THE ANALOGIC CELLULAR NEURAL NETWORK AS A BIONIC EYE

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Memorandum No. UCB/ERL M94/70

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!Frank Werblin, *Tamás Roska, and *Leon O.Chua

Dedication:

To the memory of Professor Walter Heiligenberg, outstanding scientist, friend, and initiator of our collaboration.

!DIVISION OF NEUROBIOLOGY
DEPARTMENT OF MOLECULAR AND CELL BIOLOGY
College of Letters & Science
University of California, Berkeley
CA 94720

*ELECTRONICS RESEARCH LABORATORY

College of Engineering
University of California, Berkeley
CA 94720

Summary

The conception of the CNN Universal Machine has led quite naturally to the invention of the *analogic CNN Bionic Eye* (henceforth referred to simply as the Bionic Eye). The basic idea is to *combine* the elementary functions, the building blocks, of the retina and other 2 1/2 D sensory organs, algorithmically, in a stored program of a CNN Universal Machine, through the use of artificial analogic programs. The term bionic is defined in a rigorous way: it is a nonlinear, dynamic, spatiotemporal biological model implemented in a stored program electronic (optoelectronic) device; this device is, in our case the analogic CNN Universal Machine (or chip).

The aim of this paper is to report on this new invention in a tutorial way, particularly to electronic and computer engineers.

We begin by summarizing: 1) the biological aspects of the range of retinal function (the retinal universe) 2) the CNN paradigm and the CNN Universal Machine architecture, and 3) the general principles of retinal modeling in CNN. Next, we describe new *CNN circuit and template design innovations* that can be used to implement physiological functions in the retina and other sensory organs using the CNN Universal Machine. Finally we show how to combine given retina functional elements implemented in the CNN Universal Machine with analogic algorithms to form the bionic retina. The resulting system be used not only for simulating biological retinal function, but also for generating functions that go far beyond biological capabilities. Several bionic retina functions, different topographic modalities, and analogic CNN algorithms can then be combined to form the analogic CNN Bionic Eye.The qualitative aspects of the models, especially the range of dynamics and accuracy considerations in the VLSI optoelectronic implementations are outlined. Finally, application areas of the Bionic Eye and possibilities of constructing innovative devices based on this invention (such as the bionic eyeglass or the visual mouse) are described.

Table of contents

1. INTRODUCTION

yet retaining the simple control and design of the dynamics of the 3D regular processor array The Cellular Neural/nonlinear Network (CNN) invented by Chua and Yang in 1988 [1] heralded a new paradigm [16] in massively parallel computing. This represented a dramatic departure from digital technology, incorporating the concept of simple but versatile continuous nonlinear dynamics in the processing units. Yet the dynamics are simply controlled in the design of the 3D regular processor array by allowing mainly local interactions between these units. The computing model has an architecture similar to the cellular automaton of John von Neumann (or its descendant, the systolic array). However, the processing units (called cells) and their interactions are continuous (analog), dynamic, and nonlinear. CNN has primarily a locally connected lattice architecture, but unlike general neural networks, the processing units have a much simpler connection scheme and their interactions are can generate complex nonlinear dynamics. The local interconnection scheme of each cell is called the cloning template. The simple dynamic nonlinear systems (first, second, and third order), the processing units, can be easily and effectively implemented in silicon VLSI chips [12] to achieve a trillion operations per second per chip. Depending on the actual cloning templates, the CNN arrays can calculate, for example, various image processing tasks with a million-per-second frame rate using 10,000 pixel frames (TV sets use 30 per second frame rate).

Massively parallel analog processor arrays and logic inferencing will be required to simulate the functional properties of the brain [5] while retaining the physical realizability of complex information processing systems [9]. The so called dual computing paradigm [2] (we call it analogic computing) is a general formal model combining analog array dynamics (like neural networks and CNN) and logic. The basic motivation was the harmonic interaction of the two faculties of the human cognition. Pascal called them the geometric and the intuitive mind, as already recognized by Aristotle [11].

The CNN Universal Machine and Supercomputer architecture, invented by Roska and Chua in 1992, is an analogic array computer [3], the first stored program analogic computing array which establishes a new way of computing: Stored analog instructions, a new notion easily implemented on silicon as CNN cloning templates, can be combined in a logical sequence. The CNN array makes fast array computations, and all intermediate results are stored in local analog memories. The logic of the *sequence* of the various cloning templates, forming a complete analogic program, controls the whole array computer. It is possible to implement this entire system on a single chip. Such analog instructions could, for example, find contours of a gray scale image (performed in a microsecond) or detect moving objects of a given speed. By their simple combination, the contours of objects moving with a given speed can be detected. The CNN Universal Machine can be implemented in analog VLSI (with embedded logic and with or without digital interface and optical on-chip sensors) [13,14] which leads to the analogic microprocessor, an image processing supercomputer on a chip. Other implementations are also emerging (optical and special purpose digital hardware emulation). A hardware/software toolkit for PCs is available [15] for designing and testing analogic algorithms, and used worldwide

This paper describes the first two aspects of the overall implemenation of the bionic eye: (i) the computing model, (ii) the circuit architecture with its rich, yet tractable, nonlinear dynamics, and (iii) the silicon implementation of the device..

The CNN architecture is remarkably consistent with the structure of many biological systems. Its anatomy can be represented by a 2 1/2 D regular grid (a couple of 2 D layers in the third dimension), the interactions are mainly local (the receptive field or the CNN cloning template), and the mainly uniform processing units and interconnections have nonlinear dynamics. A striking example is the retina [4,17]. It is not surprising that CNN models [6,7] and heuristic local interaction type computer programs [8] were developed independently. The term bionic is used in a rigorous way: a nonlinear, dynamic, spatiotemporal **bio**logical model implemented in a stored program electr**onic** (optoelectronic) device; this device is, in our case, the analogic CNN Universal Machine (or chip).

The *analogic CNN Bionic Eye* [18] (henceforth referred simply as the Bionic Eye). followed quite naturally from the conception of the CNN Universal Machine. The idea is to combine algorithmically the building blocks of elementary retinal functions (and other 2 1/2 D sensory organs), in the stored program of a CNN Universal Machine, with artificial analogic programs.

The aim of this paper is to report on this new invention in a tutorial way, addressed basically to electronic and computer engineers.

Chapter 1 describes some of the biological aspects of the retinal function.

(i) Section 2.1 summarizes the general principles of retinal modeling in CNN.

(ii) Section 2.2 describes the new *CNN circuit and template design innovations* implementing known or yet to be discovered retinal functions and those of other sensory organs in the CNN Universal Machine;

(iii) Section 2.3 showns how to combine given retina models implemented in the CNN Universal Machine with analogic algorithms to form the bionic retina for for generating super-retinal functions.

Chapter 3 shows how to combine several bionic retinal capabilities, other topographic modalities, and analogic CNN algorithms to form the analogic CNN Bionic Eye. Specifically:

(iv) Section 3.1 describes the programmable implementation of several bionic retina capabilities on a CNN Universal Machine.

(v) Section 3.2 outlines the combination of different sensory modalities and artificial analogic algorithms, running on the CNN Universal Machine.

Chapter 4 describes application areas of the analogic Bionic Eye and possibilities of constructing innovative devices based on this invention (such as the bionic eyeglass or the visual mouse).

In addition, Section 2.4 briefly summarizes the qualitative aspects of the models and their optoelectronic implementations introduced here.

The invention does not deal specifically with the details of how to make CNN models for any given function of a known or yet to be discovered retina (or other sensory organ) using techniques described either here or in other papers cited above. For such details the interested reader can consult [6,7,18,19,20,21]. Similarly, we are not considering here the many interesting non-programmable (in a stored program sense) VLSI implementations of some visual effects or functions. These could easily be incorporated into instructions or subroutines of the Bionic Eye.

1.1 A functional analysis of the retina

The retina is a special part of the brain that has been brought to the sensory periphery. After its photoreceptors convert the patterns of light into patterns of neuronal activity, an elaborate neural apparatus adjacent to, and driven by the photoreceptors performs a series of highly sophisticated preprocessing operations upon the visual message. There must be compelling reasons to separate the retina and its complex neural structure from the rest of the brain, because the biological complexity of the initial design is overwhelming: This complex neural tissue of the retina has been physically separated from the rest of the brain, organized into at least 5 complete neural layers (Figure 1), each containing millions of neurons, all made perfectly transparent, yet provided with an adequate blood supply.

Why has the retina been separated from the brain, what transformations take place in the retina, why are they necessary, how are they accomplished, and what forms of information finally emerge from the retina to supply the brain with the signals that allow us to perceive the extreme richness of the visual world?

A brief answer to each of these questions provides an account of the functional organization of the retina as outlined below.

Why is the retina separated from the brain?

Simply stated, visual images enter the retina via its photoreceptors, and a composite of "neural images," patterns of activity embodied in arrays of neurons, emerges from the retina via the optic nerve. Photoreceptors are connected to a series of laterally connected neural layers located very close to--only a few microns from--the photoreceptors as shown in Figure 1. This is important, because by shortening the distance signals must travel for further neuronal processing, all neuronal integration, including important lateral interactions, can be performed without the need for action potentials or nerve spikes. (The alternative arrangement would require that the photoreceptor signals be transmitted over many centimeters to reach the rest of the brain. Action potentials are required for propagation of activity over distances greater than a few microns). The absence of action potentials allows neural interactions to occur using *continuous* rather than the

more conventional pulse-like action potential signals found throughout other parts of the nervous system. Continuous signals have the advantage that the information they carry can span a broader dynamic range, and simple spatial and temporal filtering can be used to reduce noise, a problem inherent in all high-sensitivity sensory signals. It can be shown, for example, that the retinal pathway, including only the small handful of neurons that funnel information from each of the photoreceptors to ganglion cells, has a dynamic range of at least 100:1, much greater than the normal dynamic range of spiking cells. The properties of continuous signal processing are still being explored by physiologists, and such continuous signals are used to great advantage in the function of the biological retina as described below. This provides one of the strong motivations for modeling the retina using the analog VLSI technology of CNN which, not coincidentally, also processes continuous rather than digital signals.

What transformations take place in the retina?

Photoreceptor gain control.

The retinal transformations can be divided into two main functional classes, each taking place at a physically separate site. At the outer retina a variety of adjustments in GAIN take place, processes that are conventionally called visual "adaptation"[58]. At the inner retina different spatial regions are associated with one another in TIME, resulting in movement detection, directional selectivity and *contrast* gain control [55] [53]. A relatively minor but *global* form adaptation is mediated by changes in the size of the pupil which changes diameter by about 4:1 leading to gain changes of about 16:1. All other gain changes are mediated at *local* regions of the retina. The most dramatic form of adaptation takes place in the photoreceptors themselves, particularly the cones, where gain changes of one million to one can be achieved. The objective of this gain-changing operation is to center the relatively narrow instantaneous dynamic operating range of each of the cones (about 100:1) at the local ambient intensity level, so that increases and decreases in intensity around that ambient level can be detected with high gain as shown in Figure 2. This effect occurs in each photoreceptor, so the effects of local changes in gain, matched to each receptor's history of intensity can be accommodated.

Bipolar cell gain control

Following the gain changes in individual photoreceptors, a further adjustment is made in the second layer cells. These cells, called bipolar cells have a dynamic range that spans less than 10:1, so their range must be precisely aligned with the ambient levels [56]. The process is also accomplished locally, but now the local effect is broader than the area spanned by a single neuron. The effect is initiated by a class of laterally connected cells, called horizontal cells that are coupled to form a broad, continuous neural sheet across the retina. To a first approximation this sheet behaves much like a resistive grid (although the physiology is much more complicated than this). These cells are modeled by a diffusion process). The result of this operation is the formation of a

continuous spatial intensity average, with characteristic space constant across the horizontal cell layer. The level of activity at each point in this spatial average establishes a grid that sets the functional centerpoint around which the narrow dynamic range of the bipolar cells can signal increases and decreases in intensity as shown in Figure 2. Note that all of the neural activity discussed so far is carried by continuous signals, via local interactions between neighboring neurons, and can therefore be easily implemented in a CNN model which also utilizes continuous signals and local interactions.

Formation of transient activity

All of the activity encountered so far in the retina is used by bipolar cells to signal the *presence* of visual targets: to put it simply, when the target is present the bipolar cells are active when it is absent, the cells are silent. This forms one type of retinal output shown in Figure 3A. But at the synaptic output of the bipolar cells a transformation takes place that creates signals that identify, not the presence, but the arrival and departure of the targets [55]. This transformation is implemented in a variety of ways, even in a single type of retina, all of which truncate activity in the bipolar cells shortly after its initiation. In some cases a signal from the postsynaptic cells feeds back to the bipolar cell to turn it off. In other cases synaptic release from the bipolar cells is inherently transient. It is also possible that the postsynaptic cells "desensitize" to the arrival of synaptic transmitter from the bipolar cells. Whatever the mechanism, the result is that the postsynaptic cells respond, not to the presence, but to only the arrival and departure of the visual target as shown by the responses in Figure 3B. This transformation sets the stage for a variety of transient, change-sensitive operations that occur subsequently in the inner retina [52]

Broadcasting transient inhibition across the retina

The transient signals described above move through the retina in two orthogonal directions. They are communicated vertically to the retinal output cells which therefore carry information about the arrival and departure of targets (Figure 3B), and they carry information laterally, inhibiting in a transient way, activity at sites lateral to the location of the initial appearance of the target. These lateral signals mediate a variety of interesting physiological functions: 1) In some cases they inhibit all activity within range of their processes as a function of their activation. Since they are activated more by moving contrasting boundaries, they turn down gain via a shunting mechanism by an amount related to contrast in the environment, a phenomenon called "*contrast gain control.*" 2) In other cases lateral inhibition acts only in one direction, not the other. In these cases movement is inhibited in the direction of inhibition, but not in the other. This phenomenon is called "*directionally-selective movement detection.*" 3) It is also possible that this change-sensitive system responds to global dramatic changes in intensity such as those that occur when we make a saccade or blink, and the laterally directed signals then act to

turn down the retinal output during these events. This laterally directed change sensitive inhibition acts to truncate the already brief response to light as shown in Figure 3C.

The retinal output is tiled with a variety of views of the visual world

The retinal output, expressed in the activity of these several classes of output (ganglion) cells, consists of the overlay of a variety of images [52]. Each of these forms of output activity tiles the retinal output mosaic, so each form of retinal output is found everywhere across the surface of the retina. From the above discussion it is almost possible to infer the ensemble of outputs that the retina will provide for higher centers. First, the output will contain a representation of the *presence* of the visual image (3A), an output pattern derived from the bipolar cells described above. This could be described as a "*presence of target*" detector. Second the output will contain a representation of the "truncated" pattern described above (3B). Each point in retinal space will respond to the arrival or departure of a target from its area giving rise to an output pattern that exists only when the input stimulus is moving. This could be thought of therefore as a *movement-detecting system*. Finally the output will consist of a movement detecting system that is itself turned off by global movement. A target moves, its movement elicits a response to movement as well as an inhibitory field resulting from the movement, and then that movement-initiated signal is turned off by the broadcast transient inhibition described above. This output pattern could be described as an *acceleration detector*, or more accurately an *initiation-of-movement detector*. These three patterns representing the presence of the target, its movement and the finally the initiation of its movement, are interlaced across the retinal output and each fully tiles the retinal output, but in many animals the different forms of activity may travel to different and specific destinations in the brain [45]. In ways we do not yet understand, the brain integrates information about the presence of visual targets, their movement and the initiation of this movement to form a coherent and extremely vital impression of the visual world.

1.2 An overview of retinal function in different species

Basic Retinal Functions: The ON and OFF cell types.

Are all vertebrate retinas alike, or is there a wide variation in overall function? Most modern studies involve activity in a particular retina, and very few comparative studies of retinal function are available. For an overview of retinal function the reader is referred to [17]. To a first approximation, all retinas deliver at least 2 main forms of output images [17], and the response

waveforms of individual retinal output "pixels" are shown in Figure 3. Figure 3A shows the activity of a "sustained" output cell, where activity level is monotonically related to intensity over a limited range of intensities. The output (ganglion) cells in this category are referred to as ON or OFF cells. In cat, these cells are referred to as X types, whereas in monkey, they are referred to as P types. Figure 3B shows the "transient" form of activity in another class of output cells where signals are initiated at the arrival and/or departure of the visual signal. Ganglion cells in this category are referred to as ON-OFF cells, or as Y cells in cat or M cells in monkey. Figure 3C shows yet another class of change-responding cell where the activity is truncated even more rapidly, so the activity of these units seems quite brisk. Each of the 3 cell types is often characterized in terms of its "receptive fields", referring to the weighting, in space of the stimulus that determines the response characteristics of these cells. Most cells have concentric receptive fields in which a central "excitatory" region is surrounded by a region of "inhibition." For the sustained, X, or P cell types, the interactions between center and surround appear to be *linear* over a broad range of stimulus intensities, whereas the transient, Y, or M cells show a non-linear center surround interaction. This simplified description of retinal output characterizes only two main types of cell, but it is possible to dissect these types much further, and many different subtypes can be described.

Special forms of retinal function.

In addition to these general forms of activity found in all retinas, there are some special functions that are found in specific retinas. For example, the Y type cell described above and shown in Figure 3B and C will respond to movement since it generates a response at the arrival and departure of targets, not across its entire receptive field, but across subunits of that field. As a further elaboration, the retinas of some animals, notably frog, turtle, some fish, birds and rabbit, contain output (ganglion) cells that respond to movement in one direction and not at all to movement in the opposite direction. This funcion, termed "directionally-selective movement detection" is thought to be mediated by some form of asymetrical lateral inhibition involving amacrine cells, but the exact circuitry has not been elucidated in any animal. Additional properties of these cells can be found in [56].

Other differences in retinal function involve issues of acuity, an essentially optical phenomenon, issues of rod vs cone function and therefore related to color vision, for which retinal circuitry is not well understood, and issues of timing where mammalian retinal function can be faster, by a factor of about 5, than that of cold blooded animals. In the mammalian retina a special pathway connects the rod photoreceptors to the retinal output cells that differs from that in cold blooded animals.

1.3 Retinal Neuromodulation: The reprogramming of the retina.

The differences in anatomy and function between classes of retinas are significant, but differences in function for any one retinal type, mediated by different effects of neuromodulators, is even more fascinating. The best-studied neuromodulator is dopamine, which has now been shown to affect the input and output for almost every retinal cell type [50]. It is thought that dopamine is released in the light and serves to increase the speed of responses, change the size of receptive fields, switch the emphasis of retinal integration from rods to cones, and mediate a variety of other functions that are not yet understood. The extent of diffusion through various retinal layers is decreased, the strength of synaptic connections between retinal layers is, for the most part, enhanced. Specific components of different cellular responses are either up- or down-modulated. The list of specific effects on retinal elements is quite large, but the overall effect of all these effects acting in concert has not been determined. One value of modeling the retina in CNN is that it will be possible to include each and/or every experimentally measured alteration in function in the components of the model, and then measure the individual or overall effects of these changes in the retinal model output.

1.4 Other sensory organs

The retina is but one of many examples of a sensory system in vertebrates that performs its analysis using stacked 2D arrays. Other examples include the somatosensory system [41] , the olfactory system [42] , as well as the sense of taste [43] . In the auditory system, pitch is initially encoded along a single dimension at the basilar membrane. But further analyses features of the auditory input are carried out along a 2 dimensional grid including, for example, pitch and phase, or pitch and ipsi or contralateral input, at higher centers [44]. All sensory modalities except olfaction are relayed via the thalamus, another 2 stacked dimensional array, and then to the cortex, also well known for its characteristic 2D layering. In almost all cases the stacked layers each contains an in-register topographic representation of the original 2D image. As one proceeds from the periphery to higher centers in the nervous system the representation at each succeeding layer is transformed primarily via local neuronal interactions.

In many cases, more than one sensory sub-modality is carried by a single 2D neuronal array. For example, in the visual system, information about the identity of a visual object and information about its location seem to be carried by separate pathways within the same array. These so called "what" and "where" messages are carried in parallel at the retina, lateral geniculate nucleus (LGN), and early cortical areas before finally being segregated into completely separate 2D regions at the higher cortical levels of V4, MT and others [45] . In most cases we attribute these 2D arrays to cellular layers in the retina, LGN and cortex. But in some cases 2D layering also exists within the neuropil itself, as for example in the inner plexiform layer of the retina [46] .

The CNN architecture, consisting of 2D arrays of computational "cells," is a natural modeling environment for the nervous system. It matches well the preponderance of 2D arrays found throughout the sensory (and motor) nervous system, which contain overlapping, topographic maps of visual space. These maps are repeated and transformed by mostly local neuronal interactions, transformations that can be easily transformed into CNN templates. Because CNN algorithms are so flexible, it is a relatively simple matter to modify these templates according to experimental alternatives, so that "what if" experiments can be carried out. For example, it is possible to perform specific ablation experiments in the visual system to determine the role of specific interactions. These and other "experiments" will be provide an important role for CNN in unraveling some of the experimentally inaccessible mysteries of the nervous system.

1.5 The CNN model: capturing the essence and details of the 2D sensory organs

The essence of the Cellular Neural Network paradigm [1,16].

Consider a 3 dimensional regular grid consisting of a pair of 2 dimensional grid layers, and place mainly identical dynamical nonlinear systems at the grid points of each layer. These dynamical systems are the processing elements (here we will call the elements processors or units). Figure 4 shows such an arrangement. The different symbols at the grid points represent different possibly identical processors 1. Introduce, possibly nonlinear and dynamic, interactions between the units. These interactions are mainly regular and local, within a finite radius of each unit. Figure 5 shows such an interaction graph in 2D and 3D neighborhoods of 4 and 6 respectively. In a simple example with linear interactions, in which each interaction can be represented by a single number, this interaction pattern, called also cloning template (or template), can be displayed as in Figure 6 (the positive and negative values of the template elements are shown in a template matrix).

A simple unit and cloning template configuration are shown in Figures 7 and 8. Feedback refers to the case where the output is the controlling variable, whereas feedforward refers to the case where the input is the controlling variable. Figures 9 and 10 show the template elements as interactions. In Figure 10 we use the words "recursive" (where VCCS's are controlled by the cells' outputs) and "dendritic" (where VCCS's are controlled by the cells' inputs) to describe the templates in a more biologically consistent language.

In an image processing application, each picture element, or pixel, is assigned to a single CNN processing unit. The gray level of the given pixel could be coded as a voltage signal value at the input or the initial state. Normally black is coded as +1 V, white is coded as -1 V with grey values in between. Hence, two images can be coded independently as input images. The output image can be represented as the output voltage. Color images can be coded either by 3 layers or by using complex cells or by interlacing.

Depending on the models of the units and the interaction patterns, a wide variety of CNN's can be generated. Image processing systems, partial differential equations, physical and

chemical systems, population dynamics, robot control are just a few possible applications. It should be obvious now from the preceding sections that CNN is an appropriate substrate for modeling sensory organs, reflecting the anatomy and capable of modeling some important aspects of cellular and synaptic physiology. Without going into the details of the dynamic equations of the various processor and template types, we summarize the most important CNN classes in Table I [16] and emphasize that even with very simple models an infinitely rich world of spatiotemporal dynamics can be generated. Equilibria, oscillations, chaotic spatiotemporal dynamics, static and dynamic spatial patterns (like the Turing patterns) are members of this world. The interesting point is that all these phenomena can be generated by carefully designing the 1st, 2nd, and 3rd order elementary unit dynamics (defined either by equations or by equivalent electronic circuits) and the cloning templates (using memoryless or dynamic ones). Some processor circuits are shown in Figure 11. In addition to the 3rd order chaos circuit, called generalized Chua's circuit, 2nd and first order ones are also shown, including the so called artificial neuron which represents the simplest nonlinear amplifier.

TABLE I

Various classes of CNN models

Grid types	Processor types	Template types	Types of spatial dynamics
triangular, square, hexagonal	linear, piecewise linear, nonlinear	linear, nonlinear, delayed	continuous-time or discrete-time
		function of one or two variables	
constant or regularly varying grid size	passive or active		transient, equilibria, oscillating, chaotic
		memoryless or dynamic	
single or multiple resolution (e.g. fine, coarse)	first-, second-, third-order dynamical system		local or propagating
		noiseless or noisy	
planar or circular	with or without local analog memory		deterministic or stochastic
		centrally symmetric or asymmetric	
	with or without local logic		
		fixed or programmable	
	with or without noise source		
		controlled (time varying) or stored	

A typical simple dynamical equation describing a single layer CNN is as follows [1,24,19]:

$$(1) \qquad d x_{ij} / d t = - a x_{ij} + I + I_{input} + I_{output} =$$

$$= \text{e.g. } -a^*_{ij}(x_{ij}) + I + \Sigma\, b^*_{kl}\ (u_{kl}) + \Sigma\, \hat{A}_{ij;kl}(y_{kl}, x_{ij})$$

$$= \text{e.g. } -a\, x_{ij} + I + \Sigma\, b_{kl}\ u_{kl} + \Sigma\, a_{kl}\ y_{kl} + \Sigma\, a^*_{kl}\, y_{kl}\, x_{ij}$$

where the summation in the indices *kl* runs over the entire neighborhood of radius *r* .

Many , more complex yet useful dynamic equations are used extensively. Even complex partial differential equations (PDEs) can be solved [e.g. 29], and various pattern formation mechanisms can be explained and generated by CNN models. Indeed, the term "neural network" refers only to a very special case of a much broader range of types of processors and interactions.

1.6 The CNN Universal Machine and chip

The CNN Universal Machine and Supercomputer architecture [3], is the *first stored program analog processor array*. CNN type analog nonlinear spatiotemporal dynamics are combined with local and global logic, hence, it is called *analogic computing*. Based on this architecture, a new world of algorithms is emerging where an elementary step or instruction generates complex spatiotemporal dynamics. The cloning template is such an *analog instruction*.

The basic ideas behind the design of the CNN Universal Machine [3].

With the CNN array as a starting nucleus, each processor (unit) itself consists of a set of distinct yet compact functional units. Figure 12 shows the augmented processor (called also *universal cell*). The *local analog memory* (LAM) contains a few analog circuit blocks capable of *storing any* voltage value within an interval [-a, a] and which can be quickly accessed (reloaded into the unit) One block is used for storing the input, one for the initial state, and a few blocks for storing the outputs.. These memory sites are essential for the execution of multistep algorithms since they store all the intermediate results locally, unit by unit, pixel by pixel. In many applications, a CNN template is used to detect areas of an image containing certain specific features. In this case the detected pixels will be coded black and the remaining ones white. It is often useful to code these as logic YES or NO values, respectively, and store them in *local logic memory* (LLM) as ones and zeros. Consecutive logic values are stored in LLM. A *local analog output unit* (LAOU) and a *local logic unit* (LLU) are provided to operate on consecutive analog or logic values, respectively.

Each processor contains a variety of switches with which locally-stored values at each cell can be moved within this processor and to/from the outside world. A wide variety of different image processing operations can be performed, depending upon the settings of the switches. The switches are controlled globally in the sense that at any given time the *switch configuration* for all processors is the same. The global analogic program unit (GAPU) communicates with each augmented processor via their *local communication and control unit* (LCCU).

The *global analogic program unit* (GAPU) is the heart of the CNN Universal Machine architecture. It controls the whole array of extended processing units. Figure 13 shows the main

components. The *analog program register* (APR) stores the values of the analog instructions, i.e. their template elements. These values are communicated (wired) to all units (19 wires in the r=1 neighborhood). The instructions for the local logic units are stored in the *logic program register* (LPR) while the switch configurations are stored in a *switch configuration register* (SCR). All these three registers are selected by the *global analogic control unit* (GACU) which contains the physical machine code for the whole processor array.

The analogic algorithms can be programmed in a high level language (called analogic CNN language or ACL). Compilers and operating systems [26] transform the high level code to the physical digital codes of the GACU. The analogic algorithms are flow charts with elementary analogic CNN instructions (analog templates, local analog and logic storage, local analog and logic operations as well as global operations (some simple global operations are useful and available). Though this architecture was developed quite recently, many analogic CNN algorithms have already been developed for solving complex real-world problems [e.g. 27,28].

Different physical implementations of CNN architectures

As it was already mentioned, the CNN Universal Machine architecture can be physically implemented by a variety of different technologies. Using CMOS VLSI technology, both analog or emulated digital realizations have been designed. The single chip design with or without optical sensors hosting thousands of processors is called the *analogic microprocessor*. Its digital interface to the outside world for programming and its speed in the range of million million (trillion) operations per second makes it a unique stored programmed device for image technology and for the implementation of the Bionic Eye.

2 CNN IMPLEMENTATION OF RETINA MODELS AND THE BIONIC RETINA

2.1 General principles of retinal modeling in CNN

Objectives in modeling neuronal systems.

Having the CNN architecture, a modeling substrate that quite naturally conforms to the structure and function of the retina, does not in itself give us license to *model* the retina. There has to be a goal to our work that goes beyond the intellectual exercise of simply duplicating retinal function in silicon. For example, a significant model was generated in an earlier study by another group using analog VLSI (Mahawold, Mead, etc [33]). The objective of that work seemed to be the demonstration that a physical metaphor could be found to correspond to a variety of biological functions. For example, in that study, the inherent property of the phototransistor was used to simulate the log transform thought to be implemented by photoreceptors in the phototransduction process. In addition, a resistive grid was used effectively to simulate the diffusion function across an electrically coupled layer of retinal horizontal cells. Finally the diffused signal was subtracted from the photoreceptor signal to generate a difference signal that

corresponded roughly to the pattern of activity in retinal bipolar cells. That model was not intended to be perfectly biologically accurate, although in its general form it did simulate a variety of biological functions, and it generated some emergent visual functions such as the Mach bands associated with edge enhancement and various visual illusions. Similarly, the early CNN retina models were mainly based on phenomenology [7].

Different types of models answer different types of questions

Using CNN, our modeling efforts are directed towards a different set of objectives, based upon the advantages of using CNN as the underlying substrate. Different classes of model can be generated and aimed, for example, at exploring retinal physiology or testing or creating entirely new visual paradigms. The modeling possibilities open up an exciting new, and badly needed experimental tool for physiologists. During the past decade a daunting number of physiological studies have defined a vast set of *details of retinal function*. It is the current fashion for each of these studies to focus on a different set of membrane events in individual neurons. For example, a broad range of studies defines the effects of transmitter substances at a particular dendrite, and the modulation of the effects of these transmitters by a second neuroactive substance [50]. In another set of studies, the voltage-gated currents that shape a cellular response is characterized [51]. Although a great deal has been learned about these individual *membrane events*, there does not exist, at present, any effective method for bringing these individual events together to determine how each event, or the entire ensemble of such events, contributes to overall retinal function. CNN design can address these questions and provide us, for the first time with a view of the visual functions that emerge from individual membrane events as well as the emergent properties of the ensemble of membrane events throughout the retina.

Using CNN to study retinal physiology

CNN modeling is particularly useful for evaluating the results of retinal physiology. Because the CNN is easily programmable, the structure of the model is itself dynamic, so in CNN, one constructs, not a single model, but a broad class of modeling possibilities where time, space and synaptic functions (defined below) are easily adjusted. This allows a broad variety of "what if" questions to be addressed. The kinds of questions that can be addressed depend upon the level of detail in the model. For example, if the model included the now-almost-unending array of membrane events that shape cellular function, the role of these events in overall retinal function can be addressed. Neuromodulators act to "reprogram" the retina, based upon intrinsic retinal activity or extrinsic events, but these neuromodulators tend to act at *many* different retinal sites simultaneously [50] It would be impossible to determine, in a physiological experiment just how modulation of an individual membrane event contributed to visual function, but in the CNN model such "what if" questions can be easily addressed. In many cases it is impossible to make certain key physiological measurements. We can't measure, for example, the geometry of amacrine cell

activity that underlies movement detection. This kind of measurement could be made in the model by assuming a variety of different plausible geometries, and then measuring which class of geometries most closely approximates overall retinal function.

Transferring biological relevant data regarding retinal function to CNN model

The first decision to be made in this kind of modeling is where along the pyramid of detail to begin the process. If one begins at the membrane level, including all voltage-and ligand-gated conductances, the level of detail is so overwhelming that the modeling process becomes bogged down in a morass of unknown unmeasured and sometimes unmeasurable quantities. On the other hand, if one begins at the very broad, phenomenological level, the model lacks enough physiological detail to be useful in addressing any interesting physiological questions. We chose to begin these studies at the "network" level, defining the time and space constants for arrays of cells. At this level, the success of modeling with CNN lies in our ability to associate the appropriate space and time constants of retinal networks with the CNN templates that accurately reflect these values in CNN activity as described in Section 2.2.

Almost all layers of retinal cells can be characterized as having a specific space constant, which to a first approximation is due to resistive coupling between the elements of the array, although chemical synaptic coupling could sometimes be involved in extending the space constants. The space constant for a retinal cellular network was measured usually by presenting a light-dark edge at different locations across the array of photoreceptors while recording from a cell in each of the networks of interest. The space constant could then be measured as the falloff of activity as the light-dark edge was displaced across the retina. Using such an edge is more useful than a spot because it reduces the normally two dimensional radial symmetry, requiring the use of Bessel functions, to a one dimensional problem, and these space constants were most often approximated by a single exponential as shown in Figure 14. The modeling of these constants is described in section 2.2.3.

Time constants are determined, not by the *membrane* time constants themselves which were typically of the order of 1-2 msec, but by the processes of voltage-and ligand gated currents as well as second messenger events within the cells themselves, giving time constants of the order of 50 to 100 msec. Experimentally, the time constants were estimated from the normal rise and fall of the recorded cellular responses. These values can be implemented using the controllable capacitors and delays described in section 2.2.1.

In addition, communication between networks across retinal layers, relating potential in one cell with the potential in its postsynaptic counterpart, involves input-output functions, here called *synaptic functions.* These functions were measured by recording either simultaneously or sequentially from the pre and postsynaptic cells and correlating their levels of activity over a broad response range. In most cases these functions are S-shaped reflecting the dose-response function

at the postsynaptic membrane. In some cases the synaptic functions appeared to be more exponential. These functions were implemented either as analytic functions or as lookup tables. Although many of these synaptic functions have been estimated by experiment, others have not been measured directly. In some cases it was therefore necessary to assume values for these functions and show, through the modeling process, that the overall performance of the model was either consistent with the assumptions, or that wide variations in the assumed values had little effect upon the overall performance of the model. Figure 15.

The space and time constants can be defined, calculated, and measured in a rigorous way. The time constant of a retinal layer is the elapsed time from the initiation of a step-like excitation at a cell until the level of the response reaches a given percentage of the entire change of the response at the cell of the excitation. The percentage may be chosen as 50, 71 ($1/\sqrt{2}$), or 37 (1/e) % . This time constant can be uniquely measured as well as calculated by using any CNN simulator.

The space constant can be defined as follows. We apply a given constant light stimulus. This stimulus could be a light stripe with a given minimal width. The space constant is the distance from the light-dark edge of the stripe in the dark region where the activity of the cell response is the 37% (1/e) of the constant stripe stimulus (illumination).

2.2 Some circuit and template design innovations

We intoduce here four design innovations specifically aimed at facilitating the conversion of physiological and anatomical parameters in the visual system into the apropriate cloning templates for retinal modeling. These are:

- the controllable capacitors and delays
- programmable layer compression and expansion
- identifying the CNN templates by parameter measurements on the living retina, and
- some mechanisms of adaptation and neuromodulation.

Various nonlinear synaptic input-output functions that can be approximated by exponential and polynomial functions can be directly implemented in CNN by a few transistors. Standard approximation techniques using nonlinear circuits can be used to apprximate more complex shapes.

2.2.1 Controllable capacitors and delays

As mentioned in Section 1.1, biological retinas act primarily to abstract information about the dynamics of the visual scene. Movement, direction of movement, onset and termination of local and global events, expanding and contracting images associated with, for example, approaching targets, are common elements of visual function. Sometimes these dynamic effects

are directionally sensitive, there are different dynamics in the different template elements. To facilitate the template design when modeling these effects we have introduced the controllable capacitor and delay. Controllable capacitor circuits and a delayed circuit are shown in Figure 16. The usually voltage controlled capacitor can be inserted either in parallel with the state capacitor (membrane capacitor) or into a parallel or series branch of the OTA (operational transconductance amplifier) implementing the template elements as VCCS (voltage controlled current source). This controlled capacitor effect can also be implemented by switches controlled by the analogic algorithm. By switching in additional capacitors with active elements, delays can be approximated using well known allpass structures. When the delay is quite large compared to the time constants of the CNN unit, as when a single level or a signal with a couple of representative levels are to be delayed, the local analog memory of the unit can be used. In this case the delay is introduced by the analogic algorithm (by sampling the value(s) at a given time and then switching-them in later at the appropriate times.

Sometimes, dynamic effects modeled by delays can be equivalently modeled by capacitive circuits [e.g.32]. In these cases, through the controlled capacitors , the key dynamic properties of the models can be controlled (e.g. shapes, rise times, decay times, or frequencies of spike trains).

Some of the actions implementable with these elements are as follows.

• By controlling the state capacitor C_X the basic response dynamics of each unit can be changed . In motion related applications this can be used to match the CNN chip speed to the speed of the object seen by the chip.

• The control of the capacitors or delays in the different template positions provides for the implementation of directionally sensitive dynamics, i.e. modelling directionally sensitive motion detection.

• By using different time constants in different layers, as when using complex CNN units having more than one processing unit in a complex cell, the time constant differences between different retina layers can be modeled. The same effect can be used when the spatial cascading in the 3rd dimension is implemented by time multiplexing the consecutive layers.

• The application of artificial CNN dynamics to the biological models, allows us to generate controllable diffusion and wave-type effects which can be useful in various forms of motion detection..

2.2.2 Programmable layer compression and expansion

Biological retinas consists of sheets of neurons, arranged in very large arrays consisting of between 10^6 and 10^5 neurons. The number of elements decreases dramatically as one moves from the outer to the inner layers of the retina. Therefore the grain of the retina changes. In order to account for the changes in grain and to accommodate to the two major resolution systems in some species (magno and parvo systems), we include in the Bionic Eye a mechanism for programmable layer compression or expansion. Two types of compression and expansion techniques are introduced. The first changes the grain within a layer, the second changes the number of layers.

Both changes can be implemented in a programmable way, as a part of an analogic CNN algorithm.

Within a layer, the change in grain allows the number of elements and the distance between them to be modified by the program. Figure 17 shows the solution. The processing units in the coarse grid , larger boxes, have switches in their template element connections. The switches are shown in their ON positions to implement the fine resolution. If these switches were set to the OFF position then the sparse wires denoted by dotted lines will connect the processing units in the coarse grid directly and all the other units will be idle, disconnected from the coarse grid CNN system. Hence, using only one extra bit in the switch configuration register and one extra switch in the templates of the coarse grid units, the whole system can be switched ON and OFF between the two grid resolution. Using the local memories, the features detected by the fine grid can be further processed in the coarse grid with different templates, all in an algorithmically programmed way.

Multilayer CNN structures are implemented in two ways. 1) A single complex unit can be formed by packing a series of units above a given basis layer. For example, in representing color images by RGB values, the 3 layers (R,G, and B) are lumped into a single one having complex units composed of R, G, and B layer units [16]. 2) The anatomically separate units can be time-multiplexed. For example, the result of a layer is stored locally and used as input for the next iteration when the templates of the next layer are programmed. The two methods can be combined efficiently. We can use complex units for as many layers as the minimum number of layers covering inter-layer feedback ,cascading them into a time multiplexing scheme. Figure 18 shows the basic modeling scheme of multilayer systems The *layer interaction graph* of the system of consecutive layers (a) is shown in (b). This graph has a loop. The layers in a loop are lumped into a complex layer (1,2,3) and the interaction graph of the condensed layers (c) has no loops. The *loopfree layer interaction graph* is implemented in a time multiplexed way described above. The spatial sequence of layers is transformed into a time sequence on a single layer of the CNN Universal Machine by exploiting the local analog storage at each unit. The output of a layer, which will be the input of the next one can be represented as a series of values in time.. Signals with given waveforms can also be stored by sampling them at a few time instants. These values are stored in analog memory places (LAM[i]) and from these samples a simple circuit generates the signal with the appropriate waveform.

The retina can be modeled by 5 or 6 different layers, the LGN (lateral geniculate nucleus) by one complex layer, and the relevant part of the visual cortex by several additional layers. In each layer, different functional components each of which tiles the entire visual surface can be switched or combined. This applies to functions such as the magno and parvo grid (sustained and transient activity) as well as the ON and the OFF pathway. Additional layers can be introduced to make more elaborate models. Similarly, this scheme can be conveniently applied to account for the interactions between the many maps in the visual cortex, coding, for example, the "what" and the "where" aspects of the visual signal [45]. This complex *compression and expansion scheme in time and space* provides for an algorithmically controlled dynamic transformation between space and time in the 3rd dimension, as well as a dynamic control of different resolutions within the 2-dimensional layers.

2.2.3 Identifying the CNN templates by measurements on the living retina

In Section 2.1 we have defined the time and space constants of retinal networks. In reverse engineering the CNN model of a given layer of a retina we must establish the relationships between measured physiological parameters and the cloning templates. In Figure 19 we show, in 1 dimension, the measurement of a space constant and its graphical representation as a diffusion (A) template. Though the shapes are similar, the values are different. The grid constants for the space constant and the template values may differ (d and D, respectively). Even the grid constant of the activity field (where we measure) and the grid constant of the actual neurons, which are not exactly constant, may be different.

Here, we propose two ways to reverse engineer the template values from activity field measurements. The input light illumination is an edge (strip) or other form of stimulus and the output is a single point or a multiple point measurement .

A single measuring point is chosen and an edge is moved to different places across the retina. Assuming a laterally invariant structure, the change in the position of the light edge input is the same as the change in the position of the measuring point using a fixed position of the light edge (the same is true in case of other forms of light illumination shape). A simple adjustment of template values will equate the measured value at a given spatial location with the calculated value using CNN simulations. To have more precision, the learning algorithm described below can also be used.

In some cases it may be possible to perform a *single input - multiple-point* measurement where the signals representing the space constant could be measured using a multi electrode probe as shown in Figure 20. The measurement grid constant and the template grid constant may or may not be the same. Using more points in the probe as the number of template elements or using a more sophisticated or more convenient input light stimulus than an edge (lines of different orientation, moving objects, etc.) will not change the method described below.

The template values are determined by a process using genetic learning algorithms. It has been used in identifying templates from given input-output pairs [30]. In our case the input image is given. The output activity field is measured by the multielectrode probe.. The learning algorithm can be started from the template values identified by single input - single point measurements.

In more sophisticated cases we can measure waveforms and tune the template values to approximate these waveforms by the CNN model.

2.2.4 Mechanisms of adaptation

Biological retinal function is not fixed, but can be modified by internal neuromodulators as the visual scene or the goals of the host are changed. In section 1.1 and 1.2 we have summarized some of these mechanisms. For example, the "gain" in the retina is decreased by different mechanisms when global and local brightness of the visual scene increases. Gain is also decreased in local regions when the texture or contrast in those regions increases. These gain changes keep the all retinal signals within an acceptable narrow range of response magnitudes for

the individual retinal neurons, regardless of input conditions.. These forms of adaptation and neuromodulation can be implemented in the CNN Universal Machine model of the retina to simulate either local or global adaptation, and can be controlled by either intrinsic or extrinsic conditions.

In local adaptation mechanisms,

- the template values,
- the switch configurations, and
- the local logic rule

can be changed locally. These parameters can vary according to spatial location. The changes are controlled by an adaptation mechanism which senses some characteristic of the visual scene and adjusts some parameters locally. This local parameter calculation can depend either on intrinsic conditions, calculated by some local analogic subroutines, or on some extrinsic conditions calculated and/or sensed globally and fed through some global wires (channels). Typical simple examples of these possibilities are as follows. 1) A local average illumination level within a neighborhood of all CNN units can be calculated by a single template, the result is locally stored, and this value, as a bias term (I) in the next templates, will control the local sensitivity of the succeeding templates [16]. 2) Texture detection analogic algorithms can be used to identify specific features such as textures or levels of contrast. The presence of such features will effect the three local parameter classes mentioned above. As a global extrinsic parameter, the average light intensity can be sensed and conveyed to each cell and this value will then be compared to each local illumination level calculated by an averaging template.

Global adaptation mechanisms can be implemented either by modifying the 3 parameter classes mentioned above, now considered spatially invariant, or by modifying the analogic algorithm itself, according to intrinsic or extrinsic conditions. Some examples will be shown later.

. The design techniques described in Sections 2.2.1 and 2.2.2 can be used to implement additional forms of adaptation or neuromodulation.. The interaction between the low and high resolution grid (parvo and magno system) can be used, for example, to detect global motion effects and the high resolution system can be modulated according to these global signals.

2.3 Bionic retinas: an analogic CNN implementation of a given retina model combined with artificial analogic algorithms interpreting the visual world.

The *bionic retina* is an algorithmically programmable implementation of a retina model (or a part of it) on a CNN Universal Machine augmented with a possible combination of artificial analogic CNN algorithms. By constructing this combination, features of the visual world can be detected and interpreted. A fairly accurate model of a given retina can be implemented on the CNN Universal Machine, for example on a single chip analogic microprocessor with on-chip optical sensors. In what follows, we will consider the silicon VLSI analogic microprocessor implementation of a bionic retina.

One important feature of a bionic retina is that all modifications and combinations mentioned above are made *algorithmically*, through a stored program. As a simple example, suppose we are implementing the preprocessing stages of early vision with a retina model and adding some artificial CNN detection algorithms. For example, we first implement noise filtering and motion detection via a given retina model. Then we add an artificial layout fault detection CNN algorithm to detect a prescribed discrepancy in moving objects. Since both the natural and the artificial parts of the algorithm are implemented on the same analogic CNN microprocessor, any additional capability can be easily added just by modifying the program. In a simple experimental project called "bionic eyeglass", the elements of this concept were tested [33]. Since many CNN templates and analogic algorithms are already available (see for example the recent edition of the CNN library [34]), this way of combining a given natural image processing capability with artificial ones is easily implemented..

Example 1

Watermarks are generally not clearly visible under normal lighting conditions. In this example we have combined a noise removal retinal model by some artificial analogic CNN algorithms to detect the almost-invisible water mark with the same clearness as the printed text next to it.

Figure 21 shows the original image, Figure 22 shows the image processed by a simple retina model, Figure 23 is the result of the bionic retina formed by adding a parallel artificial path of image transformation to be combined by the retina model. The watermark can be clearly recognized.

Another interesting aspect of the bionic retina is to exploit deficiencies in biological vision. For example, in the case of color image processing, when modeling color blindness [25], this biological deficiency can be exploited when combined with artificial algorithms to hide information for people with normal color vision. Some recent results on color CNN processing shows similarly interesting features, in which invisible parts of a color picture can be detected by using simple additional CNN templates [37].

2.4 Qualitative aspects of the models and their optoelectronic implementations

The reliable operation of bionic retinas (and other sensory organs) requires that the biological models and their artificially enhanced versions are qualitatively correct. In our case, qualitative correctness means stability and the ability to remain within the prescribed range of dynamics. This property is essential in any algorithmically programmed implementation. Moreover, it is necessary to be able to check these properties instruction by instruction, to provide the freedom in algorithmic design (a programming style we are taking for granted when writing digital algorithms). Fortunately, we can ensure these two properties by carefully analyzing the CNN templates using available theoretical results. Hence, before inserting a new template or template sequence into the library of retinal models the stability tests and range of dynamics tests will be performed.

When placing the optical sensors on the chip in a close interaction with the processing elements, similar stability tests should be carried out. When the optical sensor is directly engaged in a template-like interaction then the detailed model of the sensor must be considered in the test

for stability and dynamic range. Modeling the local photoreceptor gain control, a high range of dynamics can be implemented. This *adaptive dynamic range* is an important method used to overcome the limitations of dynamic range in analog circuits.

The accuracy of the biological retina is probably no bettter than a about 1 per cent. Under ideal conditions we can perceive differences in adjacent contrasting regions down to about this level. In both biological retina and bionic systems accuracy is enhanced by the gain controls associated with the forms of adaptation described here[17,56].

3 Combining several bionic retinas and other topographic modalities - the analogic CNN bionic eye

Now, having the algorithmic analogic CNN implementation of any given bionic retina (or other sensory organ), we are in a position to introduce the analogic CNN Bionic Eye. We can combine the broad range of capabilities of generalized in a programmable way via artificial analogic algorithms. This is the Bionic Eye, in which the sensory processing capabilities of many species and or many neuromodulation effects, and possibly of different sensory modalities, are combined with artificial spatiotemporal analogic CNN algorithms in the unified computing platform of the CNN Universal machine.

The range of possible retinal functions (the retina universe) may include different retina models of different species and or different effects within a given retina model with all inherent neuromodulation possibilities. These neuromodulation effects are capable of changing continuously a given receptive field organization, rod vs cone function, synaptic gains and other features via the template values and/or the template structures. Hence we can use several fixed and programmable retinal building blocks, each representing one or more well-defined functions in a given retina, or a well-defined model of a retina of a given species.

Presently, the computationally most efficient physical implementation of the CNN Universal Machine is the analogic microprocessor. Hence, in what follows, we will interpret the applications of the Bionic Eye in this form .

3.1 Programmable implementation of several bionic retinas on a CNN Universal Machine

Consider the retina universe, defined in the above sense. Suppose we have several given known, or to be discovered, retina models or retinal building blocks which are implemented as bionic retinas. Since these bionic retinas are programmed implementations on the same electronic platform, we can combine them according to prescribed programs with or without adaptation mechanisms. For each bionic retina, we can write a single analogic CNN subroutine. These subroutines are then subsequently called according to a given or an adaptive sequence. In this way, for example, we can instruct the Bionic Eye to perform as any one of a variety of different retinas. Moreover, we can combine retinal building blocks so that, for example, a motion detection building block derived from a rabbit retina could be combined with the rich color processing building block derived from a bird retina.

Since different species often have similar neural mchanisms for performing similar tasks, consisting of quite similar retinal building blocks, the CNN templates which are common in more than one bionic retina need to be stored in the analog program register (APR) only once. In this way we can build up and store a bionic retina template (or subroutine) library and the various retinas are built up using already known template building blocks plus some specific instructions. Hence, a single chip analogic microprocessor, can be used to mimick a retina universe with on chip retina-specific templates and analogic instructions in the global analogic programming unit (GAPU).

Example 2

Consider the images in Figure 24. The original image is shown in the upper left . All other images are the results of transformations corresponding to various retinal and artificial analogic CNN algorithms. This is an example of the multiple output signals tiling the retial output. Combining these results by artificial or natural algorithms (like the ones taking place in the visual cortex) additional features on the original image can be detected.

3.2 Combining different sensory modalities and artificial analogic algorithms

The somatosensory model of the electric fish has inspired the development of CNN models with additional sparse global interconnections [22]. Moreover, the hyperacuity effect was successfully modelled in this extended CNN model [23]. An auditory scene analysis following the two-dimensional outputs of the basilomembrane has been initiated for detection of various alarm signals [35]. These initial results illustrate the wide applicability of the CNN models in modeling other sensory organs. Indeed, in the above two examples additional artificial CNN templates were used to modify the biological model for solving some complex tasks.

An appealing possible capability of the Bionic Eye is the combination of CNN models of different sensory modalities with artificial analogic CNN algorithms, including adaptation. All of these models are based on the same computing platform, the CNN Universal Machine. This type of Bionic Eye, capable of seeing and detecting complex "analog events," [2] containing maps of different sensory modalities, and can be implemented on the same physical device, for example, on the analogic microprocessor. Some of the non-visual sensors can also be implemented on a microchip (the so-called microsensors for sound, presssure, some chemical properties, temperature, infrared, and Xray, etc.) or can directly be interfaced to the analogic microprocessor.

Example 3

In this algorithmic example we show how to combine visual and thermographic images. The task is to detect emergency situations on a thermally exposed metal plate. This situation is defined by the presence of prescribed textures at thermally sensitive areas. Thermally sensitive areas are defined by having local thermal maximums or areas with a thermal gradient greater than a given value.

Suppose, the analogic microprocessor has two types of sensory arrays: a thermographic and a visual one. These could be either on-chip (at each processing unit) or off-chip (separate sensor array chips). The two types of input arrays are stored in two places of the local analog memory , LAM(1) and LAM(2), respectively. The thermographic template sequences (ALG1) detect the thermally sensitive areas which have either the local temperature maximums or temperature gradients higher than a given value. The visual analogic CNN algorithms (ALG2) detect the areas with prescribed texture.

The complete algorithm for solving our task would work as follows. ALG1 is applied to the thermographic input map stored in LAM(1) and the resulting map is stored in the local logic memory, LLM(1) (coding the termally sensitive areas). ALG2 is applied to the visual input map (image) stored in LAM(2) and the resulting map is stored in the next place of the local logic memory, LLM(2) (coding the areas with the prescribed suspicius textures). Now, applying a logic AND operation using the local logic unit (LLU) on LLM(1) and LLM(2), the result will code the areas where an emergency state exists.

4 APPLICATION AREAS, INNOVATIVE DEVICES

The application possibilities of the Bionic Eye are numerous. Here, we will mention but a few areas.

Medical imaging and diagnosis is definitely one of the most challanging fields. Detecting slight defects which are invisible or hardly visible for the naked human eye , even in a fraction of a second, provide for new diagnosis methodologies. Screening and enhancing images to lessen the harm (decrease the dosis) of noninvasive tests and hence using the less destructive ones are made also possible. Developing complex analogic algorithms, even adapted to the personal experience of the doctors may revolutionarize medical practice.

Remote sensing systems normally can not select the useful information in real time, the huge amount of detected or stored useless information limits the efficiency of these systems. The Bionic Eye, trained and programmed to detect the situation when, and only when the useful information is sensed, would be a possible solution, due to the very high speed in performing sophisticated algorithms in space.

Combining visual, tactile, thermographic, etc. information in robots, including night vision, all done in a fraction of a second, would enhance not only the efficiency of the robot but the reaction speed in emergency situations as well (the recent failure of NASA's Dante robot suggests a lot of improvement are needed).

Proliferating the global information and communication systems (e.g. "information superhighway") the human perception of images and other sensed information become a crucial question. The representation and the perception of these information may be divided to enhance channel capacity, yet to improve perception. The complex mechanisms of color perception is one of the many important areas to be considered as specially apt for using the Bionic Eye.

Making visual prosthetics of many different kinds is an obvious long term goal and a major challange for the development of the Bionic Eye. The possibility of mimicking retinal and other visual functions, including image sensing, on a single chip needs no justification about its usefulness. The bionic eye can reproduce and deliver to either the optic nerve, LGN or visual cortex, the many different patterns of activity that would be normally received by those sensory areas. However, the methods for connecting the signals containing these patterns to the appropriate sensory areas, chronically, at the proper depths, and in proper register, remains an unsolved problem.

The Bionic Eye concept and implementation provides for developing new visual devices. We mention only two of them briefly. New discoveries in perception mechanisms in animals and or humans provide an open ended resource of new analogic algorithms.

The visual mouse [38] is a handheld visual supercomputer capable of detecting complex features in a fraction of a second when moved across an image. The device contains functional buttons, a small color screen, a zoom lens, and the analogic CNN microprocessor, all contained in this hand held device that can detect and interpret specified patterns in the visual scene.

The Bionic Eyeglass [39] is an eyeglass-like device with analogic visual microprocessors in it. The programmable analogic algorithms provide the user with the ability to detect a broad array of visual scenes with predetermined characteristics that otherwise would remain invisible.

Conclusions and future directions:

The analogic CNN Bionic eye described here opens many new possibilities for artificial sensory processing. It implements programmable neuromorphic models, combines a given neuromorphic model with artificial analogic agorithms, and combines several neuromorphic models, possibly from different sensory modalities, in an algorithmic way. These could be used, for example, as the "front end" of a video camera, a prosthetic device designed to simulate retinal output at either the optic nerve or visual cortex, or a hand-held "visual mouse" capable of sensing, detecting and interpreting a variety of visual objects. By using artificial analogic algorithms in combination, we can not only detect, but begin to *interpret* the world through these neuromorphic artificial senses. In doing so we begin approach but have not yet rigorously studied, issues related to congnition, recognition, and interpretation of visual scenes.

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Figure captions

Figure 1 Schematic diagram of cross section of a typical vertebrate retina with array of photoreceptors at the top and retinal ganglion cells (output cells) at the bottom. In between these two layers there are additional layers of cells, each of which performs a specific function. The horizontal cells form a broad continuous sheet of interconnected neurons that average activity in space and time. This average is subtracted from the activity of the photoreceptors thereby setting a normallized level at each point in space around which the photoreceptors operate. Bipolar cells convey the result of these computations to the lower retina where interactions in space and time, such as movement detection are mediated. Most of the interactions between retinal neurons are quite local, and occur within or between layers, so they are easily modeled by CNN architecture.

Figure 2 Schematic of adaptation or gain changes in the retina. The upper curves represent a family of cone responses as a function of flash intensities. Adaptation mechanisms withing the transduction machinery of the cones control gain such that each of these instantaneous response curves is centered upon the average past history of intensity at that cone. The curves can shift by more than 6 orders of magnitude. The gain is further adjusted by the interactions between horizontal cells and cones to shift the position of the bipolar cell operating curves as a function of surround illumination. The lower curves show these shifts, for different surround levels, for the cones operating at the center curve over a range of intensities indicated by the stippled area.

Figure 3. Three different forms of retinal output mediated by increasingly more complex retinal circuitry. Response waveforms in response to a step of illumination (shown below). A. Sustained activity in response to the presence of a visual target implemented by relatively simply circuitry, B. Transient activity in response to the arrival or movement of a visual target mediated by more complex retinal circuitry, C. Transient truncated activity in response to arrival or movement, but mediated by even more complex retinal circuitry. A full description of these circuits is in [56].

Figure 4 A processor array on a 3 layer grid. The identical processors are marked by identical symbols in the grid points.

Figure 5 An interaction graph with radius r=1 in case of 1 layers with 8 neighbors (a) and 3 layers with 4neighbors in 2D and 6 neighbors in 3D (b)

Figure 6 A template matrix and its graphical representation

Figure 7 A simple circuit representation of a unit

Figure 8 The interactions, the A- and B-templates

Figure 9 The interactions to a single unit

Figure 10 The two types of the interactions related to a cell

Figure 11 Simple processor circuits: a 3rd order Chua's circuit for chaos (a), a 2nd order (b) and a first order (c) circuit, and a first order one with state is identical to output (d) [3]

Figure 12 The augmented processing unit of the CNN Universal Machine. The extension consists of a local analog memory (LAM), a local logic memory (LLM), a local analog output unit (LAOU) , a local logic unit (LLU), a local communication and control unit (LCCU)

Figure 13 The global analogic program unit (GAPU) and its parts: analog program register (APR), logic program register (LPR), switch configuration register (SCR) , and the global analogic control unit (GACU)

Figure 14. Experimentally derived space constants for different networks of neurons in the retina. A. The horizontal cells are broadly coupled, both electrically and chemically. The profile, spanning about 250 um, shown in the upper left represents activity, as a function of distance, elicited by a narrow bar of light scanning the retina. B. Bipolar cells have dendrites that span a narrower region of space, so their spatial sensitivity profile is quite narrow, spanning about 60 um. C. Amacrine cell fields measured by puffing transmitter across the expanse of their dendrites, span between 50 and 150 um. D. Similarly ganglion cells have dendritic fields spanning about 150-200 um. Each of these space constants can be represented by a diffusion or recursive template in CNN as shown in Figure 10.

Figure 15. The synaptic functions define the relation between pre- and postsynaptic activity. A. The horizotnal cell to either cone or bipolar synaptic function tends to be rather broad. B. The cone to either horizontal or bipolar cell synaptic function is somewhat narrower, and C. The bipolar to amacrine or gangion cell synaptic function is quite step and starts at a considerably more depolarized level. This approximates a "threshold" function, causing the postsynaptic cells to be brought into full activity at a given presynaptic potential.

Figure 16 The controllable capacitors can be inserted either in parallel or series into the processing unit or into the VCCS (OTA) implementing a template element. A delay line (D) or an approximation of it can also be inserted, possibly with a switch.

Figure 17 A course and a fine grid. The switches change the grain on the layer.

Figure 18 Framework for modeling the visual pathway: consecutive layers following the anatomical structure with interactions(a), the layer interaction graph (b), and the loopfree layer interaction graph (c) with the complex layer containing the original layers 1,2, and 3

Figure 19 Activity field and template values in one dimension

Figure 20 A multiple-point measurement probe with single input stimuli

Figure 21 Input image, the watermark can be hardly seen

Figure 22 The output of a retina like filter

Figure 23 The output when the retina like filter and another analogig algorithm are combined

Figure 24 Several different maps from the original image shown in the upper left corner

The Analogic Cellular Neural Network as a Bionic Eye

Frank.Werblin, Tamás.Roska, and Leon O. Chua

Prof. Frank S. Werblin
Vision Research Laboratory
Dept. Molecular and Cell Biology
Room 145, LSA
University of California at Berkeley
Berkeley ,CA 94720, U.S.A
Phone: (510) 642 7236 Fax: (510) 643 9424
e-mail: werblin@mander.berkeley.edu

Prof. Tamas Roska
Analogical and Neural Computing Laboratory
Computer and Automation Institute
Hungarian Academy of Sciences, Budapest
Kende -u. 13, H-1111, Hungary
Phone: +36 1 269 8263 Fax: +36 1 269 8264
and the
Electronics Research Laboratory,
U.C.Berkeley
e-mail: roska@fred.eecs.berkeley.edu

Prof. Leon O. Chua
Nonlinear Electronics Laboratory
Cory Hall
Dept. Electrical Engineering and Computer Sciences and the
Electronics Research Laboratory
University of California at Berkeley
Berkeley, CA 94720, U.S.A.
Phone: (510) 642 3209 Fax: (510) 845 4267
e-mail: chua@fred.eecs.berkeley.edu

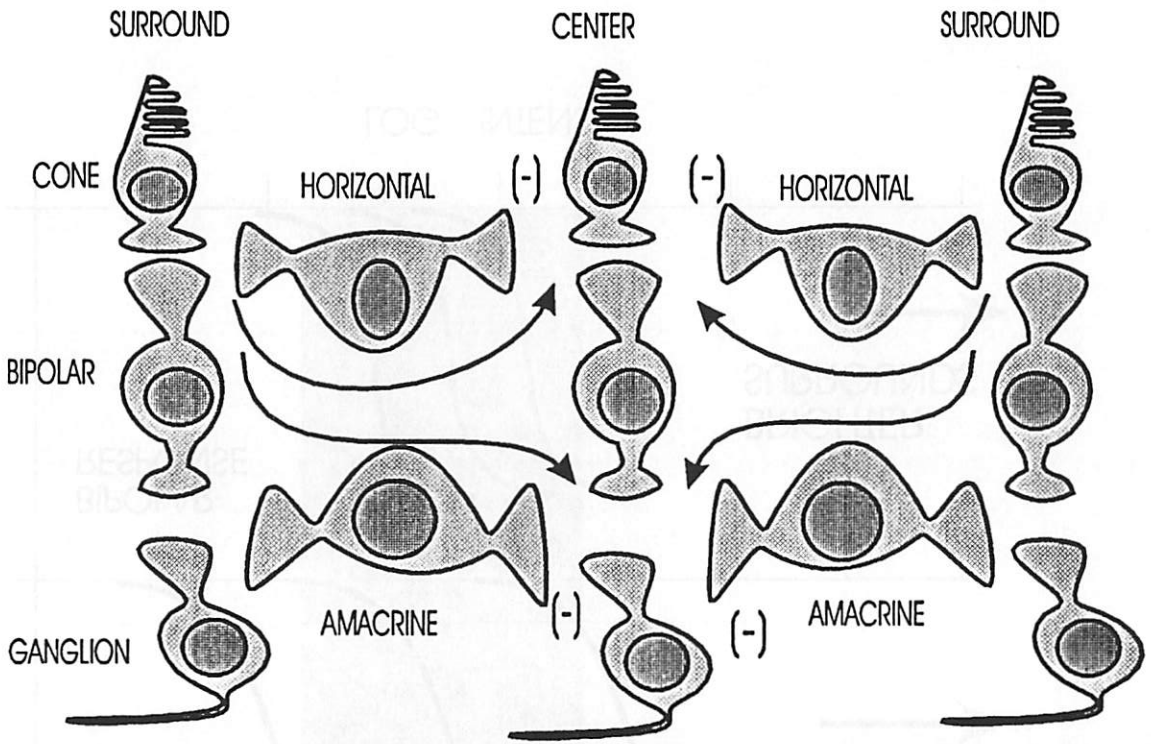

SURROUND
CENTER
SURROUND
CONE
HORIZONTAL
(-)
(-)
HORIZONTAL
BIPOLAR
AMACRINE
(-)
(-)
AMACRINE
GANGLION

FIGURE 1

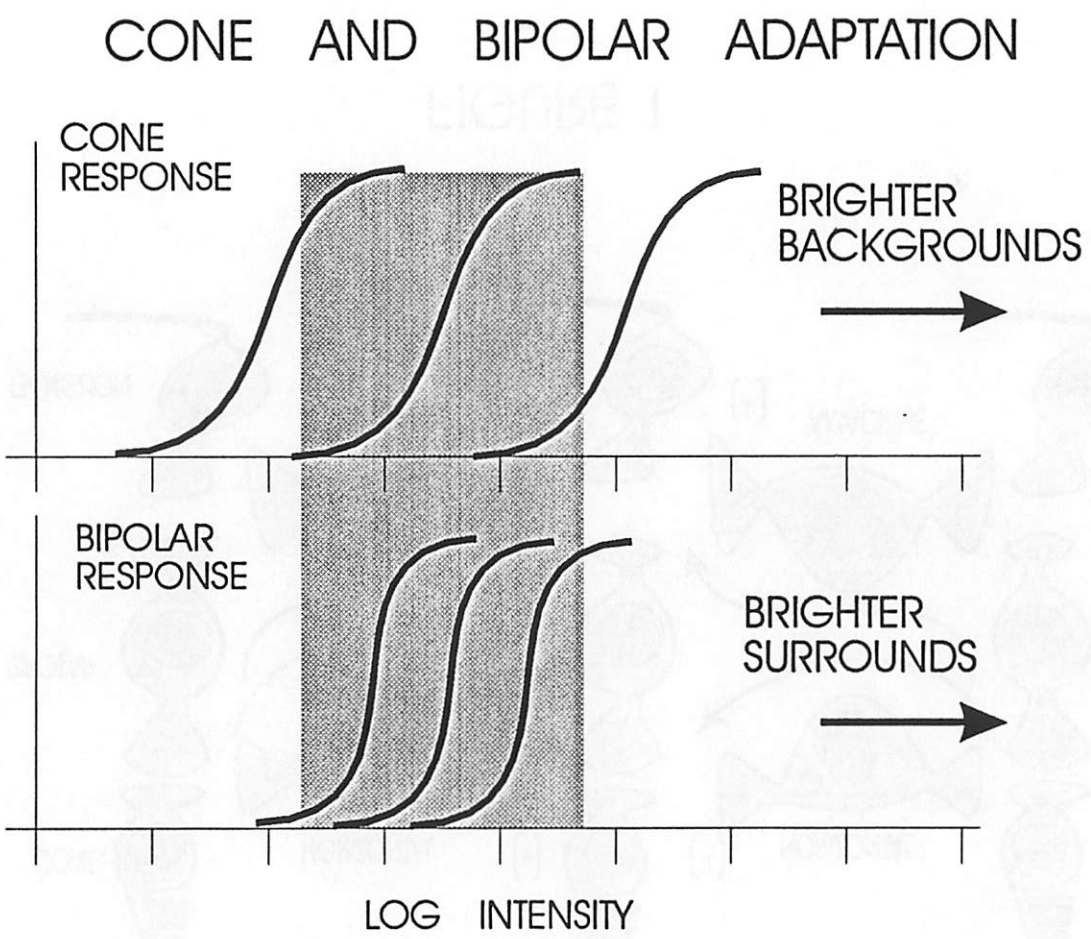

CONE AND BIPOLAR ADAPTATION
CONE RESPONSE
BRIGHTER BACKGROUNDS
BIPOLAR RESPONSE
BRIGHTER SURROUNDS
LOG INTENSITY

FIGURE 2

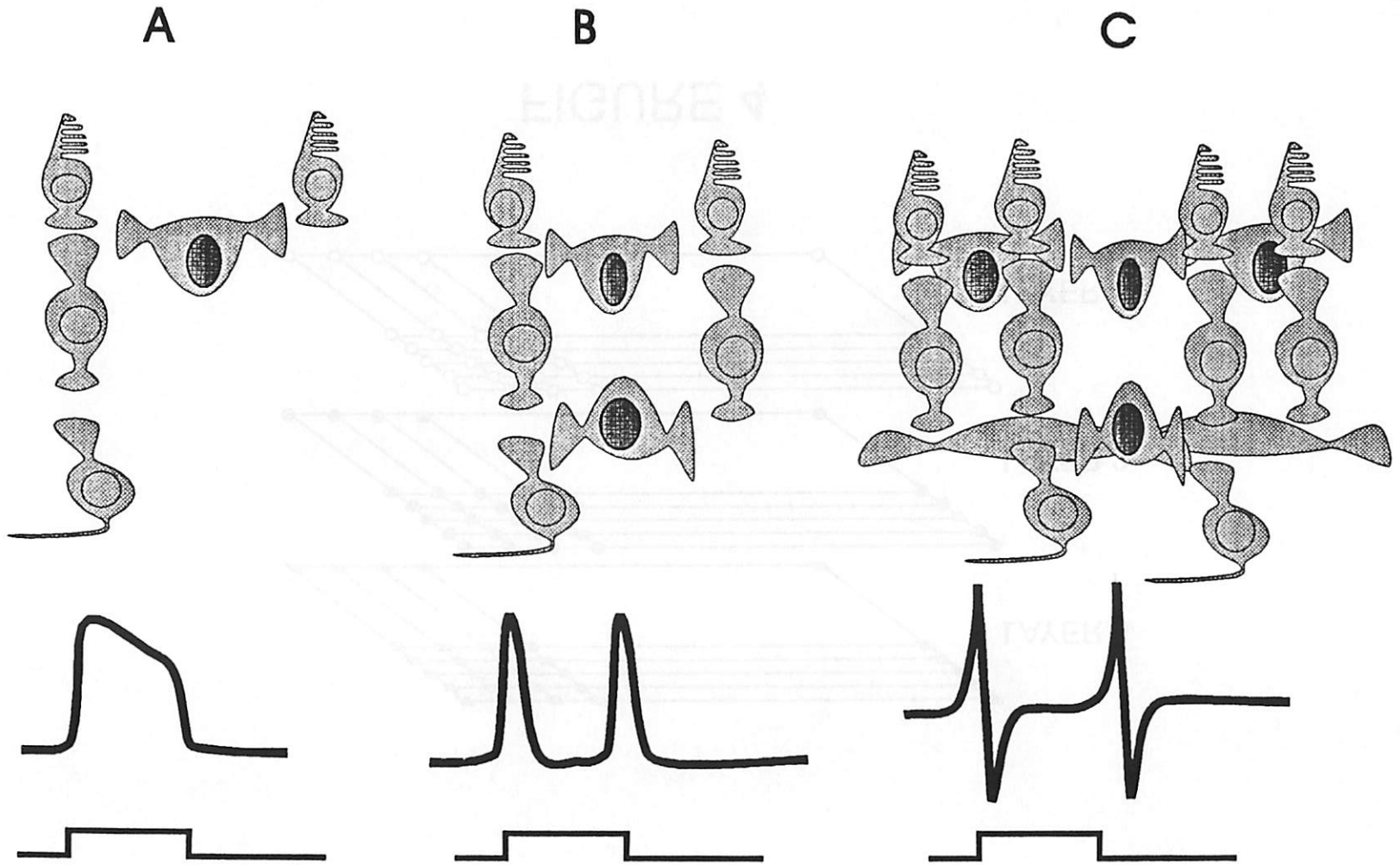


FIGURE 3

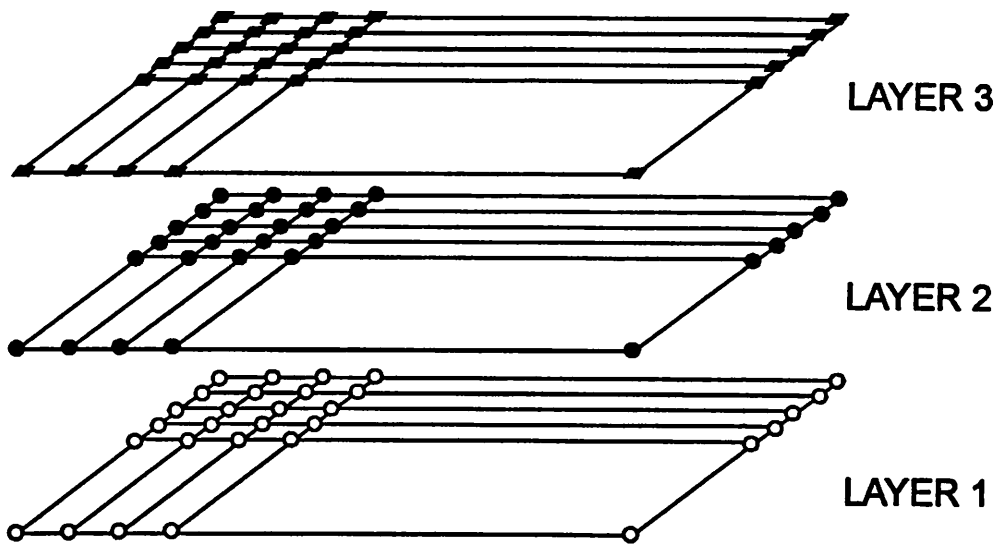


FIGURE 4

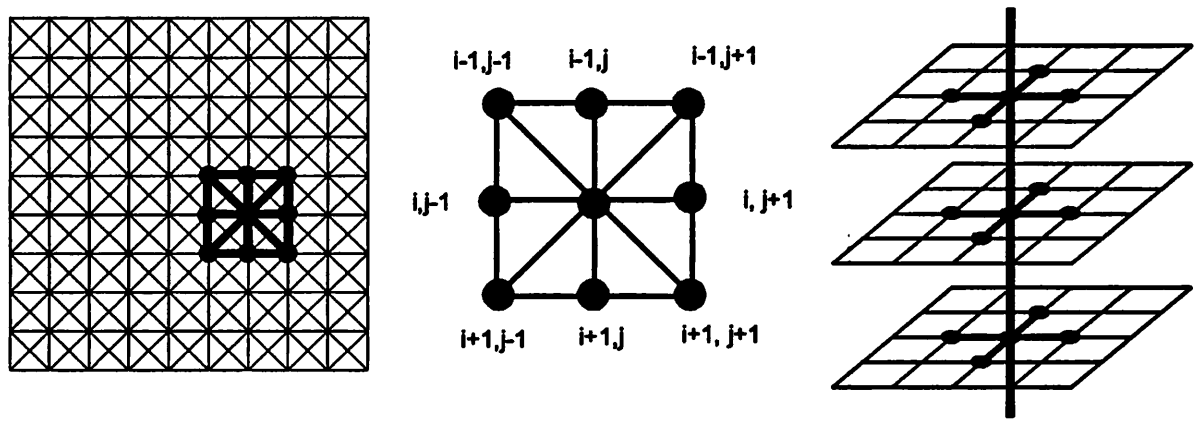
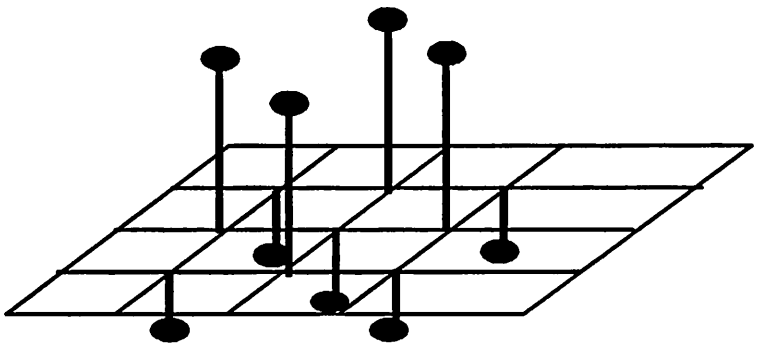


FIGURE 5



$$\begin{bmatrix} -0.5 & +1.5 & -0.5 \\ +1.5 & -0.7 & +1.5 \\ -0.5 & +1.5 & -0.5 \end{bmatrix}$$

FIGURE 6

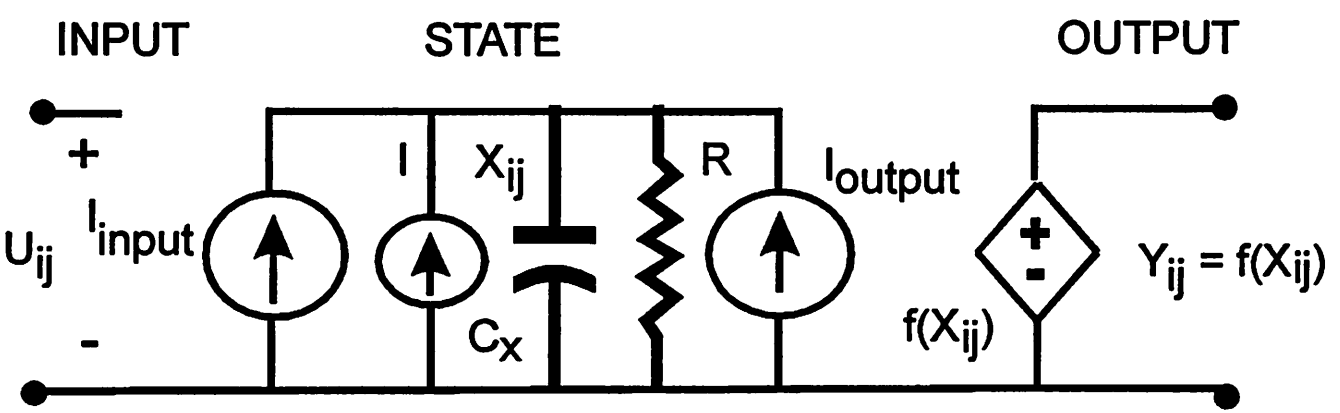
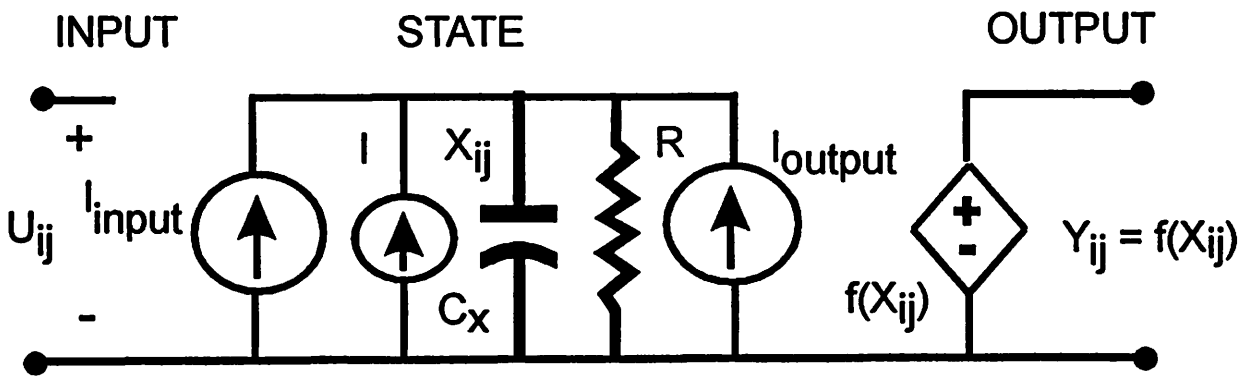

INPUT
STATE
OUTPUT
+
U_{ij}
I_{input}
-
I
X_{ij}
C_X
R
I_{output}
$f(X_{ij})$
$Y_{ij} = f(X_{ij})$

FIGURE 7



$$i_{input} = \sum b_{kl}\, u_{kl}$$

$$i_{output} = \sum a_{kl}\, y_{kl}$$

b_{11}	b_{12}	b_{13}
b_{21}	b_{22}	b_{23}
b_{31}	b_{32}	b_{33}

a_{11}	a_{12}	a_{13}
a_{21}	a_{22}	a_{23}
a_{31}	a_{32}	a_{33}

FIGURE 8

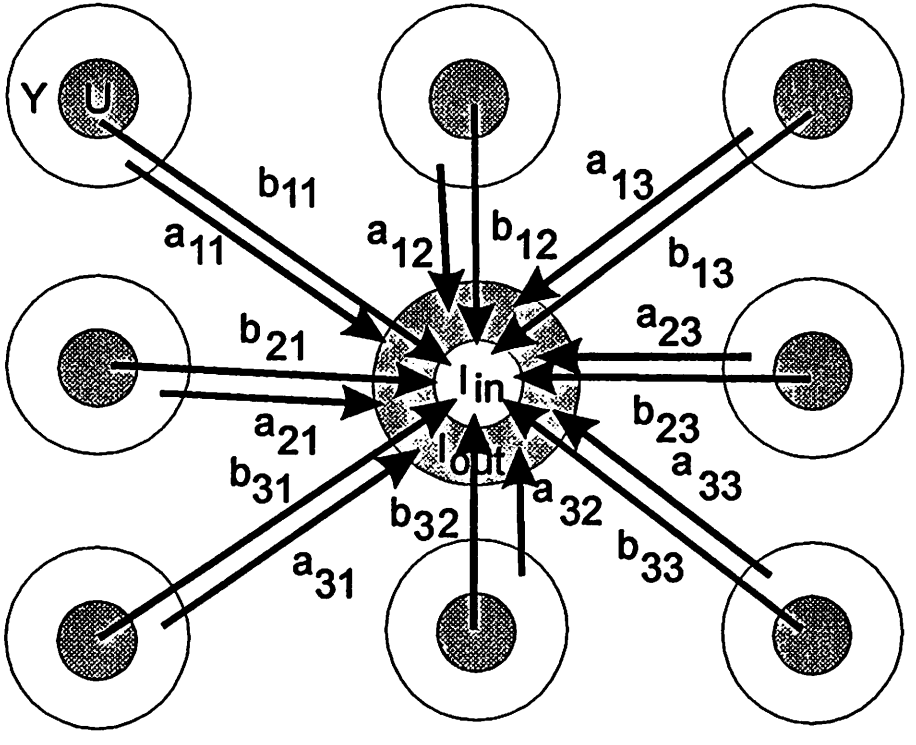

Y
U
b11
a11
a12
b12
a13
b13
b21
a21
Iin
Iout
a23
b23
a33
b33
b31
a31
b32
a32

FIGURE 9

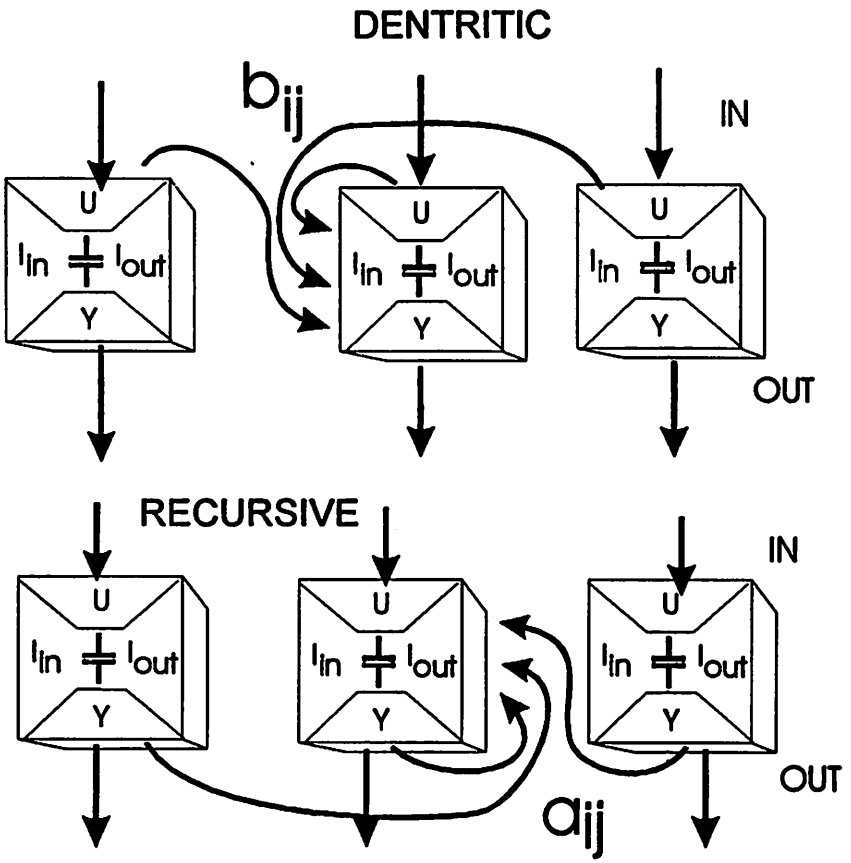


FIGURE 10

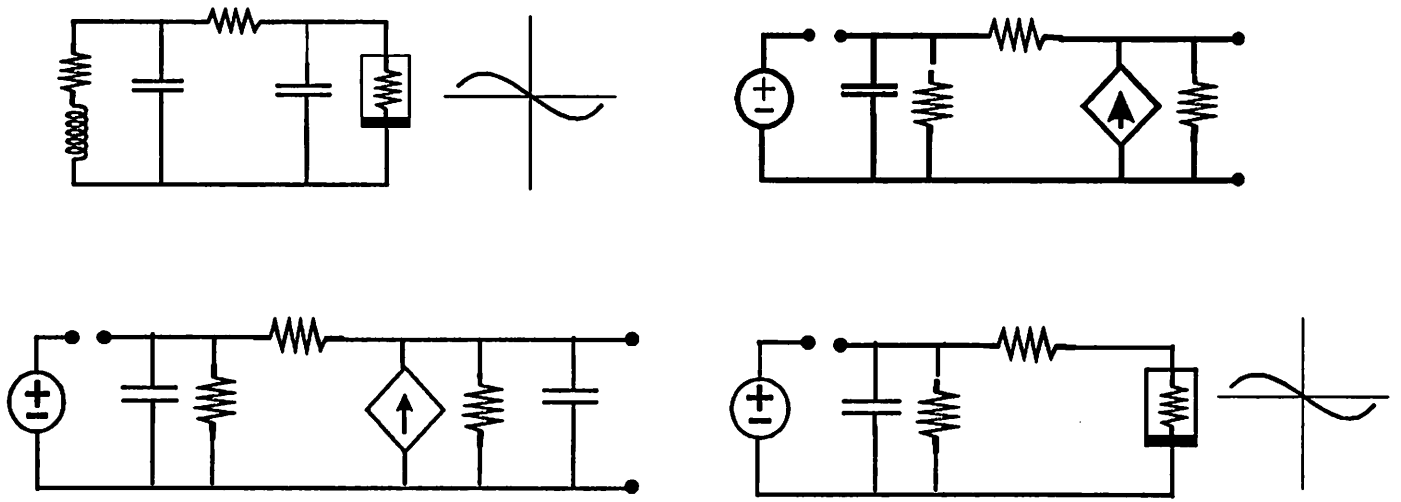


FIGURE 11

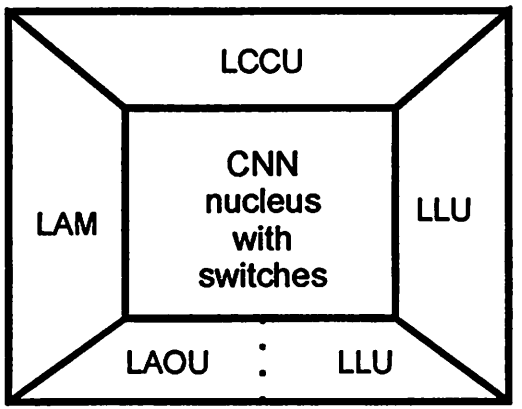


FIGURE 12

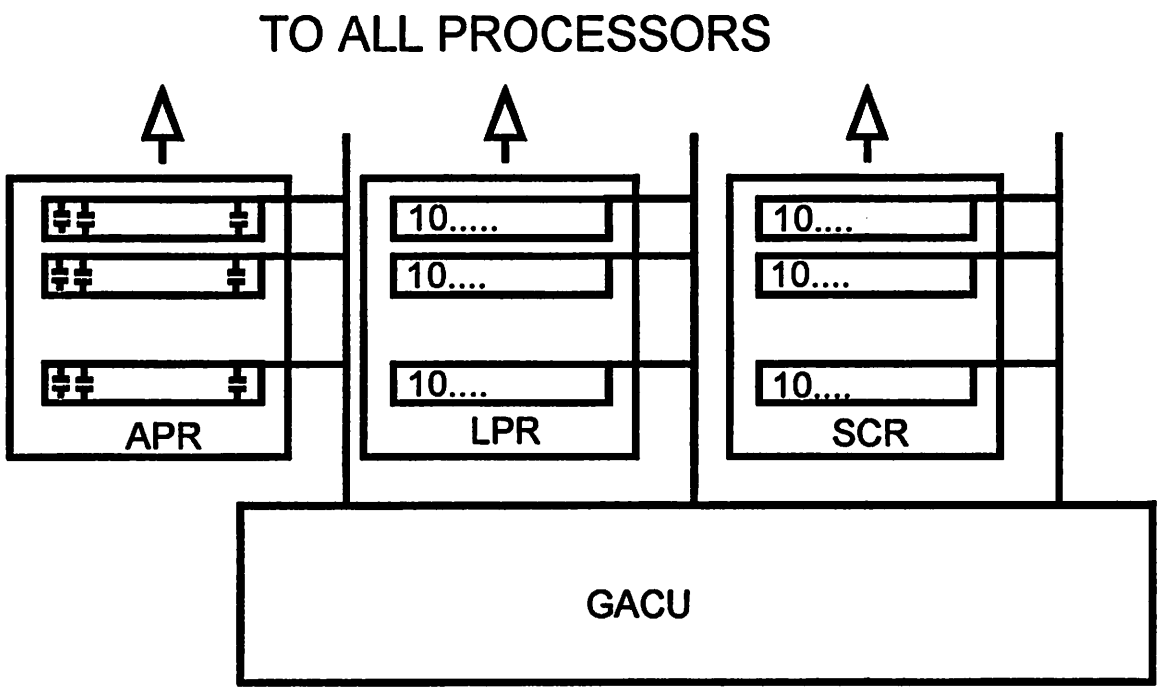


FIGURE 13

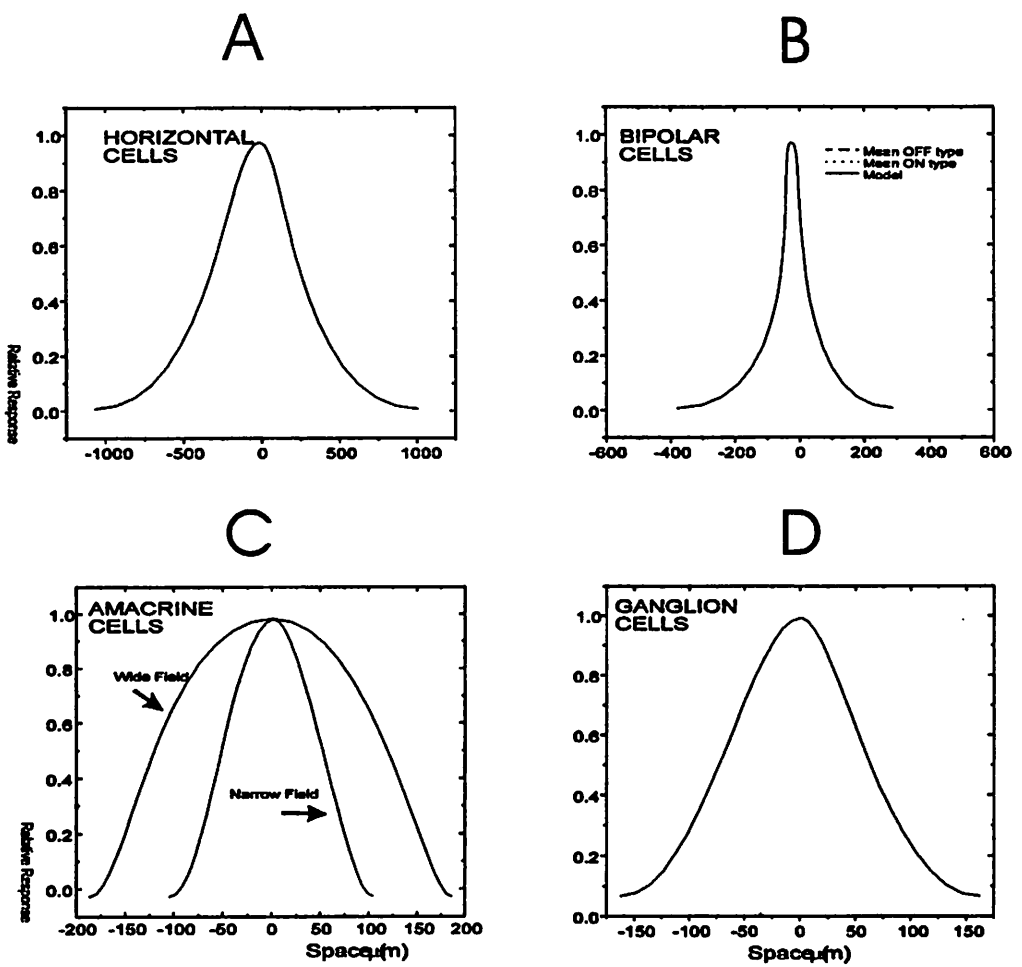

A
B
C
D
HORIZONTAL CELLS
BIPOLAR CELLS
Mean OFF type
Mean ON type
Model
AMACRINE CELLS
Wide Field
Narrow Field
GANGLION CELLS
Relative Response
Space (n)
1.0
0.8
0.6
0.4
0.2
0.0
-1000
-500
0
500
1000
-600
-400
-200
200
400
600
-200
-150
-100
-50
50
100
150
200

Figure 14

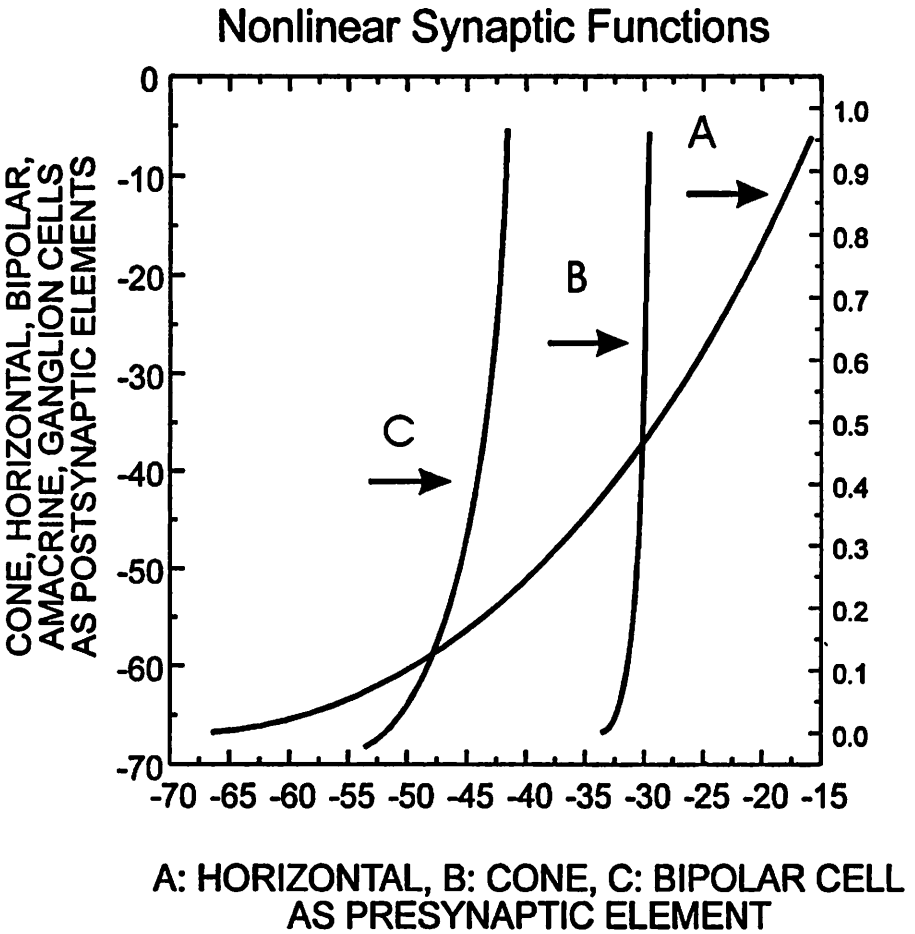

Nonlinear Synaptic Functions
CONE, HORIZONTAL, BIPOLAR, AMACRINE, GANGLION CELLS AS POSTSYNAPTIC ELEMENTS
0
-10
-20
-30
-40
-50
-60
-70
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-70 -65 -60 -55 -50 -45 -40 -35 -30 -25 -20 -15
A
B
C
A: HORIZONTAL, B: CONE, C: BIPOLAR CELL
AS PRESYNAPTIC ELEMENT

Figure 15

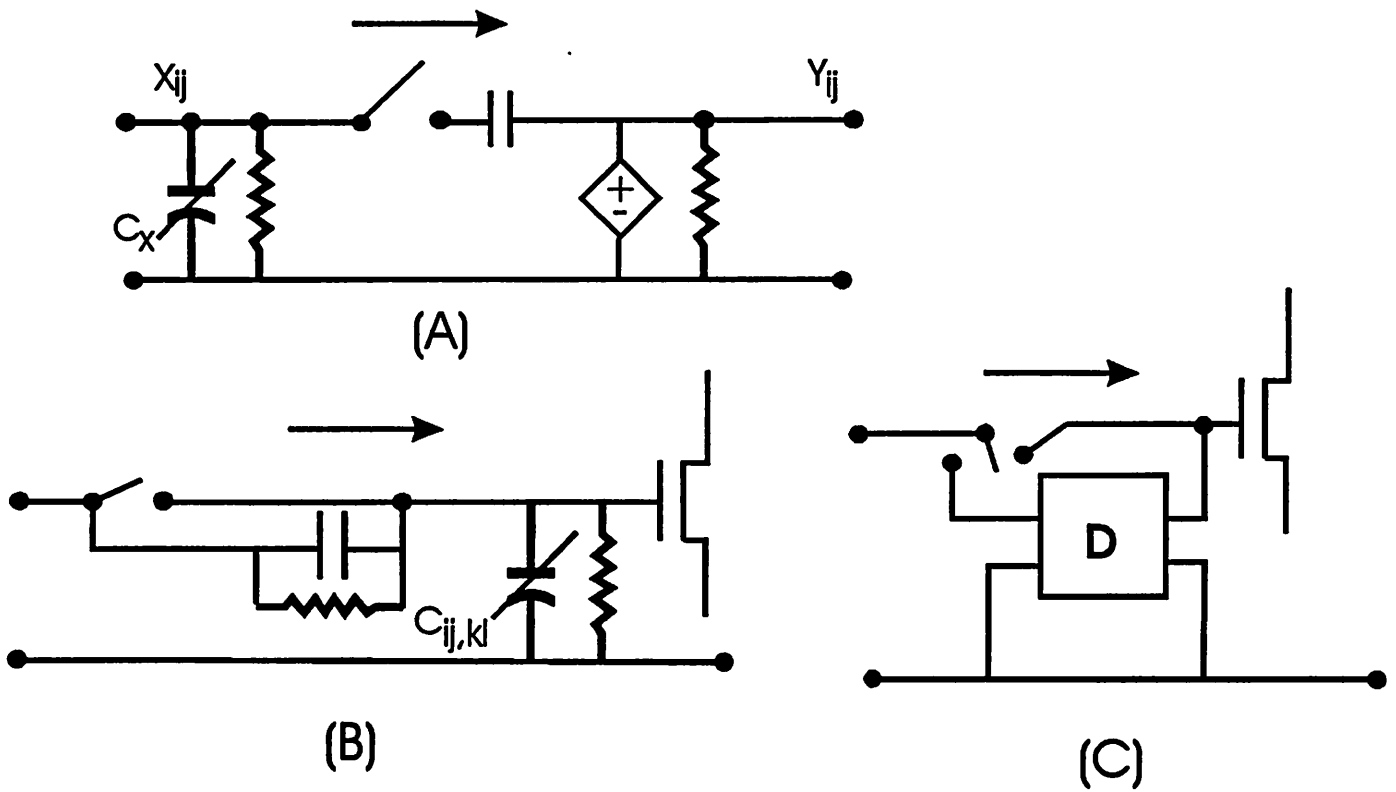


FIGURE 16

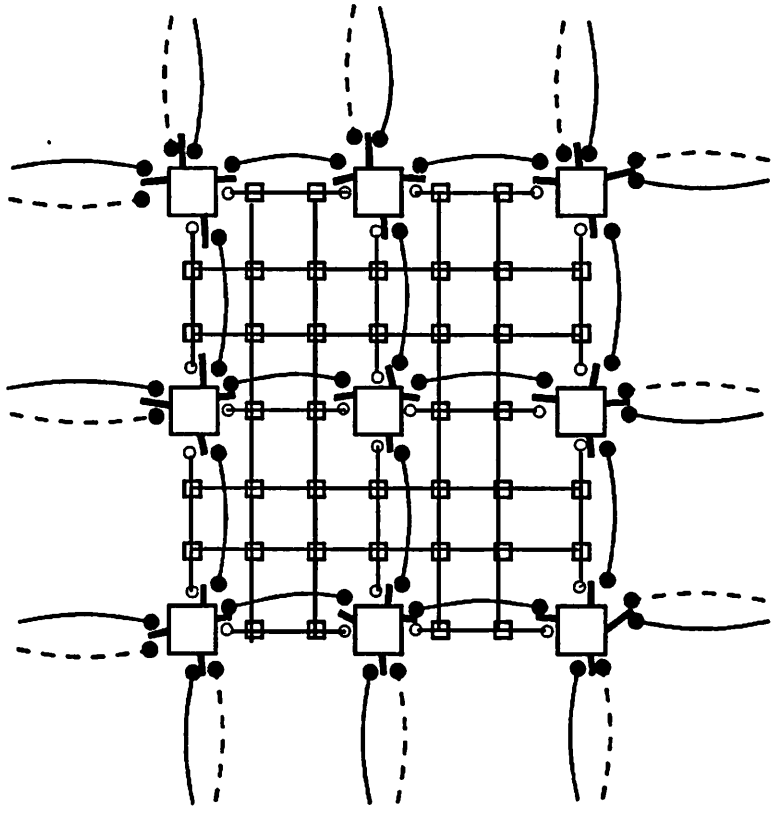


FIGURE 17

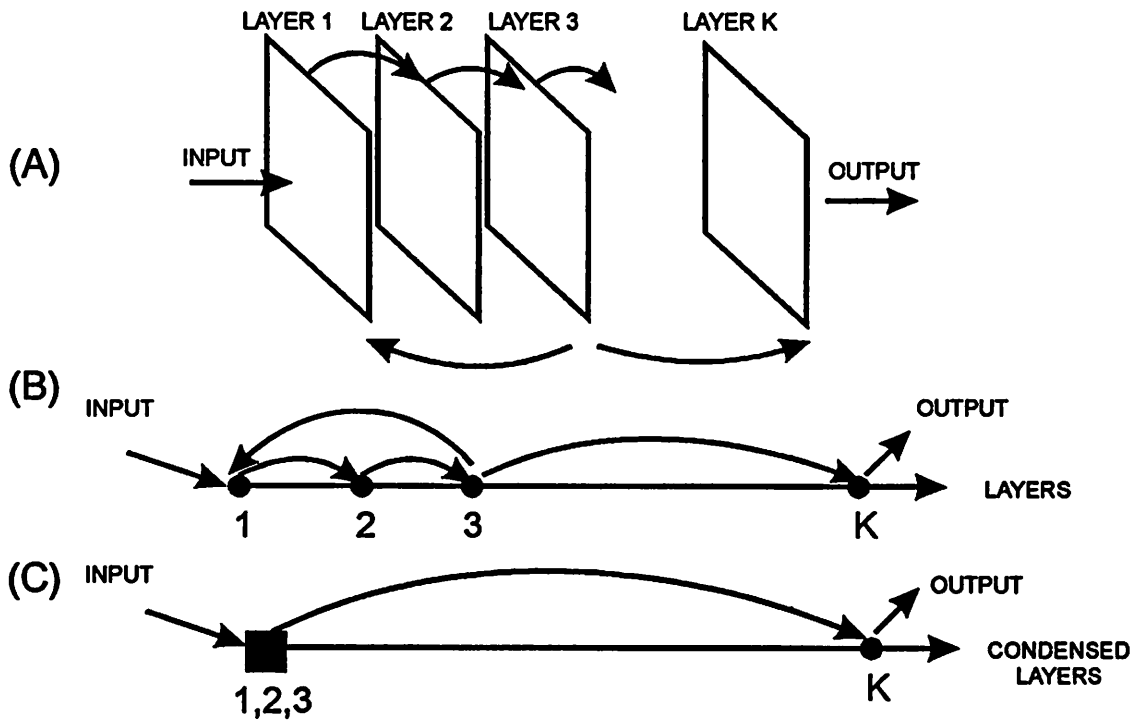

(A)
LAYER 1
LAYER 2
LAYER 3
LAYER K
INPUT
OUTPUT
(B)
INPUT
OUTPUT
LAYERS
1
2
3
K
(C)
INPUT
OUTPUT
CONDENSED LAYERS
1,2,3
K

FIGURE 18

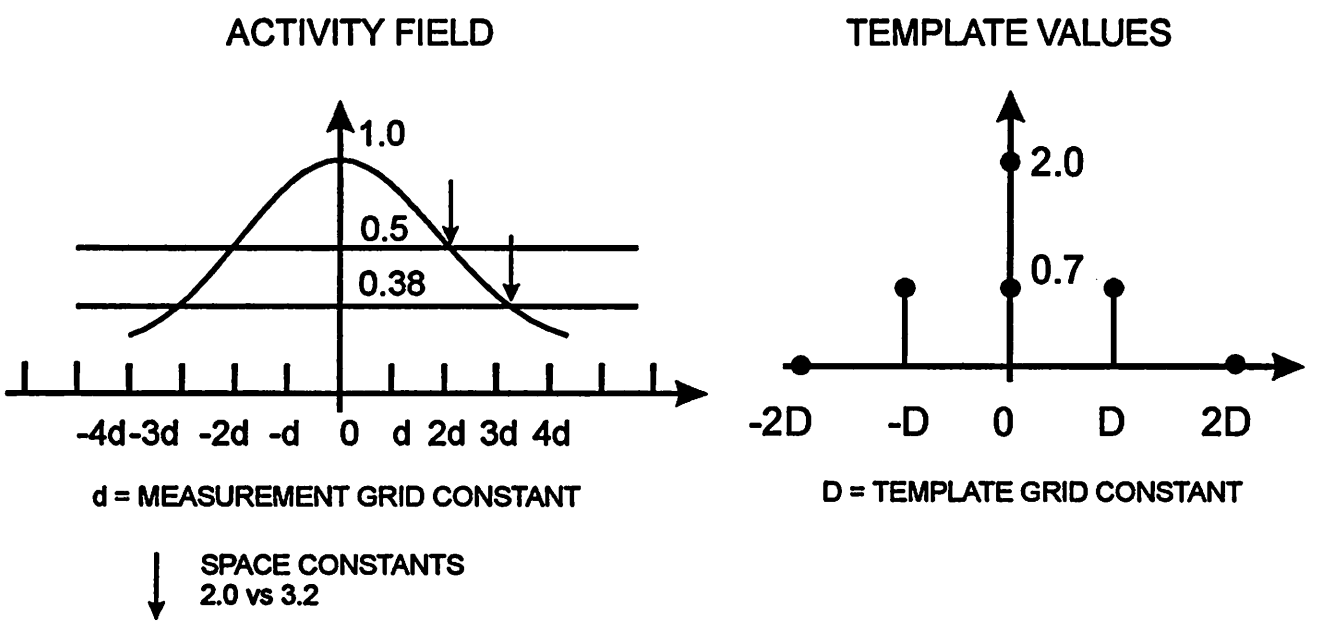

ACTIVITY FIELD
1.0
0.5
0.38
-4d -3d -2d -d 0 d 2d 3d 4d
d = MEASUREMENT GRID CONSTANT
SPACE CONSTANTS
2.0 vs 3.2
TEMPLATE VALUES
2.0
0.7
-2D -D 0 D 2D
D = TEMPLATE GRID CONSTANT

FIGURE 19

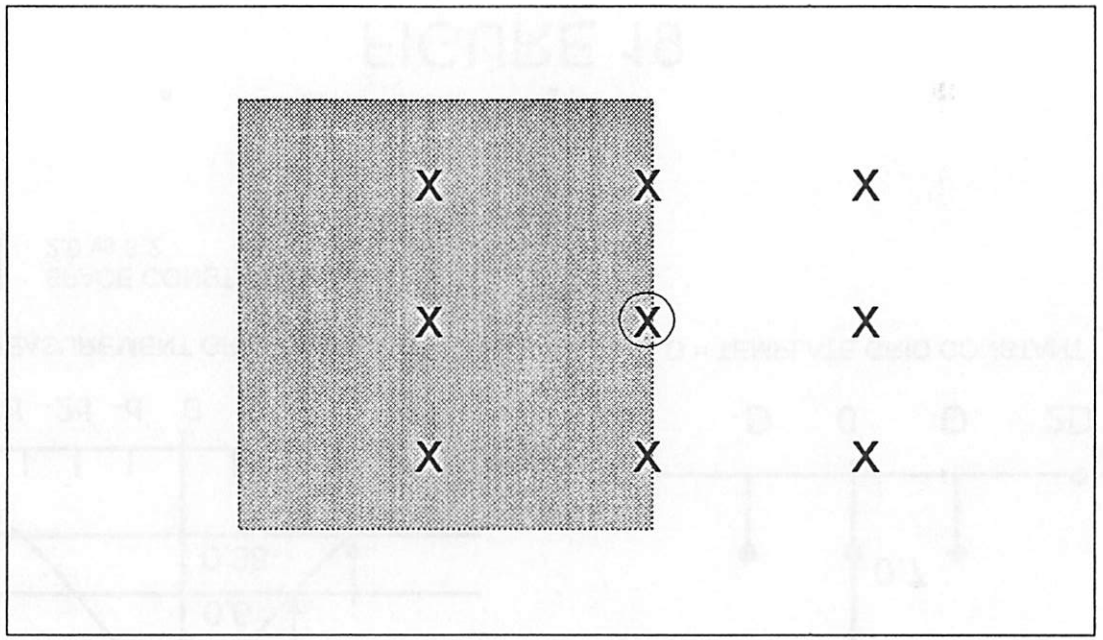


FIGURE 20

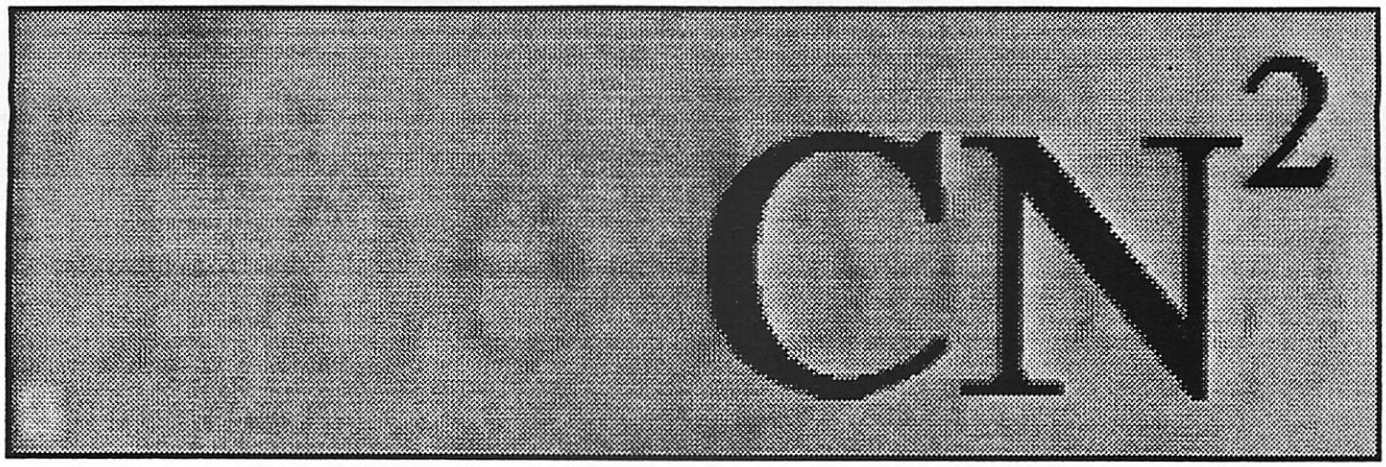


FIGURE 21

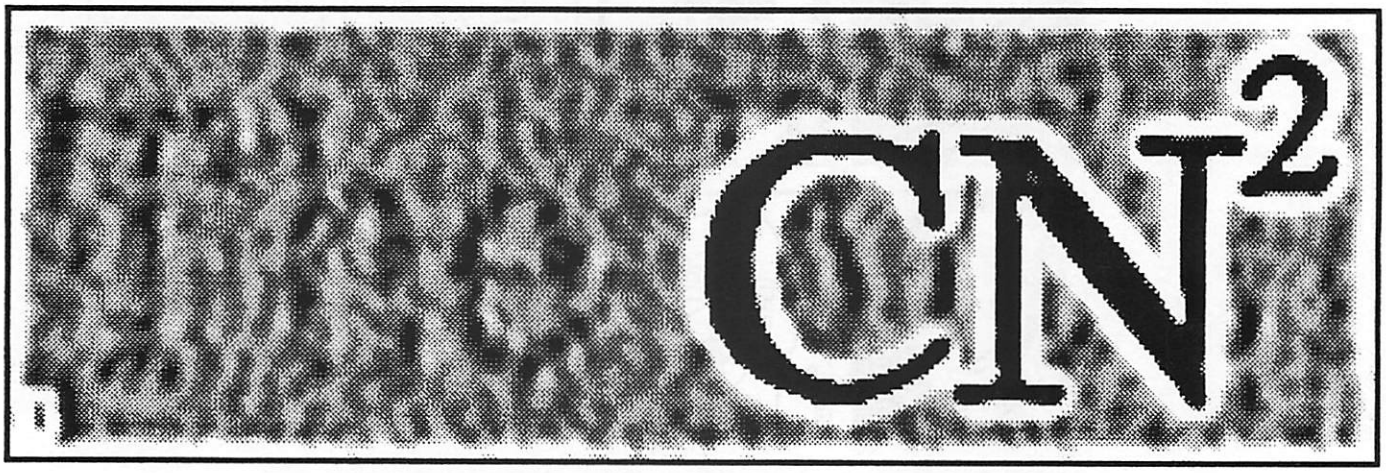


FIGURE 22

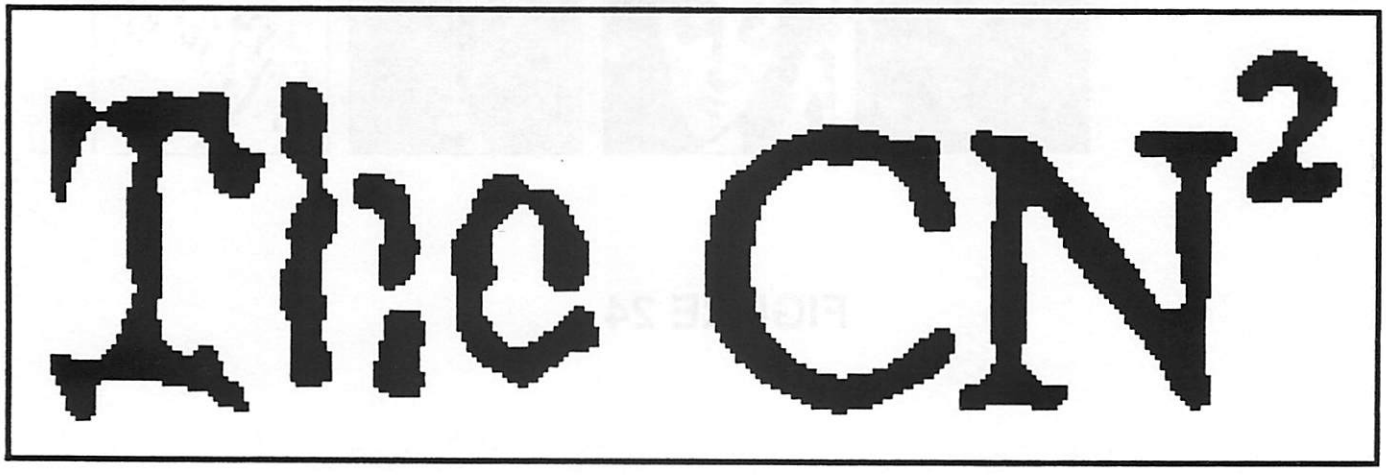


FIGURE 23

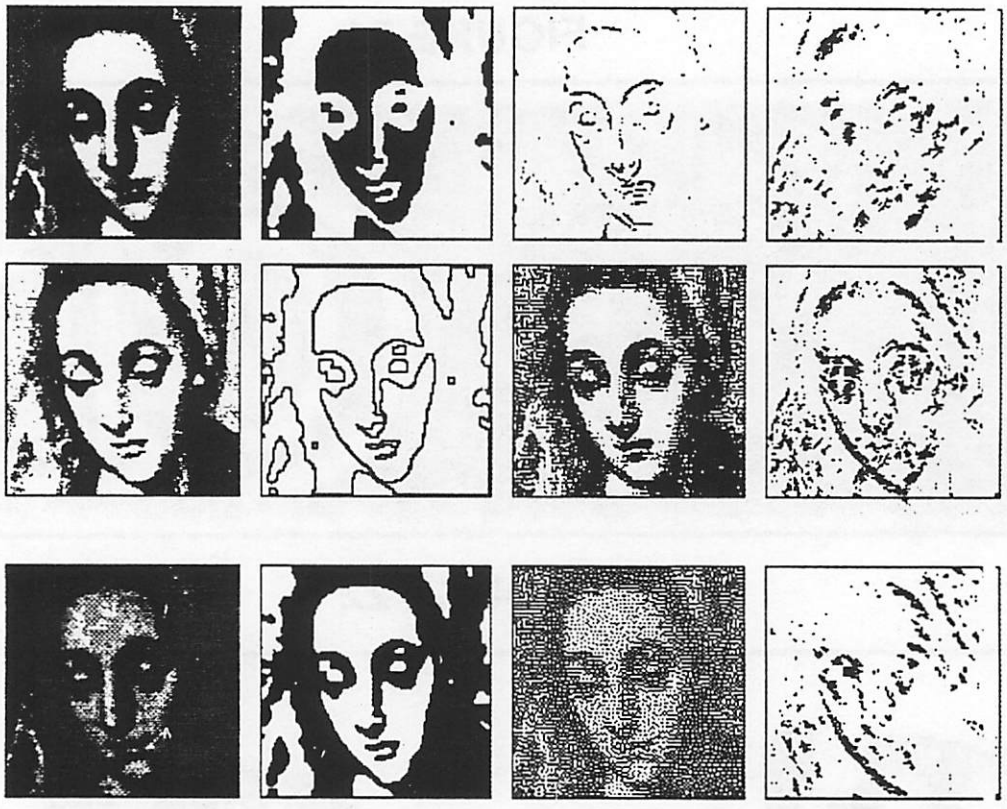


FIGURE 24