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New Trends in Neural Computation

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Preface

Neural computation arises from the capacity of nervous tissue to process information and accumulate knowledge in an intelligent manner. Perception, learning, associative memory, self-organization, fault tolerance and self-repair, planning, reasoning and creativity are basic properties of biological systems computed by the neural tissue. By way of contrast, computational machines with von Neumann architecture and conventional external programming, including knowledge based systems, have encountered enormous difficulties in duplicating these functionalities.

In an effort to escape this impasse, the scientific community has turned its attention to the anatomy and physiology of neural networks and the structural and organizational principles at the root of living systems. This has given rise to the development of the field of Artificial Neural Networks (ANN), where computation is distributed over a great number of local processing elements with a high degree of connectivity and in which external programming is replaced with supervised and non-supervised learning.

The papers presented here are carefully reviewed versions of the talks delivered at the International Workshop on Artificial Neural Networks (IWANN '93) organized by Universities of Cataluña (Politécnica, Autónoma and of Barcelona) and the Spanish Open University at Madrid (UNED) and held in Sitges (Barcelona), Spain, from 9 to 11 June, 1993. More than 160 papers were submitted, of which 111 were accepted for oral presentation and are included in these proceedings. Extended papers originated from invited talks related to the main topics considered are also included as introductions to the corresponding sections.

This workshop has been organized in cooperation with the Spanish RIG of the IEEE Neural Networks Society, and the IFIP WG 10.6, and has been sponsored by the Spanish CICYT, the Catalan CIRIT, and the organizing universities.

Collaboration of the Spanish chapter of the IEEE Computer Society, the UR&RI Communication chapter of IEEE, and the AEIA (Spanish Association for Computing and Automation) has been obtained.

We would like to thank all the authors as well as all the members of the International Program Committee for their labour in the production, evaluation and refinement of the papers. Furthermore, the editors would like to thank Springer-Verlag, in particular Alfred Hofmann, for excellent cooperation.

The papers published in this volume present the current state in neural computation and are organized in seven sections:

- Biological perspectives,
- Mathematical models,
- Learning,
- Self-organizing networks,
- Neural software,

- Hardware implementation,
- Applications:
  - Signal processing and pattern recognition,
  - Communications,
  - Artificial vision,
  - Control and robotics,
  - Other applications).

We begin with biological perspectives, including studies of the anatomical and physiological roots of neural computation. The biophysical level is enhanced and some claims on more realistic models of natural computation are included.

Thus far we have examined biology. Now we turn our attention to the world of mathematical models and organizational principles. A strong theoretical perspective is needed to seek organizational knowledge that will enable us to reproduce through synthesis some of the properties observable in living beings. Self-organization, continuous learning, and genetic algorithms are the topics more frequently addressed.

Learning is the key to neural computation. If we say that learning (self-programming) should substitute external programming, we must develop algorithms and methods of local learning comparable in clarity, completeness, and efficiency to those in conventional computation. It is true that local training requires more complex connections and redundant computations, but it simplifies the global design, includes intrinsic parallelism, and goes closer to biology. As long as the learning algorithms are executed in a general purpose computer separated from the network we are far from biology.

The next step in the proceedings is related to the development of neural software (languages, tools, simulations and benchmarks) and hardware implementations. Programming environments are usually classified as application-oriented, algorithm-oriented, and general programming systems. The simulation of neural networks in conventional computers can only be considered as a first step in the training and evaluation of models, architectures, and algorithms on the pathway towards intrinsically parallel hardware implementations.

The implementation of neural networks depends directly on which neural model and learning algorithm we seek to implement. In other words, it is necessary to distinguish between (a) what we want to implement and (b) how we do it. Once we have agreed on which computational model and what degree of autonomy we want to implement, the next step is how to do it. In all the cases the implementation can be analog, digital, or hybrid and is within a concrete technology (electronic or optical). There are two options, which we could call the simple model and the complex model.

In the first case, it is accepted that there is little autonomy. If the second option (complex model) is selected, we are forced to think in terms of neurocomputers, specifically designed for the implementation of neural networks with local computation, structural and functional parameters adjustment, and several modes of functioning (initialization, training/learning and use). Between this level (nothing in the host, all in the network) and the software simulations in conventional computers previously mentioned (nothing in the network, all in the host) there should be an ample range of intermediate situations (specific and general purpose neurocomputers) so that the closer we come to "all in the network", the closer we will be to the biological computation from which we drew inspiration.

The last part in the proceedings is related to applications. The basic question here is: what type of applications possess the computational requirements for the solution of which it would be advisable to use neural networks? Not all functions are capable of being distributed.

The majority of application tasks in neural computation can be formulated as multilayer classification functions in which a set of input configurations X = { Xm } associates itself to a set of classes Y = { Yn} after supervised or unsupervised learning. Signal and image processing and pattern recognition are the known examples in this line. Artificial vision, adaptive control, systems identification, and sensory-motor control loops are also adequate tasks to be solved using neural nets.

The most serious computational problem in the field of artificial neural nets (ANN) is the lack of theory, with direct and inverse constructive theorems. Given a specific computational family, which would be the map of individual functions and learning algorithms such that – when they operate linked by the data – they synthesize the global function)? Conversely, given a net of thousand of individual processors with local learning, which would be the global computation that emerges as a results of the cooperative integration of these local computations? It is clear that an enormous amount of work still remains to be done in neural computation, and this is a challenge for all of us.

Madrid, April 1993

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BIOPHYSICS OF NEURAL COMPUTATION

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Abstract:

This paper discusses neural computation in vision. Optimal design links structure-function relationships. This is evident at the cellular level with rod photoreceptor structure subserving detection in the presence of noise; and it is evident in the architecture of neural networks in which parallel computation is carried out in converging and diverging lines between different levels of the nervous system. Such an architecture makes possible some interesting schemes for information processing, including the computation of explicit parameters, resolution and reliability.

Keywords:

Biophysics, optimality, cells and networks, parallel processing, convergence-divergence.

Introduction:

Knowledge is an interconnected web, and so biophysical models of the brain serve as patterns for computational implementations while advances in communications and computers lead to theories, by analogy, of mental processes. In this paper I shall discuss some characteristics of neural computation in relation to vision. I have chosen vision because it is our primary sensory modality and it provides us with a richness of mental images expressed in memory and language. We know from our own experience that memory is largely visual - some people are said to have a photographic memory - and our language is full of visual metonyms for intelligent operations such as "expressing a view", "I see what you mean" and many others (Leibovic 1990).

A principle which seems to guide biological evolution is the optimization of structure and function. Therefore I shall take optimality as a theme of this presentation. I shall consider photoreceptor cells as an example of the biological components and I shall consider the architecture of neural networks for information processing. We can see at the cellular level how the components are designed for optimal detection in the presence of noise, while in neural networks we find a design that is particularly well-adapted for multivariable, parallel computations.

The Optimal Design of Photoreceptors:

The rods and cones of the retina absorb light and convert the photon energy into a neural response. These cells are more or less cylindrical and they present their circular cross sections to the pattern of light incident on the retina.

Design Considerations for Rod and Cone Diameters:

Figure 1 illustrates the arrangement of photoreceptors in the retina. It is clear that there are requirements for photon capture and image resolution, both of which are related to the aperture and cross section of the cells. A large aperture is desirable in dim illumination, but this would compromise resolution in daylight. In our case evolution has solved the problem without compromise by devoting the cones, especially in the fovea, to daylight vision, and the rods to vision in dim illumination. The diameter and spacing of our foveal cones are at the limit of optical diffraction, while our rods are capable of counting sinle photons.

In some regions of our retina (e.g., at 18° from the fovea) the rods are as slender and tightly packed as the cones in the fovea, while farther from the fovea cones are quite fat and tapered towards the tip. These variations in shape reflect different requirements subserving a foveal design, such as movement sensitivity in the periphery versus form perception in the center. Different species, in different ecological niches also show different designs. This is illustrated for rods in Figure 2: rods, like cones, can be fat or thin, long or short.

While high resolution requires a small cell diameter a large rod diameter can be advantageous not only in dim illumination, and in movement detection, but also in a noisy photic environment where the absorption of more than one photon is needed to reduce false alarms.

Considerations such as these determine photoreceptor diameter. There is an extensive literature devoted to this topic (see reviews by Snyder 1978, Pugh 1988). On the other hand, photoreceptor length has hardly been considered. I shall therefore devote the rest of this section to photoreceptor length, focussing especially on rods.

Significance of Length in Rod Function:

Responding with great sensitivity to one or a few photons, noise is an important factor in rod function. The photon energy is amplified by as much as 10^5 times in producing the neural response. This is mediated by a biochemical cycle and the longer the rod for a given diameter, the more thermal noise is produced. This argues for a short length. On the other hand, the efficiency of absorbing a photon depends on the number of absorbing layers, and this argues for a long rod. Noise and absorption efficiency are the primary variables in rod function. How can one achieve a compromise between them and optimize the design?

I have developed an optimization criterion to address this question (Leibovic 1990, Leibovic and Moreno-Diaz 1992). It is given by:

$$R = [1-\exp(-\alpha s)][1-(D/T)(s/L)]A-N(s/L) \qquad (1)$$