

**Emergent Neural Computational Architectures
based on Neuroscience**

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Preface

This book is the result of a series of International Workshops organised by the EmerNet project on Emergent Neural Computational Architectures based on Neuroscience sponsored by the Engineering and Physical Sciences Research Council (EPSRC). The overall aim of the book is to present a broad spectrum of current research into biologically inspired computational systems and hence encourage the emergence of new computational approaches based on neuroscience. It is generally understood that the present approaches for computing do not have the performance, flexibility and reliability of biological information processing systems. Although there is a massive body of knowledge regarding how processing occurs in the brain and central nervous system this has had little impact on mainstream computing so far.

The process of developing biologically inspired computerised systems involves the examination of the functionality and architecture of the brain with an emphasis on the information processing activities. Biologically inspired computerised systems address neural computation from the position of both neuroscience, and computing by using experimental evidence to create general neuroscience-inspired systems.

The book focuses on the main research areas of modular organisation and robustness, timing and synchronisation, and learning and memory storage. The issues considered as part of these include: How can the modularity in the brain be used to produce large scale computational architectures? How does the human memory manage to continue to operate despite failure of its components? How does the brain synchronise its processing? How does the brain compute with relatively slow computing elements but still achieve rapid and real-time performance? How can we build computational models of these processes and architectures? How can we design incremental learning algorithms and dynamic memory architectures? How can the natural information processing systems be exploited for artificial computational methods?

We hope that this book stimulates and encourages new research in this area. We would like to thank all contributors to this book and the few hundred participants of the various workshops. Especially we would like to express our thanks to Mark Elshaw, network assistant in the EmerNet network who put in tremendous effort during the process of publishing this book.

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Towards Novel Neuroscience-inspired Computing

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Abstract. Present approaches for computing do not have the performance, flexibility and reliability of neural information processing systems. In order to overcome this, conventional computing systems could benefit from various characteristics of the brain such as modular organisation, robustness, timing and synchronisation, and learning and memory storage in the central nervous system. This overview incorporates some of the key research issues in the field of biologically inspired computing systems.

1 Introduction

It is generally understood that the present approaches for computing do not have the performance, flexibility and reliability of biological information processing systems. Although there is a massive body of knowledge regarding how processing occurs in the brain this has had little impact on mainstream computing. As a response the EPSRC¹ sponsored the project entitled Emergent Neural Computational Architectures based on Neuroscience (EmerNet) which was initiated by the Universities of Sunderland, York and Edinburgh. Four workshops were held in the USA, Scotland and England. This book is a response to the workshops and explores how computational systems might benefit from the inclusion of the architecture and processing characteristics of the brain.

The process of developing biologically inspired computerised systems involves the examination of the functionality and architecture of the brain with an emphasis on the information processing activities. Biologically inspired computerised

¹ Engineering and Physical Sciences Research Council.

systems examine the basics of neural computation from the position of both neuroscience and computing by using experimental evidence to create general neuroscience-inspired systems.

Various restrictions have limited the degree of progress made in using biological inspiration to improve computerised systems. Most of the biologically realistic models have been very limited in terms of what they attempt to achieve compared to the brain. Despite the advances made in understanding the neuronal processing level and the connectivity of the brain, there is still much that is not known about what happens at the various systems levels [26]. There is disagreement over what the large amount of information provided on the brain imaging techniques means for computational systems [51].

Nevertheless, the last decade has seen a significant growth in interest in studying the brain. The likely reason for this is the expectation that it is possible to exploit inspiration from the brain to improve the performance of computerised systems [11]. Furthermore, we observe the benefits of biological neural systems since even a child's brain can currently outperform the most powerful computing algorithms. Within biologically inspired computerised systems there is a growing belief that one key factor to unlocking the performance capabilities of the brain is its architecture and processing [47], and that this will lead to new forms of computation.

There are several architectural and information processing characteristics of the brain that could be included in computing systems to enable them to achieve novel forms of performance, including modular organisation, robustness, information processing and encoding approaches based on timing and synchronisation, and learning and memory storage.

2 Some Key Research Issues

In this chapter and based on the EmerNet workshops we look at various key research issues: For biologically inspired computerised systems it is critical to consider what is offered by computer science when researching biological computation and by biological and neural computation for computer science. By considering four architectural and information processing forms of inspiration it is possible to identify some research issues associated with each of them.

Modular Organisation: There is good knowledge of how to build artificial neural networks to do real world tasks, but little knowledge of how we bring these together in systems to solve larger tasks (such as in associative retrieval and memory). There may be hints from studying the brain to give us ideas on how to solve these problems.

Robustness: How does human memory manage to continue to operate despite failure of its components? What are its properties? Current computers use a fast but brittle memory, brains are slow but robust. Can we learn more about the properties that can be used in conventional computers.

Synchronisation and Timing: How does the brain synchronise its processing? How does the brain prevent the well known race conditions found in com-

puters? How does the brain schedule its processing? The brain operates without a central clock (possibly). How is the asynchronous operation achieved? How does the brain compute with relatively slow computing elements but still achieve rapid and real-time performance? How does the brain deal with real-time? Do they exploit any-time properties, do they use special scheduling methods. How well do natural systems achieve this and can we learn from any methods they may use?

Learning and Memory Storage: There is evidence from neuron, network and brain levels that the internal state of such a neurobiological system has an influence on processing, learning and memory. However, how can we build computational models of these processes and states? How can we design incremental learning algorithms and dynamic memory architectures?

3 Modular Organisation

Modularity in the brain developed over many thousands of years of evolution to perform cognitive functions using a compact structure [47] and takes various forms such as neurons, columns, regions or hemispheres [58].

3.1 Regional Modularity

The brain is viewed as various distributed neural networks in diverse regions which carry out processing in a parallel fashion to perform specific cognitive functions [21, 42, 58]. The brain is sometimes described as a group of collaborating specialists that achieve the overall cognitive function by splitting the task into smaller elements [59]. The cerebral cortex which is the biggest part of the human brain is highly organised into many regions that are responsible for higher level functionality that would not be possible without regional modularity [72, 58]. A feature of regional modularity is the division of the activities required to perform a cognitive function between different hemispheres of the brain. For instances, in this volume, Hicks and Monaghan (2001) [38] show that the split character of the visual processing between different brain hemispheres improves visual word identification by producing a modular architecture.

Brain imaging techniques have successfully provided a great deal of information on the regions associated with cognitive functions [27]. The oldest of these techniques mainly involves the examination of the brain for lesions that are held responsible for an observed cognitive deficit [29]. The lesion approach has been criticised since it does not identify all the regions involved in a cognitive function, produces misleading results due to naturally occurring lesions and alternative imaging techniques contradict its findings [9]. Due to the difficulties observed with the lesion approach and technical developments, four alternative techniques known as positron emission tomography (PET), functional magnetic resonance imaging (fMRI), electronencephalogram (EEG) and magnetoencephalogram (MEG) have received more attention. PET and fMRI both examine precisely the neural activity within the brain in an indirect manner and

so create an image of the regions associated with a cognitive task [60, 9]. For PET this is done by identifying the regions with the greatest blood flow, while for fMRI the brain map is the blood oxygen levels. Although PET and fMRI have good spatial attainment, their temporal competence is limited [68]. In contrast, EEG measures voltage fluctuations produced by regional brain activity through electrodes position on the surface of the scalp. MEG uses variations in the magnetic field to establish brain activity by exploiting sophisticated superconducting quantum devices. The temporal properties of EEG and MEG are significantly better than PET and fMRI with a sensitivity of a millisecond [68].

A major issue that is currently being investigated by biological inspired computer system researchers is the manner that modules in the brain interact [66]. In this volume Taylor (2001) [68] establishes an approach to examine the degree of association between those regions identified as responsible for a subtask by considering the correlation coefficients. This approach incorporates structural modelling where linear associations among the active regions are accepted and the path strengths are established via the correlation matrix. When bridging the gap between the brain image information and underlying neural network operations, activity is described by coupled neural equations using basic neurons. The outcomes from brain imaging, as well as from single cell examinations lead to the identification of new conceptions for neural networks.

A related cortical approach is taken by Érdi and Kiss in this volume. Érdi and Kiss (2001) [24] develop a model of the interaction between cortical regions. Using sixty-five cortical regions, connection strengths and delay levels a connection matrix was devised of a dynamically outlined model of the cortex. Finally, Reilly (2001) [59] identified both feedforward and feedback routes linking the modules performing a particular cognitive function.

The concept of regional modularity in the brain has been used to develop various computing systems. For example, Bryson and Stein (2001) [12] point out in this volume that robotics used modularity for some time and has produced means of developing and coordinating modular systems. These authors also show that these means can be used to make functioning models of brain-inspired modular decomposition. Deco (2001) [18] in this volume also devises a regional modular approach to visual attention for object recognition and visual search. The system is based on three modules that match the two principal visual pathways of the visual cortex and performs in two modes: the learning and recognition modes.

A biological inspired computer model of contour extraction processes was devised by Hansen *et al.* (2001) [34] and Hansen and Neumann (2001) [33] that is based on a modular approach. This approach involves long-range links, feedback and feedforward processing, lateral competitive interaction and horizontal long-range integration, and localised receptive fields for oriented contract processing. The model depends on a simplified representation of visual cortex regions V1 and V2, the interaction between these regions and two layers of V1. Because there is a large number of cortical regions, a description of their mutual connectivity is complex. Weber and Obermayer (2001) [72] have devised computational

models for learning the relationships between simplified cortical areas. Based on a paradigm of maximum likelihood reconstruction of artificial data, the architecture adapts to the data to represent it best.

3.2 Columnar Modularity of Cerebral Cortex

Turning to a more detailed interpretation of the brain's modular construction, Érdi and Kiss (2001) [24], Guigon *et al.* (1994) [31] and Fulvi Mari (2000) [28] built on the fact that the cerebral cortex is composed completely of blocks of repetitive modules known as cortical columns with basically the same six layer structure [24, 28]. Variations in cognitive functionality are achieved as the columnar organisations have diverse start and end connections, and the cortical neurons have regional specific integrative and registering features [31]. According to Reilly (2001) [59] the columns can be 0.03mm in diameter and include around 100 neurons. These columns are used to provide reliable distributed representations of cognitive functions by creating a spatio-temporal pattern of activation and at any particular time millions are active. Their development was the result of the evolutionary need for better functionality and the bandwidth of the sensory system. There are two extreme views on the form that representation takes in the cerebral cortex. The older view sees representation as context independent and compositionality of the kind linked with formal linguistics and logical depiction. The new view holds that the brain is a dynamic system and that predicate calculus is relevant for describing brain functionality.

A model of the cortex and its columns designed by Doya points to a layered structure and a very recurrent processing approach [22]. The system provides both inhibitory and excitatory synaptic connections among three types of neurons (pyramidal neurons, spiny stellate neurons and inhibitory neurons). The pyramidal and spiny stellate neurons are responsible for passing an excitatory signal to various other cells in the column including cells of the same kind. Inhibitory neurons restrict the spiking of the pyramidal and spiny stellate neurons that are near by, while the pyramidal and spiny stellate neurons use the inhibitory neurons to control themselves and other cells in the column. In this volume, a related columnar model is devised by Bartsch *et al.* (2001) [7] when considering the visual cortex. A prominent character of the neurons in the primary visual cortex is the preference input in their classical receptive field. The model combines various structured orientation columns to produce a full hyper-column. Orientation columns are mutually coupled by lateral links with Gaussian profiles and are driven by weakly orientation-biased inputs.

There has been some research to create these multi-cellular models using cells made from many linked compartments and so a higher degree of biological plausibility. However, there is the difficulty of high processing time due to the ionic channel processing elements within the compartments [39]. To a certain extent this can be overcome by using Lie series solutions and Lie algebra to create a restricted Hodgkin-Huxley type model [30].

In general, the brain consists of a distributed and recurrent interaction of billions of neurons. However, a lot of insight and inspiration for computational architectures can be gained from areas, regions or column organisation.

4 Robustness

A second important feature of the brain is its robustness. Robustness in the human brain can be achieved through recovery of certain functions following a defect. The brain has to compensate for the loss of neurons or even neuron areas and whole functional networks on a constant basis. The degree of recovery and hence of robustness is dependent on various factors such as the level of the injury, the location and size of the lesion, and the age of the patient. Recovery is felt to be best when the patient is younger and still in the maturation period, but the approaches for recovery are complicated and variable [50, 43, 8].

Two approaches to recovery are: i) the repair of the damaged neural networks and the reactivation of those networks which although not damaged due to their close proximity to the injury stopped functioning; and ii) redistribution of functionality to new regions of the brain [14]. There is mixed evidence about the time it normally takes for repair of injured tissue. However, researchers have found that the redistribution of functionality to new regions of the brain can take longer and repair of the left superior temporal gyrus occurs over numerous months following the injury [50]. Restoration of the cortex regions is critical to good recovery of the functionality of the region and is known to inhibit the degree of reallocation of functionality to new regions [71, 73]. According to Reggia *et al.* (2001) [58] in this volume the reorganisation of the brain regions responsible for a cognitive function explains the remarkable capacity to recover from injury and robust, fault-tolerant processing.

4.1 Computerised Models of Recovery through Regeneration

It is possible to model recovery through tissue regeneration by considering the neural network's performance at various degrees of recovery. For instance, Martin *et al.* (1996) [46] examined recovery through the regeneration of tissue in a deep dysphasia by considering the attainment of a subject on naming and repetition tests. The model used to examine robustness is associated with the interaction activation and competition neural network and recovery comes from the decay rate returning to more normal levels. Wright and Ahmad (1997) [81] have also developed a modular neural network model that can be trained to perform the naming function and then damaged to varying degrees to examine recovery. A model that incorporates a method to achieve robustness through recovery that is closer to the technique employed in the brain is that of Rust *et al.* (2001) [61] in this volume, which considers the creation of neural systems that are dynamic and adaptive. This computational model produces recovery by allowing adaptability and so achieving self-repair of axons and dendrites to produce new links.

4.2 Computerised Model of Robustness through Functional Reallocation

A second form of robustness is reallocation. When considering the recovery of functionality through reallocation, Reggia *et al.* (2001) [58] in this volume devise biologically plausible models of the regions of the cerebral cortex responsible for the two functions of phoneme sequence creation and letter identification. The former model is based on a recurrent unsupervised learning and the latter on both unsupervised and supervised learning. When the sections of the models that represent one hemisphere of the cerebral cortex were left undamaged they contributed to the recovery of functionality, particularly when the level of injury to the other hemisphere was significant. In general, such graded forms of dynamic robustness go beyond current computing systems.

5 Timing and Synchronisation

Although the neurophysiological activity of the brain seems complicated, diverse and random experimental data indicates the importance of temporal associations in the activities of neurons, neural populations and brain regions [11]. Hence, timing and synchronisation are features of the brain that are considered critical in achieving high levels of performance [17]. According to Denham (2001) [19] in this volume, the alterations of synaptic efficacy coming from pairing of pre- and postsynaptic activity can significantly alter the synaptic links. The induction of long-term alterations in synaptic efficacy through such pairing relies significantly on the relative timing of the onset of excitatory post-synaptic potential (EPSP) produced by the pre-synaptic action potential.

There is disagreement over the importance of the information encoding role played by the interaction between the individual neurons in the form of synchronisation. Schultz *et al.* (2001) [62] consider synchronisation as only secondary to firing rates. However, other research has questioned this based on the temporal organisation of spiking trains [11].

Another critical feature of timing in the brain is how it performs real-time and fast processing despite relatively slow processing elements. For instance Bugmann (2001) [13] points to the role of the cerebellum in off-line planning to achieve real-time processing. According to Panzeri *et al.* (2001) a commonly held view is that fast processing speed in the cerebral cortex comes from an entirely feedforward-oriented approach. However, Panzeri *et al.* (2001) [55] were able to contradict this view by producing a model made up of three layers of excitatory and inhibitory integrate-and-fire neurons that included within-layer recurrent processing.

Given the importance of timing and synchronisation in the brain, computational modelling is used in several architectures to achieve various cognitive functions including vision and language. For instance, Sterratt (2001) [67] examined how the brain synchronises and schedules its processing by considering the locust olfactory system. The desert locust olfactory system's neural activity has interesting spatiotemporal and synchronisation coding features. In the

olfactory system the receptor cells connect to both the projection neurons and inhibitory local neurons in the Antennal Lobe, as well as the projection neurons and inhibitory local neuron groups being interconnected. The projection neurons appear to depict the odour via a spatiotemporal code in around one second, which is made up of three principal elements: the slow spatiotemporal activity, fast global oscillations and transient synchronisation. Synchronisation in this system is used to refine the spatiotemporal depiction of the odours.

A biologically inspired computerised model of attention that considers the role played by synchronisation was formulated by Borisyuk *et al.* (2001) [11] with a central oscillator linked to peripheral oscillators via feedforward and feedback links. In this approach the septo-hippocampal area acts like the central oscillator and the peripheral oscillators are the cortical columns that are sensitive to particular characteristics. Attention is produced in the network via synchronisation of the central oscillator with certain peripheral oscillators.

Henderson (2001) [37] devised a biologically inspired computing model of synchronisation to segment patterns according to entities using simple synchrony networks. Simple synchronisation networks are an enlargement of simple recurrent networks by using pulsing units. During each period pulsing units have diverse activation levels for the phrases in the period.

A related biologically inspired model addresses the effects of axonal and dendritic conduction time delays on temporal coding in neural populations, Halliday (2001) [32]. The model uses two cells with common and independent synaptic input based on morphologically detailed models of the dendritic tree typical of spinal a motoneurons. Temporal coding in the inputs is carried by weakly correlated components present in the common input spike trains. Temporal coding in the outputs is manifest as a tendency for synchronized discharge between the two output spike trains. Dendritic and axonal conduction delays of several ms do not alter the sensitivity of the cells to the temporal coding present in the input spike trains.

There is growing support for chaotic dynamics in biological neural activity and that individual neurons create chaotic firing in certain conditions [52]. In a new approach to brain chaos András (2001) [1] states in this volume that the stimuli to the brain are represented as chaotic neural objects. Chaotic neural objects provide stability characteristics as well as superior information representation. Such neural objects are dynamic activity patterns that can be described by mathematical chaos.

Assadollahi and Pulvermüller (2001) [2] were able to identify the importance of a spatio-temporal depiction of information in the brain. This was performed by looking at the representations of single words by using a Kohonen network to classify the words. Sixteen words from four lexico-semantic classes were used and brain responses that represent the diverse characteristics of the words such as their length, frequency and meaning measured using MEG.

6 Learning and Memory Storage

An additional structural characteristic of the brain and central nervous system is the manner it learns and stores memories. Denham (2001) [19] argues that the character of neural connections and the approach to learning and memory storage in the brain currently does not have a major impact on computational neural architectures despite the significant benefits that are available. A school of thought known as neo-constructivism led by Elman (1999) [23] argue that learning and its underlying brain structure does not come from a particular organisation that is available at birth, but from modifications that result from the many experiences that are faced over time. Although this model does have a certain appeal, Marcus (2001) [45] points to various limitations with it, learning mechanisms have a certain degree of innateness as infants a few months old often have the ability to learn ‘abstract rules’, developmental flexibility does not necessarily entail learning and it relies too greatly on learning and neural activity. Marcus (2001) [45] holds that neo-constructivists lack a toolkit of developmental biology and has put forward his own approach to developing neural networks that grow and offer self-organising without experience. This toolkit includes cell division, migration and death, gene expression, cell-to-cell interaction and gene hierarchies.

For many years computational scientists have attempted to incorporate learning and memory storage into artificial intelligent computer systems typically as artificial neural networks. However, in most systems the computational elements are still a gross simplification of biological neurons. There is too little biological plausibility or indication of how the brain constrains can be incorporated in a better way [66, 12, 25]. Nevertheless, Hanson *et al.* (2001) [35] in this volume outlines that artificial neural networks such as recurrent ones can perform emergent behaviour close to human cognitive performance. These networks are able to produce an abstract structure that is situation sensitive, hierarchical and extensible. When performing the activity of learning a grammar from a valid set of examples the recurrent network is able to recode the input to defer symbol binding until it has received sufficient string sequences.

6.1 Synaptic Alteration to Achieve Learning and Memory Storage

Two regions of the brain that are fundamental in learning and memory storage are the cortex and the hippocampus. However, these are not the only areas involved as shown below by Prez-Urbe (2001) [57] who describes a basal ganglion model and its role in trial-and-error learning. The hippocampus system is a cortical subsystem found in the temporal lobe and has a fundamental role in short-term memory storage and transferring of short-term memories to longer-term ones. The cortex is the final location of such memories [48].

One of the first accounts of how learning occurs is that of Hebb (1949) [36] who devised a model of how the brain stores memories through a simple synaptic approach based on cell assemblies for cortical processing. Alterations in synaptic strengths is the approach for learning, the persistence of memories and repeated

co-activation is used for memory retrieval. The determinant of an assembly is the connectivity structure between neurons that lends support to one another's firing and hence have a greater probability of being co-activated in a reliable fashion. Cell assemblies are found in working and long-term memory storage and interact with other cell assemblies. There has been a substantial amount of work on learning and memory [66, 54, 79, 74, 69, 49, 65].

Long-term potentiation (LTP) is a growth in synaptic strength that is caused rapidly by short periods of synaptic stimulation and is close to the Hebb's notion of activity-reliant alterable synapses. Given that there is an approach like LTP for strengthening links between synapses, it is likely that there is a device for reducing the synaptic strength which is known as long-term depression (LTD). Shastri (2001) [64] in this volume devises a computational abstraction of LTP and LTD which is a greatly simplified representation of the processes involved in the creation of LTP and LTD. A cell is represented as an idealised integrate-and-fire neuron with spatio-temporal integration of activity arriving at a cell. Certain cell-kinds have two firing modes: supra-active and normal. Neurally, the supra-active model relates to a high-frequency burst reaction and the normal mode relates to a basic spiking reaction made up of isolated spikes. LTP and LTD are identified by Shastri (2001) [64] as critical in episodic memory through their role in binding-detection. In Shastri's model a structure for the fast production of cell responses to binding matches is made up of three areas: role, entity and bind. Areas role and entity are felt to have 750,000 primary cells each, and bind 15 million cells. The role and entity areas match the subareas of the entorhinal cortex, and the bind area the dentrate gyrus.

Huyck (2001) [40] devised a biologically inspired model of cell assemblies known as the CANT system. The CANT system is made up of a network of neurons that may contain many cell assemblies that are unidirectionally linked to other neurons. As with many neural network models connection strengths are altered by the local Hebbian rule and learning through a Hebbian-based unsupervised approach.

6.2 Models of Learning

There have been some recent models of learning in artificial systems which are particularly interesting since they are based on neuroscience learning methods. For instance, McClelland and Goddard (1996) [48] examined the role of the hippocampal system in learning by devising a biologically inspired model. Forward pathways from the association regions of the neocortex to the entorhinal cortex create a pattern of activation on the entorhinal cortex that maximises preservation of knowledge about the neocortical pattern. The entorhinal cortex gives inputs to the hippocampal memory system, which is recoded in the dentate gyrus and CA3 in a manner that is suitable for storage. The hippocampus computerised model is split into three main subsystems: i) structure-preserving invertible encoder subsystem; ii) memory separation, storage and retrieval subsystem; and iii) memory decoding system.

The learning process is outlined by Denham (2001) [19] in this volume as a simple biologically inspired computational model. The model requires the determination of the EPSP at the synapse and the back-propagating action potential. A learning rule is then produced that relies on the integration of the product of these two potentials. The EPSP at the synapse is determined by the effective synapse current using the equation for the passive membrane mechanism.

Two biologically inspired computerised systems of learning are included in robots, which shows that these systems can improve on existing technology. Kazer and Sharkey (2001) [41] developed a model of how the hippocampus combines memory and anxiety to produce novelty detection in a robot. The robot offers knowledge for learning and an approach for making any alterations in anxiety behaviourally explicit. A learning robot was devised by Pérez-Urbe (2001) [57] that uses a biologically inspired approach based on the basal ganglion to learn by trial-and-error.

Bogacz *et al.* (2001) [10] devised a biologically plausible algorithm of familiarity discrimination based on energy. This is based on the information processing of the perirhinal cortex of the hippocampus system. This approach does not need assumptions related to the distribution of patterns and discriminates if a certain pattern was presented before and keeps knowledge on the familiar patterns in the weights of Hopfield Networks.

A related biologically inspired computerised system was devised by Chady (2001) [16] for compositionality and context-sensitive learning founded on a group of Hopfield Networks. The inspiration comes from the cortical column by using a two-dimensional grid of networks and basing interaction on the nearest neighbour approach. In the model the individual network states are discrete and their transitions synchronous. The state alteration of the grid is carried out in an asynchronous fashion.

When considering a biological inspired computerised systems for natural language understanding Moisl (2001) [51] proposes sequential processing using Freeman's work on brain intentionality and meaning. Moisl (2001) [51] proposed approach will include: i) Processing components that output pulse trains as a nonlinear reaction to input; ii) Modules of excitatory and inhibitory neurons that create oscillatory actions; iii) Feedforward and feedback links between modules to foster chaotic behaviour; and iv) A local learning mechanism such as Hebbian learning to achieve self-organising in modules.

Pearce *et al.* (2001) [56] argues that the olfactory system offers an ideal model for examining the issues of robust sensory signal transmission and efficient information representation in a neural system. A critical feature of mammalian olfactory system is the large scale convergence of spiking receptor stimulus from thousands of olfactory receptors, which seems fundamental for information representation and greater sensitivity. Typically the information representation approaches used in the olfactory cortex are action and grading potentials, rate codes and particular temporal codings. The study considered whether the rate-coded depiction of the input restricts the quality of the signal that can be recovered in the glomerulus of the olfactory bulb. This was done by looking at the outcomes

from two models, one that uses probabilistic spike trains and another which uses graded receptor inputs.

Auditory perception has various characteristics with the brain having the capability to detect growths in loudness as well as differentiating between two clicks that are very close together. Based on the findings of Denham and Denham (2001) [20] this is the result of the manner of information representation in the primary auditory cortex through cortical synaptic dynamics. When synapses are repeatedly activated they do not react in the same manner to every incoming impulse and synapses might produce a short-term depression or facilitation. When there is a great deal of activity in the synapse, the amount of resources that are available is reduced, which is likely to be followed by a period of recovery for the synapse. A leaky integrate-and-fire neuron model is then used, with the input to the neuron model gained through summing the synaptic EPSPs. In the examination of the model the reaction features of the neuron that incorporated a dynamic synapse are close to those of the primary auditory cortex.

Caragea *et al.* (2001) [15] have proposed a set of biologically inspired approaches for knowledge discovery operations. The databases in this domain are normally large, distributed and constantly growing in size. There is a need for computerised approaches to achieve learning from distributed data that do not reprocess already processed data. The techniques devised by Caragea *et al.* (2001) [15] for distributed or incremental algorithms attempt to determine information needs of the learner and devising effective approaches to providing this in an distributed or incremental setting. By splitting the learning activity into information extraction and hypothesis production stages this allows the enhancement of current learning approaches to perform in a distributed context. The hypothesis production element is the control part that causes the information extraction component to occur. The long-term aim of the research is to develop well-founded multi-agent systems that are able to learn through interaction with open-ended dynamic systems from knowledge discovery activities.

6.3 Models of Memory Storage

In this section we provide an outline of the various biologically inspired computerised models connected with memory storage in the brain. Knoblauch and Palm (2001) [42] took a similar approach to autoassociative networks as by Willshaw [79, 75, 78, 76, 80, 77] and extend it based on biological neurons and synapses. In particular Knoblauch and Palm added characteristics that represent the spiking actions of real neurons in addition to the characteristics of spatio-temporal integration on dendrites. Individual cells are modelled like 'spiking neurons': each time the potential level is at a particular threshold a pulse-like action potential is created. The Knoblauch and Palm (2001) [42] model of associative memory is included in a model of reciprocally connected visual areas comprising three areas (R, P and C) each made up of various neuron populations. In region R (retina) input patterns matching input objects in the visual field and are depicted in a 100 x 100 bitmap. Area P (primary visual cortex) is made up of 100 x 100 exci-

tatory spike neurons and 100 x 100 inhibitory gradual neurons. Area C (central visual area) is modelled as the SSI-variant of the spiking associative memory.

A biologically inspired model of episodic memory by Shastri (2000) [63] known as SMRITI outlines how a transient pattern of rhythmic activity depicting an event can be altered swiftly into a persistent and robust memory trace. Creation of such a memory trace matches the recruitment of a complicated circuit in the hippocampal system that includes the required elements. In order to analysis characteristics of the model its performance is examined using plausible values of system variables. The outcomes display that robust memory traces can be produced if one assumes there is an episodic memory capacity of 75,000 events made up of 300,000 bindings.

Forcada and Carrasco (2001) [25] argue that, although a finite-state machine could be modelled by any discrete-time recurrent neural network (DTRNN) with discrete-time processing elements, biological networks perform in continuous time and so methods for synchronisation and memory should be postulated. It ought to be possible to produce a more natural and biologically plausible approach to finite-state computation founded on continuous-time recurrent neural networks (CTRNN). CTRNN have inputs and outputs that are functions of a continuous-time variable and neurons that have a temporal reaction. It is possible to encode in an indirect manner finite-state machines using a sigmoid DTRNN as a CTRNN and then changing the CTRNN into an integrate-and-fire network.

A considerable amount of research has been carried out by Austin and his associates at York into memory storage [6, 3, 5, 53, 4, 70, 82]. An example of this work in this volume is the Correlation Matrix Memories (CMMs) which according to Kustrin and Austin (2001) [44] are simple binary weighted feedforward neural networks that are used for various tasks that offers an indication of how memories are stored in the human cerebral cortex. CMMs are close to single layer, binary weighted neural networks, but use much less complex learning and recall algorithms.

7 Conclusion

There is no doubt that current computer systems are not able to perform many of the cognitive functions such as vision, motion, language processing to the level associated with the brain. It seems there is a strong need to use new architectural and information processing characteristics to improve computerised systems. Although interest in biologically inspired computerised system has grown significantly recently, the approaches currently available are simplistic and understanding of the brain at the system level is still limited. Key research issues for biologically inspired computer systems relate to the fundamental architectural features and processing-related associated with the brain, and what computer science can learn from biological and neural computing.

The characteristics of the brain that potentially could benefit computerised systems include modular organisation, robustness, timing and synchronisation

and learning and memory storage. Modularity in the brain takes various forms of abstraction including regional, columnar and cellular, and is central to many biologically inspired computerised systems. Robustness comes from the brain's ability to recover functionality despite injury through tissue repair and re-allocation of functionality to other brain regions. While conventional computer systems are presently based on synchronised or clocked processing these systems could potentially be enriched by basing information processing and encoding on the timing and synchronisation approaches of the brain. Furthermore, as seen in this chapter and volume a particular fertile research area is the development of biological inspired computing models of learning and memory storage to perform various cognitive functions [42, 20, 63, 41, 25, 20].

To move the field of biological inspired computing systems forward, consideration should be given to how the architectural features of the brain such as modular organisation, robustness, timing and synchronisation, and learning and memory could benefit the performance of computing systems. The most suitable level of neuroscience-inspired abstraction for producing such systems should be identified. Although the findings offered by neuroscience research should be taken serious, there is a need to understand the constraints offered by computer hardware and software. Greater concentration should be given to dynamic network architectures that can alter their structure based on experience by either using elaborate circuitry or constant network modification. Finally, a more comprehensive understanding of the brain and the central nervous system is critical to achieve better biologically inspired adaptive computing systems.

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