Cellular Neural/Nonlinear/Nanoscale Network (CNN) Computing

Angela Slavova
Institute of Mathematics and Informatics, Bulgarian Academy of Sciences, Sofia, Bulgaria
slavova@math.bas.bg

Keywords: Cellular Neural Networks, Cellular Nano Networks, Image Processing, Image Recognition, Image Coding

Abstract: In this paper we present various cellular architectures. Equations describing cellular nonlinear networks are introduced and some approximation properties are provided. Applications of these architectures in nanotechnology is given well.

1. Cellular Neural Network model

We are witnessing a technical development in our fields where the sensing, computing, activating circuits and systems are becoming inherently connected; physically and theoretically, as well. Moreover, as a result of this, our notion about sensory computing, even about computing, is in a continuous transformation. Hence, we have to make a closer look about the fundamentals of computing.
How, now, can we characterize a brain-like system?
We might summarize the key properties as follows:
- Continuous time continuous (analog) valued signal arrays (flows)
- Several 2Dimensional strata of analog "processors" (neurons)
- Typically, mainly local, or sparse global (bus-like) interconnections
- Sensing and processing are integrated
- Vertical interconnections between a few strata of neuron "processors"
- Variable delays
- Spatial-temporal active waves
- Events are patterns in space and/or time

These features are already strongly modifying our view and practice in building complex electronic systems, including sensing, computing, activating and communicating devices and systems. This way of thinking, however, is supposing a completely different architecture, physical and algorithmic alike, and supposes tens of thousands or millions of parallel physical processing devices.
In developing a universal and canonical computing architecture, after having been decided the forms of data, we are tending to use the simplest possible building blocks, with the simplest possible interconnections, elementary instructions and programming constructs. Then we introduce algorithmic stored programmability to make it universal and practical. A most successful example is the digital computer, with a core universal machine on integers (Turing machine). What if we would make a brain-like computer with the properties shown above? The data are topographic (image) flows. In the simplest case, a pixel array with each pixel having a light intensity of gray values between black (say, +1) and white (say, -1) values. Color pictures are composed of several pictures with different color content. A special case is a binary mask. Now, let us construct a programmable topographic cellular sensory dynamics, as implementing the protagonist elementary instruction. The recipe is as follows.
- Take the simplest dynamical system, a cell (with input u, state x and output y)
- Take the simplest spatial grid for placing the cells with the simplest neighborhood relation (2D sheets)
- Introduce the simplest spatial interactions between dynamic cells, being programmable (called cloning template or gene, or simply template)
- Add cellular sensors.

CNN is simply an analogue dynamic processor array, made of cells, which contain linear capacitors, linear resistors, linear and nonlinear controlled sources. Let us consider a two-dimensional grid with 3 X 3 neighborhood system as it is shown on Fig.1.

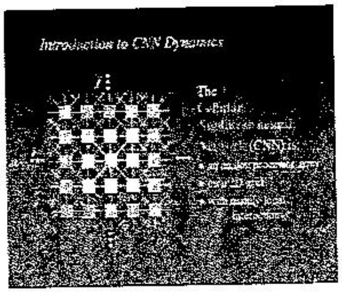

Fig. 1. Basic CNN architecture

The squares are the circuit units - cells, and the links between the cells indicate that there are interactions between linked cells.
Cellular Neural Networks (CNNs) are complex nonlinear dynamical systems, and therefore one can expect interesting phenomena like bifurcations and chaos to occur in such nets. It was shown that as the cell self-feedback coefficients are changed to a critical value, a CNN with opposite-sign template may change from stable to unstable [3]. Namely speaking, this phenomenon arises as the loss of stability and the birth of a limit cycles [3]. Moreover, the appearance of a strange attractor in a periodically driven two-cell CNN have been reported. In a three-cell autonomous CNN this attractor has properties similar to the double scroll attractor [5].

CNN is simply an analogue dynamic processor array, made of cells, which contain linear capacitors, linear resistors, linear and nonlinear controlled sources. It is known that some autonomous CNNs represent an excellent approximation to nonlinear partial differential equations (PDEs). In this paper we will present the receptor-based model by a reaction-diffusion CNNs. The intrinsic space distributed topology makes the CNN able to produce real-time solutions of nonlinear PDEs.
We will give the general definition of a CNN which follows the original one [3]:

Definition 1. The CNN is a
1-, 2-, 3-, or n - dimensional array of
b). mainly identical dynamical systems, called cells, which satisfies two properties:
c). most interactions are local within a finite radius r, and
d). all state variables are continuous valued signals.

Definition 2. An M X M cellular neural network is defined mathematically by four specifications:
1). CNN cell dynamics;
2). CNN synaptic law which represents the interactions (spatial coupling) within the neighbor cells;
3). Boundary conditions;
4). Initial conditions.
Now in terms of definition 2 we can present the dynamical systems describing CNNs. For a general CNN whose cells are made of time-invariant circuit elements, each cell C(ij) is characterized by its CNN cell dynamics :

$$\dot{x}_{ij} = -g(x_{ij}, u_{ij}, I^s_{ij}), \tag{1}$$

where $x_{ij} \in R^m$, u_{ij} is usually a scalar. In most cases, the interactions (spatial coupling) with the neighbor cell C(i+k,j+l) are specified by a CNN synaptic law:

$$I^s_{ij} = A_{ij,kl}x_{i+k,j+l} + \tilde{A}_{ij,kl} * f_{kl}(x_{ij}, x_{i+k,j+l}) + \tilde{B}_{ij,kl} * u_{i+k,j+l} \tag{2}$$

The first term of (2) is simply a linear feedback of the states of the neighborhood nodes. The second term provides an arbitrary nonlinear coupling, and the third term accounts for the contributions from the external inputs of each neighbor cell that is located in the neighborhood.

Complete stability, i.e. convergence of each trajectory towards some stationary state, is a fundamental dynamical property in order to design CNN's for accomplishing important tasks including image processing problems, the implementation of content addressable memories and the solution of combinatorial optimization problems [5]. The most basic result on complete stability is certainly the one requiring that the CNN interconnection matrix be symmetric [3]. Also some special classes of nonsymmetric CNN's such as cooperative (excitory) CNN's, were shown to be completely stable [6]. In the general case, however, competitive (inhibitory) CNN's may exhibit stable nonlinear oscillations [5].
It is known [3,5,6] that some autonomous CNNs represent an excellent approximation to nonlinear partial differential equations (PDEs). In this paper we will present the receptor-based model by a reaction-diffusion CNNs. The intrinsic space distributed topology makes the CNN able to produce real-time solutions of nonlinear PDEs. Consider the following well-known PDE, generally referred to us in the literature as a reaction-diffusion equation [6]:

$\frac{\partial u}{\partial t} = f(u) + D\nabla^2 u$, where $u \in R^n$, $f \in R^n$, D is a matrix with the diffusion coefficients, and $\nabla^2 u$ is the Laplacian operator in R^2. There are several ways to approximate the Laplacian operator in discrete space by a CNN synaptic law with an appropriate A -template [5,6].

2. Various cellular architectures

Cellular automata, introduced also by J. von Neumann, are fully parallel array processors with all discrete space, time and state values. Their beautiful properties are recently rediscovered, showing the deeper qualitative properties. Clearly, if we allow the states and time being continuous values like in CNN, a broader class of dynamics will be generated. Even more, the fundamental condition to generate complex features at the edge of chaos had been established: the need of local activity [3]. If we take one step further, and use the CNN-UM architecture, a new world of algorithms is opening. Interestingly, these cellular wave computers are, in a way, around us in many forms, we will explore a few subsequently. Seemingly, if we increase the complexity of any system, after a while, cellular architectures are becoming prevalent.

3. Towards topographic, including visual, microprocessors

CMOS technology became the mainstream silicon technology for making digital microprocessors. Indeed, there are various ways to implement CNN Universal Machine chips. These are the o Mixed mode, analog and logic technology o Emulated digital technology with different granularity o FPGA based implementations One major opportunity is to integrate the topographic sensors. In particular, visual and tactile sensors are the most natural choices, however, auditory sensor array might equally be important.

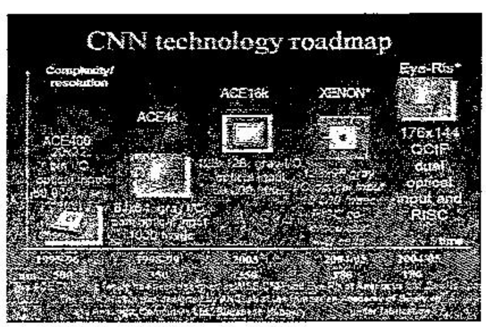

Fig. 2. Development of CNN technology

The emerging tactile sensor arrays are made via MEMS technology [1,2,4], their bio-inspired processing allows the direct use of CNN algorithms for various sensing tasks when each tactile element (called taxel) senses all 3 component of the pressure vector. Clearly, the most advanced area is related to vision and the programmable visual microprocessors are integrating the camera and the computing parts of vision; indeed, they are inseparable in more complex tasks. Unlike in "smart sensors", here, we are talking about stored programmable algorithms and related software to program our visual microprocessors. The developments on the field are illustrated on Figure 2.

4. CNN principles in optics and nanotechnology

The principle that physics is doing the computation leads us to uncover other physical and/or biological effects to implement our topographic sensory computer architecture. A quite natural choice is to turn to optics, keeping in mind that a spatial correlation can be made "instantly", with the speed of light. Taking a so called 4f focal plane system using two lenses and a programmable light valve, containing a plain with programmable light transmissivity in each pixel, a spatial correlation can be achieved. From this simple effect, a stored Programmable Opto-electronic Analogic CNN Computer (POAC) has been successfully constructed recently [4]. The simplified scheme is shown in Figure 3, using two different lasers (red and green) and a bacterio-rhodopsine film as the programmable light valve or Local Analog Memory array. The size of the templates might be as big as 31x31, presently using an acusto-optical deflector (later replaced by a semiconductor laser array). Needless to say, this cellular architecture will be a must in many nano-systems, already emerging. What kind of nano and molecular devices will be useful and practical in these new sensory computers? What would be the easy-to-implement multi-input functional units, the non-transistor-based elementary devices? Or, what are the "nano-friendly" devices and interconnections that are optimally suited to our cellular wave computing paradigm? What are the convenient computing architectures? What if the input flow, is really a continuous flow in time that contains no snapshots (like in the retina)? Instead of forcing the design of devices that we have been accustomed to, e.g. gates or amplifiers, we have to accept some functions that a given nanodevice could offer, defined by its layout. If it is locally active we can make an array of them, and locally interact the devices including also some very sparse global or semi-global lines, may be achieved via radiation or optical interconnection. The Laptop-size implementation is shown in Figure 3.

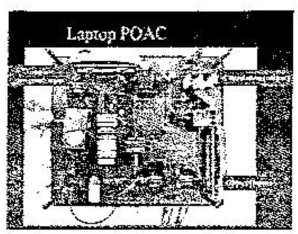

Fig. 3. Laptop size implementation

Acknowledgments.

This paper is supported by the project DID 02/15.

References:

[1] T.Roska and Á.Rodriguez-Vázquez, "Towards Visual Microprocessors", Proc. IEEE, July 2002

[2] T.Roska, "Computational and Computer Complexity of Analogic Cellular Wave Computers", Journal of Circuits, Systems and Computers, vol. 12, pp. 539-562, 2003

[3] L. O. Chua, CNN: A Paradigm for Complexity, World Scientific, Singapore, 1998

[4] D. Bálya, I. Petrás, T. Roska, R. Carmona, and Á.Rodríguez-Vázquez, "Implementing the multilayer retinal model on the complex-cell CNN-UM chip prototype", International Journal of Bifurcation and Chaos vol 14, pp. 427-451, 2004

[5] L.O.Chua and T.Roska, Cellular Neural Networks and Visual Computing, Cambridge University Press, Camridge, UK, 2002

[6] A.Slavova, Cellular Neural Networks:Dynamics and Modelling, Kluwer Academic Publisher, 2003.