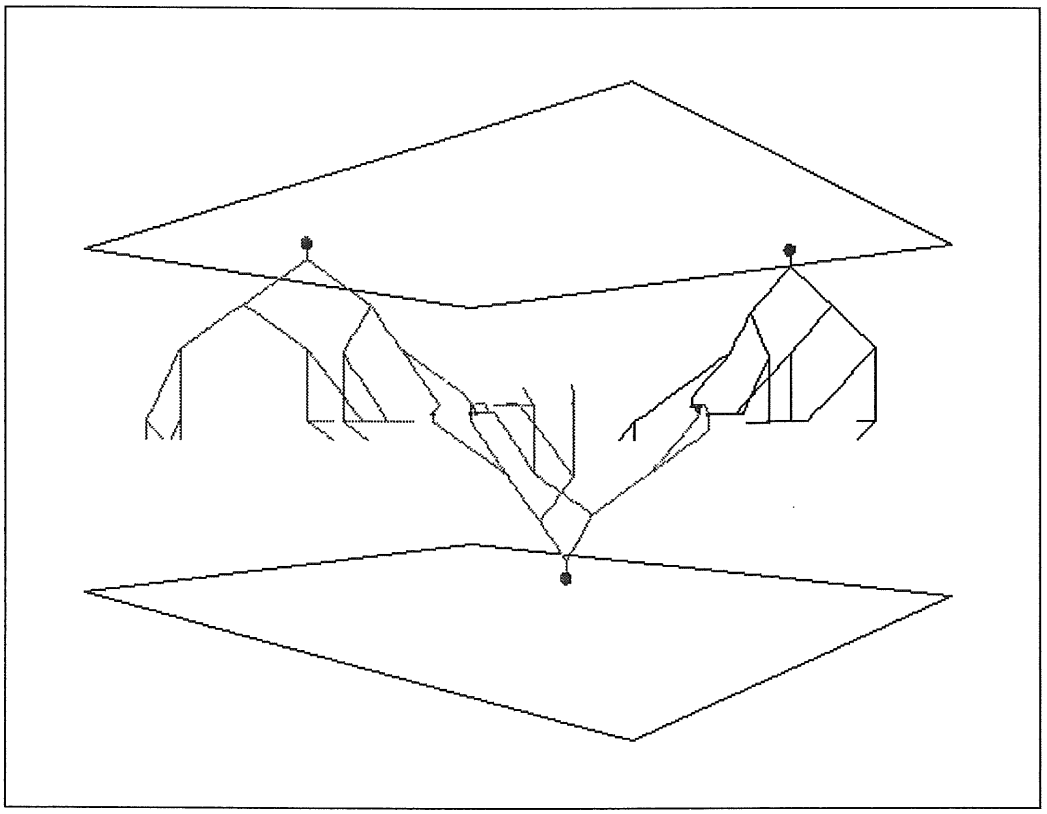


Figure 11: An example of 3D neuron growth.

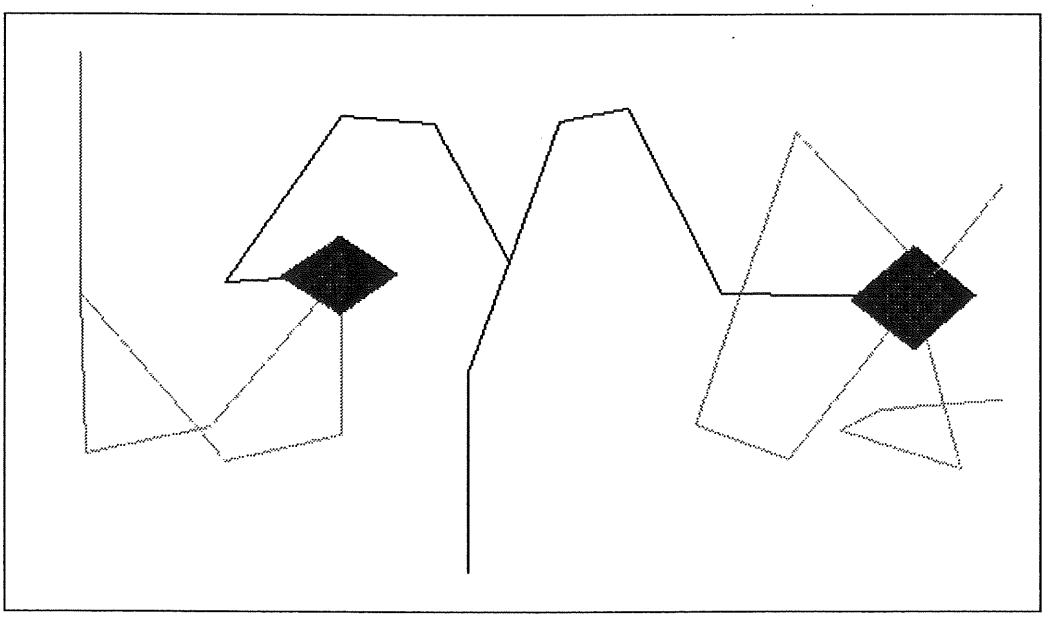
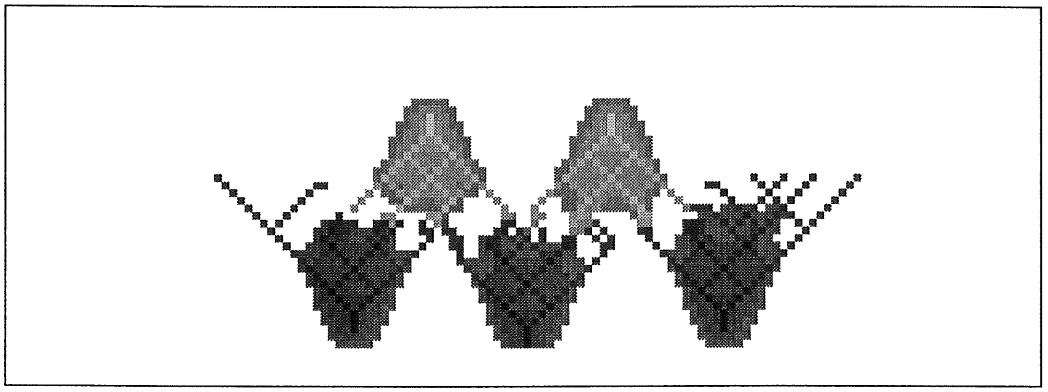
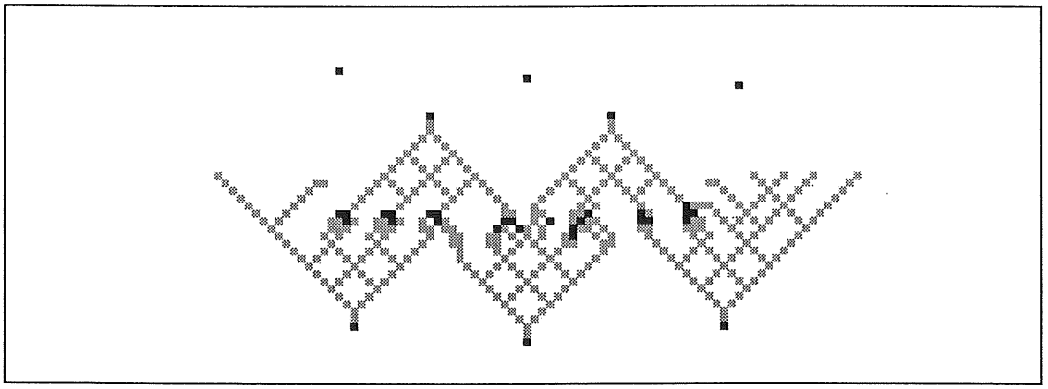


Figure 12: A simple 3D example of neuron growth.

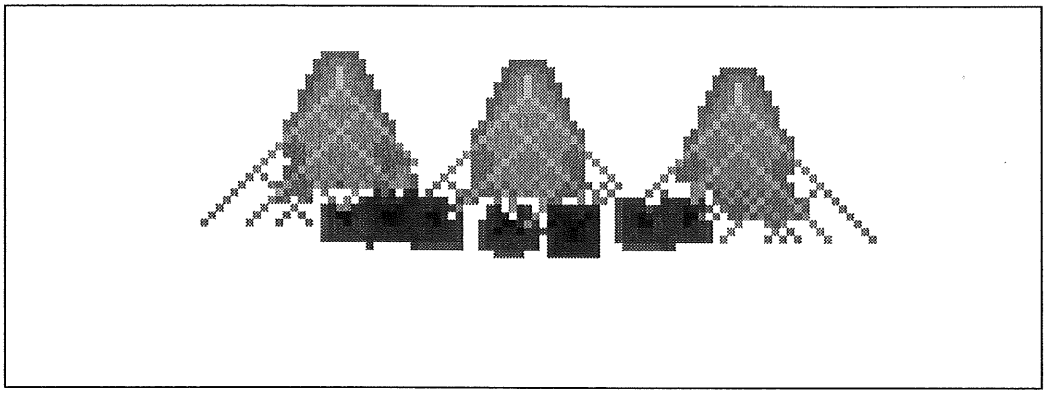


(a)

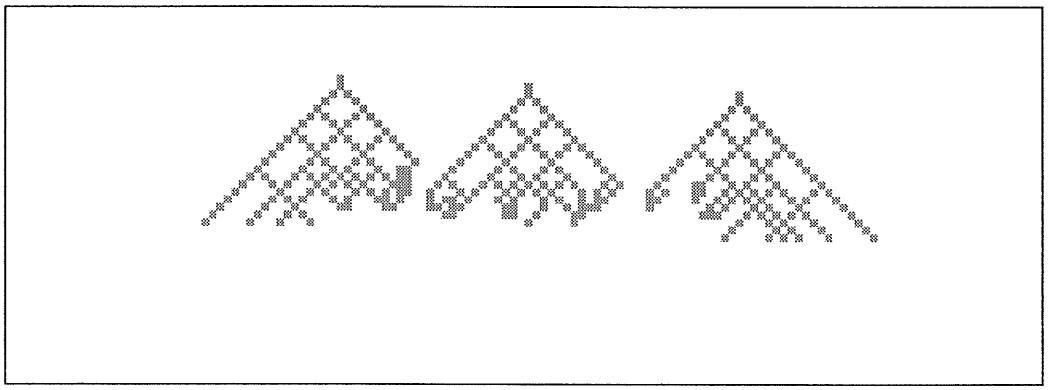


(b)

Figure 13: Growth of a 2D retina: Cones to horizontal cells (a) Chemical environment. (b) Neurite paths.



(a)



(b)

Figure 14: Growth of a 2D retina: Bipolar cells to triad junctions (a) Chemical environment. (b) Neurite paths.

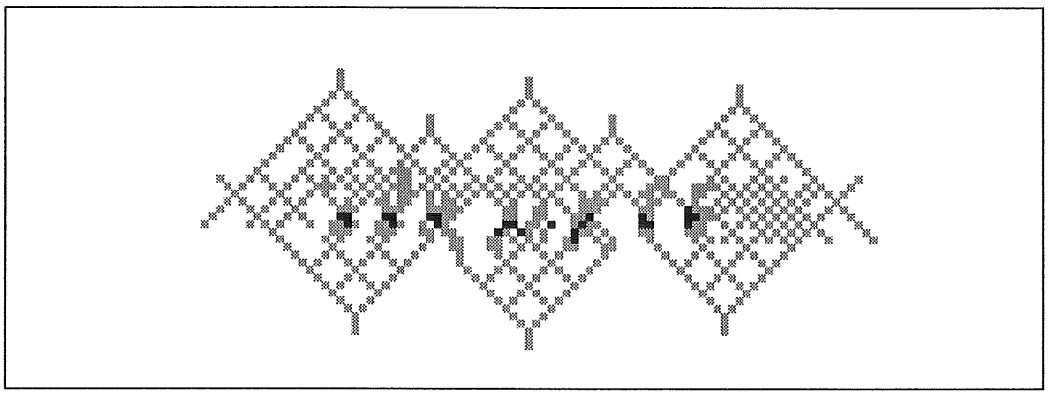


Figure 15: Growth of a 2D retina: Neurite paths.

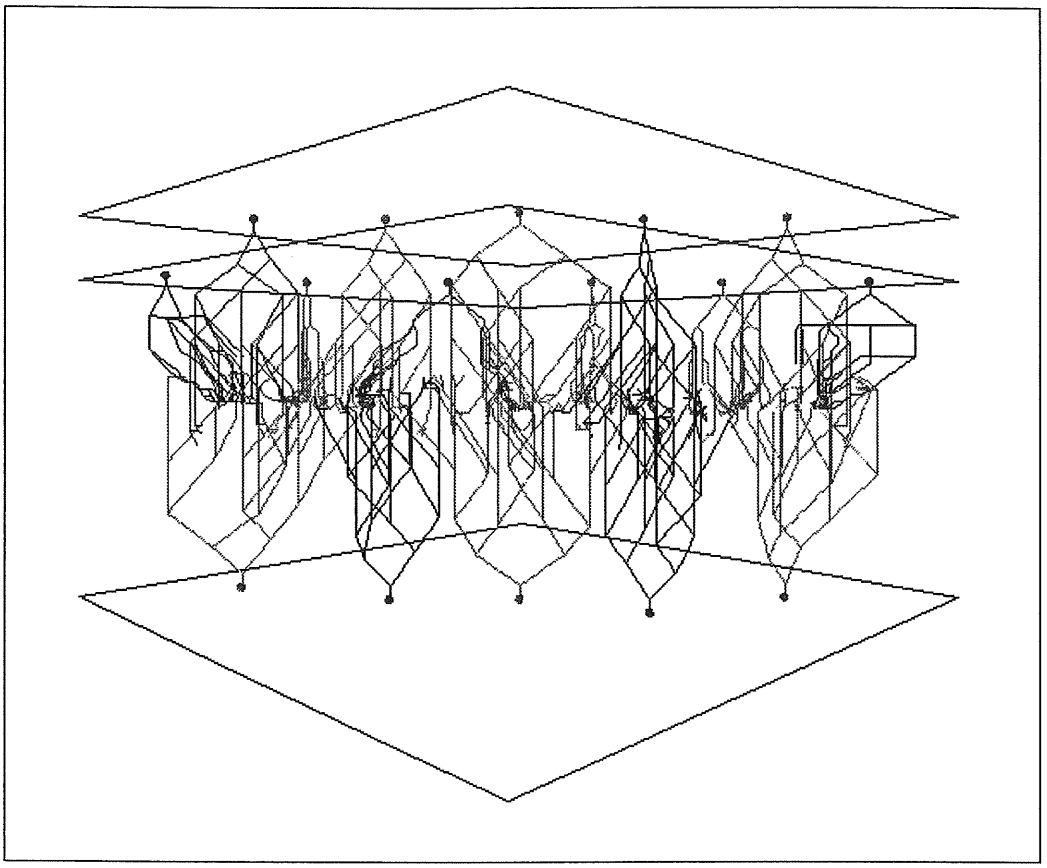


Figure 16: A 3D example of a model retina.

7.2.2 A 3D Model

An example of a 3D model of a 16 neuron retina is shown in Figure 16, where cone cells are the lower layer, horizontal cells centre and bipolar cells uppermost. Figure 16 illustrates the complexity of structures which can be grown.

Figure 17 is a snapshot of a single triad junction (polygon) that developed in a 4 neuron retina. The cell bodies of the horizontal neurons are illustrated. The lower connection (bottom, centre) is from a single cone and the upper connection (top, right) is from a single bipolar cell. The developed junction resembles a biological triad example (see Figure 3) having connections from two different horizontal cells and a single bipolar connection.

8 Discussion

To reiterate, the results presented are for the first phase of the proposed model of biological self-organisation: neural growth. This was investigated at the level of neuron-neuron connectivity. The DANN used is believed to be the first documented 3D implementation. Alternative 3D environments have only been suggested [Fleischer and Barr, 1994]. Although the model implemented is not argued to be biologically plausible, the resulting structures are neural-like in appearance. This is due both to the developmental rules used and the simulated chemical environment.

The developmental rules were specifically designed to be simple and informal. The rules however have been shown to be capable of creating complex, multi-layer neural structures. It is thought that because of the informal specification of the rules they will be more flexible than more rigidly defined mathematical encodings. The emergence of complex structure may also be due in part to the mixture of deterministic (genetic) and non-deterministic (environmental) splitting rules. Allowing growth onto existing connections (ie triad formation) further increases structural complexity. This method of connection formation

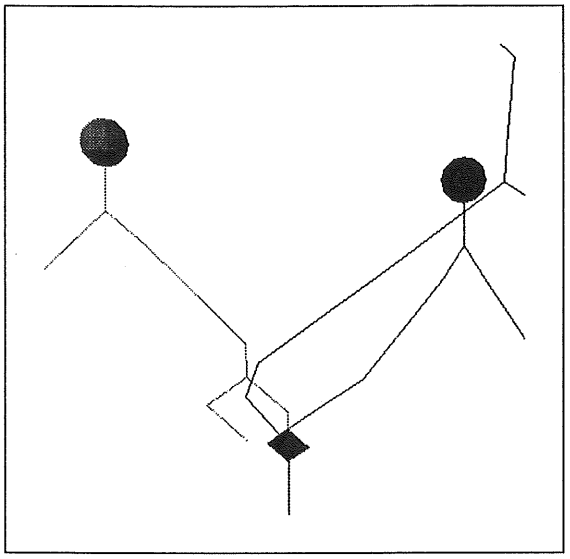


Figure 17: A 3D example of a triad junction.

may be required at subsequent stages self-organisation.

The simulated chemical environment allows greater interactions between the neurons and neurites than most previous approaches. The underlying gradient provides initial neurite guidance before the effects of target cells gradients initiates 'cell-cell' interactions. It is felt that this environment although representing a simplified model of biology, exhibits the principle mechanisms required for modelling self-organisation. The current description of the model contains a sufficient degree of biological detail without being computationally expensive and inflexible compared to more complex models [Fleischer, 1995].

The simultaneous growth of axons and dendrites is also novel. A number of DANNs implement neurite growth but this is either simplified by static target cells [Vaario, 1994, Jakobi, 1995] or growth is unaffected by neighbouring cells [Nolfi and Parisi, 1991]. The growth of two classes of neurite allows a greater range of 'cell-cell' interactions.

The methodology proposed represents a unique use of a DANN. The modelling is directed at mimicking biological structures using biologically inspired rules. Other DANN models are similarly using abstract developmental rules but evolve artificial networks for specific applications. By closely modelling biological structure it poses the question: can such simple, abstract rules provide a description of the way biological neural structures develop in Nature ?

The results presented so far demonstrate that many more connections between individual neurons are made than may be necessary. Hence the primary role of phase two (refinement using random activity) must be to prune extraneous initial connections. The next stage of the study will investigate the roles of spontaneous activity and neural regulation in refining connections in phase 2.

Spontaneous activity has been reported as playing an important role in connection refinement, where competition occurs between neighbouring neurites connected to the same target cell [Shatz, 1994]. Neurons also compete for a limited supply of neurotrophin(s) emitted by target neurons [Purves and Lichtman, 1985, Hall, 1992]. A pre-synaptic cell will die if it is unable to secure a sufficient supply of a neurotrophin. This process regulates neuron numbers. Recent experimental evidence has shown that there is a link between neural activity and the production of neurotrophins [Cabelli et al., 1995, Thoenen, 1995].

Biological structures have been used to direct the growth of the model retina towards some 'target' morphology. However, a more exacting structural definition is required than the general model currently used. The emphasis on the relationship between structure and function dictates this requirement since it is proposed that function will follow from the correct 'target' structure.

The developmental parameters used thus far have been chosen based on visual inspection of the structures grown. Although visual inspection has been used in other areas [Dawkins, 1991] a more scientific method of searching for optimal parameters is needed. It is hoped that the search for optimal parameters will demonstrate the robustness of the developmental rules. It has been proposed that by

using function as the fitness measure, multiple sets of parameter values rather than one, unique set, will be found that develop structures close to the specified target structure. Exploring the parameter space of the developmental rules will also determine the significance and sensitivity of parameter values on resulting structures [Fleischer, 1995].

A genetic algorithm (GA) will be used as the primary search tool. (The GA is used here for its search capabilities as opposed to providing a means of exploring evolution). The design of the GA's fitness function is different to other DANNs since structure is measured rather than function. The design of the fitness function is an important consideration [Mataric and Cliff, 1995].

9 Conclusion

This document has presented preliminary work involved in the design of a shape recognition system inspired by biological visual systems. The study sits within a larger programme of work aimed at investigating the self-organisation of structure that occurs during neural development. It is suggested that by modelling neural development artificial neural systems may be incrementally constructed.

A theoretical framework has been proposed which incorporates both a description of self-organisation across scales of structure and the grouping of self-organising processes into three phases. This emphasis on structure enables biological neural architectures to be defined as *target* structures, directing the development procedure. It is believed that function will follow from having the 'right' structure. The retina has been chosen as the *target* structure because of its stereo-typed architecture.

A bottom-up approach has been adopted starting with the investigation of neuron-neuron connectivity growth. The developmental growth rules used are inherently simple and informal, representing an abstraction of the key neural development processes. Growth occurs within a DANN testbed, which can simulate both a 2D or 3D chemical environment. Using a DANN to model biological as opposed to artificial structures, is novel and it is further believed that this is the first report of a functioning 3D model. A general three layer structure of a retina has been developed both in 2D and 3D. This modelling has demonstrated how simple self-organising rules can develop complex neural-like structures.

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