Report to the European Science Foundation on the

III^{d} ESF Summer Symposium
Neurotechnology: Applications and Implementation

August 25-26, 2001
Trieste, Italy

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Chapter 1

Introduction

The ESF symposium on “Neurotechnology: Applications and Implementation” was the third of a series of meetings, held on the the Miramare campus of the International Centre for Theoretical Physics, in Trieste, Italy. The symposium was held on August 25 and 26, just after the ending of the EU Advanced Course in Computational Neuroscience, held in the same location.

The symposium was advertised on the World-Wide-Web (see URL: http://www.sissa.it/cns/www/esf01.htm and on the most popular connectionist and computational neuroscience mailing lists. The first round of invitations for this symposium was made by e-mail on April 8 (see Appendix B). Out of the 32 senior researchers that we invited, only 8 declined. We also received 15 requests for participation (and funding) from junior researchers.

All together about 60 participants attended the symposium, engaging in lively discussions during and after each talk, and continuing through the breaks and the meals. The symposium budget actually paid full accommodation and travel reimbursements for only about two thirds of them (24 invited guests, and 15 junior participants). In addition, students and participants of the EU course were also invited and several did attend the symposium, which was made possible by including in the budget solely the extra nights for those few that needed to extend their stay (these are included in the list of registered participants at the end). Finally, a number of local participants from SISSA and ICTP joined in the exchanges, at no cost for the symposium budget. The low total expenditure confirms the added value of holding the symposium not at an isolated location, but in conjunction with the EU course, and within a scientific campus.

Next to the 21 oral presentations that were held during the the symposium (see Section 1.2), there were demonstrations of VLSI neuromorphic demos and poster presentations.

1.1 Goals and Background

The aim of this symposium was to bring together the neuromorphic engineering and the computational neuroscience communities. Particular care was given in choosing a balanced mix of researchers working on topics that would complement each other. Specifically, we requested the invited speakers to discuss topics that were related *both* to computational neuroscience *and* to hardware implementations (*e.g.* algorithms that could be implemented in VLSI, analog electronic circuits that reproduce the behavior of the neural circuits they model, *etc.*).

1.2 Program

On August 25, at the beginning of the symposium, the organizers gave a warm welcome to all the participants. Giacomo Indiveri briefly described the schedule of the day, Alessandro Treves gave details on the logistics (*e.g.* about the coffee breaks, lunches, dinners, *etc.*) and Rodney Douglas gave a brief account of the ESF summer symposium history and motivations, and acknowledged the European Science Foundation for the support.

The schedule of the program is outlined Table 1.1.

Table 1.1: Symposium's program

August	**25**	
	Session One: Spike based processing	
9:30 - 10:00	Wolfgang Maass	Liquid State Machines: A new Framework for Computing with Spikes
10:00 - 10:30	Alan Murray	Spikes (probably) and Strange Hardware
10:30 - 11:00	Andreas Andreou	Capacity and Energy Cost of Information in Biological and Silicon Photoreceptors
Coffee Break		
	Session Two: Learning and HW implementations	
11:30 - 12:00	Wulfram Gerstner	Neural Principles of Navigation: a model of the Rat Hippocamal System
12:00 - 12:30	Eros Pasero	NESP: a NEural Signal Processor
Lunch Break		
14:30 - 15:00	Florentin Worgotter	A DSP compatible circuit for temporal sequence learning: Classical conditioning in a behaving robot.
15:00 - 15:30	Tor Sverre Lande	Neuromorphic Medical Electronics
15:30 - 16:00	Stefano Fusi	Long-Term Synaptic Plasticity in Analog VLSI without Floating Gates
Coffee Break		
	Session Three: Neuromorphic Systems Demos	
16:30 - 16:50	Tobi Delbrück	A physiologysts friend chip
16:50 - 17:10	Jörg Kramer	An AER transient imager
17:10 - 17:30	Giacomo Indiveri	An AER selective attention device
17:30 - 17:50	Vittorio Dante	A communication infrastructure for AER devices
17:50 - 18:20	Shih-Chii Liu	An AER multi-neuron chip
18:30 - 19:30	*POSTER SESSION*	
August	**26**	
	Session Four: Learning and population codes	
9:30 - 10:00	Maneesh Sahani	Representation of uncertainty in population codes
10:00 - 10:30	Walter Senn	Development of Direction Selective Cells in V1 through Spike-Timing Dependent Synaptic Plasticity
10:30 - 11:00	Herbert Jaeger	Fast Supervised Teaching for Recurrent Neural Networks: a Redundant Basis Approach
Coffee Break		
	Session Five: Cortical systems	
11:30 - 12:00	Andras Lorincz	Neocortical architecture carved with Ockham's razor
12:00 - 12:30	Miguel Nicolelis	Action from Thoughts: using High-Density MultiElectode Recordings to Build a Neuroprosthetic Device for Restoring Motor Function

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Lunch Break		
14:30 - 15:00	Leslie Smith	Onsets and depressing synapses: a biologically inspired attempt at auditory scene analysis.
15:00 - 15:30	Massimo Grattarola	Bioartificial networks of neurons
15:30 - 16:00	Rodney Douglas	Concluding remarks

Chapter 2

Talk abstracts

The following are the summaries of the talks presented at the symposium. Next to the oral presentations, live demos of neuromorphic systems were given during the third session of the symposium (see Program in previous Section).

2.1 Liquid State Machines: A new Framework for Computing with Spikes (Wolfgang Maass)

We propose a new model for real-time computation on spike trains in neural circuits. This model is not based on stable internal states or attractors, but rather exploits the natural transient dynamics of neural circuits as universal source of information about past inputs. This approach is based on a rigorous computational model, the liquid state machine. This model guarantees universal computational power under idealized conditions, like the Turing machine, but for real-time computing on time-varying inputs with fading memory (rather than for offline-computing on static inputs like the Turing machine). Based on this framework we have for the first time been able to carry out complex real-time computations on spike trains with biologically realistic computer models of neural microcircuits. This approach also suggests a radically new approach toward neuromorphic engineering: Look for efficient hardware implementations of adaptive liquid state machines in order to build devices for real-time processing of sensory inputs (joint work with Henry Markram and Thomas Natschlaeger).

As a side result of this research project we have shown that a single layer of perceptrons (whose ”votes” are counted to give a graded circuit output) can approximate any given continuous function. Furthermore we have found (in joint work with Peter Auer and Harald Burgsteiner) a learning algorithm for these arguably simplest instances of neural universal approximators, which -unlike backprop- requires just 2 bits of communication between the global control and local processors that control individual weights. Furthermore it does not require the computation of high precision derivatives or analog error signals. Hence this learning algorithm appears to be well-suited for implementation in adaptive neural VLSI.

2.2 Spikes (Probably) and Strange Hardware (Alan Murray)

This talk will discuss the subset of ”neural” hardware techniques that use spiking, or pulsed behavior. The methods behind pulsed VLSI will be reviewed and some exemplar circuits presented - for spike-generation, synaptic ”multiplication” and learning. The potential and limitations of pulsed VLSI will be revisited in the context of the new medium that is Deep-Sub-Micron (DSM) silicon. By 2010, transistors will be smaller than 50nm - noise will be greatly amplified and irreducible. At present, no strategy exists for reliable computation with such devices. Some preliminary work in (a) probabilistic hardware and (b) spike-based learning will be discussed.

2.3 Capacity and Energy Cost of Information in Biological and Silicon Photoreceptors (Andreas Andreou)

We outline a theoretical framework to analyze information processing in biological sensory organs and in engineered microsystems. We employ the mathematical tools of communication theory and model natural or synthetic physical structures as micro-scale communication networks, studying them under physical constraints at two different levels of abstraction. At the functional level we examine the operational and task specification, while at the implementation level we examine the physical specification and realization. Both levels of abstraction are characterized by Shannon’s channel capacity, as determined by the channel bandwidth, the signal power, and the noise power. The link between the functional level and the physical level of abstraction is established through models for transformations on the signal, physical constraints on the system, and noise that degrades the signal. The models and noise are described from first principles when possible and phenomenologically otherwise.

As a specific example, we present a comparative study of information capacity (in bits per second) versus energy cost of information (in joules per bit) in a biological and in a silicon adaptive photoreceptor. The communication channel model for each of the two systems is a cascade of linear band-limiting sections followed by additive noise. We model the filters and the noise from first principles whenever possible and phenomenologically otherwise. The parameters for the blowfly model are determined from biophysical data available in the literature and the parameters of the silicon model are determined from our experimental data.

This comparative study is a first step toward a fundamental and quantitative understanding of the trade-offs between system performance and associated costs such as size, reliability and energy requirements for natural and engineered sensory microsystems.

Work from: Capacity and Cost of Information in Biological and Silicon Photoreceptors. Abshire and Andreou, Proceedings IEEE, July 2001.

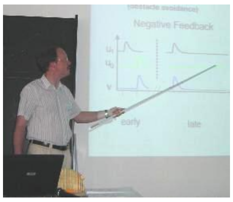
2.4 Neural Principles of Navigation: a model of the rat hippocampal system (Wulfram Gerstner)

Neurons in the hippocampus of rats respond preferentially when the animal is at a specific location in the environment. Thus activity of each single neuron ‘represents’ a certain place in the environment (place field). Two questions will be addressed in this talk from a modeling point of view: First, how can we derive place fields from visual and proprioceptive information? We show that, after some suitable preprocessing, unsupervised learning yields a stable representation of the environment by many overlapping place field. Second, how can place fields be used for navigation? We show that the dense representation by place fields that results from exploration is an ideal basis for reinforcement learning. A learned target position can be reached after 5-10 trials. The model is demonstrated on a Khepera robot with video camera head.

2.5 NESP: a NEural Signal Processor (Eros Pasero)

Analog Artificial Neural Networks (ANNs) could be the core of an ”intelligent” signal processor, with the today used digital processing replaced by a raw ”data driven” methodology. Characteristic of this approach is: analog input/output: signals don’t need A/D and D/A converters; speed: an analog system can be faster than a digital or a mixed-mode one; effectiveness: ANNs already demonstrated their power in many applications; low power: analog circuits can save power. NESP is a NEural Signal Processor which offers the above characteristics and is based on a traditional, available and not expensive double polysilicon double metal commercial VLSI process.”

2.6 A DSP compatible circuit for temporal sequence learning: Classical conditioning in a behaving robot (Florentin Wörgötter)



Learning is an important feature of animal behavior, because it makes repeated de-novo analysis of the sensorial input unnecessary. Accordingly also in many artificial systems learning algorithms are utilized and artificial neural networks, that can learn, have become of far reaching influence in physics and engineering. Recently systems have also been investigated that can learn temporally extended input patterns (time-sequences, for a review see (Dayan and Abbott 2001). These systems consist of so-called ”spiking-units” which produce an output-pulse (a ”spike”), like a real neuron, as soon as all summed inputs exceed a certain threshold. Accordingly, the temporal patterns, which can be learned, consist of sequences of such pulses. Commonly the temporal correlation between input and output determines the weight change at the network units in such systems: A weight will be strengthened only if the input precedes the output by a short interval. If the order of input and output is reversed the weight will decrease (Song et al. 2000). The size of the temporal window within which the pulse-sequence is evaluated - the correlation window - is usually rather short, in order to assure a high temporal accuracy (Gerstner et al. 1996). Therefore, learning of longer-lasting pulse-sequences requires additional mechanisms (such as multiple delay lines (Dayan and Abbott 2001). In addition, these systems cannot very easily handle additional (second or more) independent inputs and they will also fail when subjected to complex input patterns. This, however, is the normal situation in almost all biological temporal learning situations. The most ubiquitous temporal learning known, ”classical conditioning”, takes place on rather long time scales and normally requires two input stimuli, the unconditioned and the conditioned stimulus, which often arise from different sensorial modalities. The unconditioned stimulus (food) is followed by an output event (salivation). After learning the conditioned stimulus (bell), which always precedes the conditioned stimulus will elicit the same event and, thus, the unconditioned stimulus can be interpreted as a predictor of the conditioned stimulus (the sound of a bell predicts the feeding). In this presentation we will present a theoretical framework for predictive (temporal) learning which does not require pulse-coding and, is, thus, able to handle time-continuous input signals of arbitrary shape. A new learning rule is developed which utilizes the temporal change (the derivative) of the output to modify the weights and we will show, that our approach allows to analytically calculate the initial development of the weights. In addition, we will demonstrate that this approach is directly compatible with modern DSP architectures and its performance is demonstrated by means of a behaving robot.

[1] P. Dayan, & L. F. Abbott, *Theoretical Neuroscience*, (MIT Press, Cambridge MA, in press).

[2] S. Song, K. D. Miller, & L. F. Abbott (2000) *Competitive Hebbian Learning Through Spike-Timing-Dependent Synaptic Plasticity* Nature Neurosci. 3, 919-926.

2.7 Neuromorphic Medical Electronics (Tor Sverre Lande)

The merits of Neuromorphic engineering regarding applications in real products is not very impressive. In spite of promising research results the only available commercial product is the Logitech optical mouse. Even this one has only marginal relations to a neuromorphic style of engineering. In my search for applications for neuromorphic systems, implantable medical electronics showed up as potentially interesting. Several neuromorphic features like low power, high computational efficiency and minimal size could be advantageous in these applications. The best of all is that an increasing number of implantable electronics are nerve stimulators where spikes are the ”natural language”

A key to both neuromorphic engineering and medical electronics is a fundamental understanding of information coding in the human nervous system. Recent research has moved the timescale of our nerve system from milliseconds to microseconds (maybe even to nanoseconds). As a consequence we have to treat the temporal information with much more respect.

In many medical electronic applications some sort of real time signal processing is required like filtering and gain control. Instead of using traditional analog or digital signal processing strategies, several of these tasks may be done directly on neuromorphic coded information (spikes). The hybrid nature of neuromorphic codes (discrete value, continuous time) simplifies the circuits required and gives digital, programmable control. An interesting feature of these systems is to mimic nature by using redundancy.

As an example a neuromorphic cochlea implant is presented. A major issue of this system is to code the temporal information as good as possible. The main commercial vendors of cochlea implants have shown significant interest in this approach.

A convenient way of handling neuromorphic systems is ”Address Event Representation” (AER) where spikes are multiplexed on a digital bus. This way of ”neuromorphic communication” might be usable as a general interface to implantable medical electronics. Due to the increased importance of temporal information a trade-off between temporal errors and value errors (event loss due to collisions) should be done. The weak arbitration scheme is trading event aging for bus crowding.

There is an increasing number of new applications for nerve stimulators and neuromorphic engineering is well suited for these systems, so hopefully in due time we will see commercial medical neuromorphic systems around.

2.8 Long-Term Synaptic Plasticity in analog VLSI without Floating Gates (Stefano Fusi)

Floating gates seem to be the natural candidate for implementing in aVLSI a dynamical synapse with long term memory. Here we present an alternative solution based on the theoretical observation that the performance of the network is not degraded if the synapse can preserve only a discrete set of values on long time scales, provided that the updating rule is stochastic. Stochastic learning solves the stability-plasticity problem in many interesting situations but raises new issues related to the generation of the proper noise driving the synaptic dynamics. However we show that a simple, fully deterministic, spike-driven synaptic device can make use of the network generated variability in the neuronal activity to drive the required stochastic mechanism. Randomness emerges naturally from the interaction of deterministic neurons, and no extra source of noise is needed. Learning and forgetting rates of the network can be easily controlled by changing the statistics of the spike trains without changing any inherent parameter of the synaptic dynamics.

2.9 An AER transient imager (Jörg Kramer)

We present an electronic imaging sensor that responds to temporal transients in the image, which typically correspond to moving contours. The transient response depends on local contrast and is insensitive to global image brightness. The DC response is suppressed, irrespective of image brightness. The transient signal is computed and rectified within each sensor pixel in parallel, such that positive (ON) and negative (OFF) transients appear at different output terminals. The output of the pixel is a binary, rate-coded pulse train. The signals from the different pixels in the sensing array are multiplexed onto a binary address bus, where each pulse is coded as the address of the sending pixel. The data flow is controlled by the activity of the different pixels rather than by an external clock. This coding of fast changes in the image brightness as opposed to absolute brightness, together with activity-driven multiplexing reduces the redundancy present in image data and allows for efficient use of communication bandwidth, particularly for highly-correlated images and sparse moving features. Furthermore, it facilitates object recognition, which typically requires contour extraction.

The presented version of the sensor has an array of 48 x 48 pixels and codes for ON and OFF signals of each pixel with different addresses. The response threshold can be varied, such that the level of spontaneous activity can be regulated or the DC response may be completely suppressed. Furthermore, a refractory period determining the maximum spiking frequency of each pixel can be set. For long refractory periods each pixel responds with a single spike to a moving image feature, which allows subsequent processing stages to perform computations based on spike timing rather than on mean firing rates. The image sensor has been used as a front end for a variety of biologically-inspired image processing systems, implementing models for orientation tuning, motion sensing, attentional selection and cortical development.

2.10 Modeling Selective Attention using neuromorphic analog VLSI devices (Giacomo Indiveri)

Selective attention is a mechanisms used to sequentially select and process salient subregions of the input space, while suppressing inputs arriving from non-salient regions. We present a neuromorphic hardware model of a selective attention mechanism implemented on a VLSI chip, using analog circuits. The chip makes use of a spike based representation for receiving input signals, transmitting output signals and for shifting the selection of the attended input stimulus over time. It can be interfaced to neuromorphic sensors and actuators, for implementing multi-chip selective attention systems. We describe the characteristics of the circuits used in the architecture, and present experimental data measured from the system.

2.11 A communication infrastructure for AER devices (Vittorio Dante)

We describe a general-purpose board designed to interface the AER bus with the standard PCI bus. The present implementation allows 1) to connect up to four sender AER chips and up to four receiver AER chips, 2) to emulate a further, ’virtual’ AER sender chip, 3) to tap transactions on the AER bus, to attach a time label to the AER events and to forward them to a PC via PCI (”monitor” function), 4) to implement a (programmable) connectivity pattern among the units in the AER chips (”mapping” function), 5) to inject synthetic events in the AER bus, thereby emulating external, AER compliant inputs to the AER chips (”sequencer” function). The board will be demonstrated through an experiment involving real-time communication between neuromorphic chips (retina + attention chip).

2.12 Simple cortical cell modeling with aVLSI spiking neurons and dynamic synapses (Shih-Chii Liu)

Multi-chip VLSI neuronal systems greatly shorten the simulation time of neuronal networks. These programmable systems support the study of spike-based information processing models. The modules in these systems communicate using an asynchronous address-event representation (AER) protocol. Recently, we used such a system to demonstrate both orientation-selective and direction-selective responses of neurons mapped using simple cortical models. The system consisted of a silicon retina, a mapper module, and a multi-neuron chip. This chip has an array of integrate-and-fire neurons together with simple current-integrating synapses. I will describe a new multi-neuron chip that has additionally dynamic synapses. Using spikes recorded from a lateral geniculate neuron of a cat as inputs to one of the neurons on this chip, I show responses from a neuron mapped using a feedforward model that utilizes the dynamics of a depressing excitatory synapse and a non-depressing excitatory synapse together with an integrate-and-fire neuron to generate direction-selectivity.

2.13 Population Coding in the Face of Uncertainty (Maneesh Sahani)

Theoretical work on population coding in perceptual systems has, to date, focused primarily on the representation of simple stimulus features. Beyond the first few stages of processing, however, the brain must represent the products of perceptual inference rather than raw stimulus attributes. In many cases, noise and the ill-posed nature of the perceptual problem lead to uncertainty in the inferred quantity. In other situations – for example when multiple objects are present – the result of the inference is genuinely multi-valued. Accurate perception requires that the uncertainty be represented and manipulated, and distinguished from multiplicity; indeed, experiments suggest that observers do correctly handle uncertainty while making behavioral choices. How can a population of neurons encode the requisite information?

We consider a simple case in which an perceptual computation is trained by information drawn from a different modality. Simple assumptions about the learning process lead to a natural proposal for a novel form of population code. We examine this code, and show by the construction of an explicit decoding procedure that it is sufficiently powerful to represent, and distinguish between, both uncertainty and multiplicity.

2.14 Development of Direction Selective Cells in V1 through Spike-Timing Dependent Synaptic Plasticity (Walter Senn)

Extracting the direction of motions is a basic element in visual scene analysis. To assure a high performance in different environments one might want to adapt the motion extraction capabilities to the statistics of the scenes. Here we show how direction selectivity (DS) in the primary visual cortex could evolve in an activity-dependent manner. Direction selective cells in the primary visual cortex are usually explained by two groups of afferents with spatial offset and different delays. Alternatively, short-term synaptic depression causing a phase advance of the synaptic response with respect to a sinusoidally modulated stimulus, could equally explain DS (Chance et al., 1998). We show that the appropriate spatial arrangement and the appropriate degree of synaptic depression can develop within a stochastic stimulation scenario by means of a temporally asymmetric spike-timing dependent synaptic learning rule. Assuming an initially symmetric arrangement of depressing afferents we show that stimulations with drifting gratings of random speeds and random directions will break the symmetry and produce directional receptive fields. Frequency tuning curves and subthreshold membrane potentials akin to those measured for non-directional simple cells are thereby changed into those measured for directional cells. If synaptic down-regulation dominates up-regulation the overall synaptic strength adapts in a self-organizing way such that eventually the postsynaptic response for the non-preferred direction becomes subthreshold. To assure the stability of the acquired DS within the stochastic input scenario, an additional learning threshold is required.

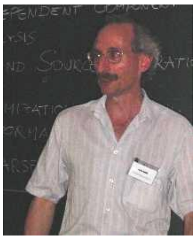
2.15 Fast Supervised Teaching for Recurrent Neural Networks: a Redundant Basis Approach (Herbert Jaeger)

The talk introduces a constructive learning algorithm for the supervised training of recurrent neural networks, which is characterized by two properties: (1) a large ”dynamical reservoir” recurrent neural network is used as redundant basis of complex dynamics; this network is not changed by learning; (2) only the weights of connections from the ”dynamical reservoir” are learned. The basic mathematical idea is sketched (”why it works”), and a number of examples are given. They demonstrate a number of novel phenomena in recurrent networks; for instance, the training of short-term memories with large memory spans (100 time step delayed recalls are easily obtained), the training of infinite-duration memories (input-switchable multistate attractors), or the training of arbitrary periodic sequences (n-point attractor learning).

2.16 Neocortical architecture carved with Ockham’s razor (Andras Lorincz)

The goal of brain modeling is to describe the large body of neurophysiological, anatomical and behavioral data from the smallest possible set of assumptions. Many different neural models have been proposed. These models can be characterized by (i) the complexity of the set of assumptions they use and (ii) the value of these assumptions, the predictive power of these models. Here, a model of the memory organization of primates is presented, which can be derived from a single assumption: a conceivable resolution to the homunculus fallacy. The derived model is able to capture the most significant properties provided by experiments. Although the described architecture is strongly correlated with the entorhinal-hippocampal loop, we make an effort to project it to the neocortical organization, too. The theory behind the proposed architecture leads us to the putative approach that we may gain a better understanding by considering that anatomical and functional layers of the cortex may differ.

2.17 Onsets and depressing synapses: a biologically inspired attempt at auditory scene analysis (Leslie Smith)



Finding the directions of sound sources in an environment with many competing sound sources is a task which humans with normal hearing do easily, and without conscious thought. We describe a binaural algorithm based on the neurobiology of early hearing which appears to be able to do this task. It is based on the observations that (i) animals have neurons which are very sensitive to onsets and (ii) onsets are not damaged by reflections. The technique uses cochlear filtering, stochastic spiking neurons, and a novel phase locked onset detector. We use the times of sound onsets in cochlear bandpassed channels to group signals apparently from a single sound source prior to using the phase locked onset detector to determine the interaural time difference (ITD) between these clustered onsets. In this way, we can find the ITD and hence the azimuthal bearing of a number of competing sound sources. We note that the algorithms used exploit both stochastic neurons and depressing synapses: in addition, the technique is causal, and could be re-implemented in hardware. It is thus a good candidate for neuromorphic implementation.

2.18 Neuroengineering : Bioartificial Networks of real neurons (Massimo Grattarola)

Networks of neurons can be cultured and kept in healthy conditions for a long time in experimental in vitro preparations. The characterization of the collective emerging properties of networks of neurons in more and more taking advantages of the tools offered by microfabrication technologies, originally developed for the microelectronic industries. Therefore a new area of research (”Neuroengineering”) is emerging at the interface between neurobiology and microelectronics, where neuroscience research issues are approached under brand new perspectives and by means of powerful new tools. A specific example of micro-hardware is represented by the development of thin-film based planar and 3D arrays of substrate microelectrodes (MEAs) to be in vitro coupled to populations of cultured neurons. MEAs technology offers the unique opportunity to simultaneously monitor/stimulate the multi-site spatial and temporal electrophysiological activity of cultured networks of neurons , on a time scale that is long enough (i.e. up to weeks) to identify the emergence and development of synaptic connections and of spatial patterns of coordinated behavior. Examples of the MEA approach, based on data present in the literature and on our own data, will be presented.

Chapter 3

Conclusions: Rodney Douglas

The presentations and discussions of the Workshop showed that there have been substantial advances toward understanding neural computation. The engineers described and demonstrated novel aVLSI circuits, and elementary systems that give confidence in a future generation of neuromorphic processors. The mathematicians described (with examples) dynamical systems that can be construed as a novel form of computational engine, and the computer scientists offered novel architectures that could be used to interpret natural computation. The neuroscientists, for their part, begin to frame their experiments toward answering computational questions. Thus, it seems that the there is a strong move toward the kind of interdisciplinary questions that the ESF Trieste workshop set out to encourage. What is also clear, is that the hard work lies ahead: We need to move toward a understanding of natural computation that is not only descriptive, but constructive in quality. Such constructive methods have been extraordinarily effective in progress of the classical computer sciences, and are probably a *sine qua non* for any future practical applications based on natural computation and neurotechnologies. We hope that ESF will continue to support progress toward these exciting, and economically significant, goals.

Appendix A

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