Applications of Cellular Neural/Nonlinear Networks in Physics

Theses of the Ph.D. Dissertation

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”The real danger is not that computers will begin to think like men, but that men will begin to think like computers.”

Sydney J. Harris

1 Introduction and aim

Many areas of sciences are facing problems concerning the computing power of the presently available computers. Solving more and more complex problems, simulating large systems, analyzing huge data sets for which even storing represents a problem, are just a few examples which reminds us that computing power needs to keep up with its exponential growth, as expressed by Moore's law [11]. We are aware however that this process can not continue much further solely with the classical digital computer architecture, containing a few processors on a chip, and new computational paradigms are necessary in order to keep up with the increasing demands.

Progress in computation is always driven and deeply influenced by the available technology. After the breakthrough introduced by John Von Neumann's invention of digital stored programmable computers [12], for a long period computation was approached by using discrete variables on one processor, and the instructions were defined via arithmetic and Boolean logic. The revolution of microprocessors made cheap computing power available almost for everyone. It started in the 1970s and led to the profitable PC industry of the 1980s. Since then a continuous increasing speed of the newly appearing processors has been observed. This evolution of speed is strongly connected to the characteristic size of the elements of the processors, which was constantly decreasing. Nowadays, this process is slowing down due to the fact that atomic-size limit is very close and the dissipation of a CMOS chip hits the ~ 100 W limit. Since ~ 2003 this power dissipation limit saturated the clock frequency. Instead, the number of processors is increasing, leading also to a cellular, locally high-speed - globally lower speed architecture [13, 14].

Another reason why the classical digital computers will need to be replaced or at least supplemented, is due to the revolution of sensors of the 1990s, which probably will lead to a new industry. Cheap micro-electro-mechanical systems, different kind of sensors, like artificial eyes, nose, ears etc., are constantly appearing and will be soon available. All these are producing analog signals waiting for processing. Classical digital computing, even with a dozen or 20 cores, does not fit well to this task.

Until recently, when thinking about computing, it was trivial that all data are discrete variables, time is discrete, and the elementary instructions are defined on a few discrete numbers (via arithmetic and Boolean logic units). The geometrical position of the physical processors, if there were more than a single one, at all, had no relevance. Nowadays, the scenario is drastically different. We can place a million 8-bit microprocessors on a single 45 nm CMOS chip, the biggest supercomputer has a quarter million processors (the Blue Gene), and the new cellular visual microprocessor chip (Q-Eye) contains 25k processors, each one hosting 4 optical sensors. Moreover, until recently, physical parameters, like wire delay and power dissipation did not play a role in the algorithmic theory of computing [13]. These systems are much more complex than the classical parallel computers, so the question arises: what will be the prototype architecture of the nano-scale devices and systems, having, maybe, a million processors, and several TeraOPS computing power, and what kind of algorithms could handle these systems?

In the light of the presently emerging quantitative neuroscience, it became possible to understand the signal representation and processing in some parts of our nervous system. Parallel with this a new and revolutionary different way of computing is arising. The several thousands of microprocessors (cells) placed on a single chip locally interacting with each other become similar to a layer of neurons, imitating some basic principles of our nervous system. One suggested prototype architecture for this unconventional computation is the Cellular Wave Computer [15, 13, 14], a special case of it being the Cellular Nonlinear/Neural Network Universal Machine (CNN-UM) [16, 17].

The history of CNN computing starts in 1988, when the theory of cellular neural/nonlinear networks (CNN) was presented [18]. Few years later a detailed plan for a computer using cellular neural networks was developed. This is called CNN Universal Machine (CNN-UM) [16] and is an analogic (analog+logic) computer which has on its main processor several thousands of interconnected computational units (cells), working in parallel. Since then many experimental hardwares were developed and tested [19, 20, 21]. As mentioned, the new chip Q-Eye, included in the self-mantained camera computer, Eye-Ris [22], has 25000 processors, each one hosting 4 optical sensors, it can capture 10000 frames/second, and it consumes only 2500 mW on a 30 mm^2 chip. These chips can be easily connected to digital computers and programmed with special languages. Although the CNN computer is proved to be a universal Turing machine as well [23], its structure and properties make it suitable mainly for some special complex problems, and it is complementing and not replacing digital computers.

Most of the CNN-UM based chips are used and developed for fast image processing applications [24]. The reason for this is that the cells can be used as sensors (visual or tactile) as well. A CNN computer can work thus as a fast and "smart" camera, on which the capturing of the image is followed in real time by analysis [21]. As a computational physicist, I was convinced, that the physicist community can also benefit from CNN based computers. It has been proved in previous studies that this novel computational paradigm is useful in solving partial differential equations [25, 26] and for studying cellular automata models [27, 28]. All these applications result straightforwardly from the appropriate spatial structure of the CNN chips. Moreover, the new nano-scale devices might lead to new CNN like architectures.

During my Ph.D. studies my goal was to develope several new applications related to statistical physics. The first of them was a realistic (true) random number generator which can use the natural noise of the CNN chip for generating binary random numbers [1] (see Chapter 3). This random number generator served as a base for implementing different kind of stochastic simulations on the CNN chip. In this aspect algorithms for the site-percolation problem and the two-dimensional Ising model were developed and implemented on the ACE16K chip [2] [4] (Chapter 4). In a more theoretical part of my research I also studied cellular nonlinear/neural networks with locally variable connections. I have shown that a CNN on which the templates can be separately controlled for each cell could be useful in efficiently solving NP-hard problems. As a specific problem, energy minimization on two-dimensional spin-glasses was considered [3] (Chapter 5). As a last topic I studied a non-standard cellular nonlinear/neural network in which the cells are simple, globally coupled oscillators communicating with light. Although this is a first part of a longer project, interesting collective behavior and weak synchronization phenomena were observed [5] (Chapter 6).

2 Methods

In the course of my work theoretical methods, computer simulations and experiments were harmonically combined.

The theory of Cellular Nonlinear/Neural Networks , including the theorems demonstrated by Chua *et. al.* [18], were used for finding the appropriate algorithms and templates, and demonstrating the analogy between CNN and spin-glass type systems. Statistical physics and well-known stochastic simulation methods were also used.

From a methodical point of view, the development of the realistic random number generator is original because the physical phenomena (thermal noise of the hardware) is successfully combined with a chaotic cellular automaton. The random number generator and also the other stochastic algorithms developed for the CNN based architecture, were first tested using the CNN simulator of the Aladdin software [29]. The programs were written in Analogic Macro Code (AMC). After successful testing with simulations the programs were directed to the Bi-i v2 camera computer [21], which contains a DSP and an ACE16K CNN chip with 128×128 cells. Time measurements were also made on this chip.

When simulating a locally variant CNN, I was obliged to renounce on the CNN simulator of the Aladdin software, in which the templates can not be separately controlled for each cell. I also needed a very fast simulation method, because the NP-hard optimization of spin-glasses was a time-consuming simulation. Finally I wrote the simulation of my locally variant CNN in C, using the 4th order Runge-Kutta method for the simulation of the PDE's. After carefully testing my program with well-known templates, I could use it for simulating the considered NP-hard optimization method. The results obtained with the new method were also compared with results given by the classical simulated annealing. This program was also written in C.

The experimental setup for the non-conventional CNN composed of oscillators communicating with light, was developed by Arthur Tunyagi and Ioan Burda [5]. They built a system very suitable for experiments. Beside an interactive program in which parameters of the system could be changed, measurements could be also made in an easy manner, the states of all oscillators were written out in files in function of time. These data-files could then be easily analyzed with Matlab or C.

3 New scientific results

Thesis ♯1: *Generating non-deterministic sequences of true random binary images on the CNN-UM, using a chaotic cellular automaton perturbed with the natural noise of the CNN-UM chip [1] [4].*

For successfully implementing stochastic simulations the crucial starting point is a good random number generator (RNG). Taking advantage on the fact that the CNN-UM chip is a partially analog device, I used its natural noise for generating "realistic" random numbers, more precisely non-deterministic sequences of random binary images. This assures an important advantage relative to digital computers, especially for Monte Carlo type simulations. The natural noise of the CNN-UM chip is usually highly correlated in space and time, so it can not be used directly to obtain random binary images. My method is based thus on a chaotic cellular automaton perturbed with the natural noise of the chip after each time step. Due to the used chaotic cellular automaton, generated by appropriate CNN templates, the correlations in the noise will not induce correlations in the generated random arrays. Moreover, the real randomness of the noise will kill the deterministic properties of the chaotic cellular automaton [1].

1.1. I developed an algorithm based on a chaotic cellular automaton perturbed with the natural noise of the CNN-UM chip, generating random binary images with equal (1/2) probability of the black and white pixels.

I used one of the pseudo-random number generators already developed on the CNN-UM [28, 30] called the PNP2D. This is a chaotic cellular automaton (CA), relatively simple and fast, which passed all important RNG tests and shows very small correlations, so it is a good candidate for a pseudo-random number generator. It generates binary values, 0 (white) and 1 (black), with the same 1/2 probability independently of the starting condition.

In my algorithm after each time step the result of the chaotic CA is perturbed with a noisy binary image (array) (using exclusive-or operation). The noisy image is simply obtained by using a threshold CNN template on a uniform gray-scale image with value a, at a threshold value of $a + z$. This way in each cell showing a noise level higher than z, the value of the random image will be changed. This perturbation is usually very small, and due to its nature it will not change the good statistics of the CA, as I also proved it by correlation tests (see Chapter 2) [1]. Although the deterministic property of the CA will be lost, two random sequences starting from the same initial condition will become different quickly (Fig. 1).

My experiments were made on the ACE16K chip with 128×128 size in the Bi-i v2 camera computer. Time measurements show that with this size of the chip, the time needed for generating one random binary value is roughly 7 ns. On a Pentium 4, 2.8 GHz machine, generating only pseudo-random values, this time is approximately 33 ns. We can see thus that, beside the advantage offered by the

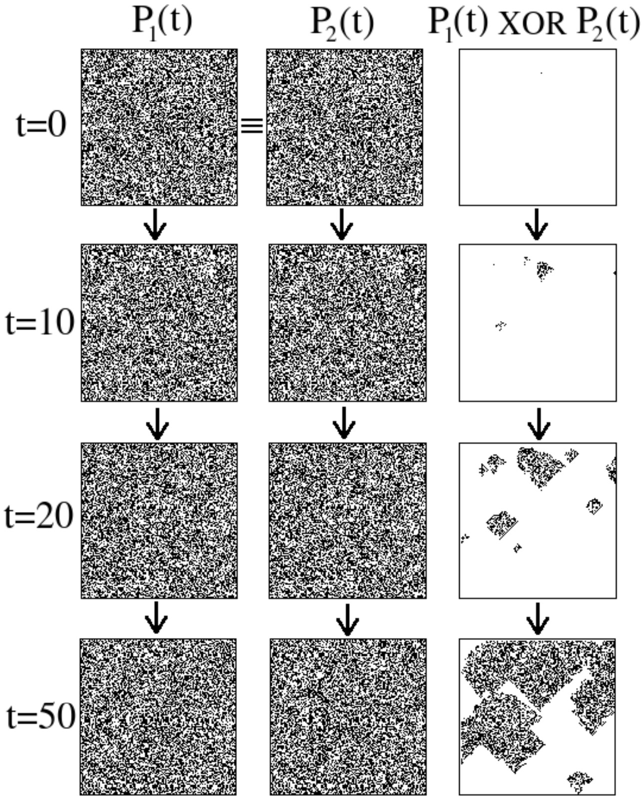

Figure 1: Illustration of the non-deterministic nature of the generator. The figure presents the $P_1(t)$ (first column) and $P_2(t)$ (second column) images in the $t = 0$, 10, 20, 50 iteration steps, resulting from two different implementations with the same initial condition $P_1(0) = P_2(0)$. The third column presents the result of an exclusive-or operation: $P_1(t)$ XOR $P_2(t)$. In case of a deterministic generator the image sequences started from the same initial condition would be identical, so the XOR operation should yield a totally white image. Here we can see how small perturbations appear and propagate over the image.

analog device, parallel processing makes CNN-UM also faster [1].

1.2. I constructed an algorithm which can generate random binary images with any probability, p, of the black pixels using more images with probability $1/2$, generated with the previous algorithm.

When using the RNG for implementing stochastic simulations, it is very important that one should be able to generate images with any probability of the black pixels. I solved this problem by constructing an algorithm which combines n images with $1/2$ probability of the black pixels $P_1, \ldots, P_n$ (generated with the previous algorithm). From these images we then construct n independent images $I_1, \ldots, I_n$ (without overlapping: I_i AND $I_j = \emptyset$ for any $i \neq j$), each of them with $p_i = 1/2^i$ probability of the black pixels. Using this set any image with a probability p, represented on n bits, can be constructed (for details see Chapter 3) [1].

Thesis ♯2: *Developing CNN-UM algorithms for Monte Carlo type simulations of some classical problems of statistical physics and implementing them on the CNN Universal Machine [1, 2].*

Once a properly working RNG is available on the CNN-UM, it is possible to implement Monte Carlo (MC) type simulations for two-dimensional lattice-type models. Generating random initial conditions for cellular automata models is straightforward, and many simple stochastic lattice models can be relatively easily solved. I have chosen two well-known problems of statistical physics: the site-percolation problem [31, 32] and the two dimensional Ising model [33]. Both of them opens a huge class of problems, and in many cases my algorithms can be easily modified for studying more special cases related to these models. For both of the algorithms the previously developed RNG, the parallel structure of the CNN, special CNN templates and the analog-and-logic nature of the implementation plays an important role.

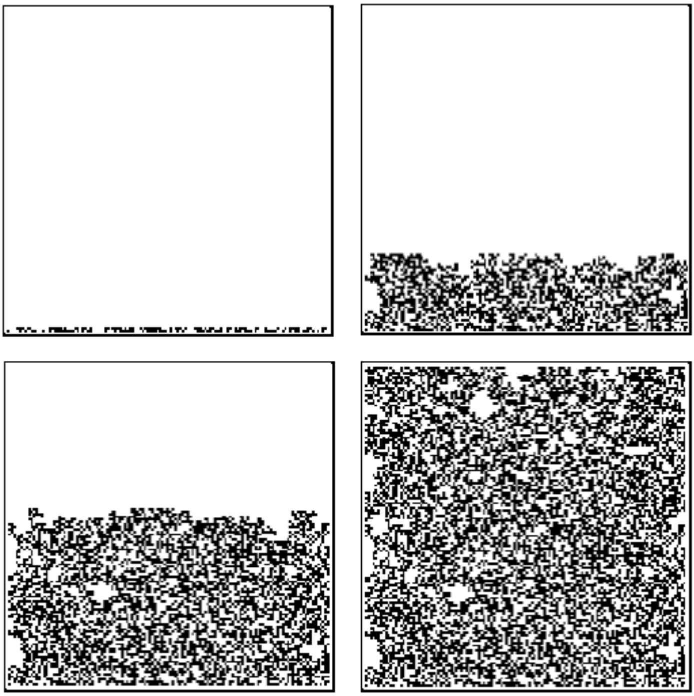

Figure 2: Four snapshots of the dynamics of the template detecting percolation. A flow starts from the first row, and everything connected to this becomes black.

2.1. I showed that it is possible to detect site-percolation on a binary image, using one single CNN template, called "figure recall"; I developed and tested the algorithm on the ACE16K chip included in the Bi-i v2 camera computer [1] [4].

I used the CNN template often called as "figure recall" template (included also in the image processing library of the Bi-i v2 [34]) to efficiently detect site-percolation on a binary random image. The input picture of the template is the actual random binary image, and the initial state will contain only the first row of the image. For percolation, both nearest and next-nearest neighbors (or the N_1 CNN neighbors) are considered. The template values are chosen in a way that pixels which have an input value equal to 1 (are black), and have at least one neighbor with state value 1, will become black. In this manner a flow starts from the first row making black all the pixels which were black on the input picture, and are connected through neighbors to the first row (see Fig. 2). If on the final output will remain black pixels in the last row, then percolation exists.

I tested this simple algorithm on many different binary images, with different probabilities of black pixels. The probability of having percolation in function of the probability of the black pixels, shows a phase-transition at $p = 0.407$ density of black pixels [35]. Results obtained on the ACE16K chip are in good agreement with results given by MC simulation results obtained on a digital Pentium 4, $2.8GHz$ computer, using a recursion-type algorithm for detecting percolation.

2.2. I implemented the two-dimensional Ising model on the ACE16K chip by modifying the Metropolis algorithm to fit the parallel structure of the CNN [2] [6].

There are many Monte Carlo type algorithms used for simulating the Ising model, but most of them are of serial nature. I modified one of the most known algorithms, the Metropolis algorithm [36], to fit the parallel structure of the CNN-UM. In this algorithm first I used

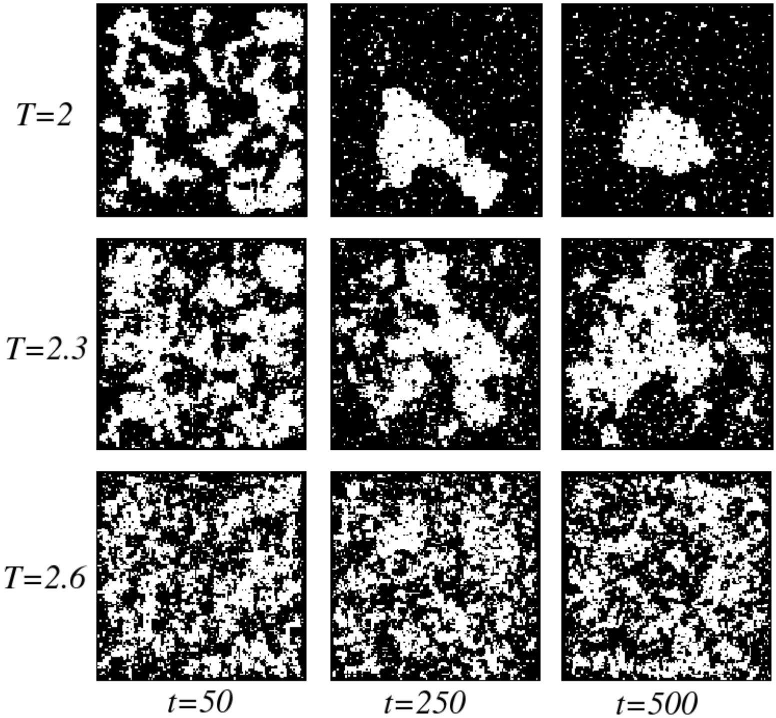

Figure 3: Snapshots of the Ising system simulated on the ACE16k chip, for temperature values $T = 2, 2.3, 2.6$ (the Boltzmann factor is taken $k = 1$), and after $t = 50, 250, 500$ Monte Carlo steps. The critical temperature is around $T = 2.3$. At lower temperatures ferromagnetic ordering can be observed, at higher temperatures paramagnetic disorder characterizes the system.

simple CNN templates like shifting and logic operations, for building the masks marking the spins with different energy. According to the Metropolis algorithm, the spins will be flipped in each Monte Carlo step with different probabilities depending on their energy: $p = exp(-\Delta E/kT)$, if $\Delta E > 0$ and $p = 1$ if $\Delta E \leq 0$. For randomly selecting the spins which will be flipped in each step we use the random number generator, previously presented. The totally parallel updating process causes some unexpected problems: because the flipping probability is always calculated based on the states of the 4 nearest neighbors (defining the energy of the given spin), we have to avoid flipping the nearest neighbors simultaneously. It may cause the appearance of unrealistic patterns (for more explanations see Chapter 4). For avoiding the problems caused by the total parallel update I introduced an additional (chessboard type) mask and allow only those spins to flip which correspond to black (white) pixels if the time-step is odd (even) (for details see Chapter 4). This way nearest neighbors can never be flipped simultaneously, but the parallel nature of the algorithm is still partially preserved: each Monte Carlo step is realized with two consecutive steps. [2, 3].

I implemented the algorithm on the ACE16K chip (lattice size 128×128) in the Bi-i v2 (Fig. 3), and also tested the algorithm simulating it on digital computer in C, and comparing the results of simulations and experiments with the results given by the classical Metropolis algorithm. The results are in good agreement. Time measurements performed on the ACE16k chip are also promising [2, 3].

Thesis ♯3: *NP-hard optimization of frustrated, two-dimensional spin-glass systems, using locally variant CNN templates [3] [7].*

I have shown that using a CNN-UM in which the connections (and respective template parameters) can differ from cell to cell, it is possible to study a huge variety of complex problems. NP-hard optimization would be one of the promising applications of this kind of hardwares [37]. I simulated a locally variant CNN and developed an algorithm for optimization of frustrated spin-glass systems.

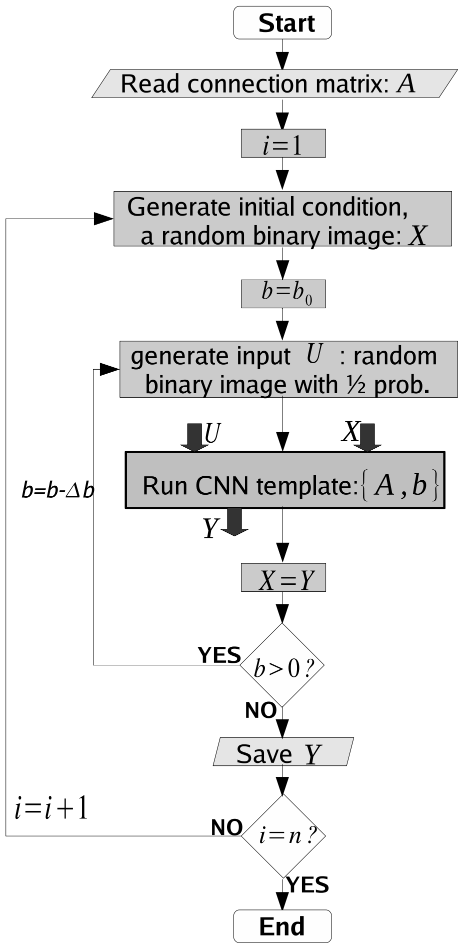

Figure 4: Flowchart of the CNN optimization algorithm used for two-dimensional spin-glass systems with connection matrix A.

3.1. I demonstrated that a CNN with locally variant connections is the analog correspondent of a spin-glass system: all local energy minimas are equivalent.

I used a CNN in which the A parameters are locally defined: $A(i,j;k,l) \in [-1,1]$, where (i,j) and (k,l) mark two neighbor cells. I also considered centrally symmetric connections: $A(i,j;k,l) = A(k,l;i,j)$ and $A(i,j;i,j) = 1$ for all (i,j); the parameters B which control the effect of the input image will be taken simply as: $B(i,j;i,j) = b$ and $B(i,j;k,l) = 0$; $z = 0$. Based on the theorems demonstrated by Chua *et al.* [18], I proved that the Lyapunov function defined for this CNN is equivalent with the energy of a spin-glass system [38, 39] where the connection matrix is described by parameters A. The only difference between the two systems is that in the CNN we have analog values and not discrete ones(± 1) like usually in the spin systems. I also proved that the local energy minimum states of the two systems coincide, so the result of the CNN template will always yield a local energy minimum of the spin-glass system.

3.2. I constructed a CNN algorithm based on principles similar with simulated annealing. This finds the global optimum of frustrated spin-glass systems with a good approximation and promising speed.

Using the properties demonstrated in the previous subthesis, I built a CNN algorithm for finding the optimal state of two-dimensional spin-glass systems. The algorithm is based on principles similar with simulated annealing [40]. Noise is introduced with input images, the role of temperature is taken by parameter b, which is slowly decreased during the algorithm. The details of the algorithm can bee seen on Fig. 4. I tested the algorithm with simulations, measuring the steps needed for an acceptable error rate. Estimations on the speed of the algorithm are very promising (see chapter 5) [3] .

Thesis $\sharp$4: *Weak synchronization phenomena observed in a non-standard CNN built from globally coupled, biologically inspired, electronic oscillators which are communicating with light pulses [5].*

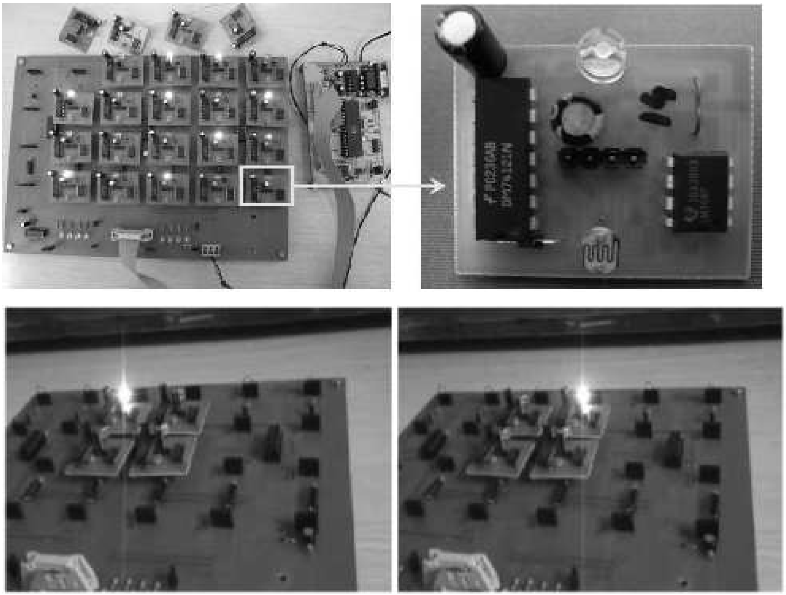

Figure 5: Experimental setup. The oscillators are placed on a circuit board, in form of a square lattice. The system can be placed inside a box with matt glass mirrors, assuring a global coupling.

I studied a simple system composed of biologically inspired, electronic oscillators, capable of emitting and detecting light-pulses (Fig. 5). The constructed units are integrate and fire type oscillators [41] with a modified (inhibitory type) interaction rule: their behavior is designed for keeping a desired light intensity, W, in the system. Each oscillator has a characteristic voltage, U_i, which decreases as the global light intensity grows. There is a global controllable parameter G in the system, identical for all oscillators. If the voltage of an oscillator grows above this threshold ($U_i > G$) the oscillator will fire, this meaning its LED will flash. This flash occurs only if a minimal time period T_{min_i} has elapsed since the last firing. The oscillator has also a maximal period, meaning if no flash occurred in time T_{max_i}, then the oscillator will surely fire. In laymen terms firing is favored by darkness and the value of the controllable G parameter characterizes the "darkness level" at which firing should occur. Through this simple rule the G parameter controls the average light intensity output of the system.

Experimental and computational studies reveal that although no driving force favoring synchronization is considered, for a given interval of W, a weak form of synchronization, phase-locking, appears [5]. The goal of this ongoing project is to develop a programmable system where the oscillators can be separately controlled. Placing these oscillators on a square lattice, the whole system can be described as a non-standard cellular nonlinear network in which the state value of a cell (an oscillator) is the measured light intensity. Studying the behavior of this non-standard CNN could reveal interesting synchronization phenomena, which could be used as basic, programmable functions in such kind of systems.

4 Application of the results

The application possibilities resulting from Thesis 1 come straightforward. Generating random numbers on the CNN-UM is important not only in statistical physics, as proved in Thesis 2. Random sequences and stochastic algorithms are also common in other areas as well (image processing [42, 43], process control, games, numerical calculations etc.). Pseudo-randomness and a repeatable random number series is sometimes helpful. It makes easier the debugging of the codes and can be a necessary condition for implementing specific algorithms. It also carries some limitations. Since it is deterministic and results from a chaotic update rule, for many initial conditions it might have finite repetition periods. The fact that the natural noise of the analog CNN-UM chip can be used to generate non-deterministic sequences is an important advantage relative to digital computers. This can be useful in Monte Carlo type simulations, when solving complicated statistical physics problems with large ensemble averages, as discussed in Thesis 2.

Although the algorithms presented in Thesis 2 were developed for two classical models of statistical physics, we feel that as the CNN-UM is further developed in the future they could be used with success for several similar problems. The methods presented here are important because they give a CNN-compatible algorithm for studying the proposed problems. I have shown that the recursive type algorithm for detecting site-percolation can be replaced by one single CNN template, and Monte Carlo type algorithms (in this case the Metropolis algorithm) can be modified to fit the parallel architecture of the CNN-UM. The two problems discussed here represent a whole class of problems in statistical physics, many of these still intensely studied in the present days. In case the CNN-UM chips are further developed (for example using locally variable templates, like discussed in Thesis 3) these algorithms could be easily modified to implement bond-percolation, directed percolation, diluted Ising models, etc. [44].

The algorithm presented in Thesis 3 could be tested only with simulations. I believe however that it can be used for many important applications. Solving NP-hard problems is a key task when testing novel computing paradigms. These complex problems are associated with life sciences, biometrics, logistics, parametric database search, wireless communications, etc. [37]. The deficiency of solving these problems in a reasonable amount of time is one of the most important shortcomings of digital computers, thus all novel paradigms are tested in this sense. As shown in Thesis 3, CNN computing shows good perspectives for such kind of problems, and this should also motivate the further development of CNN chips in the indicated direction. The specific NP-hard optimization problem studied here has also many applications. Besides its importance in condensed matter physics, spin glass theory has in the time acquired a strongly interdisciplinary character, with applications to neural network theory [45], computer science [37], theoretical biology [46], econophysics

[47] etc. It has also been shown that using spin-glass models as error-correcting codes, their cost-performance is excellent [48], and the systems usually are not even in the spin-glass phase. In this manner finding acceptable results could be very fast even on big lattices considering the parallel architecture of the CNN.

Thesis 4, being the first part of a longer project, is much more theoretical. It contributes in understanding the collective behavior of a system of electronic oscillators. The system is interesting because the considered integrate-and-fire type oscillators are communicating with light, thus global coupling can be achieved. Although the inhibitory type interactions do not necessarily favor synchronization, phase-locking is observed. Our goal is to further develop the system, separately controlling the parameters of all oscillators. By placing the oscillators on a square lattice, the whole system can be described as a non-standard cellular nonlinear network in which the state value of a cell (an oscillator) is the measured light intensity. Studying the behavior of this non-standard CNN could reveal interesting synchronization phenomena, which could be used as basic, programmable functions in this kind of systems. These studies are also important because the accent in information technology is slowly moving from the development of single processors to systems using many interacting units. The evolution of these processing systems is still marked by the lack of proper algorithms.

During my Ph.D. studies I had the possibility to observe how different is the attitude of physicist and engineers, when considering applications of the results. Physicist are mainly driven by their curiosity and desire of understanding, while engineers are always focusing on the application possibilities. One important thing I learned is that both are equally important, a healthy balance and cooperation should be maintained between these groups.

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6 Publications

6.1 The author's journal publications

[1] **M. Ercsey-Ravasz**, T. Roska, and Z. Néda, "Perspectives for monte carlo simulations on the cnn universal machine," *International Journal of Modern Physics C*, vol. 17, no. 6, pp. 909–923, 2006.

[2] **M. Ercsey-Ravasz**, T. Roska, and Z. Néda, "Stochastic simulations on the cellular wave computers," *European Physical Journal B*, vol. 51, pp. 407–412, 2006.

[3] **M. Ercsey-Ravasz**, T. Roska, and Z. Néda, "Statistical physics on cellular neural network computers," *Physica D: Nonlinear Phenomena*, vol. Special Issue: "Novel Computing Paradigms: Quo Vadis", 2008. accepted, http://dx.doi.org/10.1016/j.physd.2008.03.028.

6.2 The author's international conference publications

[4] **M. Ercsey-Ravasz**, T. Roska, and Z. Néda, "Random number generator and monte carlo type simulations on the cnn-um," in *Proceedings of the 10th IEEE International Workshop on Cellular Neural Networks and their applications*, (Istanbul, Turkey), pp. 47–52, Aug. 2006.

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[6] **M. Ercsey-Ravasz**, T. Roska, and Z. Néda, "Statistical physics on cellular neural network computers." *International conference "Unconventional computing: Quo vadis?"*, Santa Fe, New Mexico, U.S.A., Mar. 2007.

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