Computational Models of Cognition

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Declaration

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Ph. D. is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Abstract

Existing connectionist computational models of neural networks idealise the biological process in the neuron to a discrete summation, and fail to provide an efficient substrate for computation involving the spectral data that is the input to the biological perceptual process. This work presents a computational model of neural function that introduces a continuous analogue process and explores the computational uses of sub-threshold oscillations of the membrane potential. The goal of this work is to present an initial examination of the advantages to the practitioner that are afforded by a new computational model of the neuron that includes sub-threshold oscillations as a component on an equal footing with axonal impulses themselves. The relevant evidence that these effects are important in a biological neural network is presented. The new resonate-and-fire model is presented and mathematically defined, and shown to be a superset of the ubiquitous integrate-and-fire model. The behaviour patterns of the model are explored initially in single neurons and then networks are examined and shown to be capable of exhibiting useful excitation patterns such as tonic oscillation, selective innervation and resonance. An unsupervised learning algorithm is defined and shown to generate networks that naturally organise to perform Fourier-style transforms central to spectral manipulations. Finally, the model is examined with respect to the current theories of computational neuroscience and cognitive science, and its potential uses in these domains described.

Chapter 1

Introduction

The application of artificial neural networks (ANN), otherwise referred to as connectionist approaches, to problems of pattern recognition and classification has met with success where standard symbolic algorithms failed. The artificial neural networks described in Rumelhart and McClelland (1987), Kohonen (1990) and as early as Rosenblatt (1958) provided a novel and effective tool to tackle pattern classification.

A particular instance of ANN has several characteristics. The overall organisation of the interconnections between the elements is referred to as the topology of the network. The topology defines the complexity and degrees of freedom of the system. Under normal circumstances, the topology of the network is matched to the predicted complexity of the problem space. The topology should introduce as many degrees of freedom as are necessary to accommodate the complexity of the data set being processed, but no more than are necessary as this will result in lengthened training times and over-fitting to the training data.

The behaviour of the individual neurons in the network is the second, and most important determinant of the behaviour of the network as a whole. There are several variations in the computational model of the neuron that are used in standard networks. They vary from very abstract, idealised models, to systems that attempt to faithfully reproduce the activity of the biological cell down to the flow of individual ions across the membrane. The algorithms and rules governing the behaviour of the artificial neuron itself will be the primary focus of this thesis.

A key component of ANN design is the training algorithm used to modify the network in response to sample inputs from the domain of interest. There are hundreds of such algorithms, most of which are variations on a core of a dozen or so paradigms. This thesis will examine ANN designs from the perspective of whether their training algorithm is biologically plausible. Particularly, we will explore the adaptive behaviour that emerges from rules that are local to individual neurons in their application.

There are two major groups of computational models of the neuron. The first group consists of the compartment models used by neuroscientists to examine the behaviour of individual neurons, or very small groups of neurons. The second group is that used in ANN or connectionist systems the purpose of which is to solve a problem of pattern recognition or classification. Connectionist systems must be capable of scaling to thousands of nodes with dense patterns of connectivity. They must be speedy, and therefore relatively simple to simulate. The current model of the neuron used in connectionist systems reduces the biological cell soma and dendritic field to a single structureless node and in general ignores many potentially important aspects of neural funciton.

Existing connectionist systems falter when applied to the type of data that is most prevalent in real world situated cognition tasks, spectral data of the form processed most efficiently by biological systems. Moreover, connectionism in its current incarnation fails to naturally accommodate the shift and temporal invariance exhibited by natural perceptual systems.

This thesis proposes that the standard model of neurons used in connectionist applications can be improved upon by taking into account certain aspects of the biological neuron that existing models deem irrelevant. Specifically, the processes at work while the neuron is below its firing threshold are examined and a model developed to describe the primary effects of this aspect of neural function. The fundamental improvement in the new model is an enhanced ability to process spectral data of the type that biological perceptual systems must deal with.

By *practitioner's* neural network applications I refer to the application of artificial neural networks to problems in computer science, as opposed to the use of simulations of neural networks the goal of which is exactly modelling a biological system in order to better understand its functioning. While emphasising the sub-threshold aspect of neural behaviour as important can be taken as an assertion about the biological neural function, the goal of this work is to present an initial examination of the advantages to the practitioner that are afforded by a new computational model of the neuron that includes sub-threshold oscillations as a component on an equal footing with axonal impulses themselves.

Efforts to produce computational models of the information processing occurring in nervous systems must first address the fundamental properties of biological information processing systems. The method of information encoding is a basic constraint on any model that has great influence on the capabilities of the system. When modelling cognitive structures, the correct formulation of encoding techniques is critical to the ability of the system to capture the phenomena of interest. The granularity chosen is a basic determinant of the capabilities of the system as a whole.

The goal of this thesis is to present a new computational model of the neuron that takes into account the sub-threshold oscillation of the membrane potential in contrast to traditional models which ignore this phenomena. It will be demonstrated that incorporating this aspect of neural function leads to useful and potentially powerful computational characteristics. A further goal is show that this new model is a useful computational building block that can perform tasks that traditional artificial neural networks are not well suited to. Finally it is proposed that incorporating the oscillatory phenomena in the neural substrate into models of cognition can help to explain and support some of the current theories of cognition.

We will examine the relevant aspects of computer science and neuroscience and then proceed to describe the new computational model of the neuron.

1.1 Computer and Cognitive Science

Interaction between the fields of computer science and cognitive science is increasingly common. However, the interaction is complex. Simulation of cognitive processes through computational models is rightly viewed as the testing ground for those theories of cognition specific enough to provide a detailed description of the underlying mechanisms upon which they are based. In the other direction, research in neuroscience provides computer science with the blueprints for the workings of the brain. From this we can construct simplified machines that perform similar tasks, in a limited domain, to their biological counterparts.

A theory or system that gives a detailed account of the operation of individual neurons will typically not prescribe much regarding the operation of aggregate perceptual systems. Conversely, models which capture elements of perceptual processes will generally ignore the basic neural activity, preferring to make general statements regarding the computational substrate. This is a natural consequence of the need for any model or theory to describe the substrate on which it rests at a convenient level of granularity. The ideal scenario, whereby a large aggregation of components can be accurately described with a brief closed-form expression is unlikely to ever be achieved given that connectionist systems are fundamentally non-linear, and realistic implementations are also asynchronous. Despite this, computational models are useful experimental tools at the disposal of the cognitive scientist and will undoubtedly become increasingly pervasive.

Theories of mind and cognition produced by cognitive scientists inform computer science in so far as they present theories of how biological systems can achieve behaviours and computational feats as yet beyond the abilities of their artificial counterparts. In this respect the fields of neuroscience and cognitive science are conducting the most difficult feat of reverse-engineering yet attempted. As their theories are refined it is through modelling that they are validated. As their theories are validated, computer science is given new tools that can be applied to problems that require some degree of replication of the capabilities of the human brain.

1.2 Computational modelling

The creation of mathematical models describing physical phenomena is as old as mathematics itself, indeed it could be argued that mathematics, however abstract, must in some form reflect or embody some aspect of the physical environment. This relationship has not always been obvious, twentieth century ideas such as relativity theory and quantum mechanics, information theory and cryptography have demonstrated that mathematical constructs previously assumed to be purely abstract do in fact describe the fundamental structure of certain aspects of reality. In the case of relativity theory, Reimann and tensor mathematics is used to describe the geometry of space time itself. Quantum mechanics gives real meaning and physical implications to imaginary numbers. Information theory in conjunction with recent explorations of modern physics has developed a new paradigm that states that the fundamental entity pervading the physical universe is not matter/energy, but rather information itself (Frieden, 1998). Cryptography has placed that most austere of mathematical pursuits, number theory, at the centre of one of the most active and practical fields of research of the computer age.

Of these observations, the most salient to the present discussion is that information is in a sense a fundamental entity, both in a physical and philosophical sense. Without going so far as to appeal to solipsistic notions, it is important to recognize that the information content of a physical system fully characterizes its physical properties.

In this thesis a pragmatic approach will be taken, and the philosophical debate on whether a biological substrate affords some unique characteristic is sidestepped. Here it is proposed that the computer is as valid an experimental apparatus as any other physical entity. With the computer and sufficiently sophisticated numerical means for performing discrete simulations the differential equations describing the physical system of interest, we can accurately simulate the system and investigate its behaviour under whatever conditions we please. This condition holds true where the information content of the model is equivalent to the information content of the physical system. The fact that the model does not have physical extension in the real world is regarded as irrelevant. What will be our focus is the task of extending the existing computational models of practitioners' artificial neurons by the smallest possible degree that introduces a realistic model of the sub-threshold behaviour of the membrane potential.

Given the hypothesis that information content is the fundamental characteristic of all entities, the claims regarding the neural medium amount to claims regarding the particular class of information systems supported by neural media. The research presented in this thesis seeks to explore the implicit assumptions of the computational models used to date to describe the neural media. The results presented demonstrate that there are advantages in terms of explanatory power and biological plausibility when one revises the basic assumptions of existing models of information processing in the brain.

1.3 Representation in Computational Models

When modelling a system, the first determinant of the accuracy of the model is the number of variables modelled. The degrees of freedom of the model must be commensurate with the underlying degrees of freedom in the physical system. If the model is too simple, it will fail to properly represent and capture the behaviour of the phenomenon.

An over-simplified model may describe the fundamental properties of a real-world system, but will fail to incorporate all aspects thereof. For many problems, an approximate model is sufficient, particularly when the system in question consists of a small number of entities with relatively simple interactions. In complex dynamic systems with feedback, even the smallest discrepancy between the model and the true system will result in gross differences between prediction and reality.

The nature of the representation is a fundamental decision in the modelling process, it is not always obvious what numbers are significant, what simplifying assumptions can be made. When we model weather systems, the erosive effects of gale force winds and tidal currents are irrelevant to the subject and can thus be ignored. Not all such decisions are obvious, however; many major advances have arisen as a result of re-examination of an aspect of the system previously deemed negligible.

A recent example of such a transition is the emergence of the science of chaos as a result of the recognition by Lorenz (1963) that weather systems display sensitive dependence on initial conditions. Previously, the fourth decimal place of a few variables in a large weather model were assumed to have no effect on the evolution of the model as a whole. Lorenz noticed that in certain classes of dynamical systems if the initial conditions are modified slightly then as a consequence the system will quickly evolve into a vastly different state than it would have otherwise.

For most of the brief history of the field of modern artificial intelligence, research has focused on systems of declarative logic and discrete mathematics. Expert and rule based systems consist of a large number of declarative facts such as *All men are mortal* and *Socrates is a man.* When coupled with inference rules such a system gains the ability to infer that *Socrates is mortal.* It is important to note, that there is no semantic level to the machinations behind such inferences. The system blindly shuffles symbols devoid of any intentional connection with reality. There is no concept of man, mortality or Socrates. Recent projects, such as Cyc (Lenat, 1995), have attempted to address this particular shortcoming of declarative systems, by compiling so huge an array of facts that the system can be said to possess semantic appreciation of concepts such as "man", "truth" and so on. The fact remains that the engine underlying a system in possession of ten million facts is the same as that containing a few hundred. The declarative logic systems have no real-world embodiment, nor do they address the problem of perception of that real world. This thesis argues that embodiment is a fundamental requisite to the creation of intelligent artefacts; without perceptual and motor apparatus which binds an entity to the real world in a manner provisioning meaningful information bandwidth the resultant apparatus can not be said to address the problem of intelligent behaviour. Behaviour by definition involves interaction, exploration, discovery and reaction; a system which addresses the problem of intelligence must first address the problem of perception, as this is the foundation of all interaction with the environment.

In contrast to declarative logic and rule-based systems, recent years have seen the burgeoning of interest in sub-symbolic systems. Artificial neural networks and other parallel distributed processing architectures are the most common manifestation of such ideas. All such real valued models can be shown to be a subset of declarative systems, in that a sufficiently powerful (Turing complete) declarative logic system can be shown to be capable of representing any real valued model. There is a semantic problem with this; the logical systems from which simple arithmetic and more complex mathematical structures stem become part of the substrate upon which the simulation is executed. There is a point below which it is not possible to assign meaning other than to refer back to the system being modelled in a recursive fashion. While it is true that the fundamental mechanisms of all computational devices can be described in declarative terms, in order to understand the system under scrutiny we must ground ourselves in the appropriate substrate. In a similar vein, when biologists discuss their field, they do not find any advantage in constantly referring to the quantum mechanical mechanisms which ultimately underlie the phenomena of interest - instead they focus at the level of the organic compound, the cell, the organ or the organism, as is appropriate for the problem being addressed.

With the aforementioned considerations in mind, the fact remains that the critical point in any endeavour which seeks to investigate phenomena through computational modelling is the question of what to model and how to model it. Computational feasibility, the fact that we cannot wait forever for our calculations to complete, is a significant limitation. It forces us to make difficult choices in our effort to reduce the complexity of the system by eliminating irrelevant variables. In doing so there is always the risk that we will ignore a key aspect of the system. Beyond feasibility itself lies the constraint that any machine that is to interact in a meaningful way with the environment should do so in a prompt manner. If the reaction is not timely, the event which initiated the response is long-gone, and it is likely that further salient events have occurred in the meantime that require the attention of the device.

When attempting to model physical systems, we are forced to produce models of a sort that humans are particularly ill equipped for. Instead of prescribing rules as we are used to doing in an algorithmic step-wise fashion which describe the behaviour of the system as a whole, we must instead prescribe local rules. Such rules describe the local conditions which determine the behaviour of a single unit of the system, such as a single cell. Investigators into artificial life systems attempt to create systems by specifying local rules governing molecules only; such systems are then simulated, the goal being that the model will exhibit some interesting property of living systems such as homoeostasis (Rosen, 1985). The aim is to have such properties as homoeostasis and cell division *emerge* as a result of the local rules of the system. The lack of success of such systems to date is a testament to the difficulty people have when formulating systems governed by local rules. Examples of successes include the modelling of flocking of birds and fish. The surprising aspect of flocking studies is the very simplicity of the set of rules required to produce a system which exhibits extremely accurate flocking behaviours. The problems introduced by being faithful to the rules of "no non-locality" are profound, and represent a very new class of problems which current techniques struggle to deal with.

1.4 Models in Cognitive Science

Cognitive science attempts to describe information processing in the human brain. Computational models are used in order to test theories that propose models accurate enough to be formalized in a mathematical system. The theoretician's goal is to describe a system with sufficient accuracy so that it can be modelled. The subsequent hope is that the model should behave in a manner similar to the phenomenon being modelled. The degree of detail in such models is typically inversely proportional to the scale of that being modelled; a model which seeks to say something about the whole brain's activity will likely say very little about the activity of single neurons. Conversely, a model which indulges in great detail describing the activity of individual neurons will likely have little to say about the task of processing large "chunks" of information in the brain.

It is possible that adherence to the principles of elimination of non-locality and a simple but fundamental change in our view of the neuron can result in a statement on the overall nature of information processing. The model described herein argues that the focus to date on "digital" axonal pulses as the means by which computation is performed to the exclusion of all else is flawed. Instead the waveforms supported by the dendritic process are emphasised as the means by which information processing in the brain is achieved. The model does not specifically prescribe the mechanisms for the execution of the wide variety of tasks achieved by the cognitive apparatus, nor does it specify much regarding the role of the various nuclei of the brain. The primary focus is a re-exploration of the attribution of importance to the basic cellular activities underpinning computation. In the final chapter, we briefly examine the potential impact that the resonate and fire model would have on a model of conscious cognition Global Workspace Theory (Baars, 1988). While the territory which is to be traversed is thus bounded, what we will discuss has implications for all facets of cognitive modelling.

The research activities leading to this thesis began with an examination of the subject-object relationship in the realm of human computer interaction. We developed a virtual environment (O'Nuallain et al., 2000)with a system of multi-modal input in the expectation that this would provide a fruitful platform upon which to base investigations into the use and interaction of modalities, and the interaction of natural language and visual data.

As we progressed in our investigation, it became clear that the key feature of any successful virtual environment is the model used to represent the user of the system. This determines the ability of the system to scale and handle novel input and provide satisfactory responses to such user input. Through an examination of the implicit user models extant in any user interface, coupled with the philosophical viewpoint expounded thus far in this introduction, we embarked on a re-examination of how best to produce intelligent systems.

The results of this revision are presented throughout the body of the rest of this thesis. We began with an examination of extant computational models and paradigms for the implementation of biologically inspired computational schemes. The pervading models are examined and the advantages and disadvantages of each are appraised with respect to the desire to produce a biologically plausible and computationally efficient model. Having examined the computational models at large, we progress into a more detailed examination of the neuroscience which inspires our modelling efforts. Chapter three provides an overview of the neuroscience which drives the computational model of the neuron developed in chapter four. This model extends existing techniques and provides a superset of their behaviours. We then proceed to examine the behaviour of groups of such neurons in chapter five, developing a self-organising map learning algorithm and demonstrating the formation of topographic maps in such networks. Finally, in chapter six, we delve into the implications of the new model with respect to more encompassing theories of cognitive functioning.

Chapter 2

Computation

2.1 Introduction

Computation and information processing have recently been increasingly recognized as a fundamental substrate. Deutsch and Jozsa (1992) and Penrose (1990) draw on basic theories of computability to inform their explorations of physics and mentation. The brain can usefully be described as the information-processing organ, and thus the fundamentals of computation must be considered when tackling the subject of cognition. With the spread of cheap computational power, it is now possible for neuroscientists to construct increasingly accurate models of neurons. The focus of such models is usually single neurons, at most a few dozen are simulated. As the number of neurons is increased, either the complexity of the underlying model or the speed of simulation must be sacrificed. In order to tackle interesting problems of practical applications in pattern recognition and classification, we will require connectionist systems that are capable of scaling to hundreds and thousands of nodes with unlimited interconnectivity. Further, simulation speed must not be excessive in any application in which human interaction is required. Our goal therefore is to formulate a model of the neuron that is as simple as possible, but which still retains the essential features of a true model of ion flow and sub-threshold process so that the advantages afforded by such features are retained by the model.

2.2 Symbolic Computation

Symbolic computation refers to the practice of manipulation of a set of symbols (vocabulary) according to a set of rules (state transitions) in order to transform a specified input. An essential point to recognize for symbolic systems is the fact that the method whereby the manipulations are performed is considered irrelevant to the computation. Whether on an abacus, calculator, supercomputer, or solely in the human mind, a fundamental assumption of the doctrine of symbolic computation is that there is no relevant difference; the implementation details may be ignored and abstracted away.

All conventional computing devices are symbolic computation devices. Even simulations of sub-symbolic processes on conventional devices can ultimately be seen to be sophisticated forms of symbol manipulation. The granularity of the symbols is heightened, and the semantics of any given symbol is intentionally blurred in order to achieve the trappings of distributed processing and storage, but the fact remains that such systems are ultimately shunting around symbols just like the rest of them. Despite this, it is convention to refer to such simulations as sub-symbolic, given the fact that the increased granularity afforded by the appropriate physical devices would ultimately have little impact on the results of a particular computation.

The natural and efficient expression of algorithmic forms requires a level of description that is suited to the problem space. The proliferation of experimental languages in the field of AI is a testament to the belief that given the right mode of expression, an efficient algorithm for the solution of a class of problems will be given natural expression. As any practitioner knows, the correct choice of implementation language will often determine the success or failure of the project. The search for the correct mode of expression is a theme which will be revisited later in this thesis; it is argued that the prevailing integrate and fire model of the neuron is a mode of expression used by practitioners to describe their cognitive models at the level of the biological substrate. As such, the model requires examination; it is ultimately a language used by individuals to express ideas. The resonate and fire model described later is an expansion of the vocabulary and grammar available to the practitioner, with greater expressive power than is currently available.

2.3 Computational Neuron Models

Symbolic approaches to problem solving involve the formulation of an explicit set of rules designed to produce a solution to an instance of the problem in an ordered fashion. Sub-symbolic approaches such as neural networks describe a system whereby a generic model is modified through exposure to examples of the problem to be solved. The learning rules gradually tune the parameters of the model until an acceptable level of success in classification of the inputs is achieved.

The field of sub-symbolic processing, primarily in the form of Parallel Distributed Processing (PDP) (Rumelhart and McClelland, 1987), has flourished in recent years. The success of this approach is limited to very specific domains, and is not universally applicable as it was once hoped it would be. Nonetheless, it represents a paradigm shift in terms of the evolution of computational approaches. The prevailing artificial neural network architectures are inspired by biological information processing organs, a fact which places them at centre stage in any attempt to model cognition computationally.

The fundamental component of these models is the computational neuron. This entity is very loosely based on the biological neuron, but with simplifying assumptions which render it merely analogous as opposed to faithfully representative. The degree to which artificial neurons are a simplification of their biological counterpart brings into question the validity of referring to them as neurons at all.

2.4 The Artificial Neuron

In connectionist computational systems, the computational model of the neuron reduces the cell soma and dendritic field to a single node. Most of the interesting properties of the neuron are thereby excluded from the computational model. The artificial neuron receives one or more inputs, each of which may be a positive or negative real number. These inputs take the form of real numerical values. The neuron maintains a vector of weights associated with its input field. The neuron's activation is calculated based on the instantaneous value of the inputs and the associated weights. The activation function has myriad forms, but the most common is simply to sum the products of the inputs and their associated weights. The result of the activation function is then processed by the transfer function. The transfer function calculates the neuron's output. Typically transfer functions are some form of squashing function, bounded between small values such as 0 and 1 or -1 and 1. Often the particular function is chosen so that it is continuous as certain connectionist training algorithms require that the transfer function be differentiable. Once the transfer function has calculated the output, the result is then passed on to the next layer of neurons as the input, and the process is repeated.

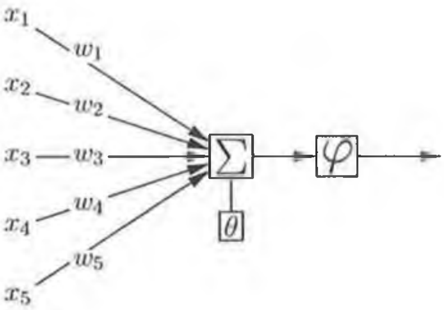

Figure 2.1: Artificial Neuron

Figure 2.1 characterizes this process. Mathematically, the steps for calculating the neuron's output are quite straightforward.

First, the sum of product, or activation, is calculated:

$$A_i = (\sum_{j=0}^{n} w_j x_j) - \theta \tag{2.1}$$

Where θ is a constant referred to as the threshold, which results in better mathematical properties of the system in the case where all inputs are zero.

Next, the transfer function is calculated. For the sake of example we will use the sigmoid transfer function. The transfer function will return a value between one and zero regardless of the activation level. The value returned will be very close to either zero or one, unless the activation level is very close to zero.

$$o_i = \frac{1}{1 + e^{-A_i}} \tag{2.2}$$

The output, o_i, typically forms the input for another neuron, that is, o_i for the current neuron is used as an input x_j for another neuron.

The standard artificial neuron is very computationally efficient. When special restrictions on the transfer function are permissible, the task of calculating a neuron's response amounts to vector multiplication of the input vector with the weights vector.

The weight vector applied to the input of a neuron is the primary configurable parameter in typical artificial neural networks. This follows from the basic premise in the field that synaptic plasticity is the primary, if not only, factor responsible for the adaptive behaviour of biological networks. A consequence of this premise is the over-simplified model of the neuron used.

2.5 Neural Network Models

There are a variety of artificial neural network architectures, each of which results in very different computational properties. The primary dichotomy among the set of all architectures is the classification into feed-forward and recurrent networks. A feed-forward network is topologically equivalent to a directed acyclic graph, links between nodes are unidirectional, and there are no feedback mechanisms. Typically feed-forward networks are arranged in layers, and data is fed from layer to layer in a discrete fashion.

The computational consequence of the absence of recurrent connections in feed-forward networks is that the output of a particular stage of processing is functionally determined by the current set of inputs at that stage. There is no provision for internal temporal states in such networks; the set of weights is generally enough to completely describe an instance of a topology.

The absence of recurrent connections in feed-forward architectures simplifies their mathematical analysis, and such architectures are better understood in general. In recurrent networks, the range of topologies is unlimited, and therefore the set of possible behaviours is considerably less constrained. Some recurrent networks utilize layers as an organizing principle, but feedback connections and lateral links within a layer are permitted. The modelling of any systems with state requires the use of recurrent networks. Since biological systems are inherently feedback systems in which the current state of the system to a large degree determines its next state, biologically inspired models must be implemented by architectures in which recurrence or some other state maintenance mechanism is a feature.

This modelling power comes at a high price. Recurrent architectures may exhibit unstable or chaotic behaviour. Given a set of inputs it may take a long time for the system to settle into a stable response state, if such a stable state is reached at all. While these features are often seen as problems to be overcome in computational modelling their presence is a necessity when describing complex biological systems.

2.6 Perceptron

Rosenblatt (1958) described a single layer feed-forward network model commonly referred to as the Perceptron. While the possibility of multiple layers was recognized and studied, there was no effective learning algorithm that could solve the problem of credit assignment for hidden layer nodes.

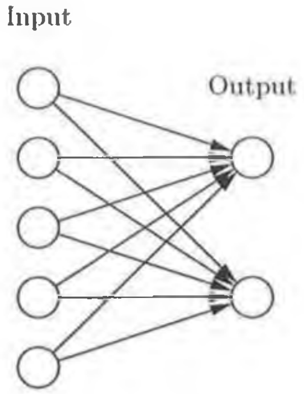

Figure 2.2: Perceptron Topology

Notice that each output unit is independent of all the others, and can therefore be considered in isolation. The perceptron is surprisingly efficient at implementing certain Boolean functions, such as the majority function which outputs a 1 if more than half of the inputs are 1. This function can be represented using a single perceptron unit with all weights set to 1 and a threshold of n/2, where n is the number of inputs. A similar task would require a decision tree of $O(2^n)$ nodes.

Another positive point regarding the perceptron architecture was

Rosenblatt's proof that the perceptron learning rule, a variant of standard gradient descent is guaranteed to converge. There are no local minima in the space describing the error surface.

These advantages were ultimately rooted in the perceptron's primary drawback. The severe limitation to the perceptron as Minsky and Papert (1969) proved is the simplicity of the class of functions which may be modelled by it. The single layer architecture could not learn any classification that was not linearly separable. This meant that a Boolean operation such as XOR can not be implemented by the perceptron in a single layer configuration, nor can most other classification tasks of practical use.

2.7 Hopfield

The Hopfield network Hopfield (1982) is inspired by physical processes. Despite the fact that it is a recurrent network, it is possibly the architecture most amenable to mathematical analysis. There is a strong similarity in the operation of Hopfield nets and physical systems such as spin-glass networks (Graubard, 1989).

A Hopfield network consists of a rectangular array of nodes. Each node is bi-directionally connected to each other node, giving a total of N^2 connections in an N node network. The links may only assume the values -1 or +1, and the output of a node must be either +1 or -1, such nodes are referred to as Bipolar.

The architecture behaves as an associative memory. After training on a set of examples, the presentation of input will cause the network to settle into a state corresponding to one of the training examples that most closely resembles the input.

The number of neurons in a Hopfield network determines the number of patterns it can reliably store, since the number of neurons directly determines the number of connections, which are the parameters of the model. A Hopfield network can reliably store approximately $0.138 * N$ training examples. Any more than this and training new patterns into the network will result in the destruction of the ability to recall previously trained patterns. Therefore, a 100-node network can store approximately 13 examples (Hopfield, 1982).

An important feature of Hopfield networks is that they are the simplest architecture to exhibit important features of dynamical systems, such as attractor states, limit cycles and bifurcations. For this reason, they are a paradigmatic example of recurrent networks, despite the fact that they are considered computationally inefficient as content addressable memories.

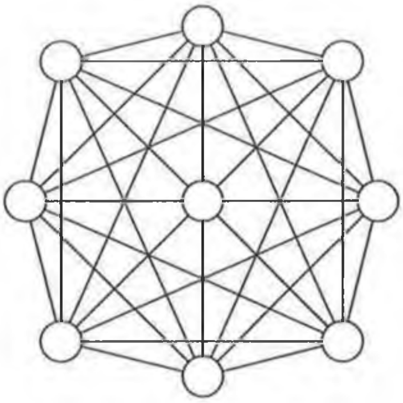

Figure 2.3: Hopfield Topology

Other variations augment the Hopfield architecture with one or more hidden layers. These hidden layers provide a variety of features: the most common desire is to increase the number of distinct patterns that a network can store without having to artificially increase the node count of the standard Hopfield solution.

2.8 Multi Layer Perceptron

The MLP architecture (Rumelhart and McClelland, 1987) is generally associated with the Backward Propagation of Errors algorithm, so the two will be discussed together here. An MLP consists of an input layer of nodes, the outputs of which feed into the hidden layer nodes. There may be more than one hidden layer, and connections are only permitted between nodes in adjacent layers.

The hidden layer nodes are often viewed as *feature extractors*, since in practice a given hidden layer node's output is generally functionally determined by the state of a subset of the input vector. The particular state of the subset which causes the node to fire is then referred to as the feature which that node is extracting.

The backprop algorithm operates in two stages. First, the example input is fed into the input layer of the network, and the response of each hidden layer is calculated in turn. The output layer's response is then calculated, and compared with the desired response for the given input. The difference between the desired and the actual response gives a measure of the error.

The second stage of processing involves assigning error measures to

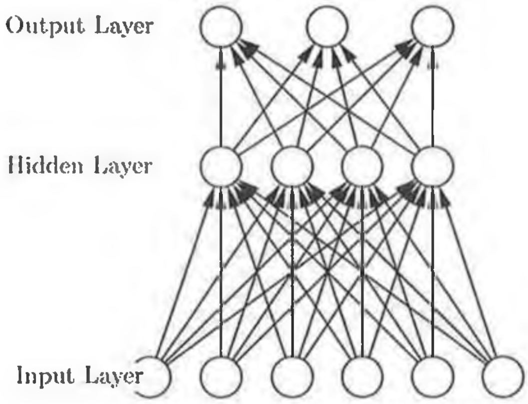

Figure 2.4: MLP Topology

the hidden layer nodes. This "credit assignment" was ultimately the limitation that prevented Perceptrons progressing beyond the classification of linearly separable data sets. The solution was to be found in a straightforward but elegant application of the chain rule of elementary calculus (Werbos, 1974). The technique amounts to a method for computing the error on a hidden node that is related to the output node's error in combination with the hidden node's contribution to that error.

Standard backprop is an alias for the generalized delta rule, the training algorithm that was popularized by Rumelhart, Hinton, and Williams in chapter 8 of Rumelhart and McClelland (1986), which remains the most widely used supervised training method for neural nets.

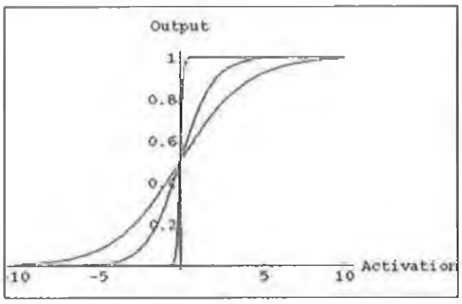

Figure 2.5: The Sigmoid Transfer Function

The nodes in the Backprop MLP use a sigmoid transfer function. Three separate plots of such a function are illustrated in figure 2.5. The gradient of the curve is determined by the coefficient β as shown for the Fermi function in equation 2.3.

$$o_i = \frac{1}{1 + e^{-\beta A_i}} \tag{2.3}$$

This function has particularly useful features; it is continuous and therefore differentiable, which is essential for the use of backprop. It is also asymptotic, to zero in the negative direction and to one in the positive direction. This means that large activation values do not saturate the network.

2.9 Competitive learning

These architectures implement competitive networks that provide a topological mapping from the input space to the clusters. The Self-Organising Map, or SOM was inspired by the way in which various human sensory impressions are neurologically mapped into the brain. In the motor and somatosensory cortices neurons that are spatially proximate respond to sensory input that is closely related, such as the visual impression of lines of similar orientation (Hubel and Wiesel, 1959). Such arrangements, referred to as topographic maps, pervade much of the brain's organization and was seen as an appropriate candidate for computational simulation. The most common and successful of these schemes is due to Kohonen (1990), so much so that SOMs and Kohonen architecture networks are synonymous. Many other competitive schemes were designed and simulated, starting with Rosenblatt who as early as 1959 had contrived a variation of his perceptron that exhibited the basic features of competitive learning.

In a SOM, the neurons (clusters) are organized into a grid - usually two-dimensional, but sometimes one-dimensional or (rarely) three- or more dimensional. The grid exists in a space that is separate from the input space; any number of inputs may be used as long as the number of inputs is greater than the dimensionality of the grid space.

The output units of the SOM are initialized so that the weights of their inputs are set to random values. During training, each input pattern is presented to the network in turn. For each pattern, the neuron whose weights match the input vector most closely, as measured by Euclidean distance, is declared the winner. All neurons within a certain distance of the winning neuron then have their weights updated according to the rule:

$$w = (1 - \alpha)w + \alpha x \tag{2.4}$$

Where w is the weight vector, x is the current input vector, and α is a parameter of the algorithm that determines the stability of the network. The higher the value of α the less stable the network will be, and the faster it will change to adapt to new input.

When a vector x is presented the weights of the winning neuron and its neighbours are modified so that they are closer to x. The result is that after many learning cycles the neurons in the output layer form areas in which proximate neurons respond to similar inputs.

The size of the neighbourhood is large at the start of learning, to avoid undesirable effects such as distant areas of the network becoming attuned to the same class of inputs. The learning rate parameter α is initially set to a large value (close to 1.0) in order to quickly align the network with the input space. As training progresses, the neighbourhood size is gradually reduced until it contains a single neuron only. The learning rate is also reduced in order to heighten network stability.

The Kohonen SOM is biologically plausible, since no non-local interactions are permitted; it is also an extremely effective computational tool and has found many applications involving dimensionality transforms. For this reason, it is often considered to be the closest approximation of any computational model to an aggregate phenomenon of neurophysiology. Topographic maps are of particular interest to the perceptual process, as they have been found in a variety of important brain structures, such as the striate cortex (Hubel and Wiesel, 1959).

2.10 Radial Basis Functions

Radial basis function networks (RBFs) can learn arbitrary mappings and are attractive due to their computational efficiency. For many classification tasks better performance is achieved in a shorter time frame by RBFs than is possible using conventional MLPs.

RBF networks can be viewed as a variant of the MLP architecture, but there is a very special difference in the behaviour of the hidden layer units. RBF hidden layer units have a receptive field that has a centre: that is, a particular input value at which they have a maximal output. Their output tails off as the input moves away from this point. Generally, the hidden unit function is a Gaussian, or normal curve.

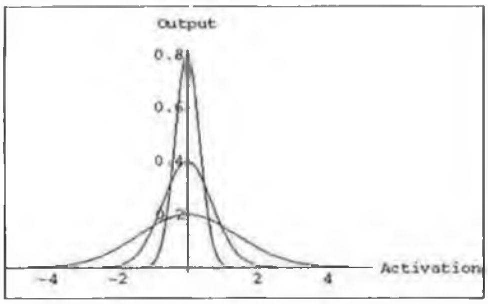

Figure 2.6: Plots of three Gaussian curves with varying standard deviations

Figure 2.6 shows the Gaussian transfer function used in hidden layer RBF units. The Euclidean distance of the input vector to the centre of the Gaussian is calculated. This is used as an inverse measure of activation; the larger the distance from the centre point, the lower the activation. This activation is then fed into the Gaussian transfer function and an output value results. For the example in the above figure, the input space is one-dimensional and the closer the input is to zero, the higher the output. In typical RBF networks, the input space is multidimensional and the centre of the Gaussians in the hidden layer units is a point in hyperspace treated as a parameter of the network that is learned during the training process.

The RBF network classification scheme can thus be visualized as a set of points in hyperspace representing the centres of the hidden units' Gaussians. Input vectors are points in this same space, and the proximity of the input point to the existing Gaussian centres is the essential measure used in classification. The standard deviation of the Gaussians is also important, since the transfer function extends to infinity in all directions, all receptive fields overlap. The response of the hidden units to input is then a function of both Euclidean distance and the standard deviation.

The output layer weights are then trained using the Delta rule. RBFs have the advantage that one can add extra units with centres near parts of the input that are difficult to classify. Such an operation is computationally inexpensive. While it is unlikely that biological systems actually implement such a classification technique, the algorithm is particularly attractive due to its general flexibility and computational efficiency.

2.11 Adaptive Resonance Theory, or ART

Invented by Grossberg (1976) this architecture was one of the earliest attempts at explicitly modelling a neurophysiologically plausible structure in a computationally feasible and useful way. ART networks were designed based on detailed differential equations with a view to biological plausibility of the result. In practice, ART networks are implemented using approximations to the original model.

ART comes in several flavours, both supervised and unsupervised. As discussed by Moore (1988), the unsupervised ART's are similar to many iterative clustering algorithms in which each case is processed by:

1. Finding the nearest cluster seed (prototype or template) to that case.
2. Updating that cluster seed to be closer to the case.

where *nearest* and *closer* can be defined in many different ways, and ultimately are determined by the character of the data to be classified. In ART, the framework is modified slightly by introducing the concept of "resonance" so that each case is processed by:

1. Finding the nearest cluster seed that resonates with the case.
2. Updating that cluster seed to be closer to the case.

Resonance is just a matter of being within a certain threshold of a second similarity measure. A crucial feature of ART is that if no seed resonates with the case, a new cluster is created as in Hartigan (1975) leader algorithm. This is similar to the manner in which RBF networks add hidden nodes when no existing nodes cover the input satisfactorily.

A common feature of other architectures, particularly backprop, is that depending on learning parameters, they may become either too slow to learn new data on the one extreme, or too quick to destroy old parameters to accommodate newly learned data. This is commonly referred to as the *stability-plasticity dilemma*. It is difficult, if not impossible to design a backprop network that has a satisfactory trade-off between stability and plasticity. ART's creation of new seeds as needed is said to provide a solution to this problem.

The ART architectures simulate aspects of biological processing but do not attempt to model the substrate from which their behaviour emerges. They do not exhibit an adherence to the principle of local effect training mechanisms - the idea that supervised learning algorithms are not biologically plausible.

Neurons are added to the ART network once an externally measured threshold is reached whereby the current capacity of the system cannot accommodate more information without disrupting that already stored. No system is described which could account for the "recruitment" of idle neurons to the task of classification once some external high-water mark is crossed. The ART approach needs to be informed by techniques used in cellular automata design which emphasize the essential principles of biological systems. This primarily amounts to designing autonomous units which engage in local interactions with each other and whose constituent behaviours when aggregated amount to a complex holistic phenomenon. No arbitrary external structures should be required in order to get the system to exhibit the desired behaviours, if that system is to be deemed an accurate model of biological information processing mechanism.

2.12 Biological Plausibility

The existing architectures have a broad range of uses, and are becoming ever more common in general usage for speech and handwriting recognition applications. However, they are all inadequate for the faithful modelling of neurophysiological structures and their properties. Neither are they particularly useful in the exploration of general techniques for modelling the perceptual process in biological systems. As noted when discussing symbolic processing, the solution to a class of problems is often only forthcoming once the appropriate language for describing the solution is available. In a similar vein, perception is a problem, and the language most appropriate for describing its solution is yet to be defined.

2.12.1 Spectral Data

The primary shortcoming of current neural models is that they do not accommodate spectral data well. Spectral data requires processing systems in which the previous state influences the next. A single sample of spectral data is meaningless on its own, devoid of context. To properly process spectral data, it must be aggregated into meaningful units, in the manner in which sounds are aggregated into phonemes. There is a basic temporality about spectral data, in that the rate of arrival of data is important. Wavelength, amplitude and phase are the three primary constituents of spectral data; these properties can not effectively be represented without either carefully considering the time dimension, or first translating into another representation which combines the initial properties with their evolution in time. It is straightforward to prove that an MLP with sigmoid transfer functions is a universal function approximator; in practice, the domain of existing artificial neural networks is far removed from the domain of spectral data.

This disparity of domains results in the existing architectures being computationally inefficient when faced with the classification of data from the spectral domain. Continuous time series data must be sampled at twice the maximum frequency in the signal in order that all information in the original signal be preserved (Shannon, 1948). Using conventional MLP's or variants with recurrent connections, the processing of even a short period of spectral data with relatively low frequencies becomes computationally infeasible.

2.12.2 Invariance

Biological processors seem to have a natural ability to handle invariance. A table is still recognized as a table regardless of the viewpoint. Faces are recognized and classified with ease despite the vast contortions possible through various facial expressions. Existing artificial neural networks have no natural ability to handle invariance. For instance, an MLP trained for handwritten character recognition will adequately categorize upright characters, but rotated characters will be completely misclassified. Stopgap solutions exist whereby input images are preprocessed and rotated so that they are roughly upright, but the fact remains that the architectures have no innate capacity for handling rotational (and other) invariance.

2.12.3 Feature Detection Invariance

Biological systems have the ability to extract common features that can be recognised as being the same in quite different contexts. For instance, the note middle C is recognised as being similar to C an octave higher; even an untrained ear will agree. Similarly, colour and texture are perceptually invariant - we recognise similarity despite the fact that the objects exhibiting similar features may on the whole be very different.

2.13 Genetic Algorithms

A Genetic algorithm is an optimization technique inspired by the concepts of Darwinian evolution. A population of individuals, each representing a potential solution to the problem to be optimized, undergoes a process analogous to biological evolution in order to derive an optimal or at least near-optimal solution.

The solution offered by each individual is assigned a measure of fitness: a single numerical value that indicates how well that solution performs. New individuals are generated by procedures analogous to biological reproduction, with parents chosen from the existing population with a probability proportional to their fitness. The new individuals may replace less fit members of the population, so the overall population fitness improves with each generation.

Individuals store their potential solutions as a collection of genes. In a GA, these may be arrays of bits, integers or floating-point numbers, representing parameters of the problem to be optimized. An individual's total collection of genes is called its genome.

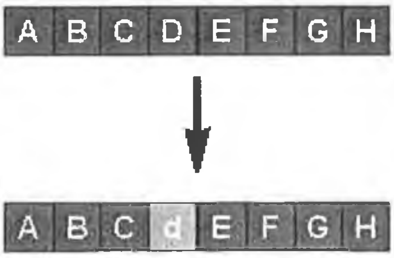

Figure 2.7: Example of mutation in GA

Asexual reproduction, or mutation, is performed by randomly selecting a parent with a probability related to its fitness, then randomly changing one or more genes representing part of the solution it encodes. The fitness of the new individual is assessed, and it replaces a less-fit member of the population if one exists.

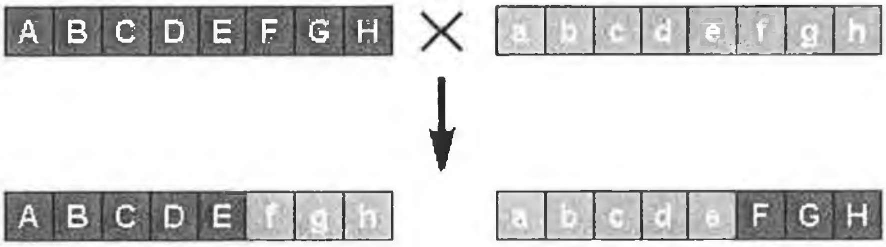

Figure 2.8: Example of crossover in GA

Sexual reproduction, or crossover, is achieved by randomly selecting two parents, again at a rate related to their fitness, and generating new individuals by copying genes from one parent, switching to the other at a randomly-selected point. The two new individuals then replace less-fit members of the population as before. The creation of new individuals by mutation and crossover is repeated until an acceptably fit individual is produced. In a steady state GA, only one individual is created per generation; in a generational GA, many new individuals are created at each new generation.

When using GA to optimize solutions, practitioners are faced with two primary difficulties. First, the design of a suitable measure of fitness can be problematic.

Typically, GAs are used to tackle ill-defined problems with poorly constrained parameter spaces, consequently the design of a good measure of fitness may be problematic. In many cases, the only solution is to apply the candidate solution to a representative sample of the problem population and use its average performance as a fitness measure. This has the disadvantage of being computationally expensive, but results in very accurate fitness measures.

The second difficulty is with the syntactic validity of the results of mutations. For example, if we were to encode the topology and interconnection of an MLP as a genome for use in GA optimization, one can envision a wide range of problems. For example, each interconnect would probably be encoded by three numbers, representing the source node, destination node, and weight respectively. Should a mutation occur which modifies the destination node number, the result may be a number for which there is no corresponding node in the topology of the network. In this case, we would be left with a link that goes nowhere and a completely useless network as a result. Careful consideration of the mapping from genome to target system can usually eliminate many of these problems, which drastically slow the evolution of near-optimal solutions.

2.14 Blackboard models

The blackboard architecture (Erman et al., 1980) was developed to deal with the difficult characteristics of the speech understanding problem: a very large search space, error prone or incomplete input data, and imprecise problem solving knowledge. These characteristics require a problem solving model that supports the incremental development of solutions, can apply diverse types of knowledge, and that can adapt its strategies to the particular problem situation. The blackboard model has proven popular for complex problems because it supports incremental problem solving and because it provides a great deal of flexibility in structuring the problem solving process. For example blackboards facilitate problem solving techniques in which the system dynamically switches among different levels of abstraction and in which multiple lines of reasoning are concurrently processed.

While the blackboard model supports the kind of problem solving that is appropriate for complex problems, there are still many issues that must be addressed in order to solve such problems. In particular, effective control is critical in blackboard applications that involve significant uncertainty in the data and problem solving knowledge. However, it can be difficult to effectively utilize the features of the model that are the source of its flexibility because they complicate the process of selecting actions with the maximum expected value. As a result, control was a major issue in the formulation of the architecture and it continues to be an active area of research in the field of blackboard systems.

In the blackboard model that emerged from Hearsay II developed by Erman et al. (1980), a blackboard system is composed of three main components: the blackboard, a set of knowledge sources (KSs), and a control mechanism. The blackboard is a global database, shared by all KSs that contains the data and the hypotheses, where hypotheses represent potential partial solutions. The blackboard is structured as a loose hierarchy of levels, particular classes of hypothesis are associated with each level, and hypotheses are typically linked to hypotheses on other levels. The levels themselves are structured in terms of a set of dimensions. This makes it possible to provide an efficient associative retrieval of related hypotheses based on the notion of an area of the blackboard. The set of knowledge sources embody the problem solving knowledge of the system KSs examine the state of the blackboard and create new hypotheses or modify existing hypotheses as appropriate. Ideally, KSs should be independent: their execution should not explicitly depend on the execution of other KSs and any communication of information between the KSs occurs only via the creation and modification of hypotheses on the blackboard.

Among the essential ideas behind the blackboard model are that problem solving should be both incremental and opportunistic. Incremental problem solving means that complete solutions are constructed piecewise and concurrently at different levels of abstraction.

Because KSs in the HSII blackboard model are both independent and self activating, in a sense there is no need for any additional control mechanism: when a KS finds that it is applicable given the current contents of the blackboard, it executes. Despite the appeal of a model without any control component, this approach has two serious problems. First, because of the prevailing computer architecture, the execution of KSs must be sequentialised. This means that KSs cannot really execute as soon as they become applicable. It also means that the checking of KS preconditions must compete with the execution of KS actions for processor resources. The second problem with the approach is that blackboards are typically applied to combinatorially explosive problems. Such problems become intractable if the system attempts to execute all the KS actions that are applicable prior to finding a solution. When "unpromising" actions are executed, they waste processing resources by triggering further actions that do not move the system closer to a solution.

For these reasons, practical applications such as Hearsay II use a supplementary control mechanism. All possible actions are placed onto the agenda, on each cycle the actions are rated, and the most highly rated is chosen for execution.

2.15 Example of Blackboard application - speech recognition

In a typical blackboard system for speech recognition, the blackboard and its KSs or *agents* are segmented into the following broad categories:

1. Phonemes
2. Words
3. Syntactic
4. Semantic

When an utterance is processed, the first level of agents attempts to categorize the sounds into a series of phonemes. In modern speech recognition systems, the output of this stage is a large set of alternative phoneme strings, with associated probability measures. The fact that all potentially viable solutions are posted to the blackboard from the outset is an important point. This way we do not enter a cycle whereby an upper level-processing unit rejects a potential solution, and then requests that the initial transformation of sounds into phonemes be executed again. It also has the advantage that the solution which will ultimately be selected as the "winner" exists in seed form in the pool of possible solutions from the outset. This has the effect that the solution is converged upon more quickly, since each stage of processing should result in monotonically increasing probability assignments to the winning solution.

Stage 2 processing attempts to translate the phoneme strings into word strings. Certain phoneme strings will contain series of phonemes for which no word exists. Such strings are eliminated from future processing. The remaining phoneme strings are then associated with word-strings that are assigned probabilities. At this point, the assumption is made that the boundary between any two phonemes is a potential word boundary.

It should be noted that at this point, stage 1 processing may analyse the productions of stage 2 processing and decide that the word-boundaries chosen for certain translations of phoneme strings into word strings are invalid. Stage 1 is permitted to do this since it has expert knowledge on the auditory form of the utterance, which no other level has. If the word boundaries chosen are below a certain threshold probability, stage 1 can eliminate them from future processing and remove them from the blackboard.

Stage 3 processing analyses the word strings produced and eliminates those which it deems to be syntactically invalid. Typically this stage is conservative, and will only eliminate word strings containing sequences that have a high probability of being complete gibberish. While eliminations are rare, the probability of each word string is adjusted given its syntactic viability. Syntactic analysis is normally carried out at the sub-clause level, since comprehensive grammars which are applicable at the level of sentences and which do not result in a large degree of false negative classification have yet to be developed. Due to the complexity of nuances in human speech and the variability of speech patterns over relatively small geographical areas it is arguable as to whether it is possible for a syntax validation system to be universally accurate. In many database query applications, the domain of inquiry is closed, and the form of valid queries is imposed upon the user from the outset. In such a situation, the syntactic analysis module has far greater influence on the classification problem.

At this point, as before, the lower stages (1 and 2) may again analyse the word strings remaining on the blackboard, and adjust their associated probabilities.

Stage 4 processing analyses the semantic content of the word strings. In practical applications such analysis is only possible when a closed domain is used. Sonas is such a system in which the semantic level of analysis and processing concerns the actions possible within the virtual environment. Utterances are given meaning through reference to objects in the environment and the actions that may be carried out upon them. Similarly, other systems will attribute semantic content to phrases based on the particular domain of application.

The blackboard architecture has a proven record of success in domains in which classification problems require the application of disparate expertise. The ability of such systems to apply knowledge simultaneously from a variety of levels of feature granularity in many ways simulates the manner in which many cognitive processes (for example vision) are known to operate. It is this essential feature of the architecture that will be revisited in later chapters.

2.16 Summary

In this chapter, we have given a representative sample of the current computational techniques available to computational modellers. Some, particularly the Kohonen architecture, are both biologically plausible and computationally effective; others, such as the standard feed forward MLP are completely implausible due to their supervised learning methodologies. What is in evidence is that there is no single architecture that embodies more than a small number of the essential aspects of biological information processing systems.

The next chapter will examine neurophysiology in some detail. The information presented and referenced therein will be used in subsequent chapters to create a new model of the neuron and an associated architecture. Many of the ideas presented in this and the following chapter will be embodied in this new architecture. Some trade-offs between computational efficiency and simulation accuracy are inevitable, yet it is the intention of this research to create a model that strikes an acceptable balance. For this reason, the following chapter dwells at length on the nature of the biological neuron.

Chapter 3

Neuroscience

3.1 Introduction

In the brain, there are a variety of neuron types, with widely varying characteristics (Burnod, 1990). Here we outline the basic features of a neuron, which are common to most of the family.

The neuron cell consists of a cell body, or soma, containing the cell nucleus. The dendrites form a tree-like structure around the cell; their purpose is to receive input from other cells. A single long fibre called the axon transmits electrical impulses from the cell down its length and to output synapses. The synapse is a gap between the end of the axon and a dendrite. When an electrical impulse reaches a synapse, chemicals are released which traverse the gap and cause an electrical impulse in the post synaptic cell.

3.2 Ion Channels and Action Potentials

Action potentials are generated and sustained by ionic currents through the cell membrane. The ions most involved are sodium, Na+, calcium, Ca++, and potassium, K+.

The neuron at rest maintains a potential difference between the inside of the cell and the surrounding medium. The Na+/K+ ATPase is a transporter that transports Na+ ions out of the cell and Ka+ into the cell. For each 3 Na+ ions it transports out, 2 Ka+ are transferred in. The result is that a net charge is established across the cell membrane. The interior is negatively charged with respect to the exterior. This charge is referred to as the resting potential. In neurons the resting potential is typically in the region of -70mV.

The charge across the membrane is reduced by certain external stimuli. The stimuli may be mechanical, for instance through cell deformation, stretching or compression. Such mechanical effects are the means by which sound and vibration is transformed into neural activity. A similar process is involved in tactile sensory cells, whereby the deformations of receptor cells caused by physical contact result in action potentials.

Neurotransmitter chemicals making contact with receptors on the cell membrane or dendrite surface result in a the opening of gated channels on the cell membrane. This will result in a tiny current flowing into the cell, thereby depolarising it slightly.

The membrane of the neuron has transmembrane proteins embedded in it. These proteins permit the passage of certain molecules under particular conditions, and are therefore referred to as channels. The Na+ channel is voltage-gated, meaning that when the voltage rises above a certain threshold, the gate opens, and sodium ions may pass through the channel. The rules governing the opening and closing of channels can be reasonably complex. Channels may open in response to voltage changes, chemical stimulation or mechanical deformation. Channels may close as a result of any of these stimulants, or they may close after having been open for a certain period. The flow of a particular type of ion across the membrane is a function of the density of that ion's channels, their activation, and the relative concentration of such ions internal and external to the cell (osmotic pressure).

An increase in the absolute membrane potential (i.e. a depolarisation of the cell) activates (opens) Na+ and/or Ca++ channels, resulting in rapid inflow of the ions. This has the effect of *depolarising* the cell, making the interior less negative with respect to the exterior. As a result more channels will open. Such positive feedback leads to sudden and abrupt depolarisation. This triggers a relatively slower process of activation of K+ channels, which leads to increased K+ current and eventually re-polarises the cell.

These positive and negative feedback mechanisms are responsible for the generation of action potentials. There are more than a dozen of various ionic currents having diverse activation and inactivation dynamics and occurring on disparate time scales (Llinas, 1988). Almost any combination of them could result in interesting non-linear behaviour, such as neural excitability. Therefore, there could be thousands of different biophysically detailed conductance-based models. None of them is completely right or wrong.

The action potential is generated at the axon hillock, where the density of voltage-gated sodium channels is greatest. The action potential begins when signals from the dendrites and cell body reach the axon hillock and cause the membrane potential there to become more positive, a process called depolarization. These local signals travel for only a short distance and are very different from action potentials. As the axon hillock depolarizes, voltage-gated channels for sodium open rapidly, increasing membrane permeability to sodium. Sodium moves down its electrochemical gradient into the cell. If the stimulus to the axon hillock is great enough, the neuron depolarizes by about 15-20 milliVolts and reaches a trigger point called threshold.

At threshold, an action potential is generated. Weak stimuli that do not reach threshold do not produce an action potential. Thus, the action potential is an all-or-none event. Threshold is a special membrane potential where the process of depolarization becomes regenerative, that is, where a positive feedback loop is established

3.3 Computational Models of Neurons

The most detailed and successful mathematical description of the neuron is provided by the Hodgkin-Huxley equations. These describe a detailed model of the processes at work in the biological neuron. The ionic flows across the cell membrane are modelled to a reasonable level of granularity, such that one would expect that all of the major macro-phenomenon would be captured by the model. Computational implementations based on the Hodgkin-Huxley model have met with much success as tools used by neuroscientists to examine the behaviour of individual neurons in great detail and across very short time-scales. The Genesis simulator is one such implementation that uses compartment techniques. The neuron, dendrites and axon are modelled as a large group of connected cylindrical compartments. The electrical and chemical states of interest are then modelled for each individual compartment. This results in extremely accurate simulation of the biological processes at work. When simulating large numbers of neurons this approach becomes computationally expensive. It is not generally possible to use such systems to tackle practical problems such as pattern recognition and classification due to the length of time required to simulate the model.

The model of the neuron that has been most useful to computer science is the integrate and fire based model Rumelhart and McClelland (1987) as described in the previous chapter. This model is computationally efficient, and particularly well suited to vector processors. However it does not model any of the characteristics of ion flow across the cell membrane. It models the neuron as a stateless function, the output of which is determined by its inputs at the same instant.

The ANN systems built on this model of the neuron capture some aspects of biological networks, such as parallel processing, graceful degradation and adaptive learning. They fail to achieve shift invariance, any temporal sensitivity or suitability for spectral processing. A goal of this thesis is to examine the effect of the addition of the most important characteristics of biological neurons to the computational model.

3.4 Hodgkin Huxley Model

The Hodgkin-Huxley model prescribes a set of differential equations which relate the membrane potential across a neuron cell membrane to the flow of ions across the cell body. Significant computational resources are required in order to simulate a neuron using these equations. Several hours of computing time is required to simulate less than a second. For this reason, the model is primarily of use to practitioners who wish to investigate the behaviour of a particular neural cell type. Tools exist for the simulation of neural cells through compartmental models, in which the neuron is modelled as a large array of connected compartments. The Hodgkin Huxley equations are applied to each compartment independently.

$$\frac{dV_m}{dt} = \frac{-1}{C}(g_{Na}(V_m)(V_m - V_{Na}) + g_k(V_m)(V_m - V_k)) \qquad (3.1)$$

Hodgkin-Huxley equation relating the rate of change of the membrane potential to the membrane capacitance, C, conductance to sodium, g_{Na} and potassium, g_k, and the membrane potential with respect to sodium, V_{Na}, and potassium, V_k

The model was invented in the 1950's and has formed the standard mathematical formalism for modelling the dynamics of neurons at the ion-channel level since then. What is interesting is that most practitioners use the model to generate spike trains; a less utilised feature of the model is that it represents a natural resonator. In most applications and studies the resonance effects implicit in the model have been ignored or alluded to merely as being an epiphenomenal artefact. This would be acceptable were it not for the fact that the Hodgkin-Huxley model is excruciatingly detailed and faithful to the bio-chemical processes at work in the neuron.

3.5 Dynamic systems perspective

Izhikevich (2001) and others have begun to focus on the resonance phenomenon in recent times. Their work illustrates the process by which neurons may exhibit either integrative or resonance properties. Izhikevich posits that the neuron experiences a bifurcation of the rest state and depending on the outcome subsequently behaves as either an integrator or a resonator.

If the rest state disappears via fold or saddle-node on invariant circle bifurcations, then the neuron acts as an integrator; the higher the frequency of the input, the sooner it fires.

If the rest state disappears via an Andronov-Hopf bifurcation, then the neuron acts as a resonator; it prefers a certain (resonant) frequency of the input spike train that is equal to a low-order multiple of its eigenfrequency. Increasing the frequency of the input may delay or even terminate its response.

Integrators have a well-defined threshold manifold, while resonators usually do not. Integrators distinguish between weak excitatory and inhibitory inputs, while resonators do not, since an inhibitory pulse can make a resonator fire. Integrators can easily encode information about the intensity of stimulation into their mean firing rate, whereas resonators cannot. In contrast, resonators are sensitive to the fine temporal structure of the input spike train, while integrators are not because they average (integrate) it.

The resonance model better supports the known sensitivity of biological neurons to timings of spikes, such as coincidence detection.

The average size of a post synaptic potential is *less than 1 mV*, which is small in comparison with the mean size necessary to discharge a cell, around 20 mV. This suggests that integrator neurons are sensitised to a large number of coincident input spikes, or a very rapid series of spikes from a small number of inputs. It also suggests that there is room for more complex evolutions of the membrane potential, as opposed to the conventional view that the neuron behaves as a simple short term integrator.

3.6 Subthreshold Oscillation

Pribram (1991) sees the dendritic microprocess as a central location of computational activity in the brain. Spike trains, action potentials are seen more as communicative devices than as the essence of the computational process. Izhikevic's resonate and fire neuron and the neural model described later place greater emphasis on the dendritic microprocess than conventional neural network models.

An important departure in Pribram's (1991) work is the emphasis on the role of dendro-dendritic connections. Such connections are similar to normal axonal-dendritic synaptic connections; however, the entity being transmitted is not an action potential, instead it is the electrical potential of the neuron interior. In this way, Pribram proposes that computations can occur which involve multiple neurons, but which do not utilise axonal action potentials. This is not to say that action potentials are relegated to insignificance in the model; the dendritic processes have been recognised as potentially providing a key substrate within which useful computation is done.

Recent evidence from experimental studies has confirmed that subthreshold dendritic dynamics are complex and would appear to have an important role to play in the computational activity of the brain. Particularly, calcium channels (Schutter and Bower, 1993) react strongly to sub-threshold inputs (Callewaert et al., 1996). Eilers and Konnerth express the case for the dendritic process thus:

> Results obtained by using high resolution imaging techniques provide clear evidence for new forms of neuronal signal integration. In contrast to the quickly spreading electrical potentials, slower intracellular signals were found that are restricted to defined dendritic compartments. Of special significance seem to be highly-localized, short-lasting changes in calcium concentration within fine branches of the neuronal dendritic tree. These calcium signals are evoked by synaptic excitation and provide the basis for a dendritic form of signal integration that is independent of the conventional electrical summation in the soma. There is experimental evidence that dendritic integration is critically involved in synaptic plasticity.

3.7 Neural Signalling and Representation

In order to properly assess the relevance of the various characteristics of the neuron it is important to understand how such characteristics are utilised for the purpose of information processing.

3.7.1 Integrate and Fire

It was Sherrington (1906) who first suggested the concept of the integrate-and-fire neuron. Under this scheme, each neuron sums the input activity incident upon itself over a specified period. The higher the frequency of the input spike trains, the larger the input activity is considered to be. The neuron is then assumed to respond with a firing rate that is a function of the input firing rates. Pitts and McCulloch (1943) formalised the model and showed how to encode any logical proposition in a network of their neurons. Similarly, any network could be shown to encode a logical proposition.

Coombs et al. (1957) used spinal cord recordings to correlate the spike frequency with the intensity of the applied stimulus as well as the intensity of the perceived sensation. Under the frequency-coding scheme, neurons encode information by frequency modulation of action potentials output on the axon. Increased firing rates in the presence of certain stimuli were taken to indicate that the neuron under observation was reacting directly to the presence of the feature which it was tuned to react to.

An alternate view of neuronal signalling which uses frequency coding as its basic component is that of "population coding" (Pouget et al., 2003; Georgopoulos et al., 1982). Under this scheme, the intensity or salience of the content is conveyed using frequency modulation, but the content itself is represented by a distributed combination of spike trains across a population of neurons.

3.7.2 Visual Features

In terms of visual processing, the assumption of feature detection follows a Euclidean geometry hierarchy. First, there are point and line detectors. These feed into edge and boundary detectors, and so on up the scale. Barlow (1972) suggested the possibility of such hierarchies when he made the claim that aspects of perceptual awareness are related to the activity of specific neurons. The "grandmother" cell hypothesis follows logically from this sequence. This concludes that there can be a single cell in the brain which is best attuned for a single recognition task, such as the recognition of a single human face (Grandma's). There has been some experimental evidence for such "fine tuning" of individual neurons, such as the demonstration (Tanaka, 1993) of "grandmother" style cells in monkeys which respond to moderately complex figures.

There are numerous problems with such specific specialization of function at the cellular level. From a redundancy viewpoint, it is simply bad design to have a single point of failure of the recognition process as would be the case were a single cell assigned to a single pattern. A key feature distinguishing neural networks from other computational devices is the property of graceful degradation - meaning that a large part of the system can be destroyed without completely annihilating the behaviour of the system.

Hubel and Weisel's work on the receptive fields of individual neurons in the cat's striate cortex was taken by many as proof positive that visual perception followed the Euclidean hierarchy of points, lines and contours, shapes and forms (Hubel and Wiesel, 1959). Each stage was seen to be built on the previous. The basic assumption underlying this scheme is that the visual processing operation begins with a two dimensional retinal image formed by the eye. As Pribram (1991) observes, the situation is much more complex than that. The optical image is a flow in at least three dimensions, the retinal image is curved, not flat, and the perceptual system has evolved to operate under conditions where the subject is moving. As experiments (Rock, 1983) show, the primitives of perception are "relations between changes in oculocentric and egocentric direction. Lines and edges are not the primitives that configure the perceptual process; lines and edges result from the perceptual process, they do not determine it." (Pribram, 1991).

This is not to say that the whole paradigm of viewing neural perceptual stages as feature extraction exercises is wrong. Rather that it is time to examine carefully the assumptions underlying the choice of features that we think are being extracted.

3.8 Temporal Coincidence Coding

The problem of integrating perceptual data that is processed in spatially disparate locations in the brain into a coherent unitary perceptual experience is referred to as the binding problem. Given the assumption that one set of neurons will fire in response to "redness" in the retinal field, and another will fire in response to "roundness", how does the brain reconcile the two classifications into a single response which represents "red ball"?

Many researchers including Shastri and Ajjanagadde (1993) propose that the temporally coincident receipt of action potentials from the disparate feature recognition modules by a higher order feature recognition module as the solution to the binding problem. Much excitement surrounded the idea that a 40Hz oscillation detectable using EEG was somehow representative of the process of binding and thereby related to consciousness. While it would appear that the phenomenon is somewhat involved in the integration of sensory data no conclusive evidence has been produced which rigorously specifies the function being implemented.

Temporal synchrony operates as follows. Given a problem space, such as sentences of the class "John gave Mary the book" we can represent the meaning of the sentence using temporal synchrony. First, we label a neuron or group of neurons as "giver". Then in the same way, we assign the labels "recipient" "Mary", "John" and "Book".

All permutations of the sentence class, e.g. "Mary gave John the book", and indeed "Book gave Mary the John" can be validly represented under this scheme. The fact that invalid constructions are permitted is considered a drawback of the scheme. Neither syntactic rules nor internal structure is imposed by the architecture and as such its ability to represent highly structured domains without augmentation is limited.

A difficulty with temporal synchrony as a representation scheme is the fact that it relies on a "higher order" detector that is supposed somehow to integrate the synchronous data into perceptual affect. This smacks of the Cartesian Homunculus, the observer within the brain, and is therefore fraught with philosophical contradiction.

3.9 Summary

This chapter has described the biological neuron in some detail. The manner in which information is encoded in neural activities has been explored, and the prevailing position that action potentials are the ultimate bearers of data in the biological domain has been questioned. The dendritic microprocess has been presented as a potential site for the occurrence of important computational effects.

The resonant sub-threshold oscillations implicit in the Hodgkin-Huxley model, in conjunction with Izhikevich's work on dynamic systems prompt a redirection of attention from the axonal impulse to the dendritic field and the processes therein. The following chapter deals with computational issues once more. We design a model for a new type of computational neuron that is to form the basis of a computationally effective neural architecture; as such it will respond to the concerns about existing computational architectures raised in chapter three. The architecture developed will also accommodate the primary features of the biological systems discussed in this chapter.

Chapter 4

A Computational Model

4.1 Introduction

This chapter presents a new computational model of the neuron for use in connectionist systems.

The Hodgkin-Huxley model of neural dynamics describes in detail the flow of ions across the neuron membrane. The model consists of a number of detailed differential equations describing the interactions between the various flows and parameters such as the prevailing concentration of ions in the surrounding medium. The model has been used extensively to study the production of action potentials; only occasionally have researchers noted that the model actually describes a bistable system. The Hodgkin-Huxley system exhibits a stable low amplitude oscillation which can be considered in isolation to the production of action potentials.

Izhikevich (2001) has identified this characteristic from a dynamic systems perspective. He points out that the Hodgkin-Huxley model is in fact a resonator, and exhibits behaviours which are a superset of the standard Integrate-and-Fire (IFN) model. The low amplitude oscillation of the membrane potential can be sustained for long periods without the need for an action potential to result. Only when the amplitude of oscillation reaches a threshold value does depolarisation and action potential generation ensue. The resonance phase of the process is non-trivial. Complex waveforms are permissible, and would suggest that this phase of neuronal behaviour is of some importance to the behaviour of cognitive apparatus. The oscillations are directly related to the action potential, since the same parameter, membrane potential, is central to both phases. Since the action potential is of undoubted importance to the activity of the brain, it would appear that an intimately related phenomenon should be given thorough consideration. The IFN model is the result of a view of the neuron which only considers a brief period prior to the generation of the action potential. As such, we will show that the resonate and fire model is a superset of the IFN, that it is capable of capturing all of the properties of the IFN in addition to new and interesting capabilities with strong evidence supporting the idea that such properties are critical to dealing with sensory data.

4.2 Resonance

The physical basis for the sub-threshold phase of the resonate and fire model lies in the fact that every object has a frequency or a set of frequencies at which they naturally vibrate when struck or somehow distorted. Each of the natural frequencies at which an object vibrates is associated with a standing wave pattern. Standing waves are formed when oscillations are confined to a volume, and the incident waveform from the source interferes with the reflected waveform in such a way that certain points along the medium appear to be standing still. Such patterns of interference are produced in a medium only at specific frequencies referred to as harmonics. At frequencies other than the set of harmonic frequencies, the pattern of oscillation is irregular and non-repeating. While there are an infinite number of ways in which an object can oscillate, objects prefer only a specific set of modes of vibration. These preferred modes are those which result in the highest amplitude of vibration with the least input energy. Objects are most easily forced into these modes of vibration when disturbed at frequencies associated with their natural frequencies.

4.3 The Model

The model described here seeks to compromise between biological accuracy and computational efficiency. The level of granularity of the model is an essential factor in this compromise. In order to model systems with many interacting neurons, it is necessary to avoid the computational overhead of compartmental models. The current model provides no spatial extent for its neurons. The mathematical model of the harmonic oscillator is used as a basis for the development of the resonate and fire model's sub-threshold dynamics. The entity that actually oscillates is the membrane potential. The driving forces are the input spikes received on the neuron's dendritic field, and potential transfer through dendro-dendritic or gap junctions. When the neuron's activation, or membrane potential, reaches the threshold level, the model simulates the opening of Na channels and their subsequent closure, and the opening and closing of K channels. In contrast to IFN models, the RFN does not have distinct activation and output, there is no transfer function that transforms activation into output. The activation itself is the output, but is transmitted through the axon only when activation is supra-threshold.

The fundamental frequency of the neuron is a tunable parameter, in our consideration; the details which would determine this quantity in the biological instance are omitted. We treat it simply as a single parameter that may be set arbitrarily. Simulations of compartment models reveal that preferred oscillation frequency is a function of the ratio of a compartment's surface area to its volume, and those oscillations are primarily generated by Calcium ion flow (Wilson and Callaway, 2000).

4.4 Implementation

We consider an idealized harmonic oscillator, a mass on a spring. There is a single point of equilibrium in such a system, where the position of the mass is at the point where the spring is neither compressed nor stretched. The mass is assumed to be floating in free space outside the influence of the gravitational force, while the other end of the spring is bound to an idealized fixed point. The mass is displaced from the equilibrium point by the arrival of an impulse of negligible duration. The displacement of the mass then oscillates back and forth past the equilibrium position. The spring exerts a return force proportional to the magnitude of the displacement. The frequency of oscillation is determined by both the size of the mass and the magnitude of the return force exerted by the spring. All such oscillations gradually die off (and remain almost at the same frequency), due to the damping effects of friction.

When driving the motion of a simple harmonic oscillator with short impulses, to increase the amplitude of oscillation the impulse must be applied in phase with the basic oscillation. An out of phase impulse has the effect of decreasing the amplitude of oscillation. By analogy, the phase of oscillation of the post-synaptic neuron at which action potentials arrive at a synapse is significant, and may determine whether an action potential is evoked in the post-synaptic neuron.

The mathematical details of the sub-threshold phase of the model follow directly from those used to describe harmonic oscillation in bodies such as the mass on a spring and pendulums. The task here is to translate the basic ideas into a form applicable to the resonate and fire neuron. Additionally we must formulate this in a manner that is amenable to computational implementation. The implementation will be a standard discrete time finite element simulation, following directly from the equations governing the model.

The starting point for analysis is to consider the mass on a spring arrangement. Here we have a mass that is displaced from the equilibrium point by ψ at any given moment; this displacement may be positive or negative. Due to the physical form of the spring, the mass always experiences a return force in the opposite direction to the current displacement.

$$F_s = -s\psi \tag{4.1}$$

Where s is a positive constant referred to as the spring constant. This equation captures the fact that the return force is proportional to the current displacement. This is a key fact in that such systems are characterized among harmonic oscillators Main (1993).

The basic behaviour of harmonic oscillators is captured by the differential equation:

$$\ddot{\psi} \equiv \frac{d^2\psi}{dt^2} \tag{4.2}$$

By Newton's second law, we can relate the mass, return force and acceleration thus:

$$m\ddot{\psi} = F_s \tag{4.3}$$

Substituting we arrive at

$$m\ddot{\psi} = -s\psi \tag{4.4}$$

The above equation states that the current acceleration is proportional to the current displacement, and in the opposite direction.

For convenience, we rewrite the equation in its more common form, replacing m and s with the term ω, defined below.

$$\ddot{\psi} + \omega^2\psi = 0 \tag{4.5}$$

The term ω is defined as

$$\omega \equiv \sqrt{\frac{s}{m}} \tag{4.6}$$

This result allows us to re-express the acceleration term in terms of w_0:

$$\ddot{\psi} = -\omega^2\psi \tag{4.7}$$

A particular example of an equation which represents a solution to the general differential relation described above is written.

$$\psi(t) = Acos(w_0 t + \phi) \tag{4.8}$$

where A is any constant length and ϕ is any constant angle. The parameters which give an oscillator its unique properties are A, w_0 and ϕ. The value of A determines the amplitude of oscillation, how far the maximum displacement from equilibrium will be. The ω term determines the strength of the returning force. This in turn determines how quickly the mass returns to the equilibrium point (and indeed the velocity at which the equilibrium is passed). This equates to the more familiar concept of the frequency of oscillation. The frequency of oscillation is the number of complete cycles performed per second, and is the inverse of the period, the length of time required to complete a single cycle.

The period of oscillation of such a system is denoted T and related to the other terms as follows:

$$T = \frac{2\pi}{\omega} \tag{4.9}$$

from this it is apparent that

$$\omega = \frac{2\pi}{T} = 2\pi f \tag{4.10}$$

In a fashion similar to the delta functions used to describe the IFN, we now demonstrate the operation of the resonate and fire model in mathematical terms. First, we must define some variables unique to the model:

$$\omega_i = f_i 2\pi \tag{4.11}$$

Where f_i is the resonant frequency of node i. The term ω_i is the angular frequency for node i. This term is introduced since it may be calculated once the resonant frequency is specified, and thus does not need to be calculated subsequently.

$$\Delta\dot{\psi}_i = \Sigma w_{ij} o_j - \omega_i^2 \psi_i dt - \beta\dot{\psi}_i \tag{4.12}$$

The rate of change of the membrane potential ψ of neuron i, or its velocity, is denoted by $\dot{\psi}_i$. During simulation the velocity delta is calculated at each time step, of duration dt. The contribution from input pulses from all pre-synaptic neurons is calculated by the sum of products term $\Sigma w_{ij} o_j$, where w_{ij} is the weight of the connection from neuron j to neuron i, and o_j is the current (axonal) output of neuron j, which is zero if that neuron's activation is below threshold and is the difference between threshold and activation otherwise, i.e. $max(0, Activation - Threshold)$.

The return force's contribution to the velocity calculation is expressed as $\omega_i^2 \psi_i dt$, which is the expression we arrived at for $\ddot{\psi}$ previously, scaled by dt. The final term is the damping factor. The damping constant, β ranges from 0 to 1, and is typically assigned a value of around 0.01, but can be tuned depending on the desired behaviour. The effect of this parameter is to cause the oscillation to gradually die off.

$$\Delta\psi = \dot{\psi}_i dt \tag{4.13}$$

The calculation of the new membrane potential, ψ, is straightforward once we have calculated the new velocity. In a single simulation step ψ will change by the product of the current velocity $\dot{\psi}_i$ and the duration of the step dt. At this point we have calculated the new membrane potential. All that remains is to handle the production of action potentials.

4.5 Action Potentials

When the RFN's activation reaches threshold, denoted θ, the simulation enters a new state. The opening of Na channels is emulated by injecting a constant depolarising current into the neuron's activation. This process lasts approximately $1ms$ and is immediately followed by transition to a third state, wherein K channels opening are emulated by injection of a constant polarising current into the neuron. The K channels remain open for slightly longer than the Na channels, resulting in the neuron returning to well below threshold, typically it is hyperpolarised beyond resting potential. At this point the neuron returns to standard sub-threshold operation.

The mathematical structures described thus far handle axonal inputs from pre-synaptic neurons. Another major feature of the model is direct dendro-dendritic connections. This aspect is accommodated through a simple extension to the delta rule.

$$\Delta\dot{\psi}_i = \Sigma d_{ij}(\psi_j - \psi_i) + \Sigma w_{ij}o_j - \omega_i^2\psi_i dt - \beta\dot{\psi}_i \tag{4.14}$$

The new sum of products term $(\Sigma d_{ij}(\psi_j - \psi_i))$ is the sum across all neurons providing dendritic inputs to neuron i, of the products of the current membrane potential of neuron j, ψ_j, minus the current membrane potential of neuron i, ψ_i and the weight of the dendritic connection from neuron j to neuron i, denoted d_{ij}. This factor is the key element in the creation of the dendritic field, through which waveforms may propagate. The difference between the axonal inputs and the dendritic connections in this model is that axonal inputs permit the transmission of single impulses, o_j. The term o_j is non-zero only when neuron j has generated an action potential, while the term ψ_j is always non-zero, hence the difference between the two sum-of-product terms. The dendritic connections transmit electrical potentials which cause recipient neurons' membrane potentials to tend toward their own.

It is easy to extend this model to provide for propagation delays. Each neuron is modelled as a set of parameters, including the current value of ψ_i. We extend this to provide a history of the values of these parameters. As each time step of the simulation passes, the new value calculated for ψ_i becomes the "current" value, while the old value is stored in a deque. Axonal and dendritic connections are then augmented to specify which element of the history array they refer to, so that instead of using the current value of ψ_j or o_j in the delta rule, we may use the value as it was n time steps ago. For convenience of implementation, the current value is stored in the history array as element 0, element 1 is the value as it was during the previous simulation step, and so on. The terms d_{ij} and w_{ij} which represent the parameters of the connection, are augmented to account for this, with a superscript, t indicating the element of the history array that they refer to. This additional parameter is a fundamental property of the network topology of a resonate and fire network. So the final delta rule, which encapsulates resonance, axonal inputs, the dendritic field, and propagation delays, becomes

$$\Delta\dot{\psi}_i = \Sigma d^t_{ij}(\psi_j - \psi_i) + \Sigma w^t_{ij}o_j - \omega_i^2\psi_i dt - \beta\dot{\psi}_i \tag{4.15}$$

4.6 Oscillation as Threshold Modulation

The oscillation of the membrane potential can be alternatively viewed as the oscillation of the threshold at which the action potential is generated. The arrival of an excitatory pulse to a dendrite will result in the summation of the current membrane potential with the new input. If the current membrane potential is high, smaller input will result in the threshold being reached and an action potential being generated. Similarly, if the current potential is low, a larger input will be required to force the resultant potential across the threshold. From this viewpoint, the resonate and fire model can be seen to be a superset of the IFN model. The behaviour of the IFN model can be simulated with a resonate and fire neuron with a low resonant frequency (long period). Input spikes are then summed in the usual manner with negligible influence from the oscillation of the membrane potential.

4.7 Phase

The resonate and fire model surpasses the IFN model's capabilities when the concept of phase relations are considered. When a neuron is oscillating with sub-threshold amplitude, the arrival of input spikes which are in-phase with the basic oscillation will cause the amplitude of oscillation to increase. Two input spikes, each too small to force the oscillation above threshold, can combine to evoke an action potential by arriving in-phase with the basic oscillation. This does not imply that they must arrive simultaneously, or even proximately. Rather, their arrival must be separated by a period or whole-number multiple of the period of the resonant frequency of the neuron. Such an event is referred to as an "in-phase doublet". Conversely, a spike arriving out of phase with the basic oscillation will cause a reduction in the amplitude of oscillation. Out of phase effects permit one neuron to cancel out the input of another. This highlights the importance of timing when considering the "meaning" of a signal, or the meaning of a pattern of interconnectivity. Conventionally, two neurons which innervate the same post-synaptic neuron with excitatory connections would be assumed to be co-operating to force the target neuron into action-potential production. When the oscillation of the target neuron's membrane is given proper consideration, it becomes clear that the two pre-synaptic neurons may have a dynamic relationship, alternately co-operating and competing, as needs dictate. IFNs on the other hand have a more static mapping between network topology and behaviour.

The sub-threshold oscillation illustrated in figure 4.1 demonstrates the scenario in which a post-synaptic neuron receives input pulses that are not sufficient to cause the membrane potential to rise to the threshold level. Note the waveform adopts a dampened sine-wave shape, reflecting the fact that the mathematical model is based on the harmonic oscillator. At the start of the experiment illustrated, the neuron is experiencing extremely low amplitude oscillations of its membrane

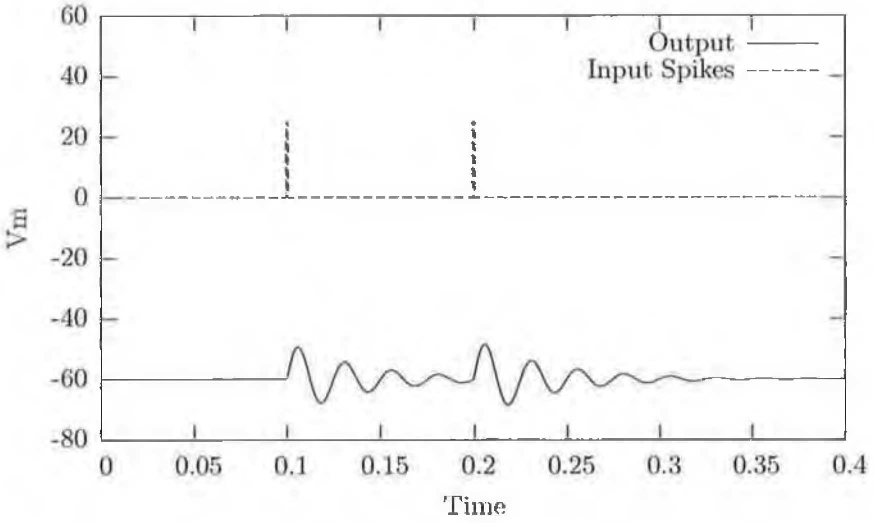

Figure 4.1: sub-threshold oscillation

potential. The first event of note is the arrival of an input pulse. This input pulse somewhat depolarises the membrane potential and large oscillations commence. The oscillations are not of sufficient magnitude to cause the production of an action potential and they gradually decrease in size under the damping force. A second input pulse arrives and is again of insufficient magnitude to cause the production of an action potential. Had the second spike arrived earlier, and in phase, an action potential would result.

The in phase doublet, illustrated in figure 4.2 causes the production of an action potential in the post-synaptic neuron as a result of the

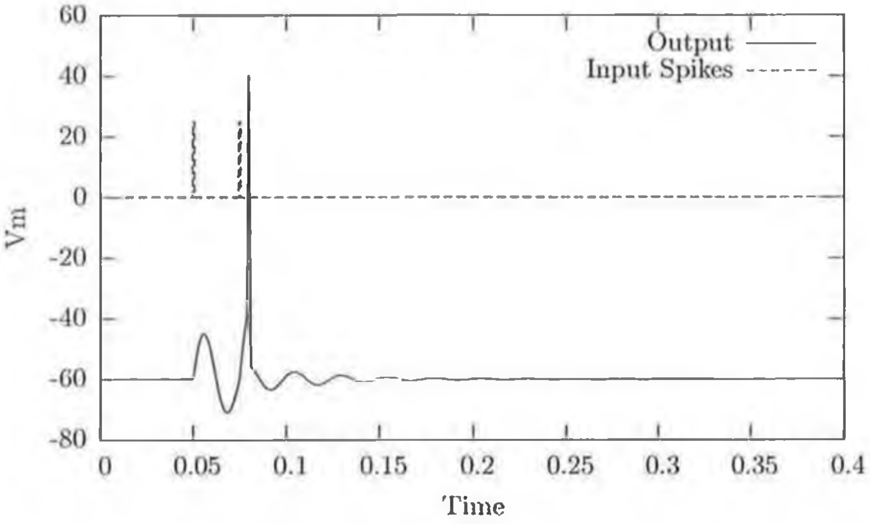

Figure 4.2: In Phase Doublet

inter-spike timing of the input pulses. Note that in this example either pulse on its own is not large enough, the spikes must arrive in phase with each other in order to reinforce the effects of the other. Note that a special case of such in-phase arrival is when both spikes arrive within the first quartile of the neuron's period, that is, both spikes arrive before the first peak of the neuron's oscillation is reached. In such a case, the resonance model behaves as a more straightforward integrator. It should be noted that for simplicity, all received input pulses are plotted on the same trace; in this particular example we consider the pulses to have arrived from different source neurons. The same reaction would occur had a single pre-synaptic neuron produced the input pulses. This is referred to as selective innervation; one such neuron can innervate thousands of others, yet selectively cause a response in a small subset by virtue of the timing of the action potentials it produces. This represents a more detailed exposition of frequency coding than is possible with the IFN paradigm.

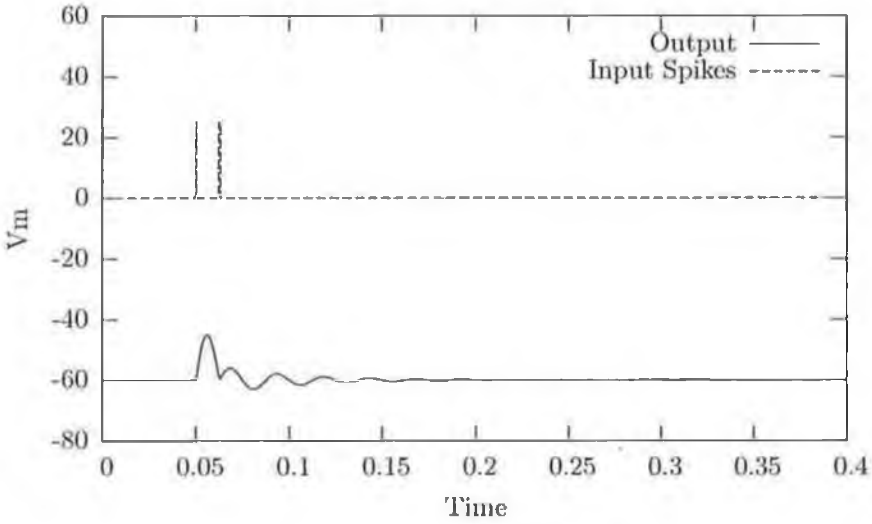

Figure 4.3: Out of Phase Doublet

The effect of an input spike arriving out of phase is illustrated in figure 4.3. The second spike actually inhibits the neuron's oscillation. This demonstrates how the model accommodates a dynamic element when the topology of a particular network is analysed in order to derive the function of its units. The IFN model, in which two neurons that innervate a third node with excitatory connection are always considered to cooperate, does not apply here. Such an event sequence also illustrates the other side of selective innervation, when the post-synaptic neuron is not selected by the pre-synaptic neuron, by virtue of the fact that its resonant frequency means that the inter-spike delay is not an integral multiple of the period of oscillation.

Such properties have obvious applications, one can envision an array of neurons forming a "spectrographic map"; each neuron in the array is attuned to a different resonant frequency. Two input neurons innervate every neuron in the map, so that when the two input neurons fire, the time between their firing (inter-spike delay) will cause a single neuron in the map to react most positively. The neuron that reacts with an action potential is the neuron whose resonant period (the inverse of the frequency) most closely matches the inter-spike delay. Such an arrangement can be generalized to implement a pseudo-Fourier transform of an input channel. Each neuron in the spectrographic map will "own" a particular narrow frequency band. The input channel is a signal containing multiple frequencies superimposed upon one another.

The input innervates all neurons in the map, which produce action potentials if their particular resonant frequency is present in the original signal.

4.8 Further Properties of the RFN

The resonant frequency of an RFN is the primary parameter that determines its behaviour. We can effectively characterise an individual neuron by reference to its resonant frequency, and can communicate the range of responses by way of a frequency response graph. The frequency response graph is obtained by inputting a spike train of gradually increasing frequency to a single isolated neuron. The response of the neuron, either in terms of output spikes produced or internal oscillations may then be obtained and plotted on a graph. This form of investigation permits us to examine the behaviour of the model under a variety of circumstances.

Figure 4.4, the frequency of the input pulses is gradually increased from 10Hz to 100Hz over a 2000 millisecond time frame. The resonant frequency of the neuron is 70Hz. The graph is termed the ZAP response of a neuron. It shows the neuron's response to a range of input

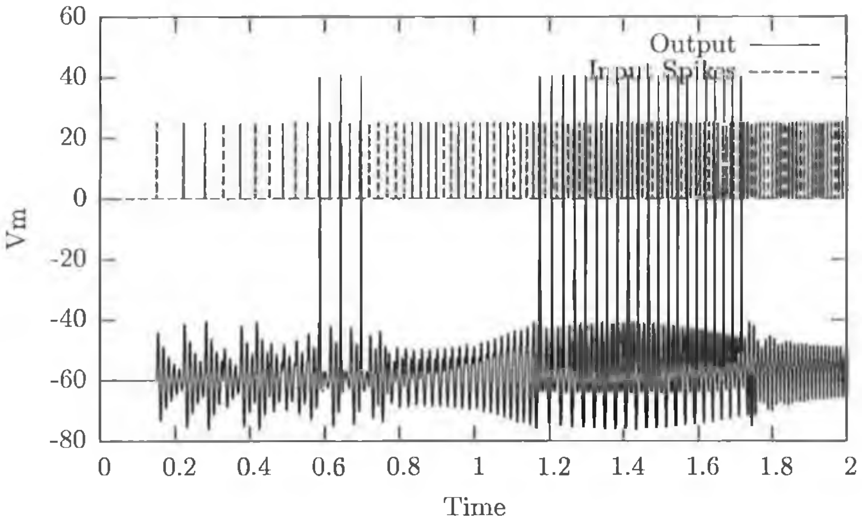

Figure 4.4: Frequency Sensitivity

frequencies, and indicates the range of frequencies of input spikes that will evoke the largest response in the neuron.

The activation curve characterizes the model of the neuron in question. It conveys many of the properties of the system when examined in detail. The primary feature of the graph is the large rise in activation at around 1.2 seconds into the simulation. The input pulse train is set to increase linearly from 10 to 100 Hz. The large rise in activation from 1.2 seconds corresponds to the point at which the input pulse train matches the resonant frequency of the neuron. An interesting feature is the generation of action potentials when the input spike train frequency is approximately half the resonant frequency. In this case, the spikes are arriving in-phase with the neuron's membrane potential oscillation, but only once every two cycles.

The existence of the lower frequency responses suggests a number of potential applications in the perceptual domain, that of sound and tone perception being the most obvious. It is easy to envision a topographic map of these neurons, one for each major note. The same neuron would react to the same note regardless of the octave.

4.9 Dendro Dendritic connections

In addition to standard inputs coming from the axons of pre synaptic neurons, the RFN model implements inputs from the dendrites of other neurons, transmitting the current activation of the pre-synaptic node. This feature is directly inspired by Pribram (1991), who emphasizes the role of such channels in the computational process in the brain.

Here we have modelled the feature in a manner similar to the standard axonal input - the sum of the products of connection weight and pre-synaptic output is augmented with the sum of product of dendritic connection weight and the current activation of the pre-synaptic neuron. Therefore, the only difference is that the current activation is used instead of the current output.

On its own, this mechanism would not be very useful. The contribution from dendro-dendritic connections to a post-synaptic neuron's activation would simply be the linear sum of the current activations of its pre-synaptic neurons. This situation is corrected by the addition of the delay mechanism discussed previously. Each dendro-dendritic connection has an associated weight, and delay. The delay corresponds to a propagation delay in the biological case. As the diagrams illustrate this mechanism permits an innervated neuron to position itself in any position in the interference field of a set of neurons, by tuning the delay parameters of its dendritic connections.

The network illustrated above has a single input which supplies input pulses at approximately 30Hz. The two neurons directly innervated by the input neuron have resonant frequencies of 30Hz, and will therefore have high activation levels. These two neurons innervate the final neuron through dendritic connections. The propagation delays assigned to these two connections, denoted d_1 and d_2, will determine whether the signals interfere constructively or destructively in the out-

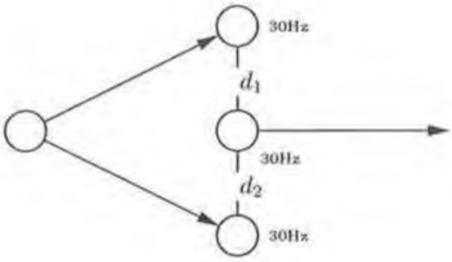

Figure 4.5: Network with two dendro-dendritic connections

put neuron.

Readers familiar with Young's slit experiment may find the analogy useful. In this case, the light source is the input neuron, while the slits correspond to the neurons supplying dendro-dendritic innervations to the output. The screen on which the interference pattern appears is the entire set of possible values of the delay constants; for a particular pair of values we are measuring the interference at a single point on the screen. So, for each experimental simulation of the network, we select a value of the delay constants. As for Young's slit experiment, if the distance from the slits to the point on the screen is exactly the same, then waves from each slit arrive in-phase and constructively interfere. If, however the distance differs by exactly half a wavelength, then destructive interference occurs and the waves cancel each other out.

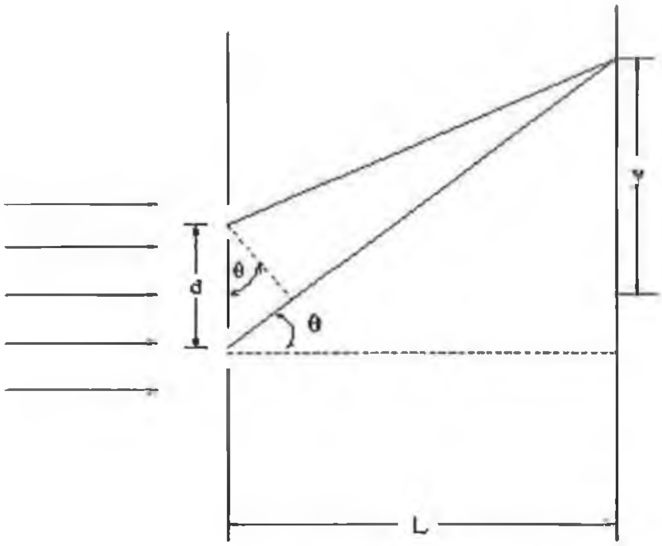

Figure 4.6: Schematic of Young's slit experiment

Figure 4.6 illustrates the apparatus for performing Young's slit experiment. The light forms two rays as a result of passing through the slits. The distance between the slits is denoted d while L is the distance from the slits to the screen. Then the difference in the length of the paths travelled by the two waves is:

$$r_1 - r_2 = d \sin\theta \tag{4.16}$$

It is assumed that the waves are in-phase when they pass through the slits; the condition then for constructive interference at the screen is:

$$d \sin\theta = m\lambda, m = 1, 2, 3... \tag{4.17}$$

The condition for destructive interference is:

$$d \sin\theta = (m + \frac{1}{2})\lambda, m = 1, 2, 3... \tag{4.18}$$

The diagram also effectively illustrates the internals of the network we are currently examining.

As will be seen, this analogy is totally accurate, since the underlying mathematics is exactly the same for both systems. The primary difference is that the distance here is expressed through the delay parameters, and is measured in milliseconds. For this reason we will discuss the period (as opposed to the wavelength) of the oscillations when comparing them with the delay.

In the case where $d_1 = 0ms$ and $d_2 = 0ms$ constructive interference occurs. The result of this is shown in the diagram.

Figure 4.7 shows the activation of the output neuron in the topmost wave trace. The wave traces are offset by plus 2 vertically for clarity, as

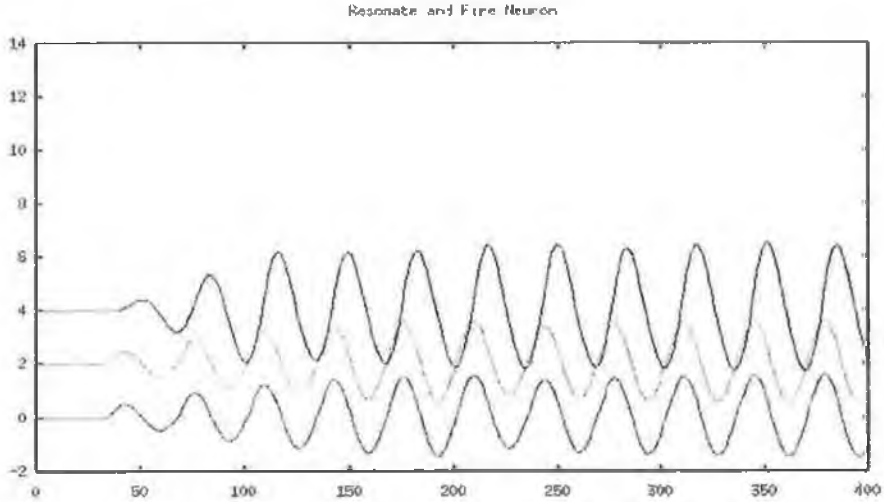

Figure 4.7: Constructive interference in dendritic fields

the overlay of all three waveforms is incomprehensible. By inspection the reader will observe that the output neuron's activation is the linear superposition of the innervating neurons' activation, mediated by the weight of the dendritic connection.

In the case where $d_1 = 0$ and $d_2 = 10$ partial destructive interference occurs. The result of this is shown in the diagram below.

In the case where $d_1 = 0$ and $d_2 = 17$ destructive interference occurs. The result of this is shown in the diagram below.

The residual oscillation is due to the fact that only integral values for the delay are supported. Given a frequency of 30Hz, this corresponds

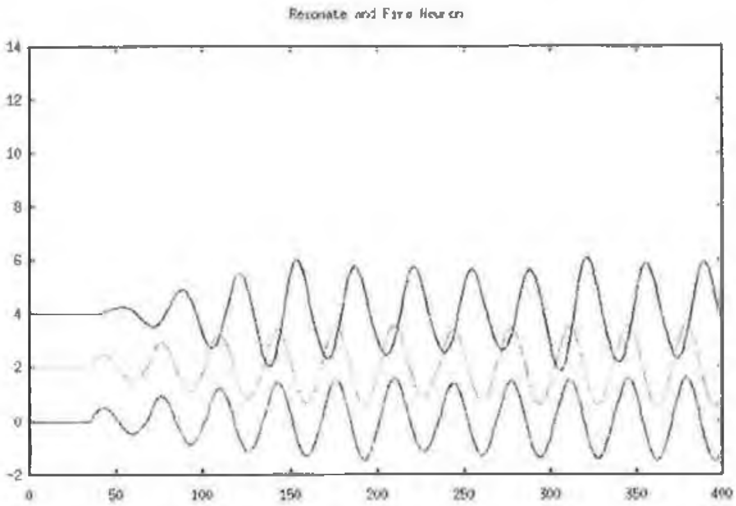

Figure 4.8: Partial destructive interference in dendritic fields

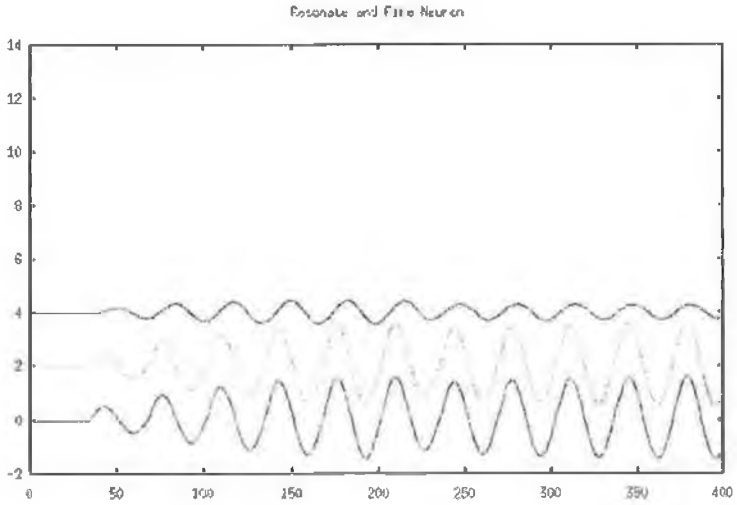

Figure 4.9: Destructive interference in dendritic fields

to a period of 33.33 milliseconds. Half of this is 16.5, so the value used of 17 causes the slight remaining oscillation.

Up to this point all of the pre-synaptic neurons have had the same resonant frequency. We now examine the case where there are two different frequencies of oscillation simultaneously active in the system.

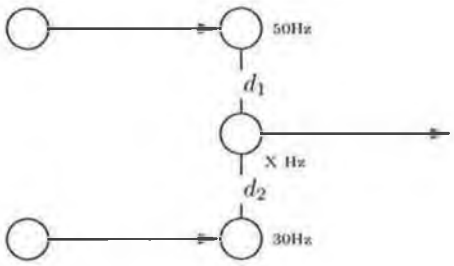

Figure 4.10: Dual frequency network

The input to the 50Hz neuron is a spike train at 50Hz, ensuring that the neuron maintains a steady oscillation of 50Hz. Similarly the 30Hz neuron is innervated by a spike train at 30Hz. In this situation the contributions of the 50Hz and 30Hz interfere with each other in the output neuron. Note that the activation of the output neuron does not display the resultant interference pattern. The contributions of both neurons are sampled at every simulated millisecond, and are treated as impulses whose influence on the oscillation of the innervated neuron is then calculated. The key parameter in determining the extent of the influence of such impulses is the resonant frequency of the neuron.

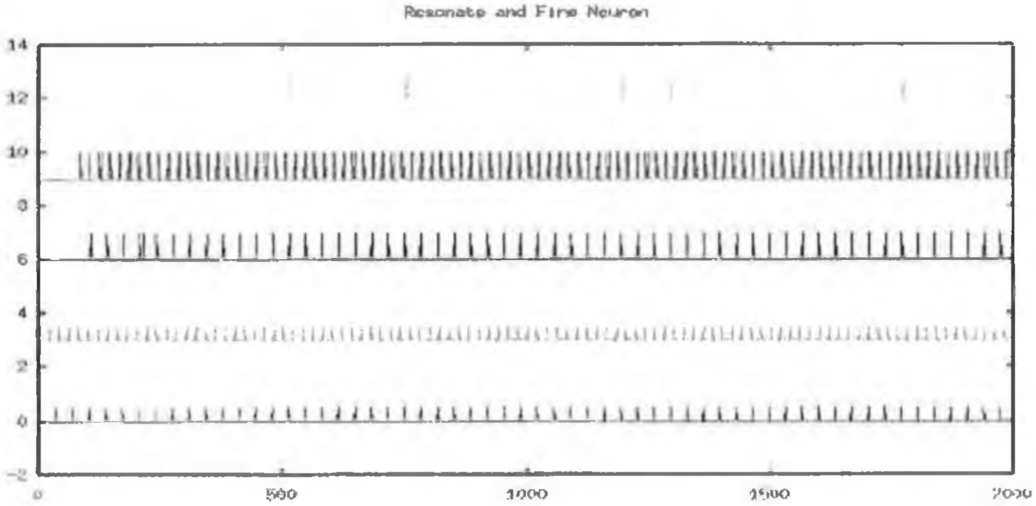

Figure 4.11: Output responses for the dual frequency network

Figure 4.11 shows the output spike responses in the network when the output neuron's resonant frequency is set to 40Hz. The bottom plot is the input neuron firing at 30Hz, the second plot shows the second input neuron firing at 50Hz. The next two plots show the innervating neurons firing at 30 and 50 Hz respectively. The final, topmost plot shows the output neuron firing sporadically and infrequently.

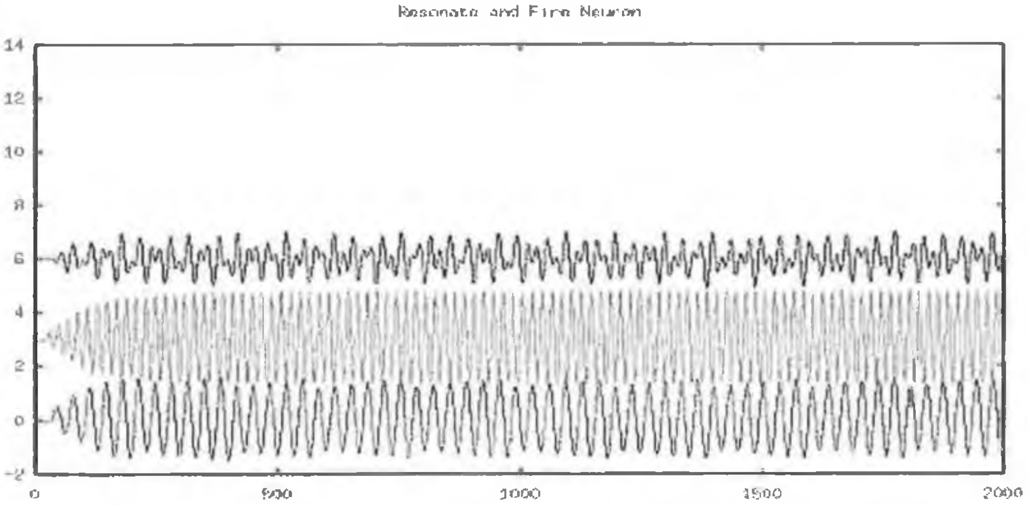

Figure 4.12: Activation of neurons in dual frequency network

Figure 4.12 shows the internal activation of neurons in the network. The bottom plot shows the 30Hz neuron, oscillating at 30Hz with high amplitude; the second plot shows the equivalent is happening in the 50Hz neuron. The topmost plot shows that the output neuron is not resonating with any input signal. Its oscillations are rather chaotic and are of low amplitude.

In this simulation the resonant frequency of the output neuron was set to 50Hz. As can be seen from the output response graph, figure 4.13,

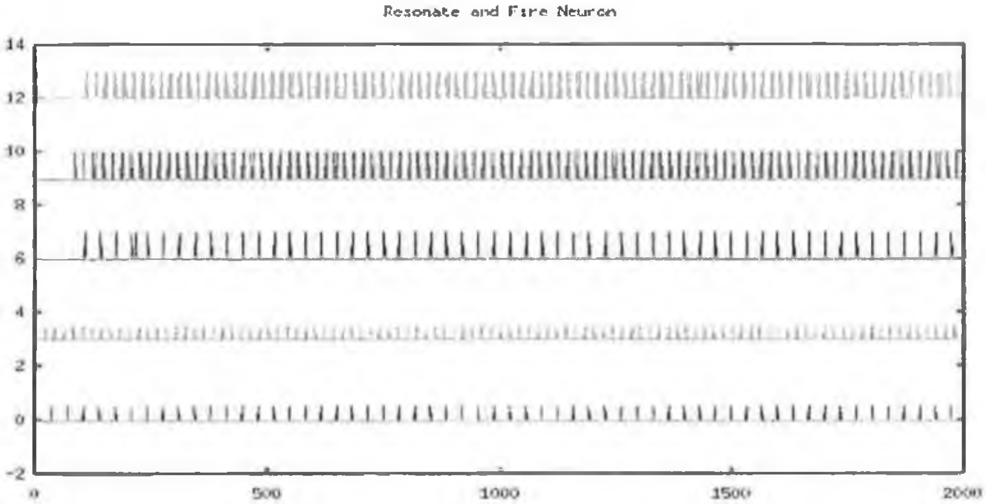

Figure 4.13: Output responses with 50Hz output neuron

the output neuron now resonates with the 50Hz input and produces a spike train at 50Hz.

As figure 4.14 shows, the activation of the output neuron is sustained, very regular and of high amplitude.

This general feature whereby neurons can "tune in" to a particular frequency component of the aggregate oscillation in the dendritic field provides an important computational asset to the model as a whole. It is also a phenomenon predicted to exist in biological neurons by Llinas (1988). The fact that the dendritic field supports such interference effects has deep ramifications; the modes by which the brain performs

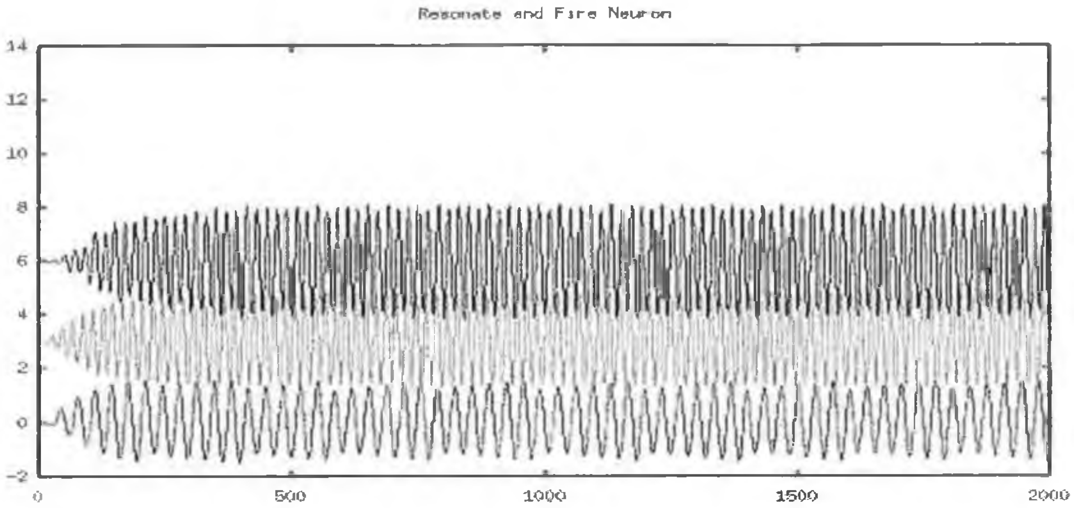

Figure 4.14: Activation of neurons with 50Hz output neuron

computation may be very different to the current action-potential centric paradigm.

4.10 Computational Features of Resonance Based Sub-Units

The advantages of the resonate and fire model are manifold. The primary distinction in this model is that computation is performed primarily in the spectral domain, using components of waves. The use of dendro-dendritic connections as a central feature represents a departure from existing models.

Many analogies with neurophysiological data and other phenomena are intuitively plausible given the current model. Symbol grounding in the motor and somatosensory cortices occurs naturally through the tendency of cortical columns in these areas to resonate which the conscious content that is broadcast throughout the cortex. These subliminal resonances constitute the “fringe” consciousness content. The language of resonance and holoscape permits a more comprehensive description of such phenomena than one restricted to treating axonal impulses as the only computational mechanism.

It is the case that the standard integrate and fire neural model is a subset of the current system. In order for the current model to reduce to the standard integrate and fire model, the input arrivals must be synchronized and forced to be in-phase with the current internal oscillation of the post-synaptic neuron. In this special case, the current model approximates the integrative activity of standard models across a half-cycle of the resonant oscillatory period.

The use of inhibition in integrate and fire networks is very different to the means by which inhibition occurs in RFNs. A pre-synaptic neuron can selectively inhibit oscillations of a particular frequency in the dendritic field by oscillating at that frequency but 180 degrees out of phase. This oscillation then effectively cancels the other out.

For axonal inputs, the input is the product of the spike amplitude and the connection weight. A negative weight will result in a negative contribution to the calculation of the neuron's instantaneous activation. However, it is possible for a single large negative impulse to cause the neuron to oscillate at above-threshold levels. The negatively weighted axonal input behaves as a force of inhibition when action potentials are received simultaneously from positively weighted axonal inputs. Conversely, the positively weighted inputs can be viewed as inhibitors of neural response due to input from negatively weighted input. The distinction is arbitrary and either viewpoint is valid.

4.11 Summary

In this chapter we have seen the specification for a new type of computational model of the neuron. The model is implicitly designed for the processing of spectral data in the temporal domain. In this way, it has been designed for application to problems of perception, with the implicit assumption that the essence of human perception lies in the spectral domain, Pribram (1991).

The ability of the dendritic field to support interference effects has been described and explored. The utility of this phenomenon as a computational tool has been described and incorporated into the computational implementation.

Some suggestions regarding potential applications of the model have been made in this chapter. These suggestions will be expanded on in the next chapter, where we look at networks of these neurons and examine their aggregate behaviours.

Chapter 5

Resonate and Fire Networks

5.1 Networks of Resonant Neurons

We now explore the performance of some elementary recognition tasks by resonance networks. The terminology used here is new, and so will be described in advance.

An input to a network is described as a channel. A single channel may be characterized as a power spectrum of frequencies and their phases. The state of a channel at a particular time is described by a power spectrum calculated by performing a Discrete Fourier Transform on the channel over a brief period.

The network's output is characterized by a group of neurons labelled as outputs. The labelling of output neurons in simple networks is arbitrary; but the correct subset of neurons that should be considered as outputs is generally obvious, as examples will show. The state of a neuron in a network is characterized by a power spectrum, again derived by performing a Discrete Fourier Transform (DFT) over a brief period.

An important difference between the mode of operation of conventional neural networks and the networks considered here is that the state of the nodes in our networks can not be an instantaneous measure of their internal state. This would simply return the momentary value of the displacement of the field from equilibrium, and would fail to account for phase, frequency and amplitude of oscillation.

While this point may appear insignificant at first, it represents a significant change of perspective. This follows as a natural consequence of the decision to emphasize spectral data over discrete, instantaneous measurements. The properties of these networks are therefore very different from the properties of conventional networks.

Networks of these neurons are more highly parameterized than standard feed forward networks. In addition to standard synaptic inputs, dendro-dendritic inputs and the resonant frequency form parameters of the model. This fact means that for an equivalent topology the RFN network has a larger number of configurations and is therefore more difficult to train; conversely, the computational power of the network is higher than its integrate and fire equivalent.

5.2 Resonant Frequency Response

A simple arrangement of nodes can be used to achieve classification of the current dominant frequency of an input channel. A simple network is used to illustrate this. An input node is used to inject a spike train into the network. Three output nodes, tuned to different resonant frequencies, are innervated by the input node. The input spike train gradually increases frequency from 10Hz to 100Hz. The response of the output neurons is measured and shown.

Figure 5.1 illustrates the connection topology of the example network. The input neuron innervates all three output layer neurons. The output layer neurons have resonance frequencies of $30Hz$,$50Hz$ and $70Hz$. Connection weights are moderate so that the output neurons are not saturated by a single input spike. The propagation delays

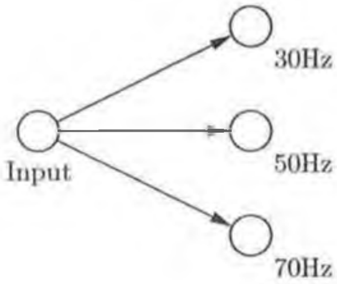

Figure 5.1: Four node resonate and fire network

are considered negligible in this scenario.

Figure 5.2 shows the input spike train supplied by the input neuron. The frequency of the spikes linearly increases from 10Hz to 100Hz. The response of the output neurons to this input will indicate the range of frequencies that each is tuned to.

Figures 5.3, 5.4 and 5.5 show the response of the neurons with a resonant frequencies of 30Hz, 50Hz and 70Hz respectively. The response of a neuron to input spike trains is determined by how close the frequency of the input is to the neuron's resonant frequency.

With this arrangement, we can see how the transformation from encoding in the frequency domain may be converted to encoding in spatial domains using the neuronal model expounded thus far. Such a

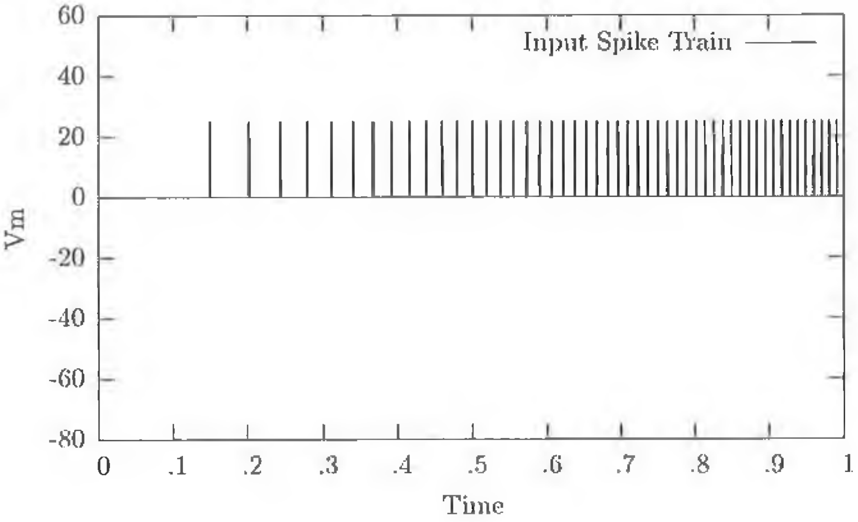

Figure 5.2: Input Spike Train

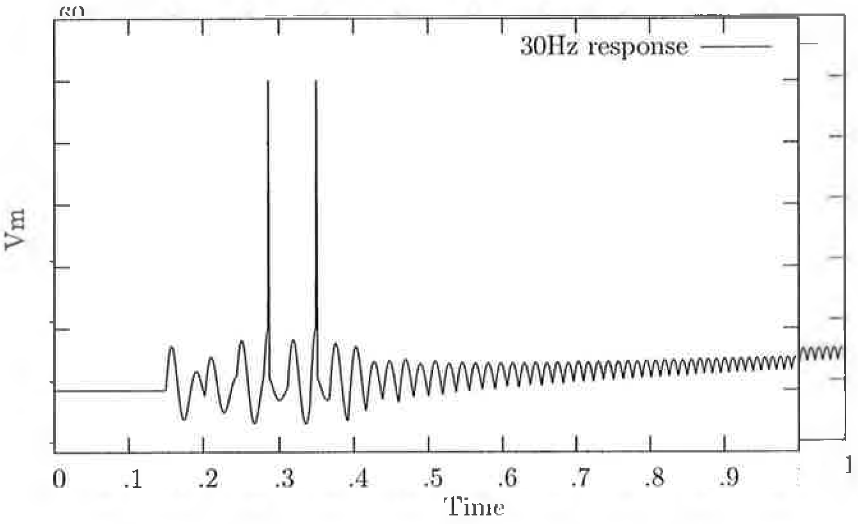

Figure 5.3: Response of 30Hz neuron

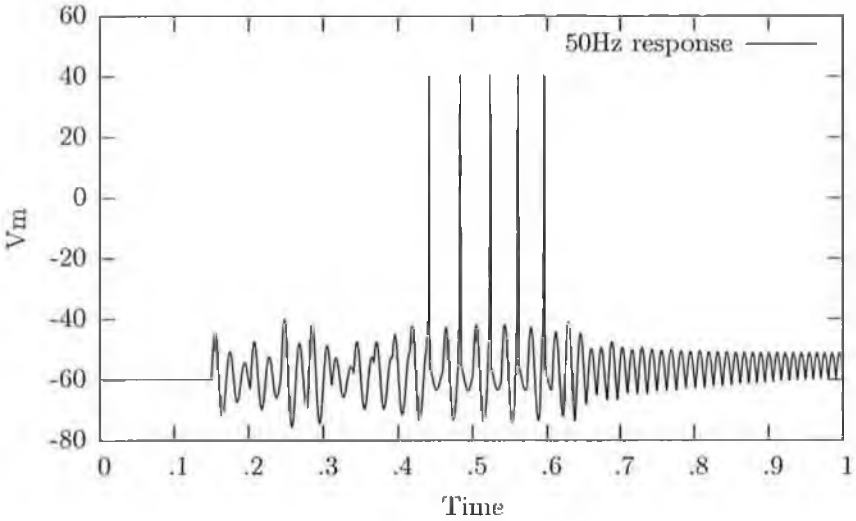

Figure 5.4: Response of 50Hz neuron

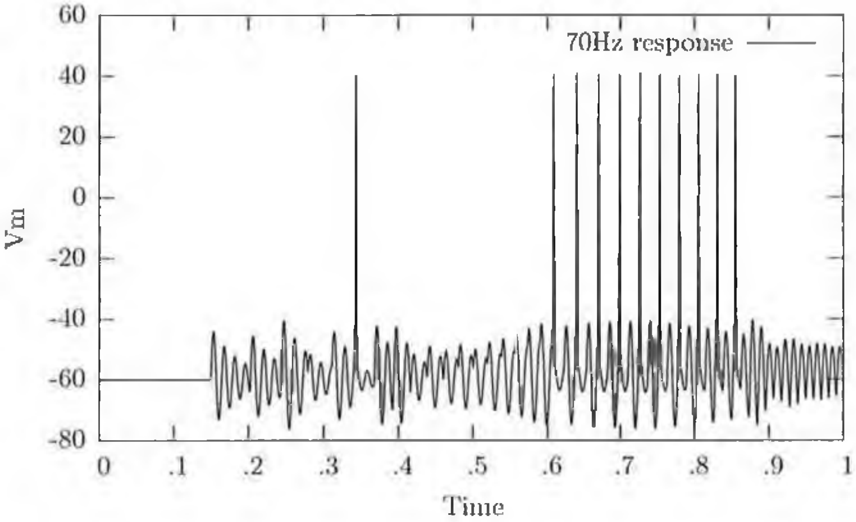

Figure 5.5: Response of 70Hz neuron

model provides a ready basis for the standard feature-extraction model of feed-forward network topologies, which has been the standard theoretical standpoint in PDP systems to date.

The focus of this work will not be on replication of the feature extraction behaviour of conventional networks. The Holonomic brain theory as proposed by Pribram (1991) suggests a more powerful paradigm whereby axonal impulses play a role more concerned with the eventual transmission of data between nuclei[1] than the computation performed thereon. The primary mechanism for computation in the systems described here will be the transmission and transformation of data as represented by sub-threshold oscillations in the ionic bioplasma of the aggregate dendritic field facilitated by dendro-dendritic synaptic and gap junctions.

5.3 Tonic Oscillation

The model described in the previous chapter accounts for propagation delays along axons. This feature can provide useful effects. Tonic oscillation, where action potentials are emitted at a given frequency by

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[1] Nuclei are groups of neurons observing a common physical organisation such as repeating interconnectivity patterns and layering of the cells themselves. Typically each nucleus will have a well defined function.

a neuron or group of neurons is one phenomenon that can be implemented using propagation delays.

The simplest possible such oscillation circuit, illustrated in figure 5.6 consists of a single neuron with a single recurrent connection. The propagation delay of the recurrent connection determines the frequency of the action potentials emitted from the circuit. Specifically the frequency f is given by

$$f = \frac{1}{d} \tag{5.1}$$

where d is the propagation delay. When a neuron with such a recurrent connection is innervated by an input spike that causes it to fire, a number of modes of operation are possible depending on the propagation delay, the weight of the recurrent connection, the neuron's resonant frequency and subsequent innervation events.

In the case where the propagation delay is long relative to the period corresponding to the resonant frequency and the weight of the recurrent connection is sufficient, the neuron will emit spikes at frequency f without interruption. This scenario is illustrated in figure 5.7. Where the weight is insufficient for the receipt of a recurrent action potential to depolarise the neuron beyond threshold, the neuron will require further input innervations for firing to be possible. These subsequent innervations should arrive in phase with the recurrent input for maximum effect.

Where the propagation delay is in the same range as the resonant period of the neuron, the phase at which the recurrent innervation arrives is important. Should the propagation delay be such that the recurrent innervation arrives out-of-phase with the membrane potential oscillation, an action potential will not result and therefore the oscillation will cease.

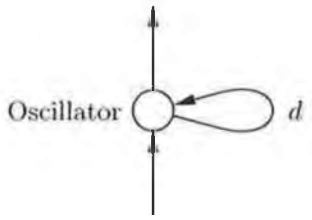

Figure 5.6: Oscillator Neuron

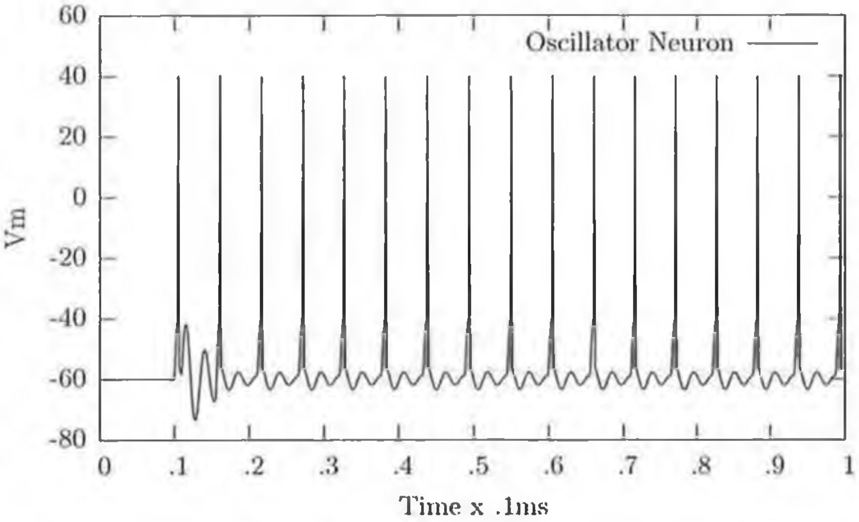

Figure 5.7: Oscillation through recurrent connection, $f = 20Hz$

5.3.1 Mutual Recurrence

We can eliminate the need for a self-recurrent connection in the oscillator circuit by introducing a second neuron. As shown in figure 5.8 the recurrent connection is replaced with a mutually recurrent loop through a secondary neuron. The frequency of spikes emitted by this circuit is given by:

$$f = \frac{1}{d_1 + d_2} \tag{5.2}$$

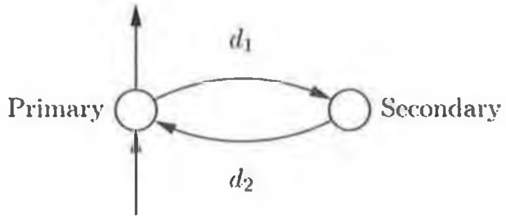

Figure 5.8: Mutually recurrent oscillator circuit

5.3.2 Configurable Frequency Generation

We can extend the concept of mutual recurrent circuits that generate spike trains of a particular frequency to show how to create a circuit that can be used to generate spike trains with a variety of frequencies.

The simplest instance of such a network consists of two sub-circuits that are straightforward mutually recurrent circuits. We will refer to the individual neurons in the mutually recurrent circuit as primary and secondary neurons. The primary neuron is the neuron whose spiking output is the output of the circuit. The secondary neuron is the neuron through which the recurrent connection loops. In the present circuit, the input neurons of the circuit as a whole are the secondary neurons of each component recurrent circuit.

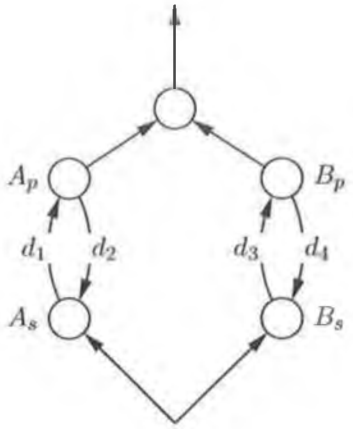

Figure 5.9: Spike Train Generator

As before the propagation delays d_1, d_2, d_3 and d_4 determine the spiking frequency. In this circuit, however, we have two independent circuits. We therefore have two possible frequencies of operation, f_A and f_B where

$$f_A = \frac{1}{d_1 + d_2} \tag{5.3}$$

$$f_B = \frac{1}{d_3 + d_4} \tag{5.4}$$

The circuit as a whole has four possible states or modes that it can be in: 1) it can be quiescent 2) circuit A activated, innervating the output with spikes at frequency f_A 3) circuit B activated, innervating the output with spikes at frequency f_B and 4) both A and B activated.

The mode of the circuit can be selected by tuning the resonant frequencies of neurons A_s and B_s. For example, set

$$f_{As} = 150 \tag{5.5}$$

$$f_{Bs} = 100 \tag{5.6}$$

then, innervating the circuit inputs with a spike train of $150Hz$ will result in activation of circuit A. The output of the circuit as a whole will then be a spike train of frequency f_A. Innervating the circuit inputs with a spike train of $100Hz$ will result in activation of circuit B, and an output spike train frequency of f_B.

Setting the delay parameters so that $f_A = 10Hz$ and $f_B = 20Hz$ we innervate the input neurons with a pair of spikes. The time between the innervating spikes will determine the subcircuit that becomes activated. The closer the frequency of the spikes to the resonant frequency of the secondary neuron, the more likely it is that that neuron will fire and activate its circuit.

In response to a pair of spikes at $150Hz$, circuit A is activated, resulting in an output spike train of frequency $10Hz$ as shown in figure 5.10. Injecting a pair of spikes at $100Hz$ activates circuit B, and results in an output spike train of $20Hz$, as shown in figure 5.11.

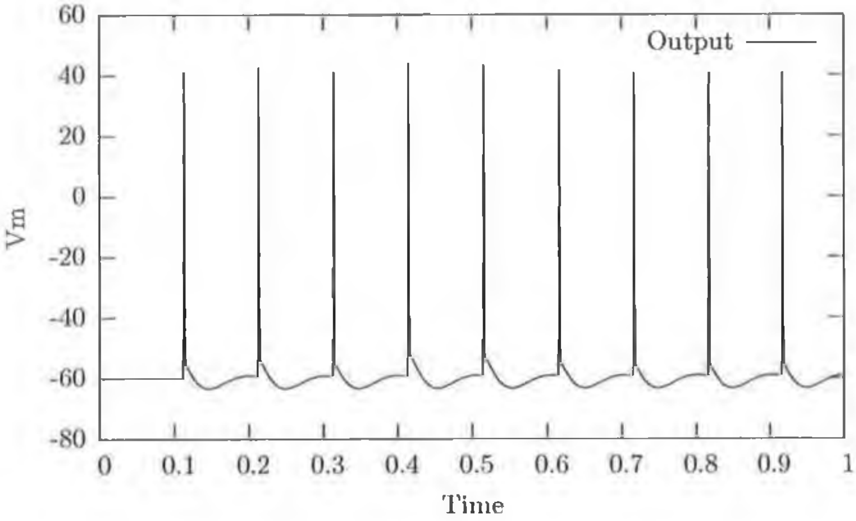

Figure 5.10: Response to $150Hz$ input, A activated, $f_A = 10Hz$

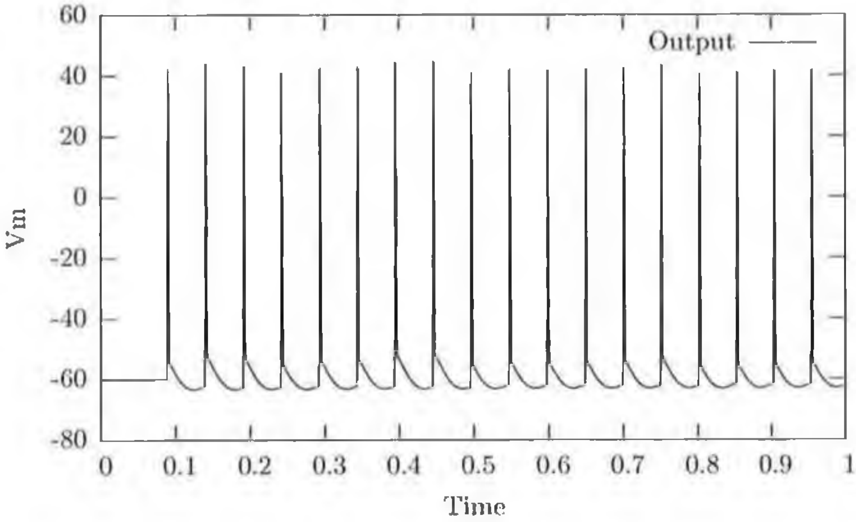

Figure 5.11: Response to $100Hz$ input, B activated, $f_B = 20Hz$

5.4 Aggregate Dendritic Field

An aggregate dendritic field results when the dendritic field, or receptive field, of a neuron connects with that of other neurons through the medium of dendro-dendritic junctions. Such junctions may take the form of standard synaptic junctions with neurotransmitter vesicles or, more interestingly, they may be gap junctions, which facilitate the direct transmission of electrical currents without the medium of chemical transmission.

In computationally oriented terms, a module (analogous to a neural nucleus dedicated to a specific task), consists of a group of dendritic fields. Each dendritic field performs a distinct computational task. Inputs to a dendritic field take the form of axonal potentials, incident upon the receptive fields of member neurons. Such inputs initiate the oscillation of the aggregate dendritic field.

In stark contrast to the situation in Hopfield models, the recognition task in this model is complete when a bifurcation point is reached. When the oscillation grows to critical amplitude and results in action potentials, these have inhibitory feedback influence on the module, by virtue of the hyperpolarisation experienced by the neurons that have fired.

The computational model developed herein treats dendro-dendritic connections in much the same way as standard synaptic connections shown thus far. In standard synapses, an axonal spike may influence the amplitude of oscillation, or activation, of the post-synaptic neuron. With a dendro-dendritic connection, the current amplitude and phase of the internal oscillation of the pre-synaptic neuron may affect the post-synaptic neuron's level of activation.

5.5 Self Organising Map

In order for the resonate and fire neural model to be a computationally useful device, an efficient learning algorithm is essential. We now present such an algorithm based upon the Kohonen Self Organizing Map, or SOM. The result of the application of this algorithm to a network of neurons is a topographic map, discussed in chapters 3 and 4. Such maps occur throughout brain structures involved in the perceptual process.

The topology of the network to which the SOM algorithm is applied is identical to that of a standard Kohonen; a single layer of input nodes (these nodes are not neurons) feeds into a layer of outputs. The output layer consists of either a simple one-dimensional row of neurons, or a two dimensional array. For the purposes of demonstration the examples illustrated will deal with the simpler one-dimensional case.

The critical parameter of any model involving resonate and fire neurons, henceforth referred to as RFNs, is the resonant frequency. While connection weights play a major role in determining the overall behaviours exhibited by the network, the resonant frequencies of the neurons determine the class of input which is of interest. For this reason, the primary parameter that the SOM algorithm will modify as part of the learning procedure will be the resonant frequency of RFNs in the output layer.

5.6 RFN SOM algorithm

In this section we present the details of the SOM training algorithm developed for use with resonate and fire neural networks. This algorithm is based on the Kohonen SOM algorithm for conventional neuron models; however, the nature of RFNs requires that a significant revision of the algorithm be performed.

Training data takes the form of a set of vectors, with the same number of elements as there are inputs in the network. The RFNN SOM algorithm begins by segmenting the supplied training data into meaningful pieces. The exact duration of a piece is a parameter of the algorithm. The training data is segmented into chunks each containing n milliseconds worth of data.

The algorithm proceeds by presenting each element in a piece of training data to the network. After each element in a piece is presented, the output neurons' reaction is calculated, and noted. When the entire piece has been presented, the output neuron that had the highest aggregate activation levels during the period is declared the winner.

The winning neuron's resonant frequency is now modified. The effective frequency of the training pulse train is measured as the piece is presented to the network, and is referred to as the input frequency, denoted f_i. The current frequency of the winning node is the value of the resonant frequency for that node, denoted f_n . The new resonant frequency is calculated as shown in equation 5.7.

$$f_n = (1 - \alpha)f_n + \alpha f_i \tag{5.7}$$

where α is the current learning rate. This value ranges between 0 and 1, and the most effective value is to be determined empirically. The value of this parameter is gradually reduced from its initial value, in order to stabilize modifications to the value of the resonant frequencies of the output neurons. If it were left at its initial high value, the network would continue to rapidly adapt to each subsequent input, and thereby undo previous learning.

After each piece of training data has been presented, the entire process is repeated, with a slightly reduced learning rate. The process is repeated as often as is specified by the "epochs" parameter of the algorithm. Typically for simple data sets the network will converge upon an acceptable solution in less than 100 epochs. For more complex data sets many more epochs may be required.

5.7 Example of training using SOM

We now present a concrete example of training a RFN network using the SOM training algorithm that has been developed. All of the plots and data presented here are derived directly from the application program that implements this algorithm.

In the example shown there is a single input channel, so the training data in this case forms a one-dimensional array. The data consists of the equivalent of 6 seconds worth of pulse trains. The first third of this data consists of pulses at 20Hz; the second third consists of pulses at 40Hz; the final third is at 60Hz.

The training data is segmented into 30 pieces of 200 milliseconds each. These segments are presented to the network in turn and the resonant frequency of the winning neuron is modified accordingly. The initial state of the network used is shown in figure 5.12.

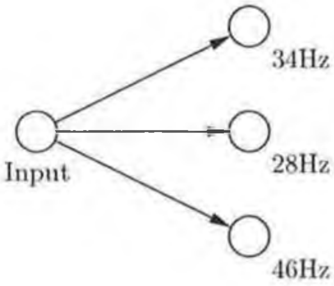

Figure 5.12: Topographic map initial random configuration

Figure 5.13 illustrates the output response of the neurons in the output layer prior to training. Neuron 1 reacts around 34Hz, neuron 2 around 28Hz, and neuron 3 around 46Hz. The selection of starting

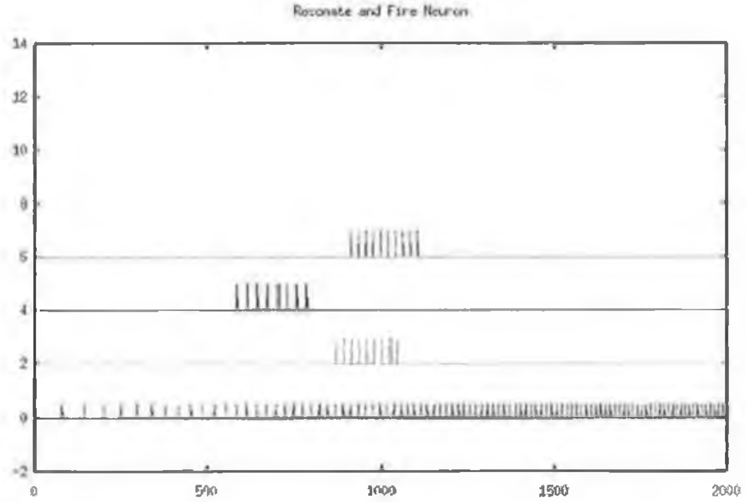

Figure 5.13: Response of output neurons prior to training

frequencies is arbitrary, and indeed is expected to be random.

The only pathological initial configuration is when all output nodes are set to the same initial resonant frequency. In such a case, each will respond with equal activation levels to the input stimulus. In such a case, a winning neuron is selected randomly. Eventually, this random selection will differentiate the neurons sufficiently and they will form an acceptable mapping of the input domain. The process will still work, it will simply take more training to achieve.

Figure 5.14 shows the evolution of the resonant frequencies of the three output neurons in the SOM during training. Initially the value of

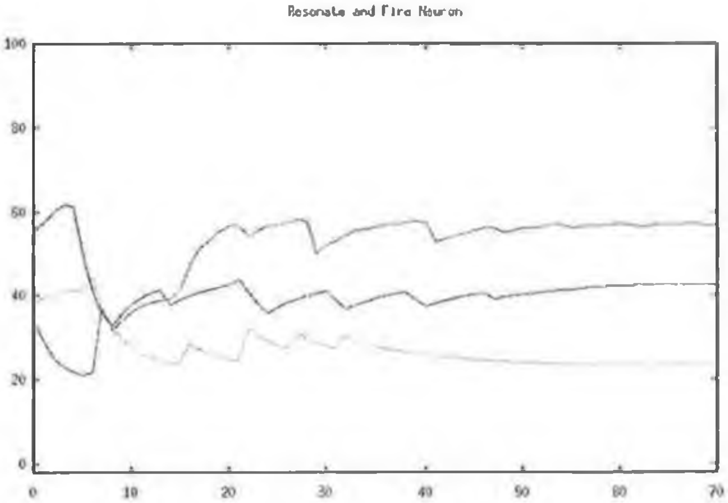

Figure 5.14: Evolution of resonant frequencies during SOM

the learning rate is high so large steps are taken and dramatic changes in the value of the resonant frequencies is observed. As training progresses, the learning rate is reduced and the neurons settle into a stable response to an area of the input domain. Gradually the neurons become highly tuned to quite specific values, matching the input to tolerances within a few percent.

The initial steps are sufficiently large and uncontrolled that the neurons actually cross each other. It would be thought likely that the neuron that begins at 46 Hz would end up covering the 60Hz input range, but the initial steps are sufficiently wild that it ends up covering the 40Hz range. This is a direct result of using a large value for the learning rate initially. This parameter is a feature of most gradient-descent methods, and there is no valid rule that informs the setting of this value for all data sets. Typically, empirical results are used to inform the calculation of the initial value of the learning rate. In this case, it could be argued that a lower value should be used, but the system still converges upon a solution, so the initial fluctuations are quite acceptable.

The important feature of the diagram is that the algorithm settles into a phase of smaller and smaller adjustments to the resonant frequencies. This indicates learning stability after an early period of high plasticity, and is an essential feature of any useful computational learning algorithm.

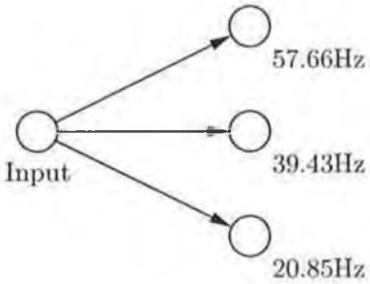

Figure 5.15: Topographic map configuration after training

Figure 5.15 illustrates the network after SOM training is complete. The neurons have become aligned to the input data, clustering roughly around 20Hz, 40Hz and 60Hz to a high degree of accuracy. Note that the connection weights have not been modified. This illustrates a mode of neural adaptation that is quite different from standard connectionist approaches in that it does not rely on synaptic plasticity. The adaptation takes place within the cell itself, not at the synaptic cleft.

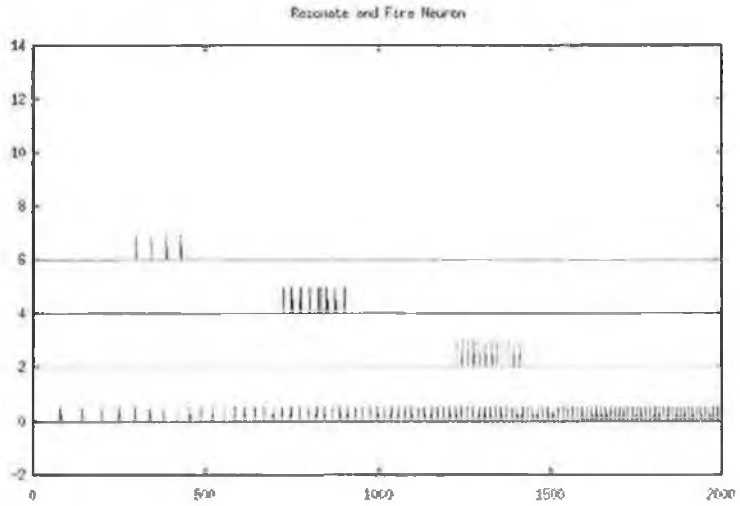

Figure 5.16: Output response of neurons after training

Figure 5.16 illustrates the fact that the neurons in the output layer have formed a topographic map. The first output neuron responds to frequencies centred on 60Hz, the second to frequencies centred on

40Hz, the third to frequencies centred on 20Hz. Note that the ordering of the magnitude of the resonant frequencies has been rearranged from the initial configuration.

In this section, we have described a training algorithm that produces topographic maps in a manner similar to the conventional Kohonen system. This algorithm uses one parameter of the network, the neurons' resonant frequencies, to achieve this effect. Connection weights of axonal connections, and dendritic connections are not modified in any way.

5.8 Relation To Existing Models

The resonance based computational model developed here is aimed specifically at revising the building blocks comprising computational models of large populations of neurons. The new model of the neuron has been shown to capture the behaviours exhibited by the default, integrate-and-fire model as a special case.

The approach taken, placing the spectral domain at a fundamental level in the perceptual processing mechanism, is directed towards solving or eliminating difficulties with conventional approaches to computational modelling of neural architectures that attempt to accommodate salient properties of cognitive systems. Examples of such properties include the ability to bind data from disparate modalities into a single perceptual experience; the ability to subsume the productions of a wide variety of expert processes that perform domain specific analysis; the ability to quickly harness large computational resources and the co-ordination of computational activity across those resources.

The primary mechanism that facilitates all of these capabilities is the fact that the analog spectral domain permits superimposition of signals. Within the dendritic aggregation of a group of resonate and fire neurons, multiple signals from disparate sources may interact. This interaction is characterised by the establishment of a dynamic electrical potential field throughout the aggregate. Even after the input signals have ceased, the field can continue to change and evolve, and cause the production of action potentials.

By redefining the basic element of the neural model in this subtle manner, we see that the form of networks based on the resonate and fire element will be quite different to those based on the integrate and fire neuron. We now compare and contrast the resonance model with some conventional artificial neural network approaches.

5.8.1 PDP Networks

The PDP approach as described in Rumelhart and McClelland (1987) is primarily dependent on integrate and fire neurons, and the sigmoid transfer function at their core. The fact that an arrangement of such nodes in multiple layers constitutes a universal function approximation mechanism was a key insight that led to the general application of ANNs. Such networks suffer from a variety of shortcomings when applied to problems housed in anything beyond the most restricted perceptual domains. Issues such as shift and scale invariance result from the implicitly spatial encoding that follows from the fact that the ANN never leaves the digital domain - digital inputs are entered, summed, and propagated. Machine vision systems based on the PDP style ANN attempted a variety of techniques such as convolution in order to overcome the difficulties that arose from the fact that they were ultimately operating in the wrong domain.

The resonance neuron is implicitly suited to data in the spectral, analog domain. Pribram (1991) convincingly demonstrates that sensory data are encoded as power spectra. This encoding avoids the difficulties of rotation, shift and scale invariance.

5.8.2 Whole-system Models

The resonance model does not prescribe specific mechanisms for the evolution of large groups of neurons. A variety of theories and models describe how neurological structures adapt to form co-operative groups that implement heuristics in order to adapt their behaviour to maximise some measure of fitness. Alternately, some other models prescribe a system based on competitive adaptation, such as Edelman's Theory of Neuronal Group Selection (Edelman and Tononi, 2000). The resonance model is compatible with such theories, since it primarily prescribes the processes at work over short time scales in individual or small groups of neurons, while TNGS for instance, prescribes the aggregate mechanisms through which complex adaptive behaviours emerge from the interactions of large groups of nuclei.

While the resonance model and such whole-system models are to an extent orthogonal, the resonance model can assist the whole-system practitioner by providing more versatile account of the mechanisms through which nuclei can interact. Additionally, the dendritic aggregate provides a wide variety of features of high utility and permits the introduction of concepts such as binding without eliminating the continuity of explanation from the level of the neuron to the level of the whole system.

5.9 Summary

In this chapter we have developed the resonance model and examined the properties of simple networks of resonance neurons. We have shown how the Fourier Transform, an operation Pribram (1991) demonstrates as fundamental to the perceptual process, may be easily approximated with simple networks of resonance neurons. An algorithm for the implementation of a self-organising topographic map of resonance neurons was then developed and demonstrated for a simple example. Such topographic maps are a common element in many neurological structures and are a fundamental building block of perceptual systems. Finally the relationship between the resonance model and existing systems was examined. Resonance neurons accommodate a superset of the behaviours of existing integrate and fire models. Whole system theories of neural adaptation and behaviour are for the most part compatible with the resonance model.

Chapter 6

Computing with Waves

6.1 Implications of the Resonance model

Placing the concept of resonance at a fundamental level in the computational activity of the brain has extensive consequences. From the point of view of the formation of basic categories, and characterizing the perceptual process, this property of neurons implies that certain invariants exist implicitly. When a neuron is stimulated at one of its resonant frequencies, we would expect the resultant perceptual experience to bear a fundamental resemblance to that which occurs when the same neuron is stimulated at a different harmonic. One candidate for such a phenomenon is our perception of musical notes - assume that there are a group of neurons which resonate when middle C is heard. When the same note is played an octave higher, even the untrained ear still recognizes it as C, but at a higher pitch. A tidy solution to this would be to attribute it to the basic properties of resonance possessed by the computational substrate.

The problem of rotational and scaling invariance has troubled anyone who has attempted to create computer vision systems. One can easily train an ANN to recognize a person's face, and the network will be capable of picking out that person's face from a myriad of others with a surprising degree of accuracy, once the picture of the face is presented in the same orientation as the training data. If the face is rotated, increased or decreased in size significantly, or the person's expression changed, the likelihood of mismatch grows quickly.

The use of spatial frequencies provides a solution to these problems. Rather than learning a template based on the explicit position of eyes, mouth and other features, a network of resonate and fire neurons becomes tuned to the signature of the spatial frequencies which result when the face or object is viewed. These power spectra are implicitly scale and rotationally invariant, and therefore the particular module tuned to recognize the presence of a particular entity in the visual field does not need to deal with the complexities of imposing invariance after the fact.

This tuning has manifold benefits; a neuron or group thereof that innervates thousands of others can selectively activate a subset by transmitting a set of spikes having resonant interspike frequency. This suggests that the idea of distribution of function can be extended further than previously attempted; individual neurons are free to participate in an array of disparate activities, adopting different roles as they are innervated by different frequency inputs.

The constructive and destructive interference effects present in the dendritic field are reminiscent of the same phenomenon in quantum mechanical systems. Lloyd (1999) has shown that some of the advantages previously thought to be the sole preserve of quantum computers exploiting entanglement can in fact be achieved with the use of ordinary light or classical wave systems. To a certain extent, given the spectral nature of sensory data it would be surprising if at least some of these properties had not been exploited by nature. A very important facet of the computational apparatus that the brain offers is the fact that it is not digital. Some neuroscience texts present the idea that sensory information is analog (continuously valued) while action potentials are digital (all or none). This is a misclassification that causes confusion. Freeman (2001) points out that

> Brain function is neither analog nor digital, as these terms are defined for computer usage. Pulse trains that appear to be digital are in fact analog as a form of pulse frequency modulation

One common misconception that results in the failure of computer systems attempting to replicate brain function is that after the first layer of our sensory systems transduces continuous sensory data into action potential responses, then from there on, all interactions in the brain are digital, mediated by action potentials alone. This scheme is flawed in that it ignores the complexity of the dendritic process, fails to recognize the computational utility of returning to a continuous-value medium, and has been proven too restrictive by virtue of the failure of computational models of this type to properly capture the essence of the cognitive processes of interest. Further, as Freeman points out, even the all-or-none action potentials are themselves analog signals and to treat them as digital events is to omit an important characteristic of reality from the model.

The second dangerous implication of the digital dogma is that it gives the impression that the brain, or any neural substrate, is ultimately reducible to a digital mechanism, the favoured ideal of which is typically the Turing machine. The basic problem with this step, which is taken very often, is that the Turing machine cannot accurately simulate systems in which asynchronous events are permitted; indeed a fundamental feature of the idealized Turing machine is that no mention of relative timing of events is required, since its operation is inherently serial and discrete. Turing himself pointed this out (Turing, 1950) . Asynchronicity introduces a plethora of difficulties that computer science is only beginning to tackle, and coherent frameworks supporting truly asynchronous systems with autonomously executing sub-processing are as yet primitive and error-prone.

The work of Hameroff and Penrose (1996) on the possibility of quantum mechanical processes exhibiting coherent evolution and entanglement in the cytoskeletons of neural cells cannot be ignored here. While the resonate and fire model does not invoke coherent unitary evolution, many of the fundamental concepts behind the resonance model follow Hameroff's work. Both models propose that a complex process in the body of neural cells must be considered in detail in order to capture important aspects of neural activity. The transmission of state between neurons through gap junctions is utilized by Hameroff as the means through which large aggregations of cytoskeletal elements can enter into coherent entangled evolution. In the resonance model, gap junctions are part of the means by which large numbers of neurons become aggregated to form a dendritic field. The Orchestrated Objective Reduction model is proposed as a potential explanation for consciousness's supra-computational competencies. The resonance model described herein cannot make any claims to facilitation of supra-computational capacity; however, the method of aggregation of many neurons into a dendritic field in which computation is facilitated represents the ability to allocate computational resources in a manner and on a scale not possible with previous models. As stated above, the distinction between discrete and continuous machines is emphasized with a view to distinguishing cognitive capacities as provided by a continuous (non-digital) substrate from the computational abilities of digital machines. With the resonance model, the dendritic microprocess may include communication between numerous neurons in a manner more rapid than that permitted by the transmission of action potentials; the membrane potential may be transmitted through gap junctions as any other electrical signal, at the speed of light.

There is evidence to suggest that biological neurons follow the resonance paradigm. It is clear that human mechanoreceptors are tuned to resonant frequencies in a manner compatible with the resonate and fire neural model. Meissner's corpuscles, which are mechanoreceptors located close to the surface of the skin, are concerned with form and texture perception. Meissner's receptors are particularly important for adjusting grip pressure, as they are particularly sensitive to small movements and react to frequencies below approximately 40Hz most favourably. Higher frequency vibration is detected by Pacinian corpuscles, located deeper in the dermis, "which follow a sinusoidal vibration stimulus by triggering a single action potential per period", Longstaff (2000). Optimal sensitivity is at about 200Hz and stimuli in this range of frequency can be perceived even at skin indentations of less than 1 millionth of a meter. Such hyper-sensitivity to a stimulus at a particular frequency indicates that the mechanism through which the stimulus is transduced has an intrinsic preference for a particular frequency. An obvious candidate for this role is the natural resonant frequency of the membrane potential in the receptor neuron itself. Computational models of the IFN neuron cannot account for this frequency tuning. The resonate and fire model not only accommodates but would suggest that all sensory modalities have elemental components which will have preferred frequency bands to which they react most strongly.

In any medium permitting the superposition of waves, the possibility of complex interference effects arises. In the dendritic field such superposition is permitted and therefore interference effects must be considered. The simplest case is for a single wave to be input into the field at a particular point. The result is a travelling wave, which disperses through the medium in the conventional fashion, with crest following trough. Ignoring more complex effects due to the particular shape of the medium, the displacement (in our case the membrane potential) at any point in the medium will follow an evolution directly attributable to the form of the original wave. In this case, if the original wave's frequency matches the resonant frequency of a particular neuron forming part of the dendritic field, that neuron will generate action potentials if the wave's amplitude is great enough.

The next level of complexity is to consider two waves of the same frequency input to the field at different locations. The result will be an interference pattern within the field. Depending on the distance of a given point in the field to the points at which the waves are input, the waves will combine at that point and either constructively or destructively interfere. The *distance* in our case is more properly the time taken for the wave to propagate from one point to another, since the speed of propagation is not necessarily constant through the medium. Such an interference effect is similar to Young's double slit experiment, where a beam of light is shone through two narrow slits. Taking the wave view of light, the two slits represent in-phase wave sources of the same frequency. The resultant interference effect, projected onto a screen, is precisely analogous to the interference effect that is set up in the dendritic field. Action potentials will result when a neuron in the field is tuned to the waves' frequency, and is located at a point of constructive interference.

One can envision complex feedback loops and evolutions within the dendritic field that can be built upon these basic properties. The possibilities are endless and the salient few will only become clear through further detailed investigation and simulation. There are many potential roles for the state of the dendritic field in cognitive processes. Perhaps it can be best characterized as *context* or perhaps it is best utilized as a *workspace*. It does permit a vast array of operations of a form impossible with IFN ANNs. The fact that these arise naturally from a quite simple computational model of the neuron which places resonance at its core is compelling, since the dendritic field is a concept championed by Pribram for many years.

6.2 Resonance with the EM field

While neural resonance can exist without subthreshold oscillations, a vast literature connects the two. For Wu et al. (2001) the oscillations emerge from membrane resonance. The resonant current is steady-state potassium current, amplified by a sodium current. Izhikevich (2002) most explicitly drew consequences from the fact that the Hodgkin-Huxley model is a resonator. Like Wu he interrelates subthreshold oscillations and bursts, coming to the conclusion that the intervals in bursts may be significant for communication.

System level phenomena are also increasingly beginning to attract attention. Wu et al. (2001) comment that a single excitatory stimulus to a mesencephalic V neuron can result in high-frequency spiking in a whole network under certain circumstances. Even more interestingly, the phenomenon of stochastic resonance (SR) has come into focus in neuroscience. SR is essentially a non-linear systems phenomenon through which, paradoxically, a noisy environment can be exploited to amplify a weak signal. In their review article, Hutcheon and Yarom (2000) comment that resonance and oscillation may have a role in such phenomena as gamma waves. Rudolph and Destexhe (2000) venture a more specific conjecture: responsiveness of neo-cortical pyramidal neurons to subthreshold stimuli can indeed be entranced by SR, and under certain conditions the statistics of this background activity, as distinct from its intensity, could become salient. Obviously, such forms could have computational consequences.

For Freeman the conversion of sensory data into meaning is mediated by those gamma wave processes. The distinction between the approach presented here and Freeman's is that we are looking for the resonant frequencies at the microscopic level in single neurons using novel solutions to the 4th order Hodgkin-Huxley equation, whereas Freeman finds them at the mesooscopic level in the characteristic frequencies of populations. Nevertheless, the thrust of the two approaches, and the critique of the integrate-and-fire model, is similar. Further, the two scales are linked by virtue of the fact that the spiking of populations of neurons creates the brain's electromagnetic (EM) field, which in turn can influence the membrane potential in individual neurons and the oscillations within their dendritic microprocess. This bidirectional feedback loop between resonant processes at the micro and the macro-scopic scales is explored in the following sections.

> While neural networks can be modeled with matrices that represent the dynamics of local integrate-and-fire elements connected globally, whether fully or sparsely, the dynamics of cerebral cortex is modelled with arrays of coupled oscillators in two spatial dimensions, with sparse but global internal connectivity to represent the architecture of the neural populations of cortex. (Freeman, 2001)

The RFN networks described in the previous chapter are arrays of coupled oscillators. The reciprocal connectivity of the neurons in the network illustrated in figure 6.1 is an example of exactly the architecture Freeman describes. The RFN model does not restrict the network topology to be two-dimensional, as the spatial extent of the network components is only accounted for in the propagation delays.

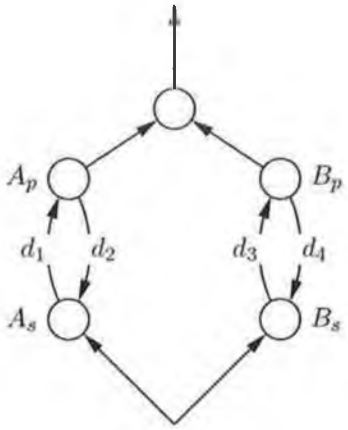

Figure 6.1: Coupled oscillators: Spike Train Generator

The oscillations of the brain's electromagnetic field, as measured by EEG, routinely reach magnitudes in the order of tens of microvolts (Haggard and Eimer, 1999) in healthy subjects and can reach many hundreds of microvolts in conditions such as epileptic seizure. EEG recordings suffer from the fact that they are taken at the subject's scalp, where the signal has already been severely attenuated. Direct measurement obtained from electrodes implanted in the cortex show extracellular potentials with peak amplitudes of several hundred microvolts (E.Niedermeyer and da Silva, 2001). The EM field exhibits a fine spatial and temporal structure (Bullock et al., 1995) suggesting that it serves some purpose in the brain's computational activity.

Freeman's experiments measuring EEG activity within the olfactory bulb of rabbits and cats (Freeman, 1991) demonstrated bursts of EEG activity in response to sensory stimuli with average amplitude of about 100 microvolts across recording electrodes that were spaced at 0.5 mm and thereby corresponding to field gradients of 0.2 V/m. Although these fields are relatively weak, at the characteristic low frequencies of EM waves, most of the potential drop occurs across the cell membrane. The trans-membrane fields are approximately 3,000 times the field in the surrounding tissue (Valberg et al., 1997) but may be even higher in cells orientated along the field. Consequently endogenous EM fields of tens of volts per metre are capable of generating fields of several tens of thousands of volts per metre, translating to up to several millivolts, across the 5nm neuronal cell membrane.

The EM field will induce intracellular and extracellular movement of charged ions, thereby directly influencing neuronal physiology. Neurotransmission through gap junctions can be voltage dependent and consequently sensitive to the EM field Draguhn et al. (1998). An obvious candidate for sensitivity to the EM field are the voltage-gated ion channels present in neuronal membranes, which have a fundamental role in the neural process and therefore clearly facilitate the influence of the EM field on an individual cell's state.

Potential changes of less than one millivolt across the membrane are capable of modulating neuronal firing (Schmitt et al., 1976). When sub-threshold oscillations are present, and the neuron's activation level is close to threshold, very tiny changes in the membrane potential, smaller than those associated with the EM field, are sufficient to determine whether the neuron will emit an action potential or not.

Several studies have demonstrated that extracellular fields play a role in recruitment and synchronisation of neuronal activity (Mann-Metzer and Yarom, 2000). Computer simulations of neuron firing patterns similarly indicate a role for extracellular fields (Bawin et al., 1984; Traub et al., 1985). A key criteria to establish is that the field's strength is greater than the random fields generated by thermal noise. The size of voltage fluctuations due to thermal noise has been estimated (Valberg et al., 1997) to be 2,600 V/m for the frequency range 1-100 Hz, which translates to 13 mV across a 5 nm cell membrane. This value is well below the several millivolt transmembrane signal that is expected to be generated by the brains endogenous extracellular EM fields.

The influence that the field has on recipient neurons depends on a number of factors. Neurons with membrane poised close to firing will be most sensitive to field effects; whereas neurons whose membranes are close to resting potential will be relatively insensitive to field effects. The geometry of neurons with respect to the field will also greatly influence their sensitivity. Neurons orientated perpendicularly to lines of equal electrical potential will be most sensitive to the field. In some cases the induced voltage may be depolarising and thereby push the neuron towards firing, whereas in other cases the induced voltage may be hyperpolarising and desensitise the neuron. Self synapsing neurons may be highly sensitive to the field where the closed loop formed is oriented orthogonally; and myelination of nerve fibres will increase their electrical excitability (Rattay, 1998). As Cooper (1984) shows, gap junctions connecting chains of cells focus the potential drop on the terminal cell membrane in the chain and thereby increase sensitivity of the entire cell ensemble to applied fields.

Freeman has explored the theme of the EM field's role at length (Freeman and Dijk, 1987; W.J., 2000; Freeman, 2001), particularly exploring the evolution of amplitude-modulated (AM) wave packets in the EM field. The similarity between the evolution of the EM field and chaotic non-linear dynamical systems initially drew much attention; however, the models were low dimensional, stationary, autonomous and noise-free; in every respect the opposite of what the conditions in the brain are (Rapp, 1993; Freeman, 2001). Despite the initial failure of standard deterministic chaotic models to capture the phenomenon, it is apparent that non-linear methods must apply. Synergetics provides the best available models such as the laser of Haken, who described microscopic particles as being enslaved by a macroscopic order parameter in a relationship of circular causality (Haken, 1991).

Freeman's characterisation of widespread oscillations in the time series derived by sampling EEG fields as limit-cycle-attractors is enlightening, and provides an interesting perspective on the problem of perception. The evidence presented shows the behavioural conditioning of an animal directly results in the generation of a new AM pattern in the EM field for each new stimulus the animal learns to discriminate. As such the recognition apparatus constructs a non-linear multistable phase-space wherein each attractor basin is correlated with a pre-habituated stimulus.

The state of the EM field is visualised using isopotentials: lines along which the EM field potential is constant. The evolution of the isopotentials show the AM wave packets' transformation, synchronised with stimulus and response.

It is notable that Pribram (1991) visualises the holoscape of his holonomic brain theory using a similar mechanism of isopotentials. In his scheme, the isopotentials reside within the aggregate dendritic field.

As McFadden (2002) argues, the EM field is sufficiently powerful to evoke action potentials in neurons suitably aligned with it and having voltage-gated ion channels. The macroscopic oscillation of populations of neurons can therefore influence spatially distant populations without direct synaptic connection. The sensitivity of gap junctions to the EM field is of particular interest, as it permits the EM signal to directly influence the aggregate dendritic field. Significantly, such influence may be more subtle than the evocation of synchronous spiking that mirrors the frequency and phase of the firing pattern that caused the EM pattern originally. The dendritic field permits selective integration of the EM signal with the local state of a nucleus.

The computational implications of this interaction are interesting and the process as a whole reveals the possibility of a variety of computational and communicative devices. For communication, we may have disparate regions of the cortex with no direct innervations that can selectively excite one another through patterned spiking. Further, neural groups may organise an array of self-synapsing and specially oriented neurons that are particularly sensitive to specific frequencies and phases in the EM field, in a manner analogous to receivers that selectively tune to channels of interest. In this case the channels are AM carrier waves with a specific frequency and orientation relative to the receiver.

The EM field is sufficiently powerful to drive voltage-gated ion channels in receiver neurons, it follows that the field can cause sub-threshold oscillations in resonate-and-fire neurons. An AM wave packet has frequency, amplitude, orientation and phase. The orientation of the packet will determine to whether a particular ion channel is affected. Channels that are suitably oriented for a particular wave packet will open and close with the same frequency as the original wave packet.

Within a population of RFNs exposed to an EM field AM wave packet of constant frequency and non-negligible amplitude, the RFN model predicts that members of the population with a resonant frequency close to that of the AM wave packet will respond to its influence by increasingly strong sub-threshold oscillations. Where the wave packet is of sufficient amplitude and duration, these neurons will commence tonic firing in synchrony with the original packet. The RFN model predicts that only a sub set of the population of neurons will experience this response for a given wave packet - specifically those with an appropriate resonant frequency.

The RFN model thus shows how an AM wave packet can spread through adjacent populations, where the sub set of each population with the resonant frequency resonates with the AM wave. More complex effects and transformations are possible. Where a population subset begins resonating and firing, it will likely innervate the other neurons in the local population, that may, due to interneuron propagation delays or different resonant frequencies, have a different natural tonic firing frequency than the original innervation. Further, the innervated neurons may recursively inhibit the resonating neurons, causing their oscillations to cease. The result of such a process is to transform the original AM wave packet into a wave packet of different frequency. An example of this type of frequency transformation was illustrated in figure 5.9 in the previous chapter.

Freeman's mesoscopic scale EM field is complimentary to the RFN model. A consideration of the basic physical characteristics of the field and its strength shows that the field is strong enough to modulate distant neurons and influence their firing. The RFN model predicts that the EM field will selectively influence the subset of neurons in a population that have resonant frequency close to that of the EM field AM wave packet. The RFN model describes how AM wave packets can be propagated by the mechanism of sub-threshold oscillation resonance. Further, examples of RFN networks demonstrate how spike trains can be transformed from one frequency to another. By the same mechanism, AM wave packets can be frequency modulated by RFN networks.

6.3 Computational Models and Consciousness

Consciousness studies as an outgrowth of cognitive science has sparked renewed analysis of the computational metaphor; many of the basic assumptions that we take for granted when we first approach the field are now being questioned. A recurrent theme in such analyses has been an increased reliance on the physical processes underpinning computation (Hameroff, 1987). This reliance on physics and information theory betrays the community's desire for a final bedrock on which to build firmer foundations of a respectable science, yet explanatory gaps between the various levels of description remain. The cross pollination of the diverse range of fields which compose the subject has left a bewildering array of metaphorical port-holes through which to view the phenomena under scrutiny. The language we as individuals use to describe our subjective experience relies heavily on metaphor, both implicit and explicit, yet as scientists it is hard literal fact rather than metaphor that we must seek.

Any of the good theories within the field today attempt to bridge one or more of the current gaps in our explanatory scaffold. Some, such as Hameroff's quantum-based computation, are careful to point out their measurable predictions; others, such Baars et al. (1995) global workspace framework, are more bent on providing a detailed account of what actually happens at a level of analysis that can provide a satisfying account of the cognitive underpinnings of conscious processing. A common feature of all theories is their very disparity. As they stand, they all address the problem at different levels. While this is a sign of healthy science, and suggests a lack of duplication of effort, it is difficult to envision how the various levels will eventually knit together to form a coherent whole.

The single theme common to all (non-trivial) theories of mentation is that of information processing; at one level or another, we are ultimately addressing the problem of how the brain computes. At a simple level then, we must figure out how the individual elements behave, and more importantly, what aspects of the minutiae of their behaviour are important to the computational activity, and what can be ignored as incidental. Secondly, the structures formed by the elemental entities need to be described in detail.

We have already discussed the details of the behaviour of single neurons in the resonance model and shown that the dendritic field of Pribram's model can be accommodated by the computational model of resonate and fire neurons. At this point we face a departure from the typical course of action. For conventional IFN based ANNs at this point we would design a circuit of neurons to implement the behaviour that the particular theory calls for. IFNs are convenient in that they may be treated as simple AND or OR logical operators, meaning that with a little practice one can translate a written description into an ANN circuit with ease. The standard logical operators such as modus ponens are ideally applicable. The problem of course is that such an exercise adds nothing to the understanding of the problem; it simply re-states it in a form which has a neurological association. Worse still, it creates the impression that because the circuit is implemented that the theory has been validated to some extent.

It is not so easy to translate into the language of the resonate and fire neuron; indeed on first impression it is a device which is sorely lacking on the user friendliness front. The reason is that with the aggregation of neurons into a dendritic field the delineation of function becomes increasingly difficult - the activity of a single neuron in such an aggregation has no meaning when considered in isolation from its peers.

The first advantage of the resonance based model is that it accommodates sensory data with ease. There is no unexplained discontinuity between the sensory domain and that of higher level processing. The model is compatible with Pribram's concepts regarding the mechanisms of perception. The second main advantage is that it permits a broad range of computational activities. The standard integration method of conventional ANNs are provided for as a subset of resonate and fire behaviour, in addition to the concept of the dendritic field which permits complex interactions between signals. Oscillations from multiple sources may be combined on a single medium so that they constructively interfere, generate standing wave patterns or cancel each other out entirely. The resonance model also permits relationships between neurons to be dynamic and modified as appropriate. By appropriately timing action potentials output, a pre-synaptic neuron can *choose* to enter a supportive or inhibitory relationship with a peer neuron that innervates the same target.

The third and potentially most significant use of the resonance model concerns the dendritic field. Consciousness is characterized by Newman, Baars and Cho thus: "Consciousness reflects the operations of a global integration and dissemination system" (Baars et al., 1995). The resonance model and associated dendritic field provide a very natural method for alternately integrating and disseminating information to and from diverse sources and targets. Information is integrated into the dendritic field by the fact that the receipt of action potentials by a neuron participating in the field causes oscillations in the aggregate membrane potential. That is, when an action potential is received at a particular dendrite, it influences the oscillation of the post-synaptic neuron's membrane potential. This newly influenced oscillation propagates through dendro-dendritic and gap junctions across the dendritic field. Along the way it will have varying degrees of influence on the base oscillation of member neurons, depending on how closely it matches their resonant frequency. Multiple such inputs can be combined in the dendritic field simultaneously. Each additional input oscillation is combined with the others through straightforward linear superposition. This superposition will determine the exact interference effects that will result from the combination of particular inputs. The final waveform that results will be a combination of a variety of waves. As Fourier theory tells us, such a waveform can always be decomposed into a set of pure sine waves. As such, we can decompose the waveform currently propagating through a dendritic field into a set of pure sine waves of various frequencies. This set of frequencies will effectively identify the neurons which will have the largest response to the original waveform. Neurons with resonant frequencies close to a frequency of a component sine wave will have a large reaction to the waveform, and will fire in response to its presence. Neurons with a resonant frequency that is not close to the frequency of any of the component sine waves will have little or no reaction to the waveform and will not react with the production of action potentials. The production of action potentials is seen as analogous to the dissemination phase of the cognitive process. while the arrival of input pulses and the evolution of the waveform through the dendritic field is seen as the phase during which integration of information from disparate sources is permitted to occur.

In Baars et al. (1995) the wagon wheel model of the Global Workspace theory of Conscious processing, neurological structures are mapped onto concepts from the GW theory. At the centre of the wheel lies the thalamus, a structure through which all sensory modalities, with the exception of olfaction, are routed. The Reticular Nucleus, or NRT, forms a sheath surrounding the thalamus. The purpose posited for the NRT is that it performs a routing function, deciding which thalamo-cortical afferent signals should be transmitted to the cortex and which should be stopped. Finally, the cortex itself forms the outer rim of the wagon wheel. Here expert functions are performed upon the information disseminated by the thalamus and NRT. The result of the processing is then transmitted back to the thalamus for further dissemination to the computational resources of the brain.

In this GW process the integration and dissemination phases of the evolution of the dendritic field, as described in the resonate and fire model, occur at two distinct points. First, inputs from cortical afferents and sensory modalities are integrated by the dendritic fields of the thalamus and NRT. The conclusion of this integration process is the production of action potentials in participant neurons, which are cortical afferents. The particular waveform present in the dendritic fields of the thalamus and NRT determine which cortical afferents are activated, in addition to how often and when. When the action potentials are received by cells in the cortex, the integration process begins again, this time in the dendritic fields of cortical columns. The cortical columns permit a variety of behaviours suited to the implementation of complex expert functions, and may invoke a series of integration and dissemination events through cortico-cortical afferents. Finally, neurons participating in cortical dendritic fields that are thalamic afferent drivers will be activated. Action potentials are transmitted back to the thalamus and the process begins again. There is, of course, room for the idea that the integration and dissemination processes in dendritic fields of the thalamic and cortical structures may run concurrently, opening the door to much more complex interactions. Indeed, certain behaviour such as the conscious prevention of a voluntary action, after the action has been initiated, would appear to suggest that the process can be interrupted and overridden by new input being integrated at any time.

The resonance model then fits into the cognitive theory of consciousness at quite a low level, it prescribes a detailed mechanism of neural interactions that is a departure from the integrate and fire convention and presents a new set of possibilities. It provides the suggestion that in the brain, workspaces are ubiquitous; every dendritic field has one. The obvious suggestion of GW, when combined with the idea that the dendritic field is the workspace, is that there is an area with a very large dendritic field, comprising very many neurons, whose afferents are sufficiently numerous to provide the potential for global dissemination, and the parameterisation of which is sufficient that it can house the productions of an effectively infinite number of expert, unconscious processes. Of course, there is no requirement that such an entity be tied to a single location, or always consist of the same set of constituent neurons. Conscious events could dynamically recruit from a pool of participant neurons as needed; both the actors on the stage and the script from which they read change from moment to moment. Some actors will be typecast, appearing regularly to play out the roles that must be played on a daily basis, whereas others will appear less often, being drawn upon only when the drama reaches a height of complexity or intensity.

6.4 Dynamic Core

Edelman and Tononi (2000) describe a *dynamic core*, equated with the conscious activity of the brain, as a large and changing functional cluster, which includes a large number of disparate neural groups and has high complexity. Degeneracy is a feature of this model, such that different neural groups can give rise to equivalent states of the dynamic core. The exact constituents of the substrate of consciousness is interchangeable, what is of principle importance is the pattern of activity of the core.

The RFN model of neural function has an analogous differentiation between the pattern of activity and the substrate. In RFN, the particular waveform currently occupying a dendritic field is characterised by physical metrics such as frequency, phase and amplitude. As such different dendritic fields can support identical waveforms and therefore they are interchangeable components from the perspective of a population of neurons co-operating to perform some transformation or categorisation task.

The concept of the functional cluster in the dynamic core hypothesis refers to a group of neurons that interact with one another such that they are highly integrated among themselves over a short period and less so with the rest of the brain during that time. This integration involves synchronous activity, direct and reciprocal innervation. This functional clustering is dynamic and as with degeneracy the participants may change from one moment to the next as necessary.

As previously discussed with reference to Freeman's AM wave packets, waveform propagation through populations of resonating neurons is a natural consequence of the RFN model. The model does not prescribe anything about the particular patterns of connectivity required for activity in one subsection of a functional cluster to cause another section to be recruited into the cluster. The RFN model defines a mechanism by which patterns of activity are propagated selectively according to the physical characteristics (resonant frequencies) of the neurons in a population. As described in the previous chapter, RFN neurons support selective innervation sensitive to frequency and interspike timing. These characteristics support the formation of specific permutations of sub-clusters that are recruited over a broadcast medium such as the thalamo-cortical loop.

The criteria that the dynamic core is a functional cluster distinct from other such functional clusters by virtue of its high complexity is an aspect of the theory that the RFN model does not address. Since the model describes the characteristics of the substrate, and does not prescribe any qualitative phase transition resulting from a quantitative change such as the number of participating neurons or the complexity of their interaction, it cannot be brought to bear on the question of how best to characterise the complexity of a particular cluster's activity any more than any other model of the neural substrate. The parameters of the model are similar from an information-theoretic point of view to those of any other model; the state of the system can be fully and completely described with a certain amount of information. As the sub-elements of the system become more differentiated, the more complex the description becomes.

The state of an RFN network at any point in time is described by the topology of the network and the state of the neurons in it. The static state of an RFN is captured by its resonant frequency. The dynamic state of each neuron requires a description of the phase, amplitude and frequency of the waveform in the dendritic field. The standard measure of algorithmic complexity reverts to a measure of how compressible the system's state is. If all neurons are quiescent, then their internal dynamic state is identical and the description of it can be greatly compressed. On the other extreme, if each neuron's membrane potential is oscillating at a different phase, amplitude and frequency to the others, the complexity of the system is definitively close to maximum; however such an arrangement is close to random and it is unlikely that any useful computational task could be accomplished. Computational utility is highest where some subsections of the system are highly differentiated while others are synchronised and integrated.

The dynamic core hypothesis has interesting links with the EM wave packet when one considers the latter's propagation; it would seem that the propagation of AM wave packets and the recruitment of sub-clusters into the dynamic core may be similar processes. Also the mechanism by which the dynamic core is constructed is similar to the manner in which the EM field can evoke resonant activity in disparate neural populations by modulating voltage-gated ion channels. The RFN model suggests how the criteria of degeneracy and clustering can be more readily supported by a neural substrate that accounts for resonance effects and the waveform in the dendritic field as a first-class parameter of the model. On the question of categorising conscious versus unconscious events according to the relative complexity of the functional cluster, RFN is on the same footing as any other computational model; its state is described by a set of numbers, complexity measures are external to the model and may be applied to it, therefore the complexity of a state is an external measure, not something which is characterised by RFN itself.

6.5 The limits of RFN

The RFN model is a simplification of reality. It attempts to capture the first-order, largest magnitude effects of the flow of ions across a neuron cell membrane prior to the emission of an action potential. It models the sub-threshold process in a minimalist manner: a single compartment model is used with an approximation of the dynamics of voltage gated ion channels based on harmonic oscillation. The model is thus limited in its ability to give a comprehensive account of the processes that occur at the sub cellular level: it does not support the concept of compartmental representations of the neuron and any phenomena that emerge from the presence of distinct volumes with separate processes governing their behaviour will be omitted from the model's aggregate behaviour.

Despite these basic limitations, RFN is an improvement over existing computational ANN models. It takes one step toward providing an account of the effects of spatial separation of the nodes in a network by modelling action potential propagation delays. As the previous chapter showed in detail, many interesting effects such as tonic oscillation in self-synapsing or reciprocal innervation result in simple networks where propagation delays are modelled accurately. The RFN model is therefore more expressive than existing connectionist accounts. It is still limited to a basic account of the spatial characteristics of networks, however, and does not provide a model of the spatial extent of cell bodies or the structure of the dendritic tree. This decision was made because to do so would involve great computational expense and would therefore render the model inapplicable to problems involving the simulation of large numbers of neurons.

The scale addressed herein is that of the individual neuron, the microscopic scale. This thesis addresses the neural substrate and attempts to draw conclusions regarding the mesoscopic and macroscopic behaviour of the brain. In this chapter the interaction between the larger scale brain activities and the substrate as modelled by RFN has been discussed and interesting possibilities for signal transmission and distribution of computation were identified, but the model is in this respect degenerate, it supports many possible theories of how the brain as a whole acts, and does not constrain or contradict the major contemporary theories. Despite this degeneracy, we have clearly shown that the RFN model has more expressive power and is as computationally efficient as the existing IFN based architectures. Further, the digital IFN has been shown to be a special case of the analogue RFN, and the new characteristics afforded would appear to be compatible with several concepts in macroscopic theories of cognition, such as functional clustering, selective innervation, broadcast media and wave packet propagation. The concept that the neuron is in any sense digital should be finally eliminated from connectionist modelling since the digital approximation, the IFN, is clearly a specialisation of a more computationally powerful analogue model that adds significant expressive power and useful characteristics at minimal computational expense.

6.6 Summary and Conclusions

Cognitive and computer science are set up to enter into a symbiotic relationship. This has already begun in the form of collaborations in the fields of artificial intelligence, human computer interaction, and cognitive modelling. The next stages of this collaboration require deeper interactions and more fundamental crossover. The particular areas of computer science of immediate concern to cognitive science such as efforts to provide computational models of neurological structures are reaching an impasse. The prevailing paradigm, based on the integrate and fire neuron, is deficient in many ways. It has provided a useful tool for the initial stages of computational modelling of large arrays of neurons, but cannot sustain the complex modular systems proposed by cognitive scientists.

Inspired by Pribram (1991) on the dendritic microprocess and the role of spectral data in the perceptual system, in addition to basic evidence for the predominance of waveform properties in cognitive apparatus, the resonate and fire neural model is proposed as a more scalable, biologically plausible and computationally more powerful mechanism upon which large scale models of cognition can be built. It has been demonstrated that the IFN model is a subset of resonate and fire and all the properties of the former can be captured as a special case of the latter. The implicitly temporal nature of the resonance model is in line with its biological counterpart and distinguishes it from purely synchronous digital mechanisms. This factor makes the resonance units more difficult to use than their IFN counterparts, since they can no longer be treated in the manner of digital logic gates. I would argue that this additional difficulty is a result of the fact that the new model properly accommodates the temporal nature of biological neurons; the additional effort is an inevitable result of using a more comprehensive, less idealized, notation.

The computational model is based on well understood mathematical physics, accessible to freshman level expertise. This fact will facilitate more detailed analysis of the properties of resonance based systems as the network topologies involved become increasingly complex. To an immediate end, this fact makes the implementation of computer programs for simulation of resonance systems extremely straightforward. The resultant code is compact and efficient and current desktop computers are capable of simulating systems of hundreds of thousands of units interacting in real time.

Finally, we examined the implications of the resonance model with respect to the prevailing paradigm for considering the cognitive apparatus underlying consciousness, Baars et al. (1995) GW model. Here we saw that the global workspace itself finds itself at home with the concept of the dendritic field, and postulated that the content of consciousness itself can be accommodated in terms of the state of the dendritic fields capable of origination of afferents to the global cognitive apparatus. Of course, such postulations are premature, and at odds with the basic tenet of computational modelling, which is to base everything on some empirical evidence. The next step is to use the resonance method to provide an implementation for the GW model, and analyse the resultant behaviour. The degree of embodiment that is required for such a system to produce interesting results is the final theoretical hurdle impeding immediate implementation.

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