IEEE SOSE 2012
7th INTERNATIONAL CONFERENCE ON SYSTEM OF SYSTEMS ENGINEERING

Cooperative and Competitive Distributed Circuits and Systems: from Art to Time

Luigi Fortuna & Mattia Frasca

Dipartimento di Ingegneria Elettrica Elettronica e Informatica
Università degli Studi di Catania, Catania, Italy
E-mail: lfortuna@diees.unict.it

Cooperative and Competitive Circuits:

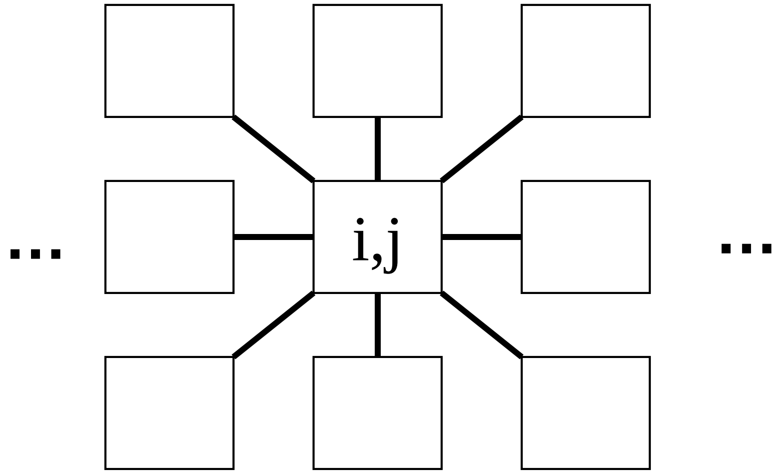
The CNN Paradigm

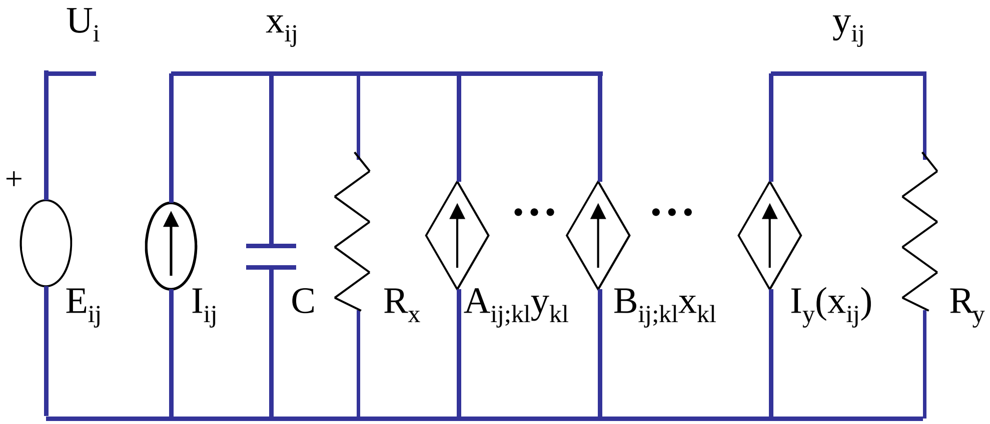
Cellular Nonlinear/Neural Network (CNN)

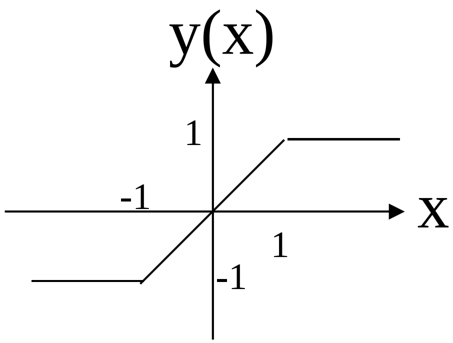
- CNNs were introduced by L. O. Chua in 1988

- The idea is to use an array of simple, identical, locally connected nonlinear *cells* to build large scale analog signal processing systems

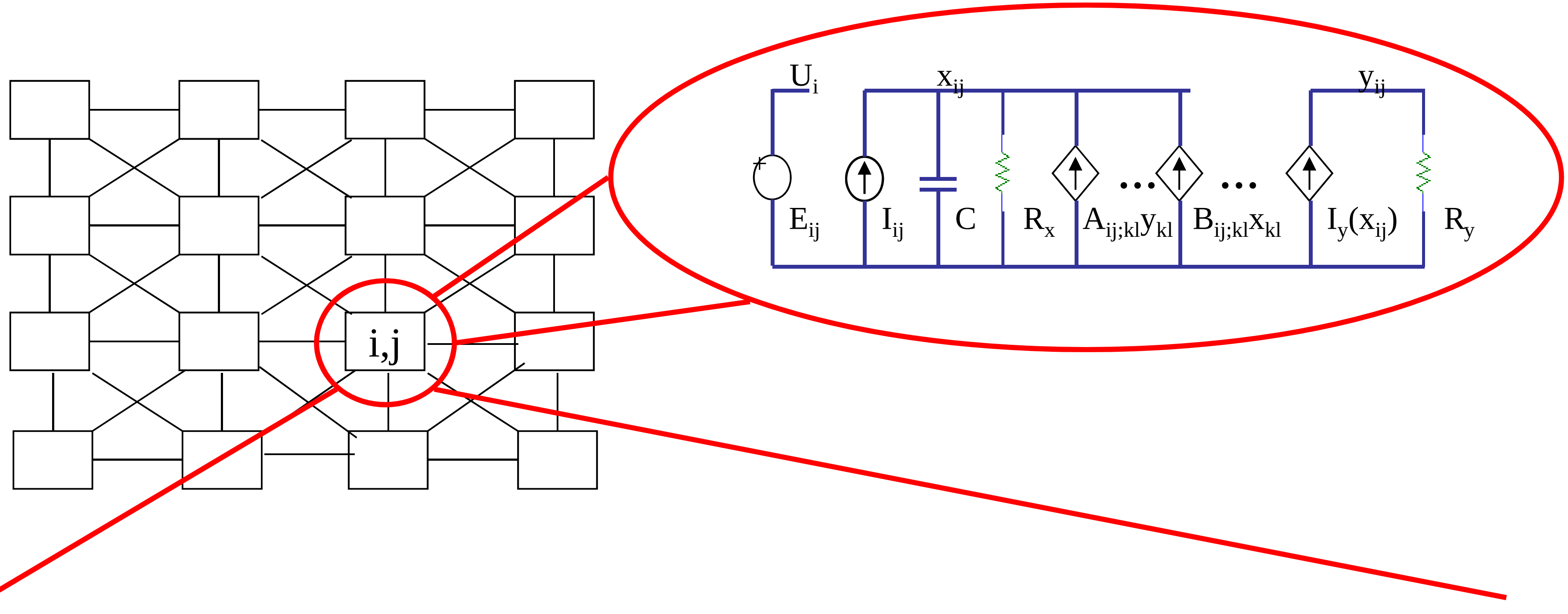
Cellular Neural/Nonlinear Network: simple first order circuits locally coupled







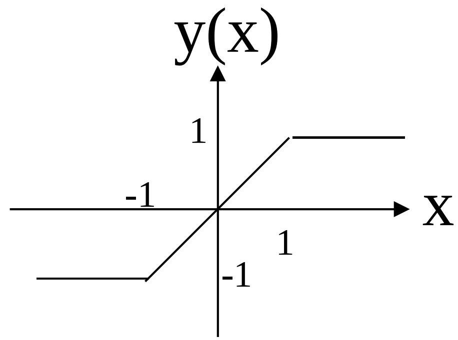
Cellular Neural Networks: equations



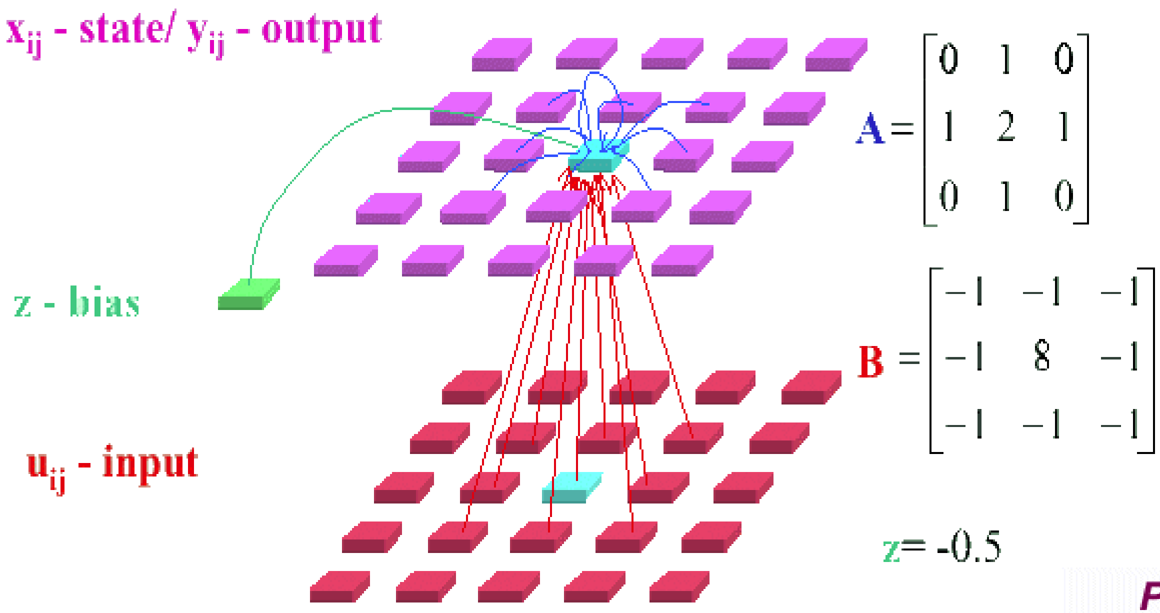
state equations of a cell C(i,j) :

$$C \cdot \frac{dx_{ij}}{dt} = -\frac{x_{ij}}{R_x} + \sum_{C(k,l)\in N_r(i,j)} \left\{A_{ij;kl}\cdot y_{kl} + B_{ij;kl}\cdot u_{kl}\right\} + I_{ij}$$

$$N_r(i,j) = \left\{C(k,l) : \max(|k-i|,|l-j|) \le r\right\} \qquad i = 1..N,\ j = 1..M$$



The paradigm of CNN

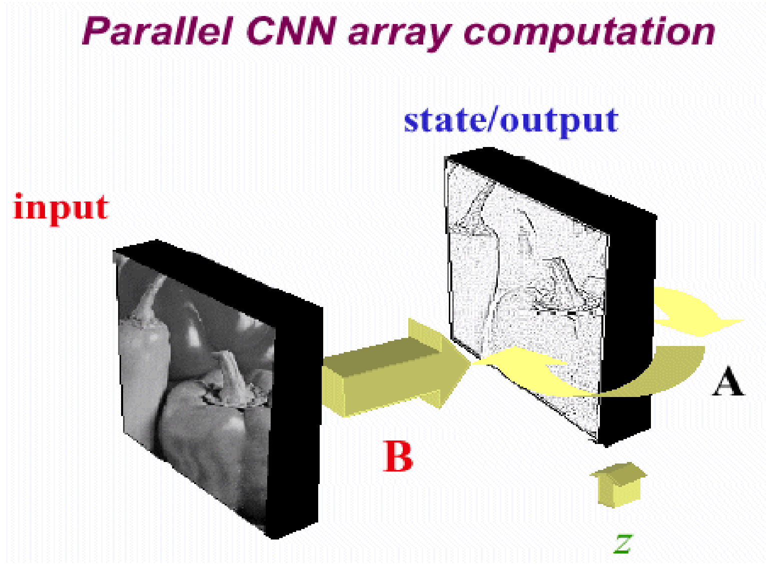


A CNN can be programmed by choosing the local connections, i.e. the *templates*:

A - feedback template

B - control template

I or z - bias



CNN generalizations

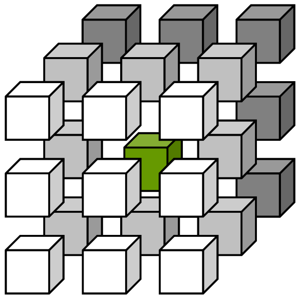
- Dependence on state variables of neighborhood cells
- Different grids
- Nonlinear interactions
- ...

Definition (by Chua)

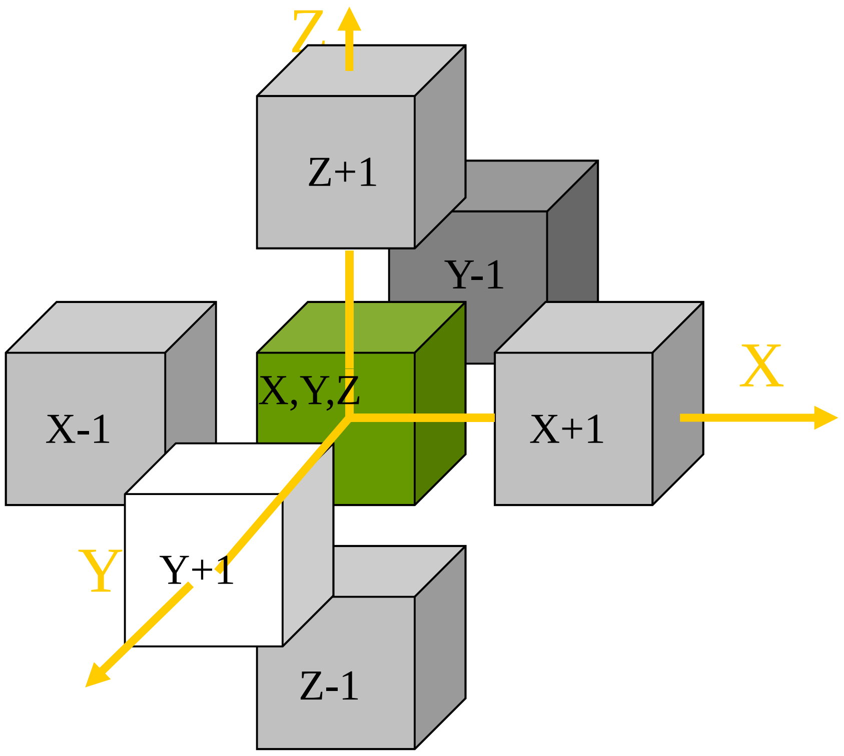
A CNN is an n-dimensional array of mainly identical dynamic systems, celled cells, which satisfies two properties: (a) most interactions are local within a finite radius r, and (b) all state variables are continuous valued signals

Generalizing the CNN paradigm: three dimensional CNN

A 3 x 3 x 3 CNN

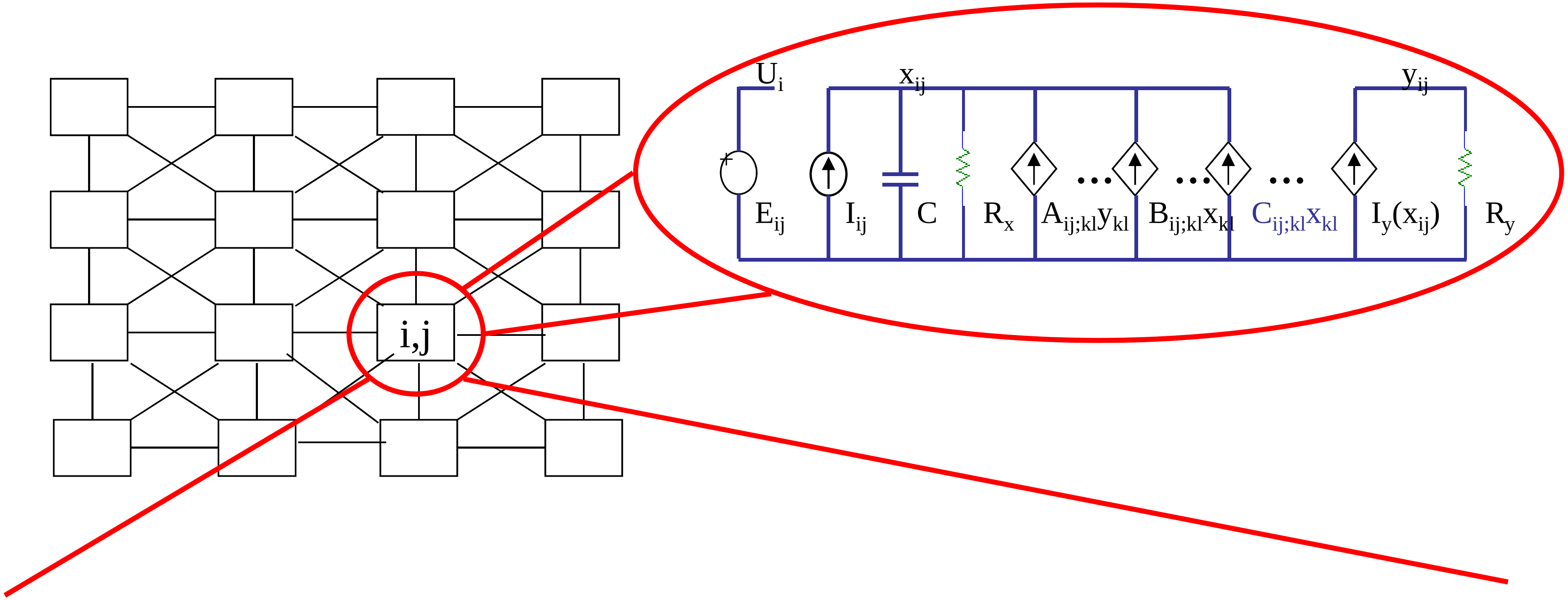


Spatial Interaction



n dimensional equation

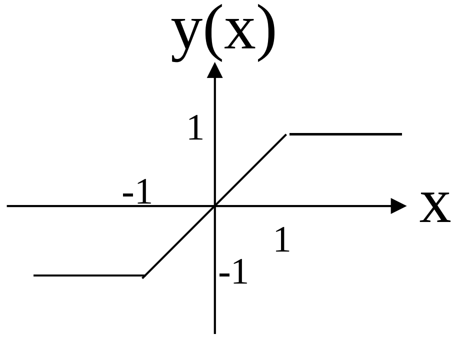
State Controlled Cellular Neural Networks



state equations of a cell C(i,j) :

$$C \cdot \frac{dx_{ij}}{dt} = -\frac{x_{ij}}{R_x} + \sum_{C(k,l)\in N_r(i,j)} \left\{ A_{ij;kl} \cdot y_{kl} + B_{ij;kl} \cdot u_{kl} + C_{ij;kl} \cdot x_{kl} \right\} + I_{ij}$$

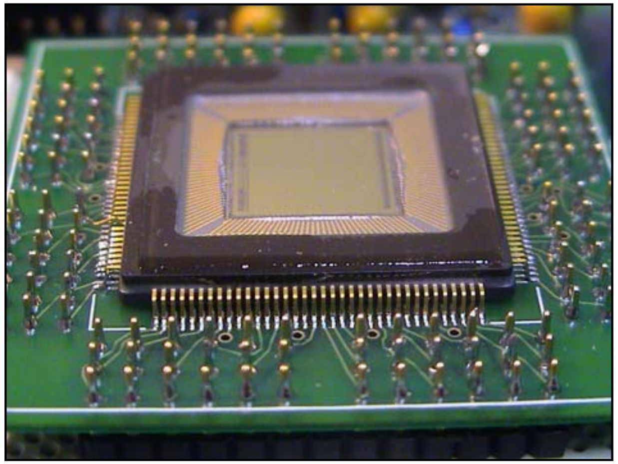
$$N_r(i,j) = \left\{ C(k,l) : \max(|k-i|, |l-j|) \le r \right\} \qquad i = 1..N,\ j = 1..M$$



CNN-based hardware systems

[Video]

ACE 16k Chip



ACE16k PROFESSIONAL BOARD	
Operation	**Frame Rate and Timing**
Grayscale image downloading	2688 frame/sec; 372 μs
Grayscale image readback	3536 frame/sec; 283 μs
Array operation	9 μs + N*100ns
Logical Operation	3.8 μs

ACE16k is a Focal Plane Analog Programmable Array Processor

- 128x128 analog processing units digitally programmable
- 8 SRAM blocks
- optical-acquisition capability
- 8 analog memories
- 2 digital memories

CNN – Applications

- Image processing
- Control of bio-inspired robots
- Spiral waves, complex systems, ...

CNN and Complexity

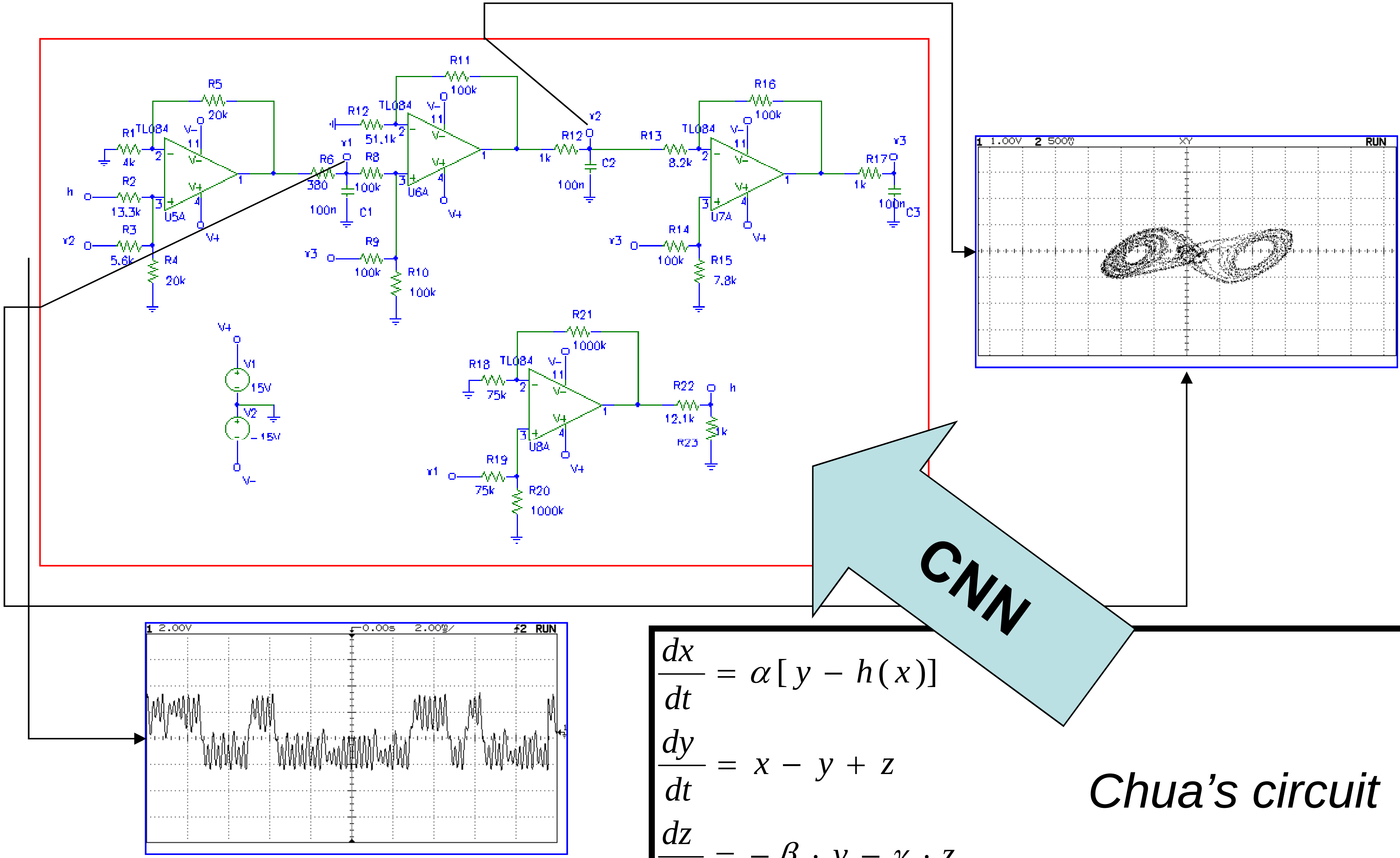
- Implementation of chaotic dynamics (ex. Chua’s circuit)

- Nonlinear phenomena in 2D arrays:

1. Autowaves
2. Turing patterns

- Spatio-temporal dynamics of arrays of nonlinear systems

CNN and the Chua's circuit



$$\frac{dx}{dt} = \alpha[y - h(x)]$$

$$\frac{dy}{dt} = x - y + z$$

$$\frac{dz}{dt} = -\beta \cdot y - \gamma \cdot z$$

$$h(x) = m_1 \cdot x + 0.5 \cdot (m_0 - m_1) \cdot [|x+1| - |x-1|]$$

Chua's circuit

P. Arena, S. Baglio, Fortuna L, G. Manganaro, "Chua's circuit can be generated by CNN cells", IEEE TCAS I, 1995.

Two-layer CNN equations

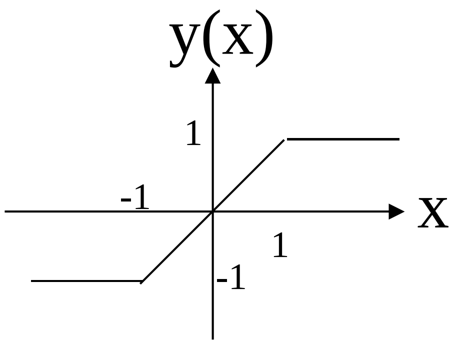
- MxN Two-layer CNN cell equations

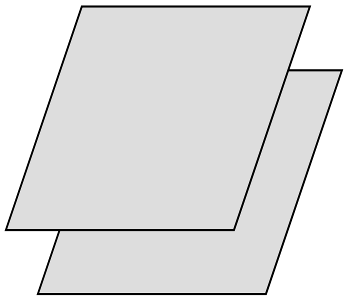
$$C \cdot \frac{dx_{1,ij}}{dt} = -\frac{x_{1,ij}}{R_x} + \sum_{C(k,l)\in N_r(i,j)} \left\{ A_{11}^{ij;kl} \cdot y_{1,kl} + A_{12}^{ij;kl} \cdot y_{2,kl} + B_{ij;kl} \cdot u_{1,kl} \right\} + I_{1,ij} \qquad 1 \le j \le N$$

$$C \cdot \frac{dx_{2,ij}}{dt} = -\frac{x_{2,ij}}{R_x} + \sum_{C(k,l)\in N_r(i,j)} \left\{ A_{21}^{ij;kl} \cdot y_{1,kl} + A_{22}^{ij;kl} \cdot y_{2,kl} + B_{ij;kl} \cdot u_{2,kl} \right\} + I_{2,ij} \qquad 1 \le i \le M$$

- Neighbourhood $N_r(i,j) = \left\{ C(k,l) \,\middle|\, \max(|k-i|,|l-j|) \le r \right\}$

- PWL Output





Two-layer CNN equations

- Equations & Parameters

$$\frac{dx_1}{dt} = -x_1 + (1+\mu)\cdot y_1 - s\cdot y_2 + i_1$$

$$\frac{dx_2}{dt} = -x_2 + (1+\mu)\cdot y_2 + s\cdot y_1 + i_2$$

$$y_i = 0.5\cdot\left[\left|x_i+1\right| - \left|x_i-1\right|\right]$$

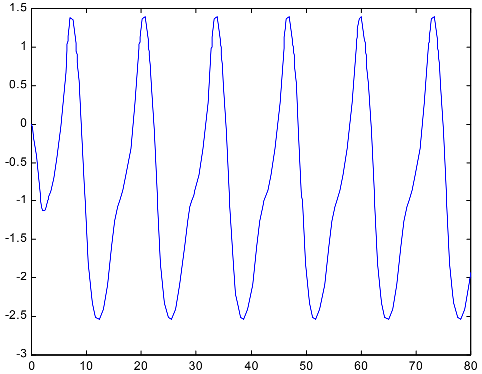
$$\mu = 0.5;$$

$$s = 1;$$

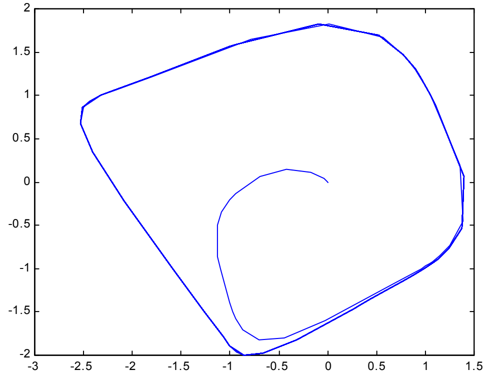
$$i_1 = -0.3; i_2 = 0.3$$

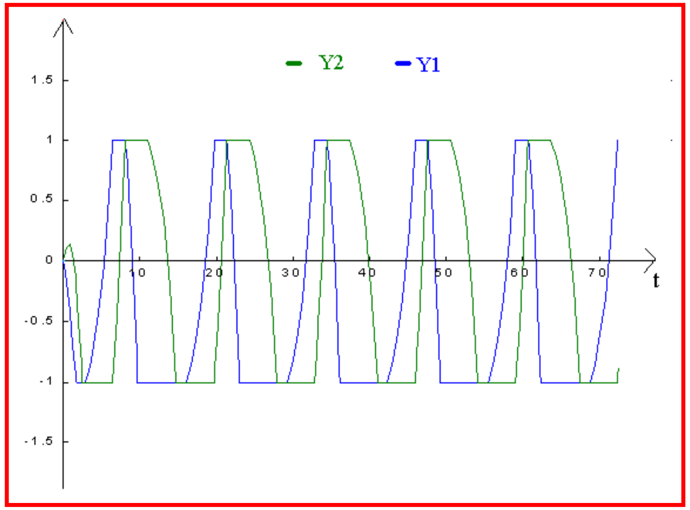
- Behaviour

x_1



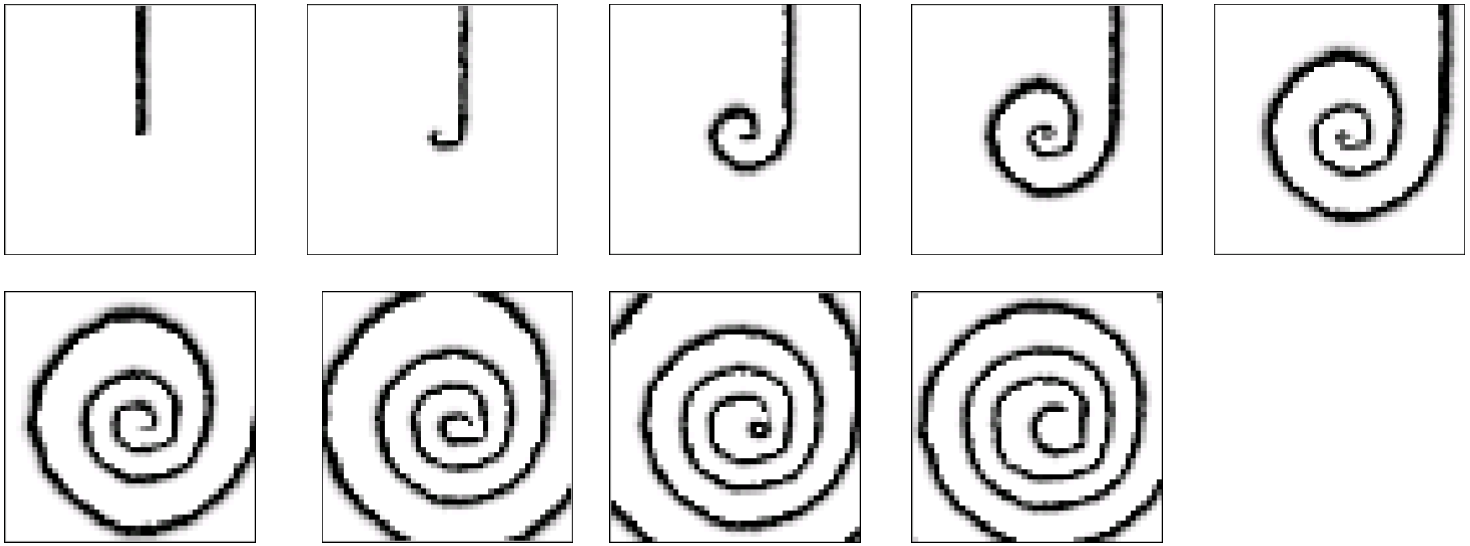
$x_1 - x_2$





Autowave propagation

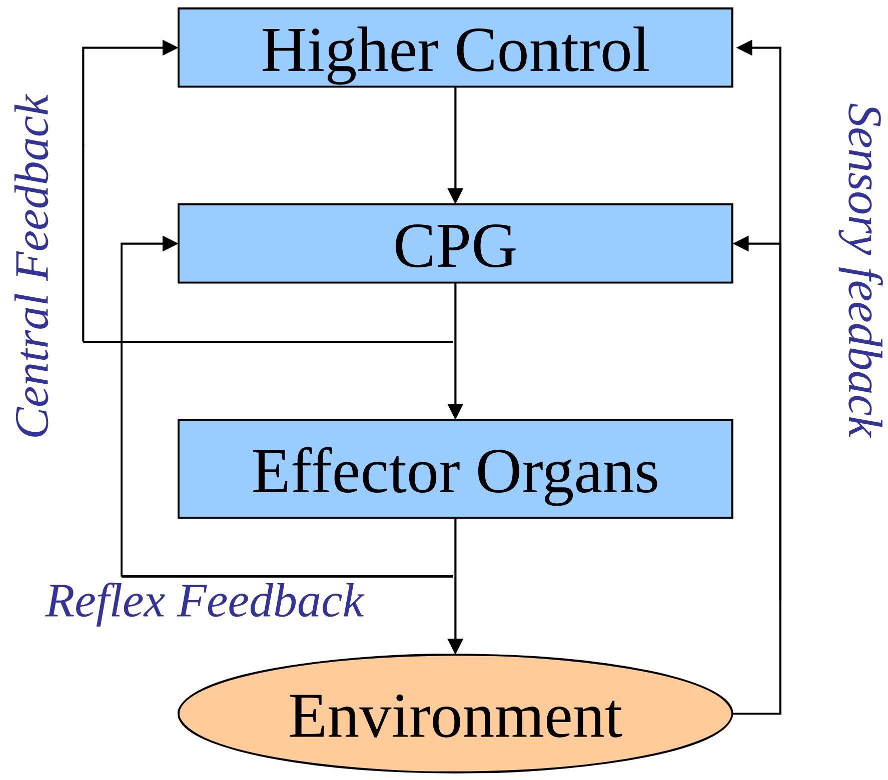
- Two-layer CNN as a reaction-diffusion medium
- Each cell is a second-order nonlinear oscillator (reaction)
- Each cell is connected to the neighbor cells (diffusion)



Video RCN15%

Video 3D

CNN for bio-inspired control of locomotion

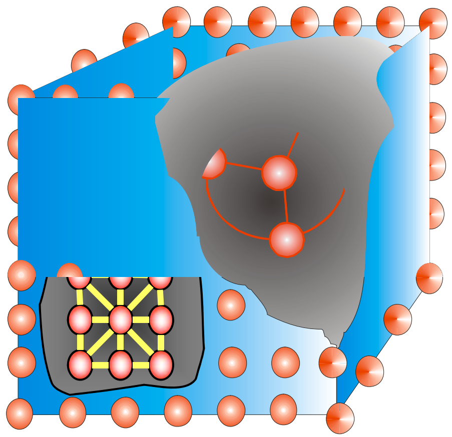


The motor system

- Definition: A neural circuit that can produce a rhythmic motor pattern with no need for sensory feedback or descending control

ARENA P, FORTUNA L, FRASCA M, PATANE' L, “A CNN-Based Chip for Robot Locomotion Control”, *IEEE TCAS I*, 2005.

3D CNN

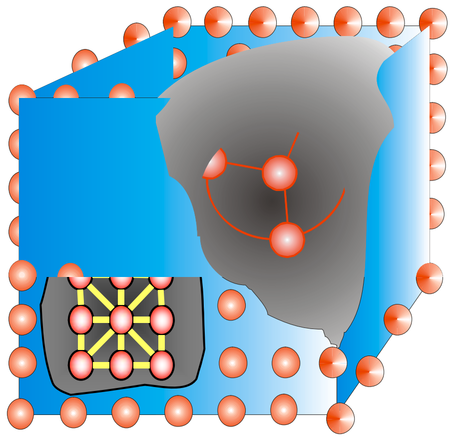


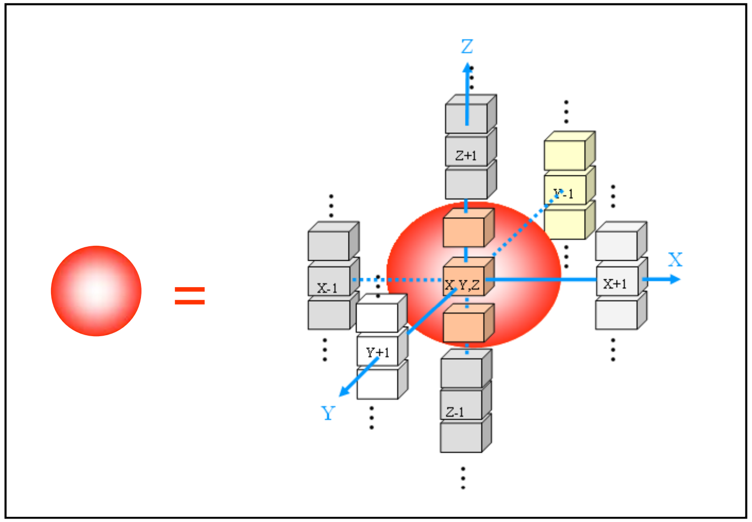
This paradigm translates the concept:

MERGING → E-MERGING

according to the sentence reported in F. Orsucci, *CHANGING MIND, Transitions in Natural and Artificial Environments*, World Scientific, 2002.

Generalized Architecture of a Node

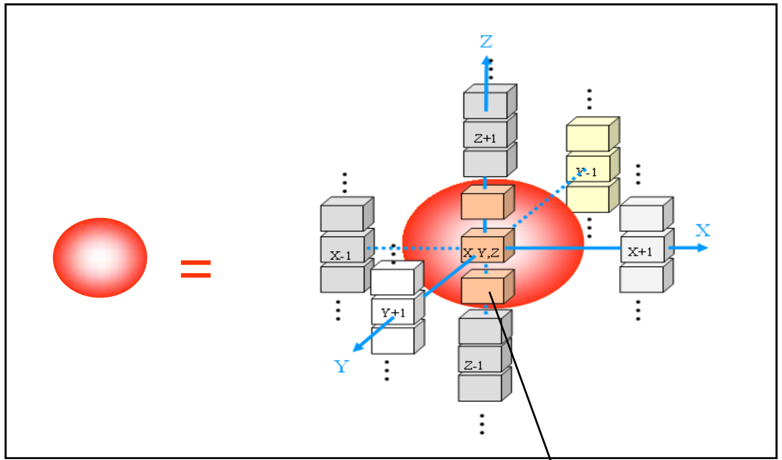




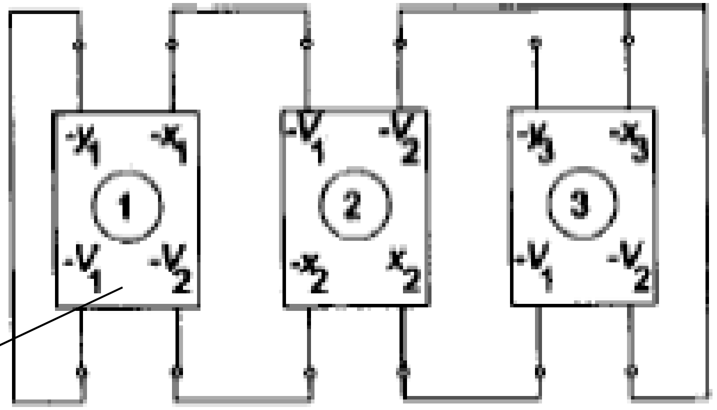
L. Fortuna, A. Rizzo, M. G. Xibilia, “Modeling Complex Dynamics via Extended PWL-based CNNs”, *Int. J. Bifurcations and Chaos*, 2003

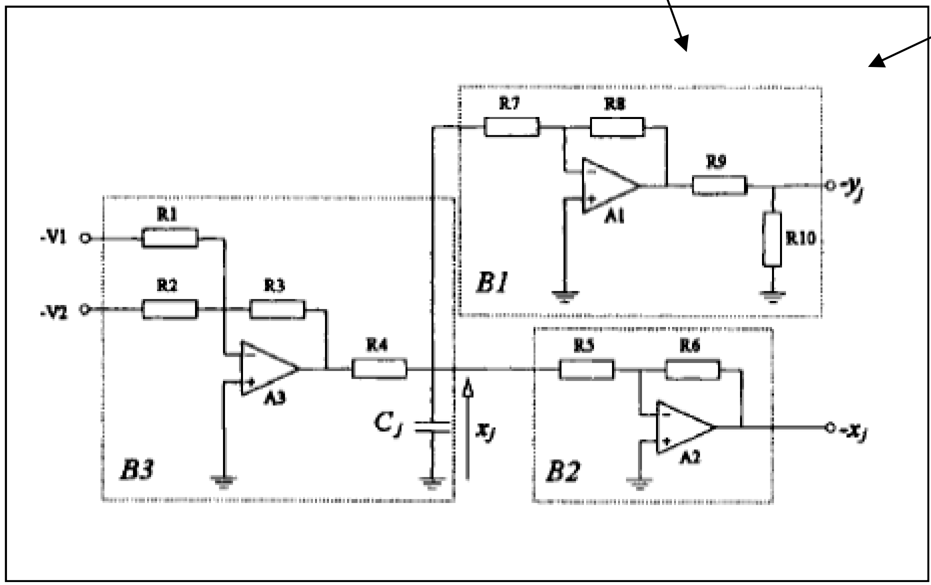
MODELING COMPLEX DYNAMICS VIA EXTENDED PWL-BASED CNNS

Generalized Architecture of a Node - Example

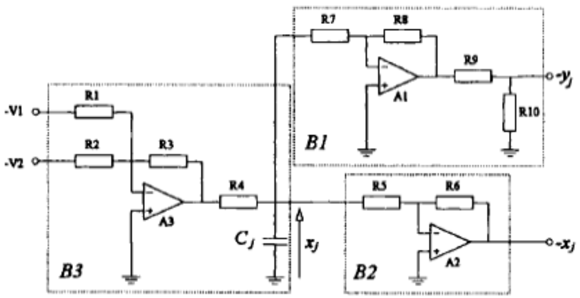


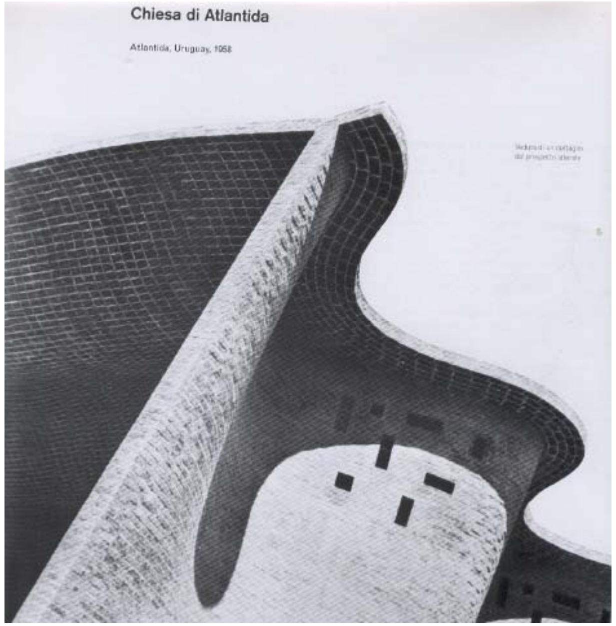
Chua's circuit

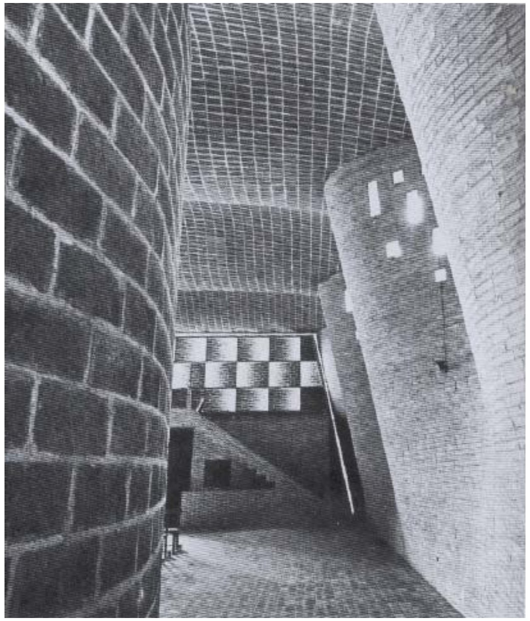


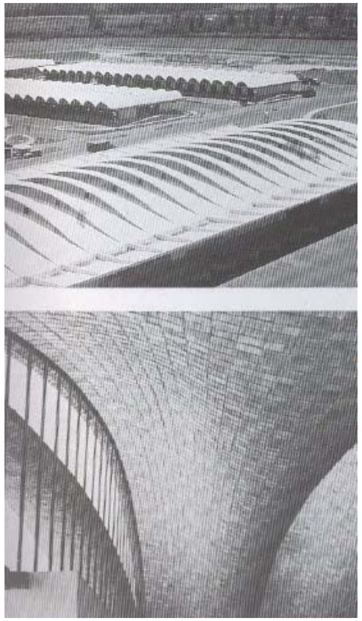


Eladio Dieste’s complex architectonic structures

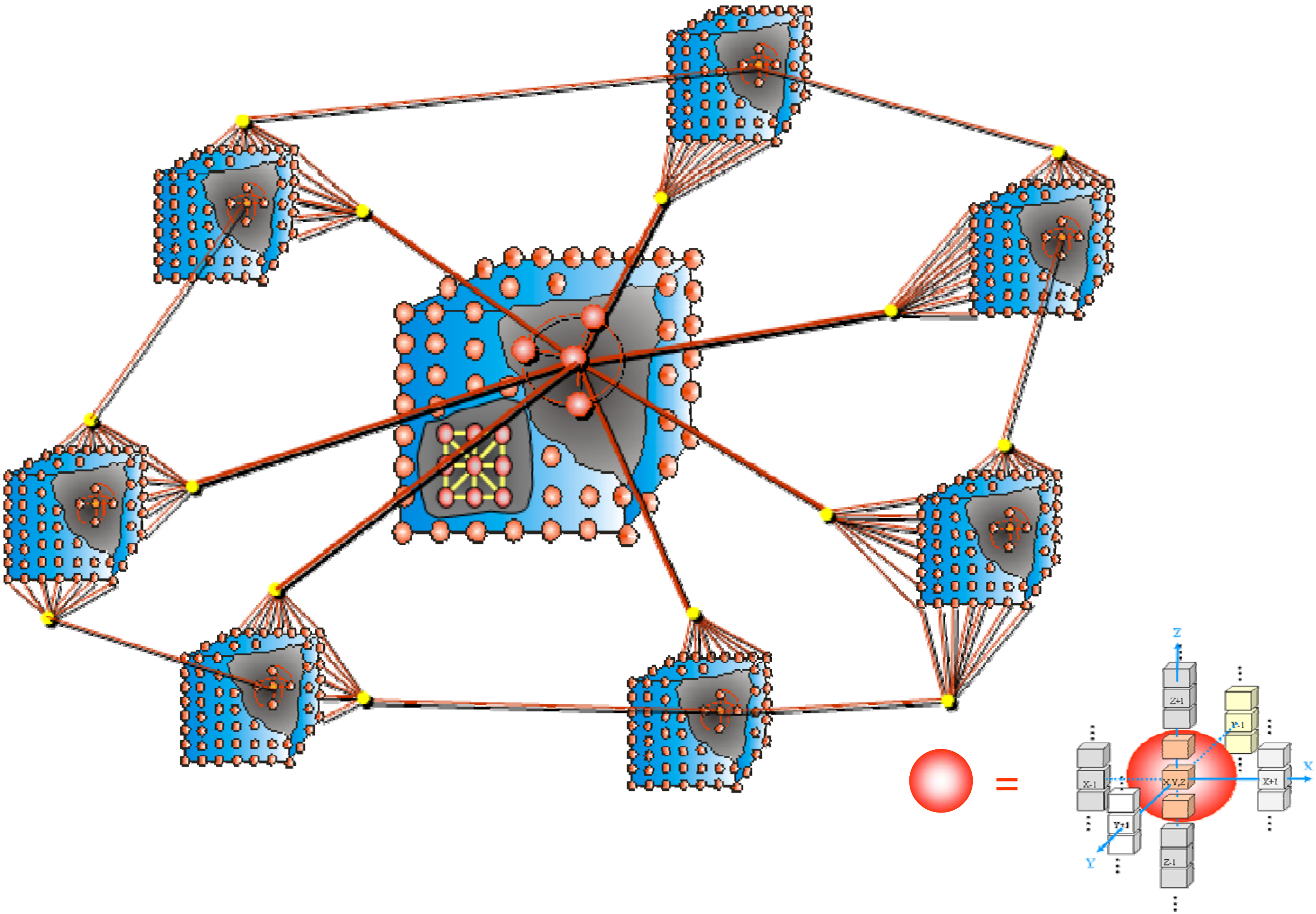






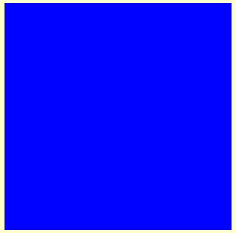
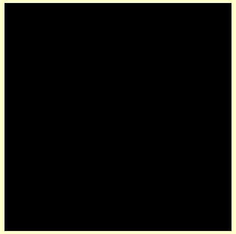
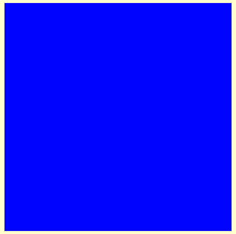


E^3

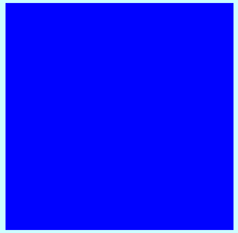
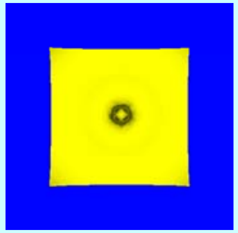
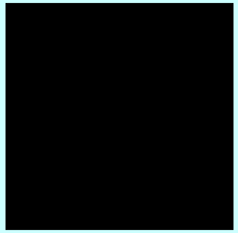


E^3 Simulation results

Chaotic systems

Rossler	$\begin{cases}\dot{x} = -y - z + D\nabla^2 x \\ \dot{y} = x + ay \\ \dot{z} = b + xz - cz\end{cases}$	
Lorenz	$\begin{cases}\dot{x} = \sigma(y - x) + D\nabla^2 x \\ \dot{y} = rx - y - xz \\ \dot{z} = xy - bz\end{cases}$	
Chua	$\begin{cases}\frac{\partial x_1}{\partial t} = \alpha(x_2 - f(x_1)) + D\nabla^2 x_1 \\ \frac{\partial x_2}{\partial t} = x_1 - x_2 + x_3 \\ \frac{\partial x_3}{\partial t} = -\beta x_2\end{cases}$	

Neuron models

FitzHugh -Nagumo	$\dot{u} = \frac{1}{\varepsilon}u(1-u)(u - \frac{v+b}{a}) + D\nabla^2 u$ $\dot{v} = u - v$	
Inferior Olive	$\begin{cases}\frac{dx}{dt} = \frac{x(x-\gamma)(1-x) - y + I}{\varepsilon} + D\nabla^2 x \\ \frac{dy}{dt} = -\Omega z + r(A - z^2 - r^2) \\ \frac{dz}{dt} = \Omega z + z(A - z^2 - r^2)\end{cases}$ $r = \left(\frac{y}{M} - x\right)$	
HR neuron	$\dot{x} = y - ax^3 + bx^2 + D\nabla^2 x$ $\dot{y} = c - dx^2 - y$ $\dot{z} = r(s(x - x_c) - z)$	

ARENA P, BUCOLO M, FAZZINO S, FORTUNA L, FRASCA M , “The CNN Paradigm: Shapes and Complexity”, *INTERNATIONAL JOURNAL OF BIFURCATION AND CHAOS IN APPLIED SCIENCES AND ENGINEERING*, 2005

Shapes, Forms and Structures

- During its evolution each of these 3D dynamic complex systems creates shapes, forms and structures which change in time

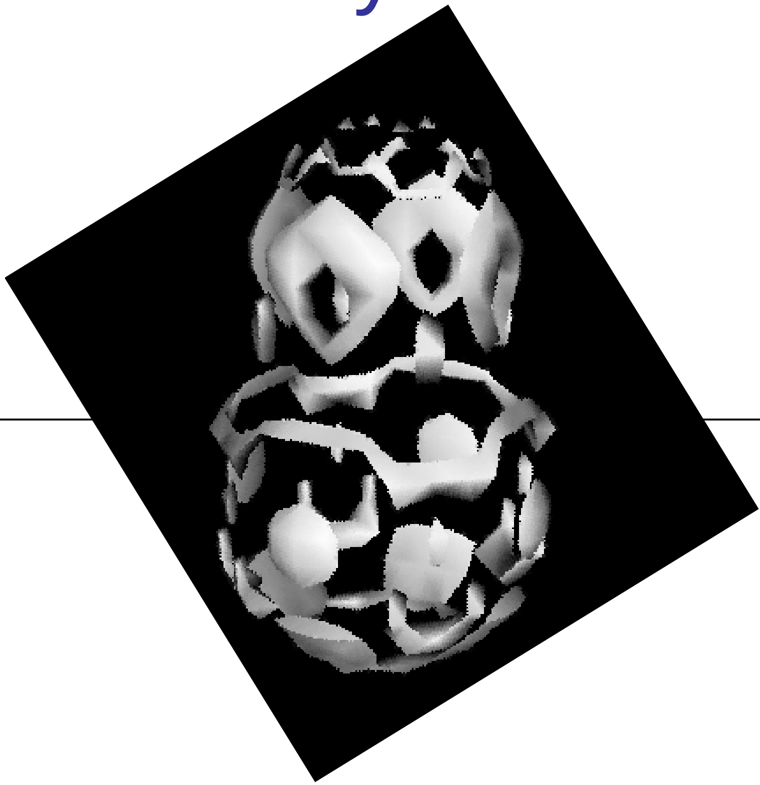
- Are these forms related to some human process?

CNN and Art

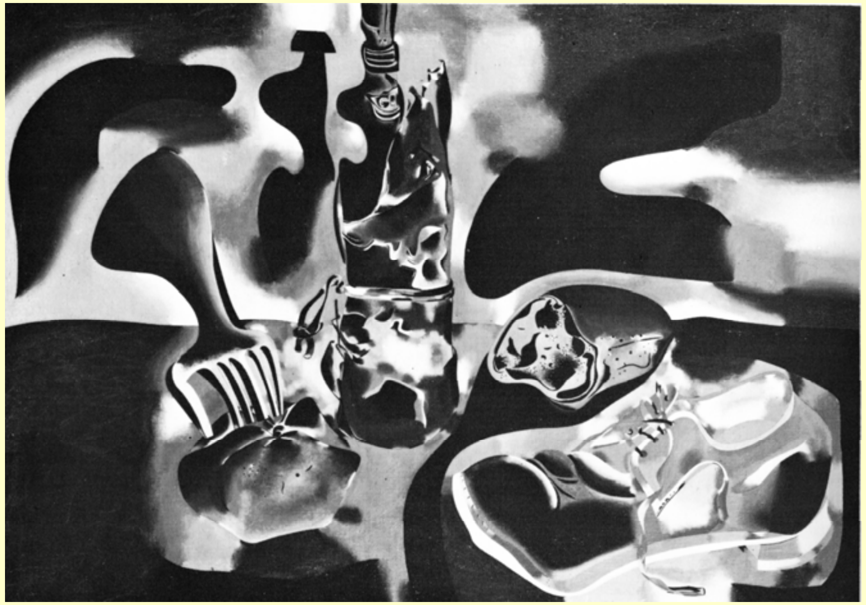
- 3D RD-CNN

$$\frac{\partial u}{\partial t} = F(u) + D \cdot \nabla^2 u$$

- Each cell is a Lorenz system



Paint of Mirò

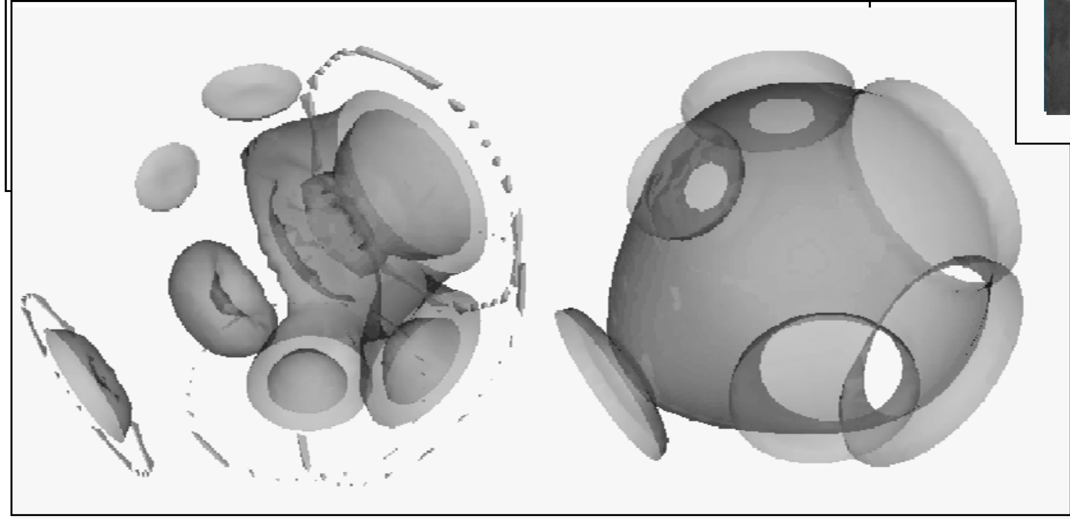


CNN and Art

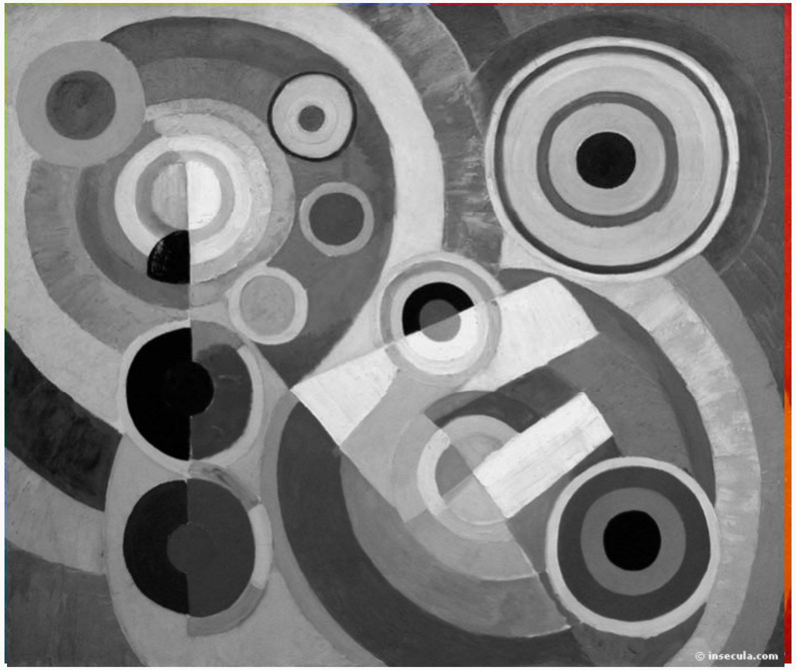
- 3D RD-CNN

$$\frac{\partial u}{\partial t} = F(u) + D \cdot \nabla^2 u$$

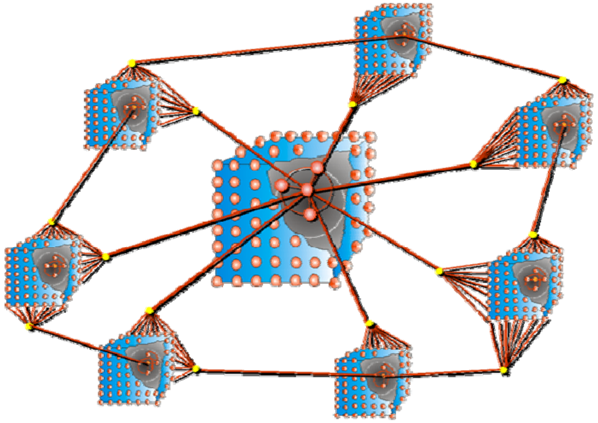
- Each cell is a Hindmarsh-Rose neuron

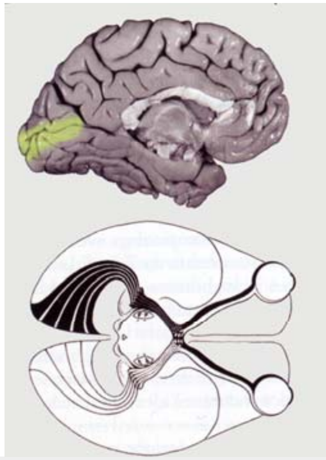


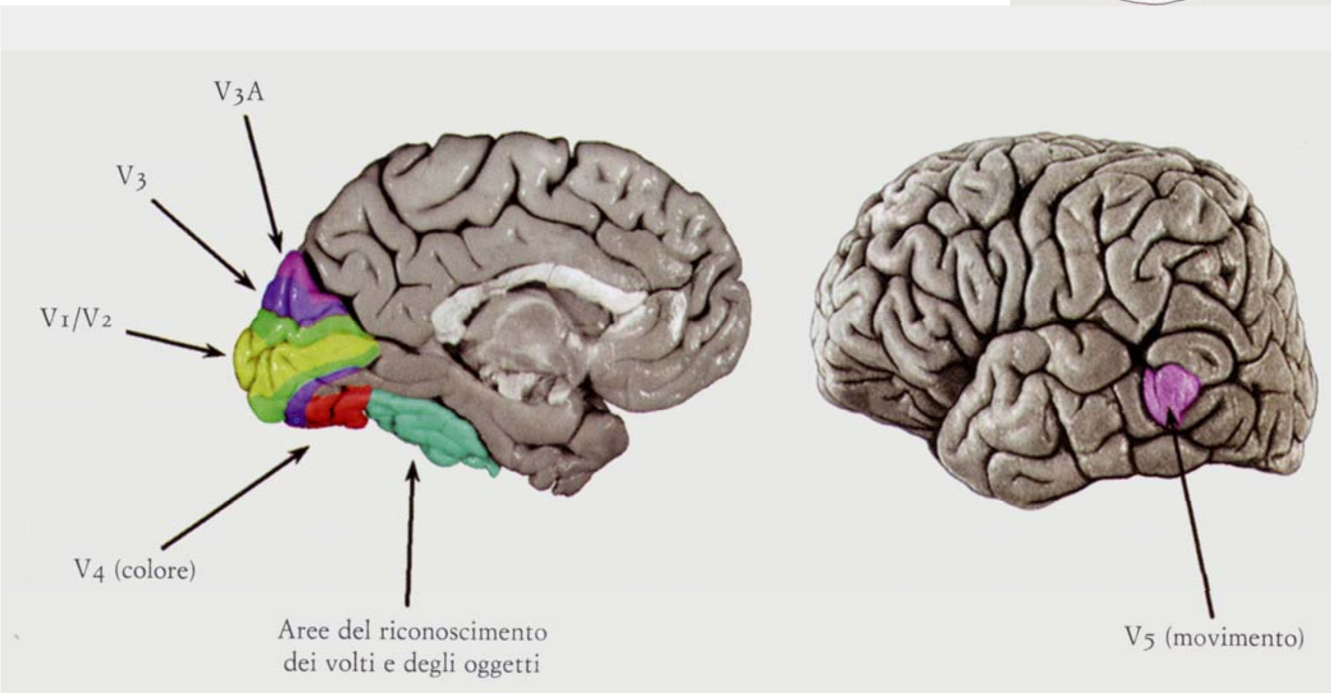
Delaunay, “Joie de vivre”



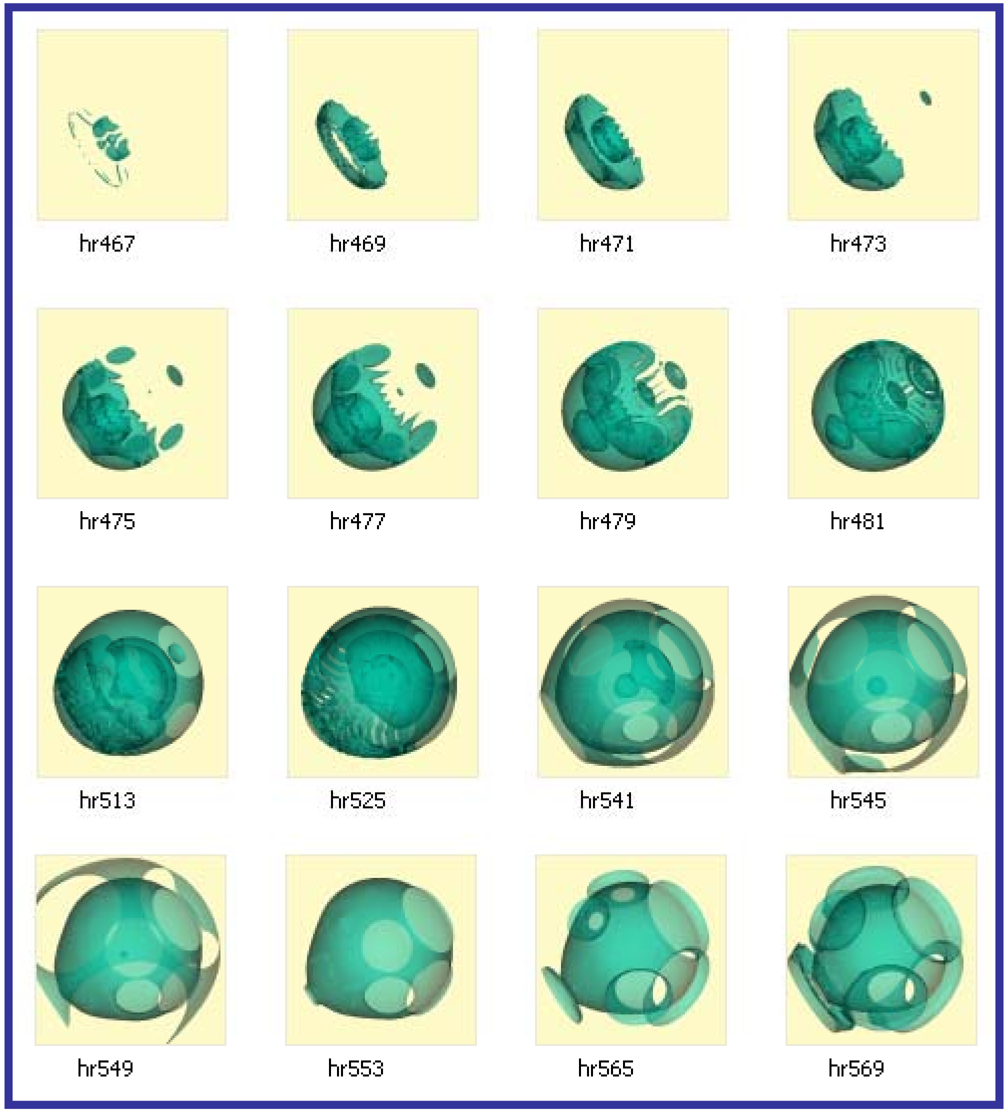
The Visual Cortex







CNN and Hallucination

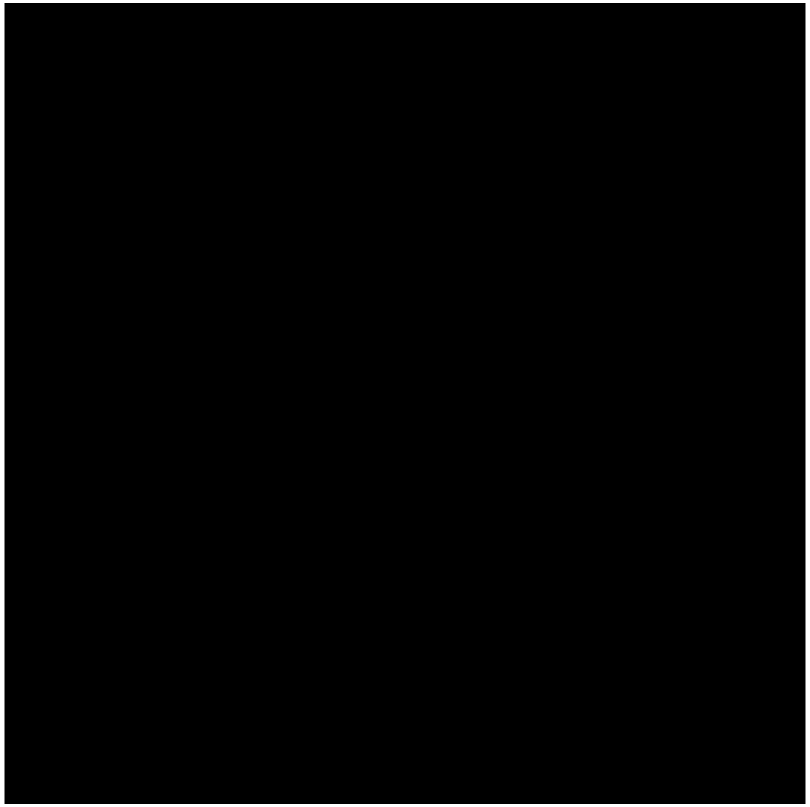


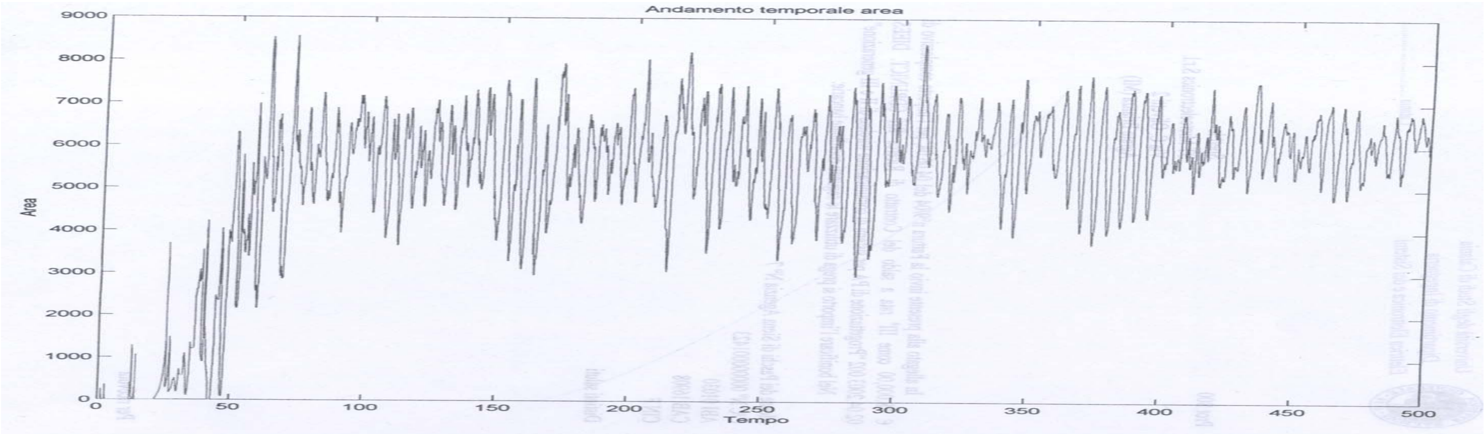
3D RD-CNN: each cell is a Hindmarsh-Rose neuron (model of cortical neurons)

$$\frac{\partial u}{\partial t} = F(u) + D \cdot \nabla^2 u$$

Evolution of the surface $u_1(i,j,k)=cost$

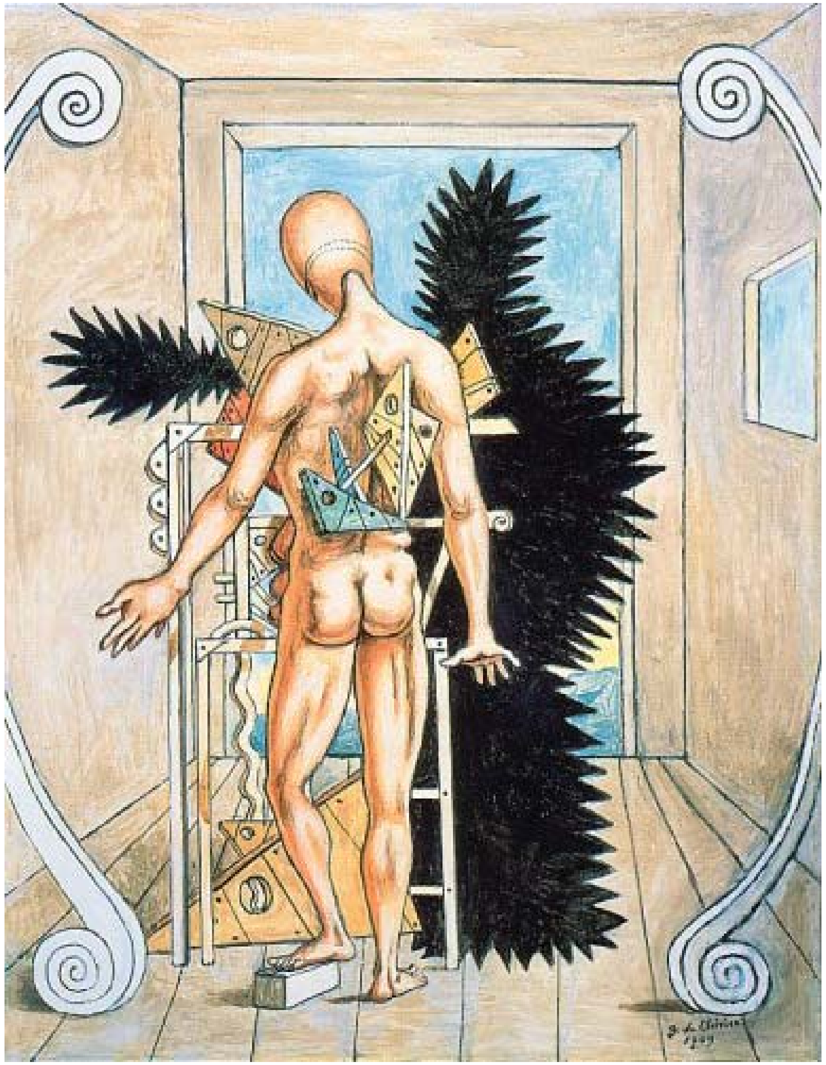
CNN and Hallucination





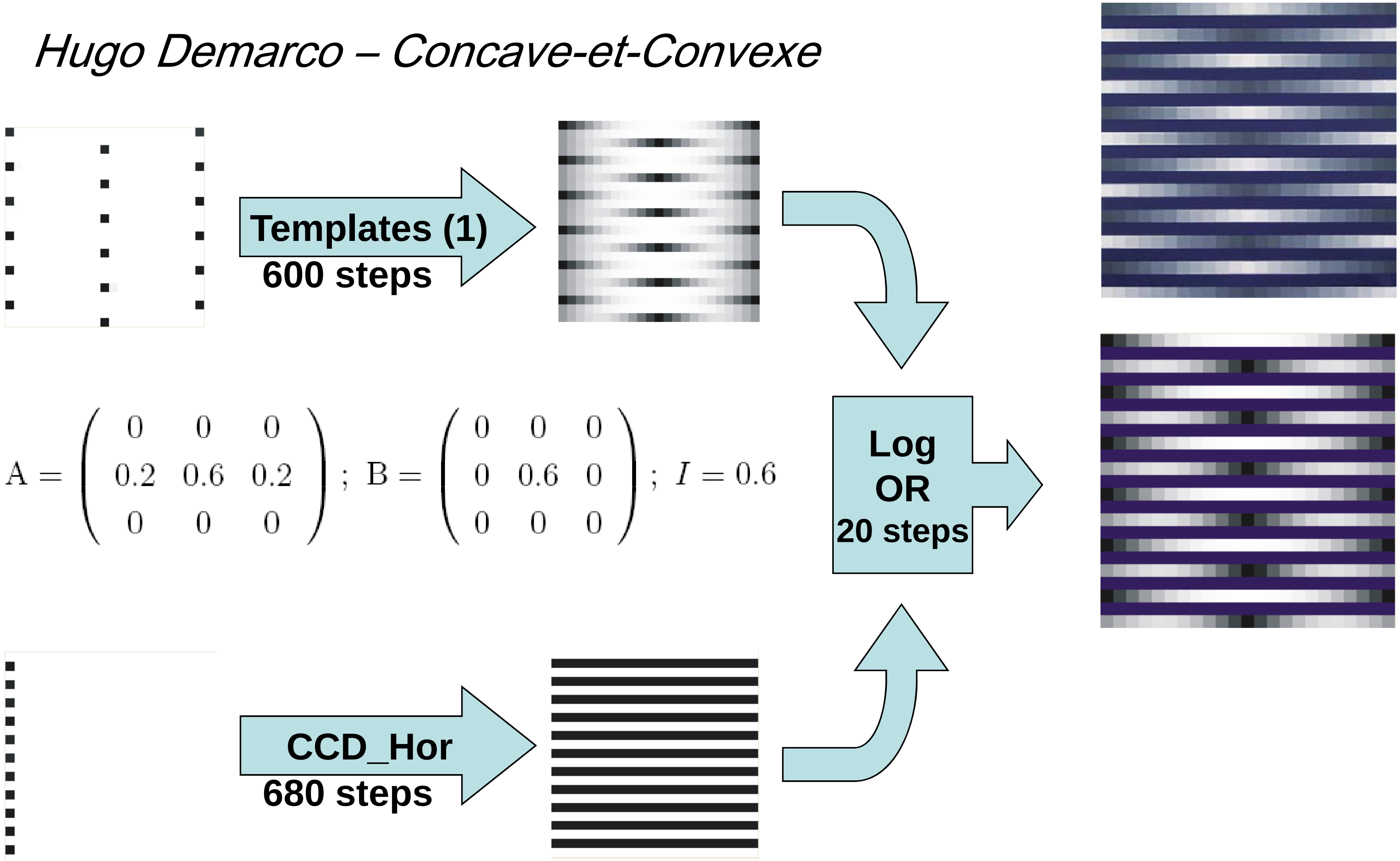
Giorgio De Chirico

- Migraine aura: a complex phenomenon emerging from the interaction of many units
- The complexity of metaphysical art: emerging beauty. The "whole" is more expressive than the sum of the single parts
- CNN: a paradigm for complexity



Spatio-temporal algorithms: one example

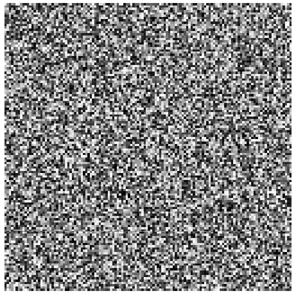
Hugo Demarco – Concave-et-Convexe



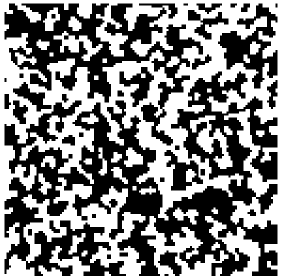
$$A = \begin{pmatrix} 0 & 0 & 0 \\ 0.2 & 0.6 & 0.2 \\ 0 & 0 & 0 \end{pmatrix};\ B = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0.6 & 0 \\ 0 & 0 & 0 \end{pmatrix};\ I = 0.6$$

Spatio-temporal algorithms: a second example

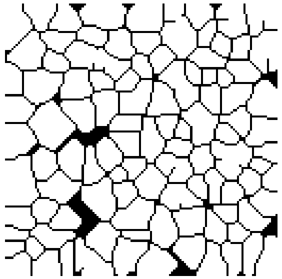
Alberto Burri – Cretto G1



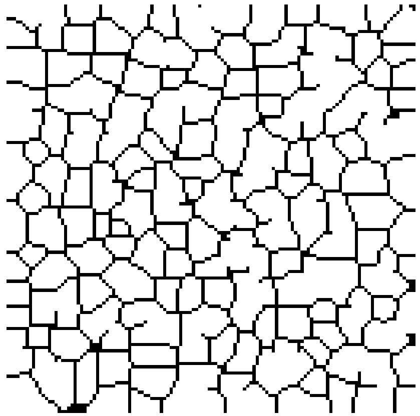
Patches
100 steps

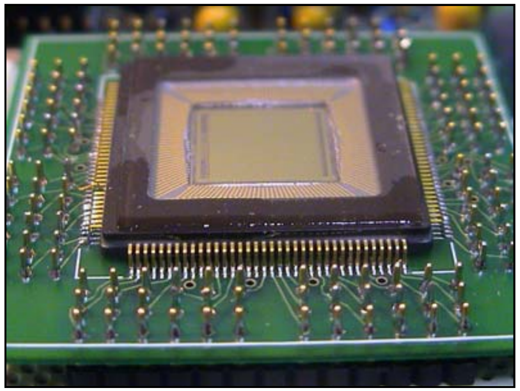


Closing



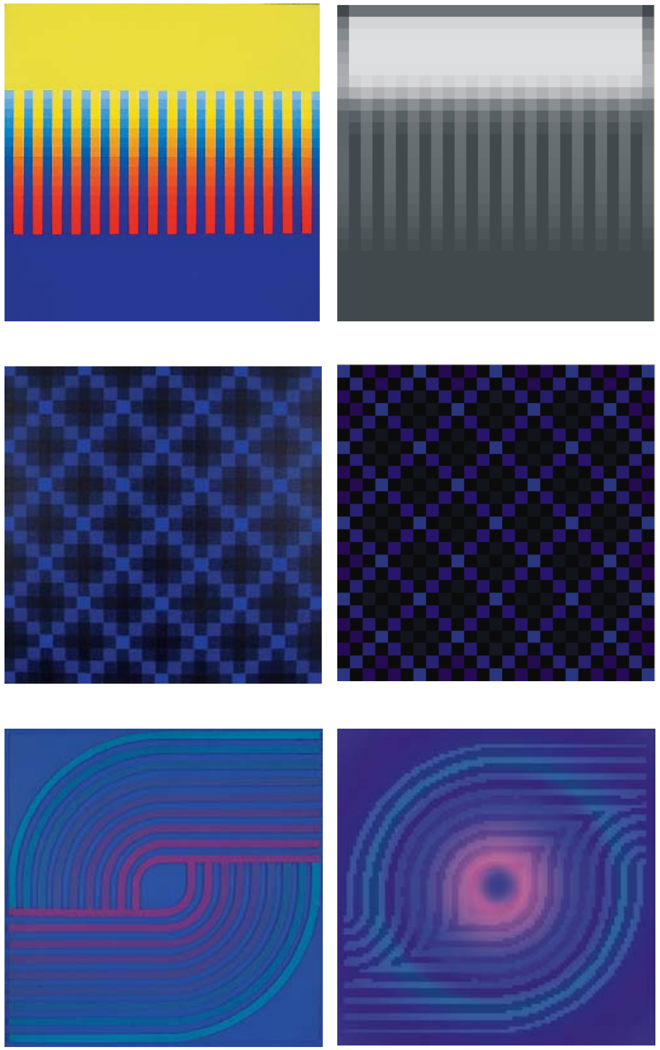
Skeletonization

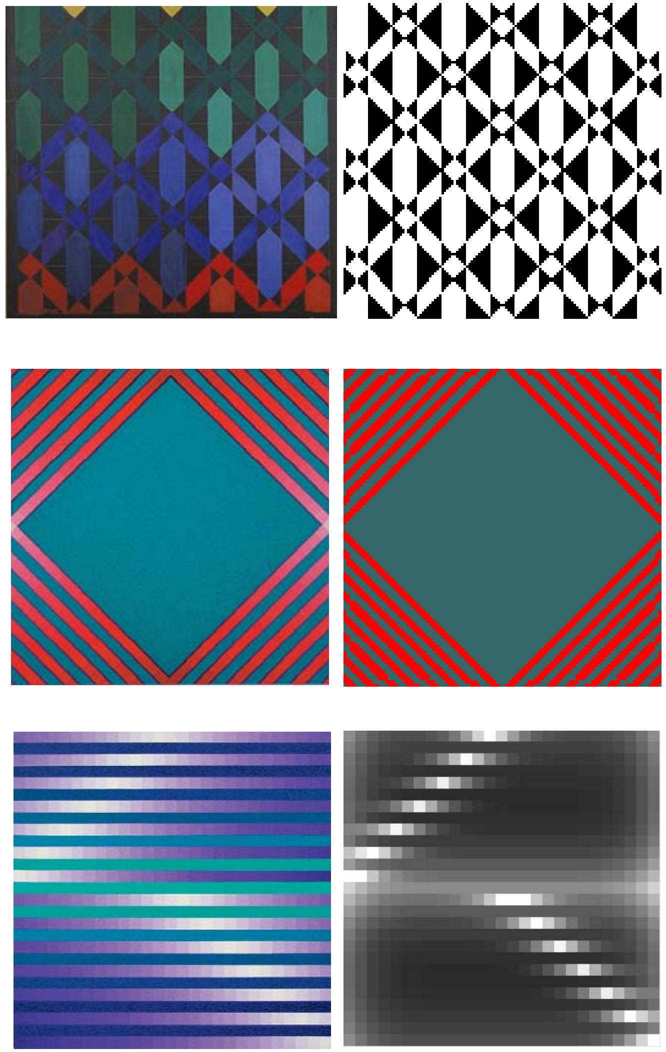




ACE 16K

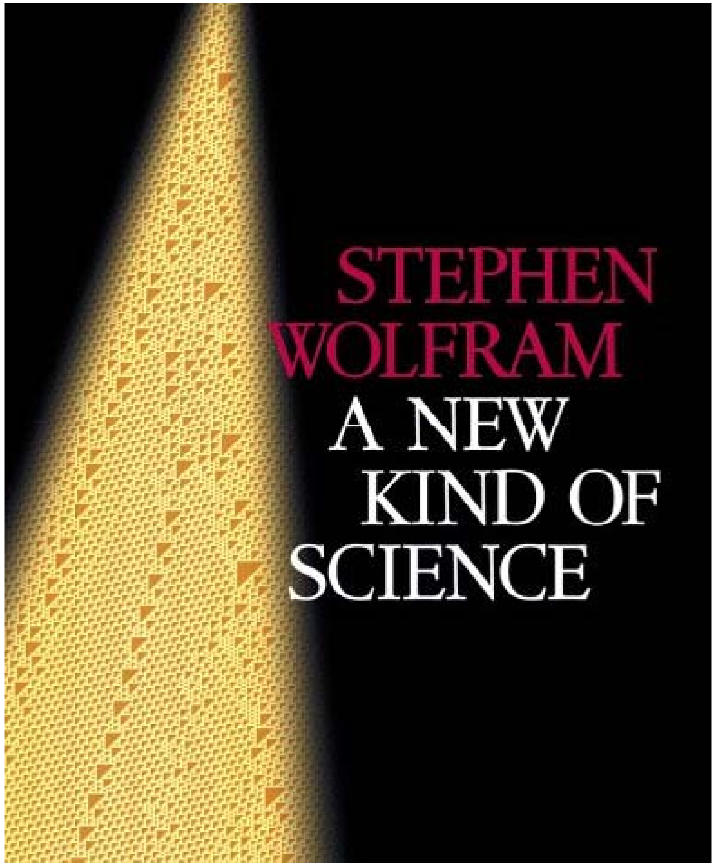
CNNs and creations by Hugo Demarco and Giacomo Balla

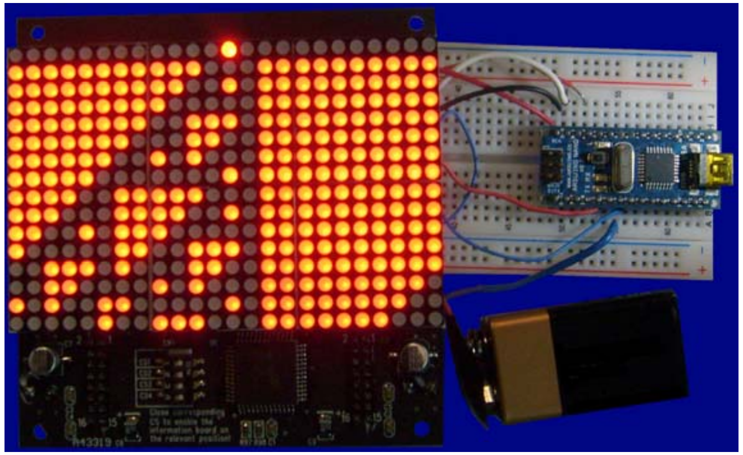




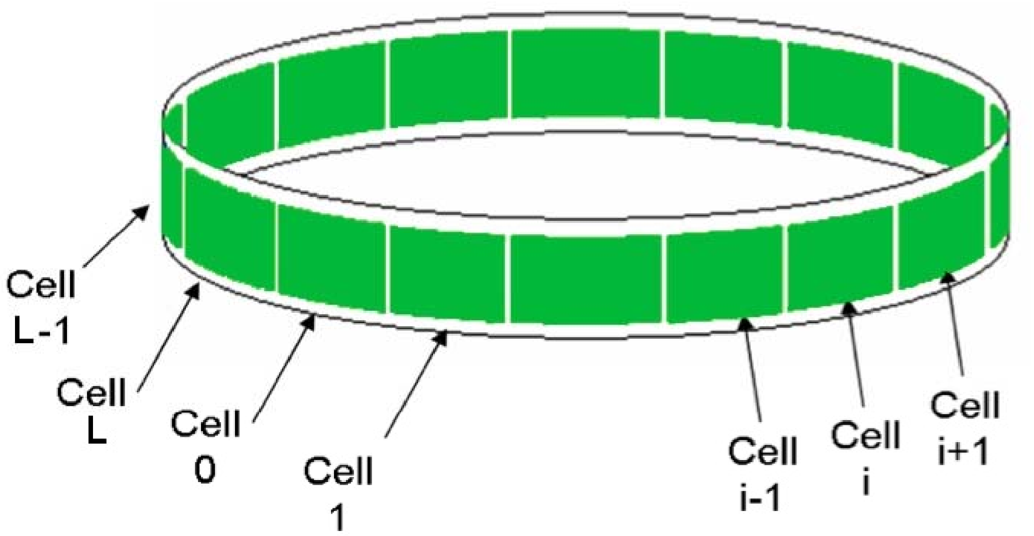
M. Bucolo, A. Buscarino, L. Fortuna, M. Frasca, M.G. Xibilia, “From Dynamical Emerging Patterns to Patterns in Visual Art”, *International Journal Bifurcation and Chaos*, vol. 18, no. 1, pp. 51-81, 2008.

Emulation of complex networks: The Wolfram Machine

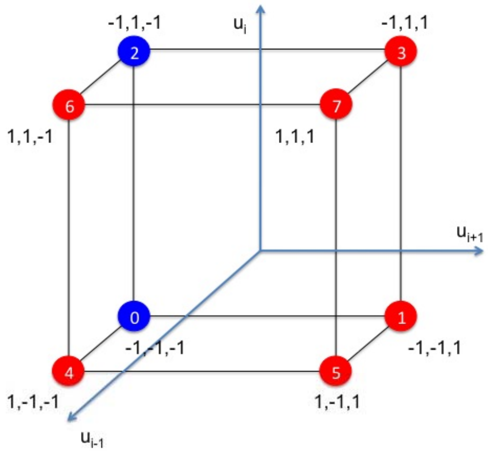




Model of the Wolfram Cellular Automaton

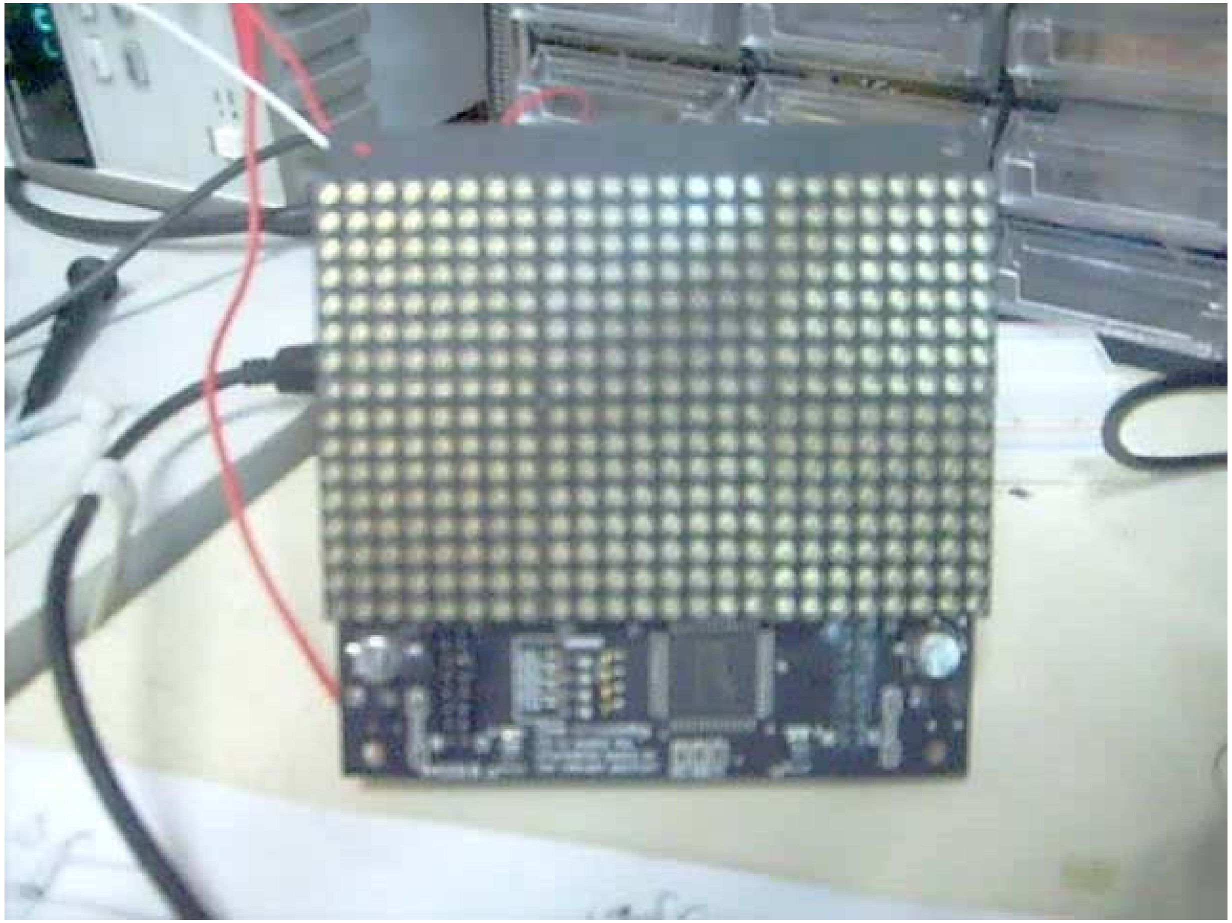


ring of coupled cells



$y = R(u_{i-1}, u_i, u_{i+1})$

The Wolfram Machine

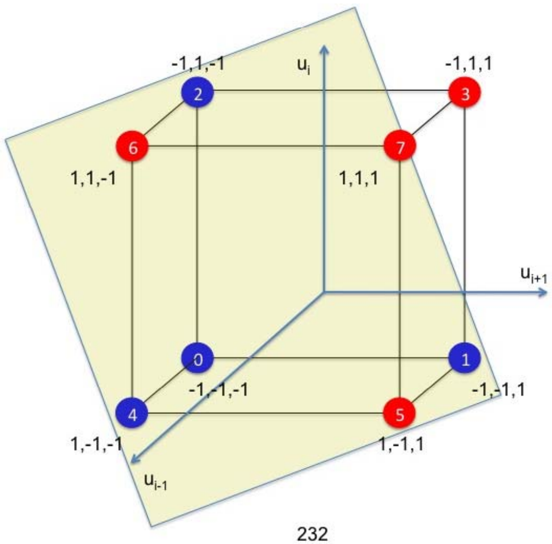


FORTUNA L, M. FRASCA, A. SARRA FIORE, L. O. CHUA, “The Wolfram Machine”, *INTERNATIONAL JOURNAL OF BIFURCATION AND CHAOS IN APPLIED SCIENCES AND ENGINEERING*, vol. 20, p. 3863-3917, 2010.

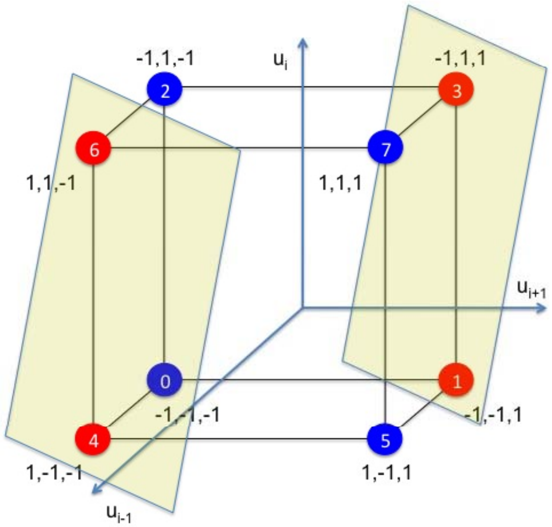
Wolfram's cellular automata

It is possible to define a complexity index k starting from a transition function defined as a minimal number of parallel planes necessary to separate the vertices of the Boolean cube representing the function into the clusters of the same values.

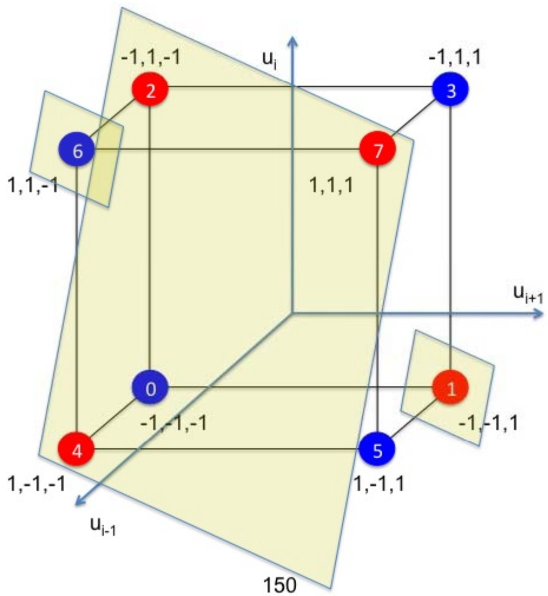
There are three possible values of complexity index.



232

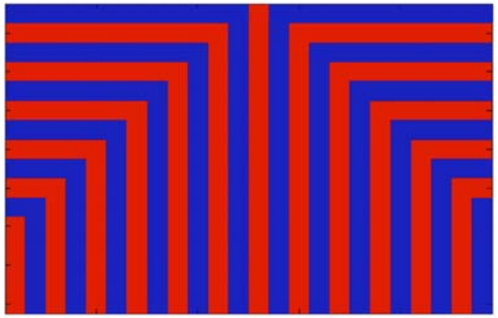


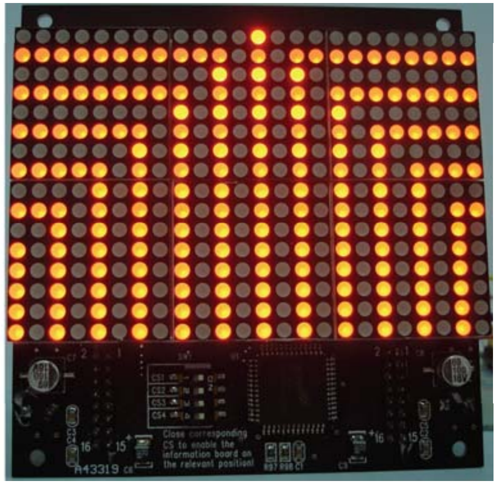
90



150

Rules emulated by Wolfram Machine

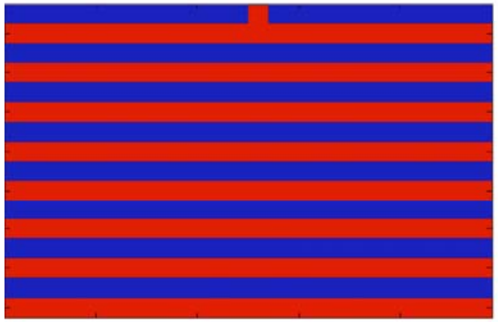


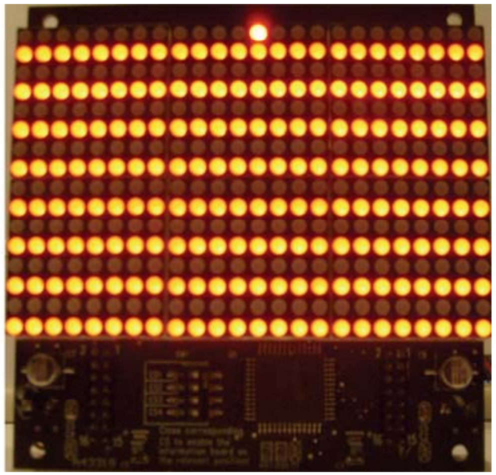


Rule 77
K=1

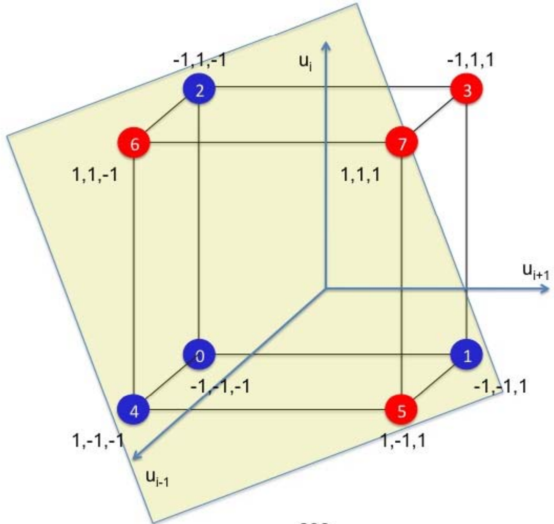
The rules with complexity index one are 104 and exhibit a periodic behaviour.

k=1

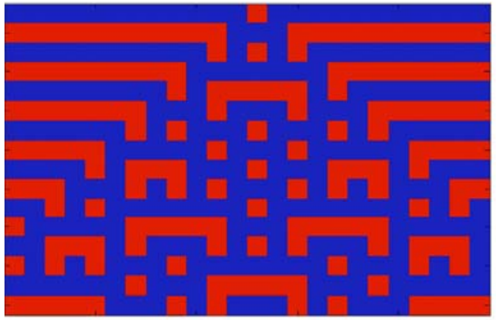


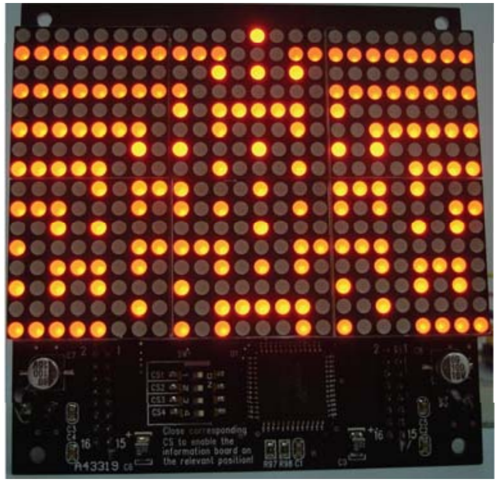


Rule 87
K=1

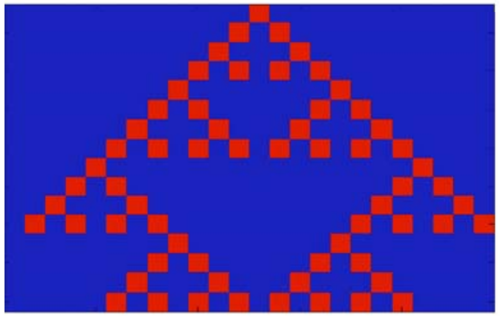


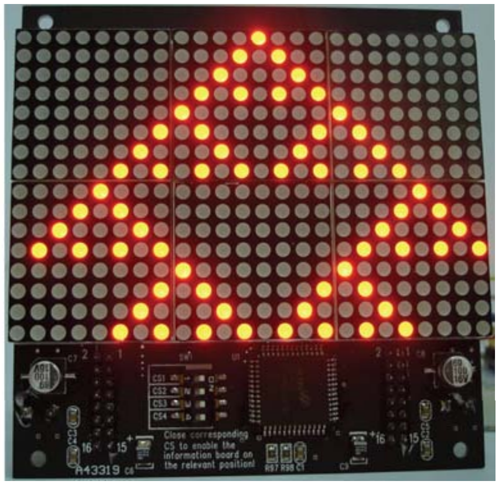
Rules emulated by Wolfram Machine





Rule 73
K=2

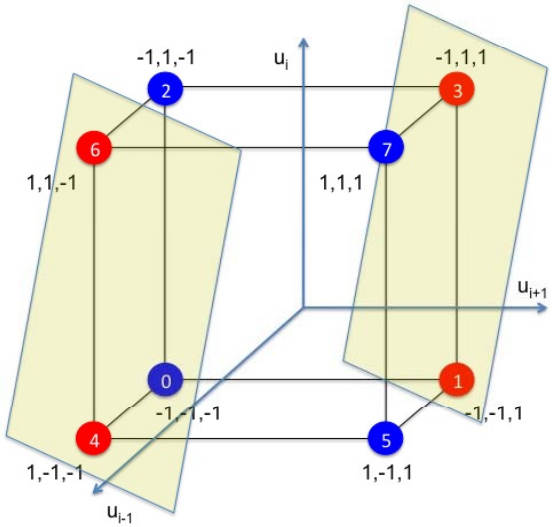




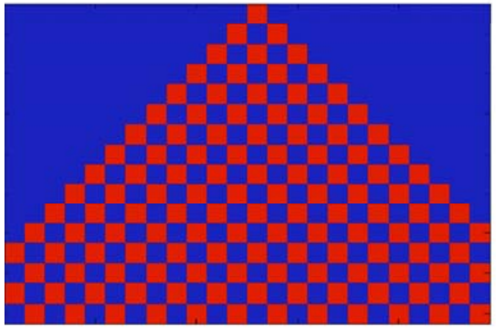
Rule 82
K=2

The rules with complexity index two are 126 and exhibit gliders and non-trivially interacting propagating patterns.

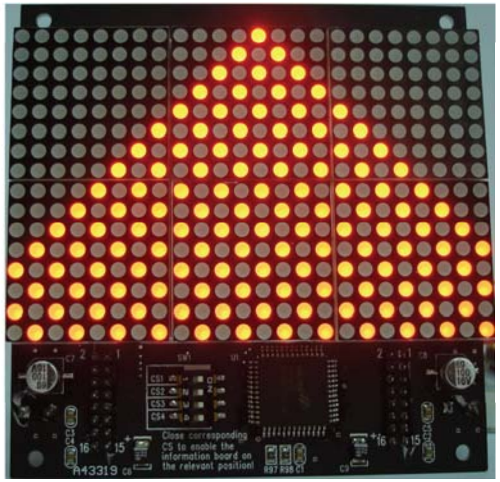
k=2

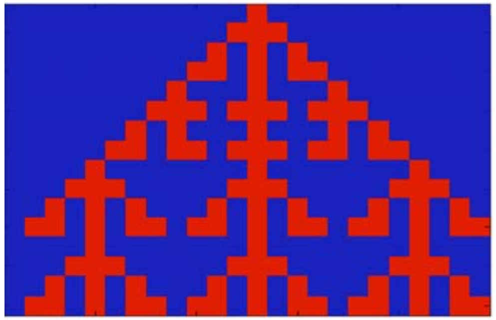


Rules emulated by Wolfram Machine

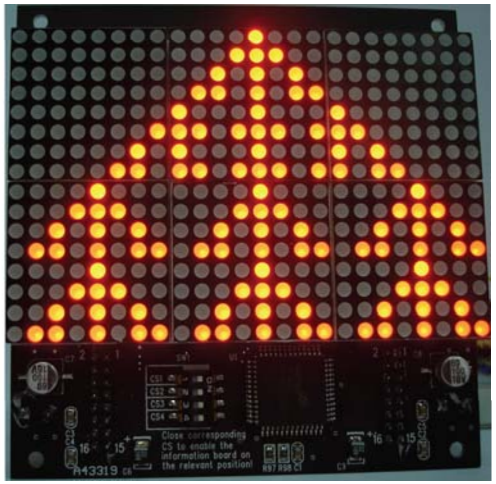


Rule 114
K=3



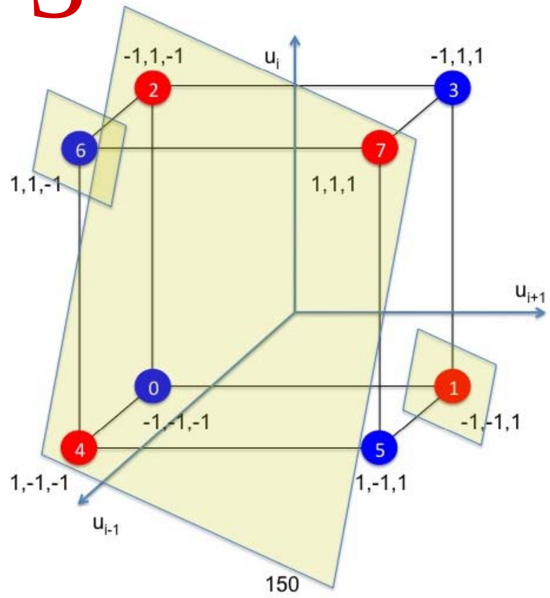


Rule 150
K=3

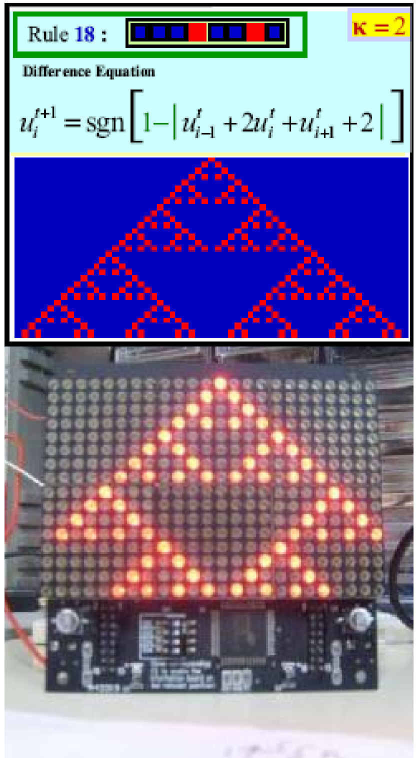


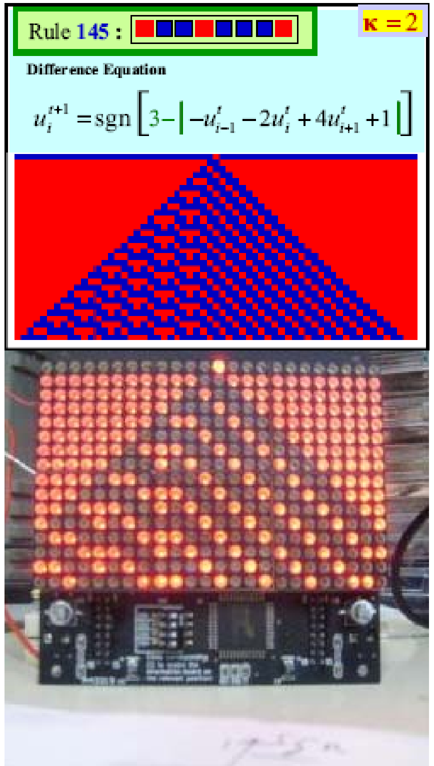
The rules with complexity index three are 26 and have complex behaviour at the degree of unpredictability.

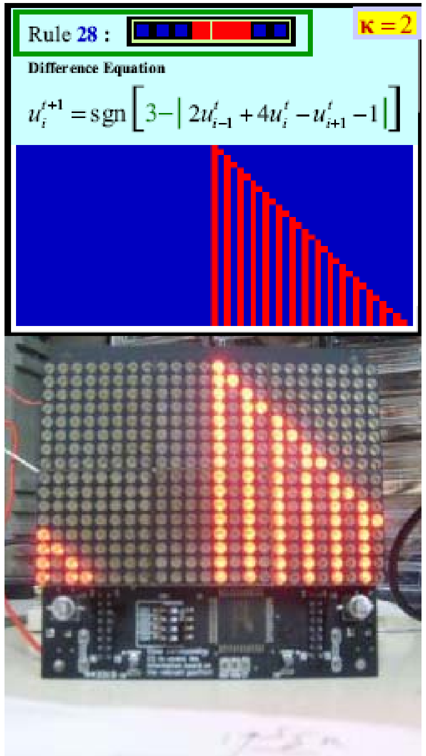
k=3

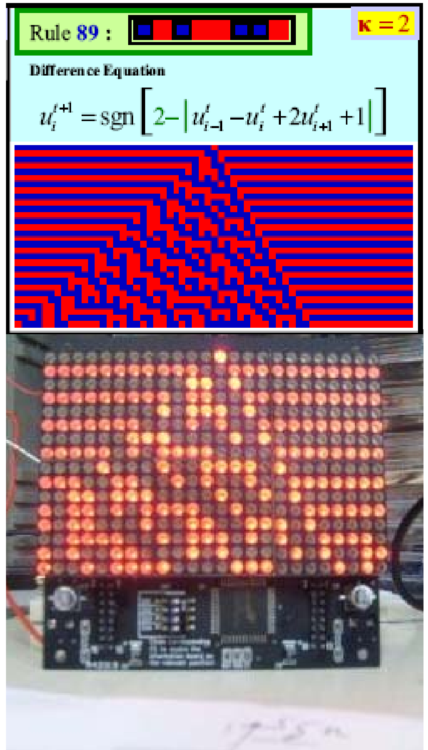


More examples



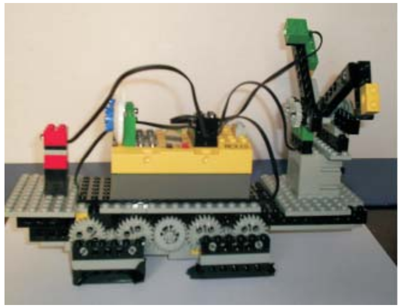


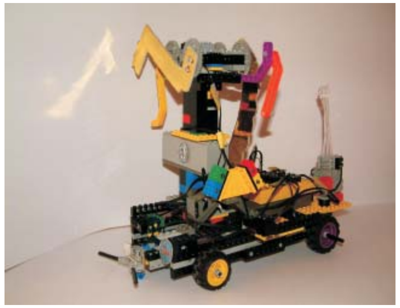


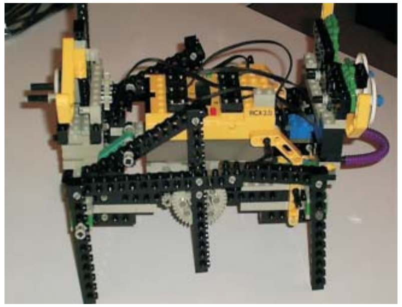


Chaotic robots and art

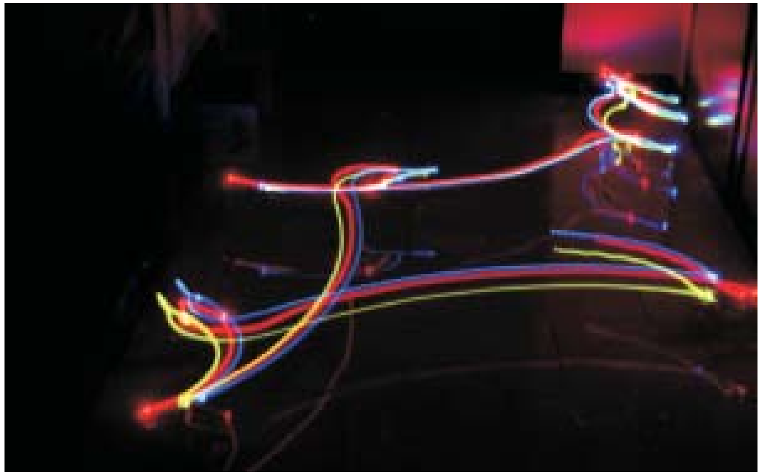
CNN → chaos → robots → trajectories

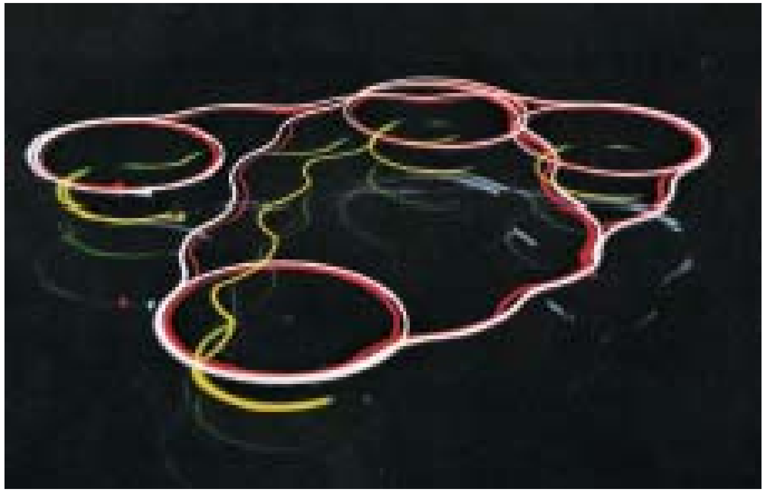


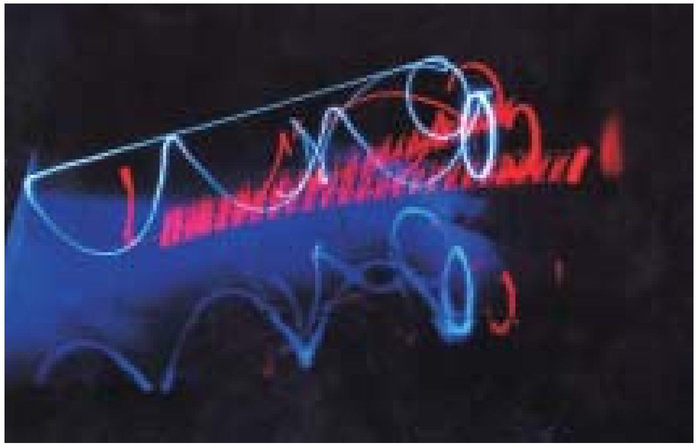


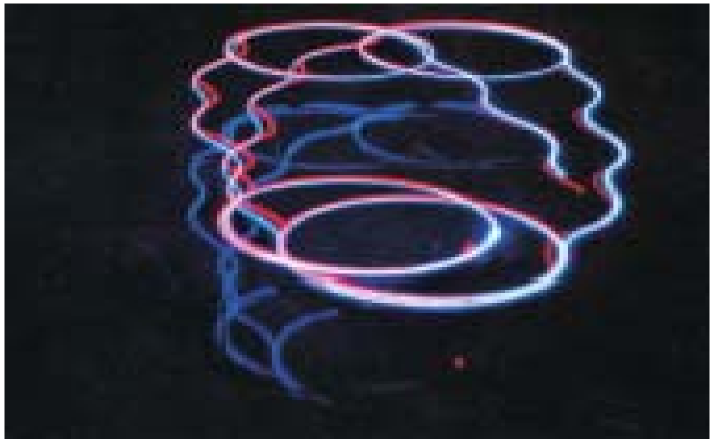


Trajectories of a single robot

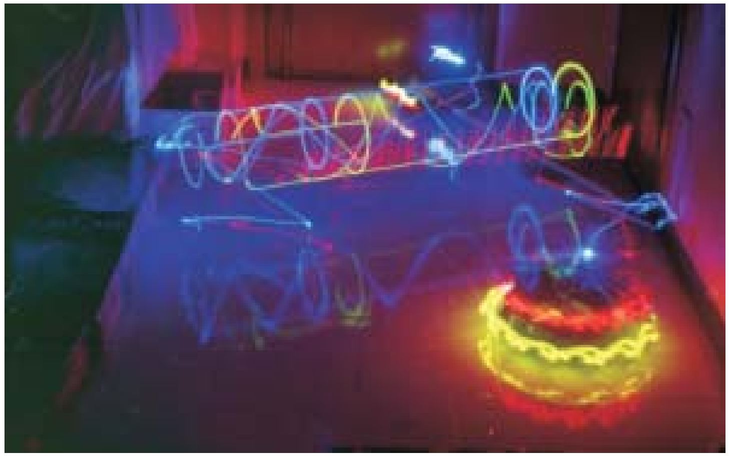


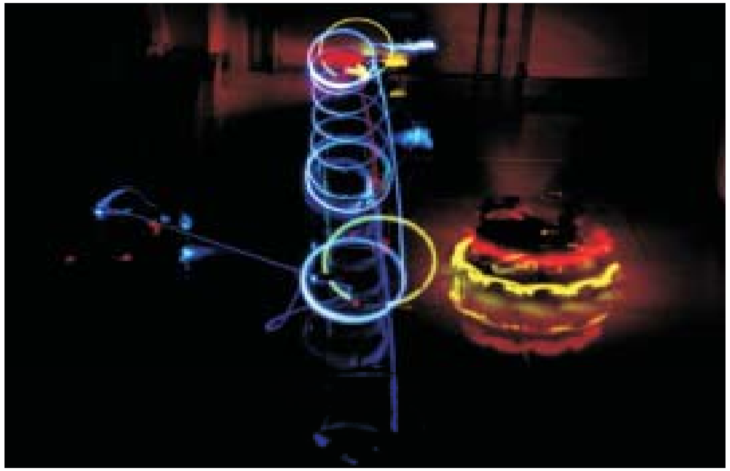




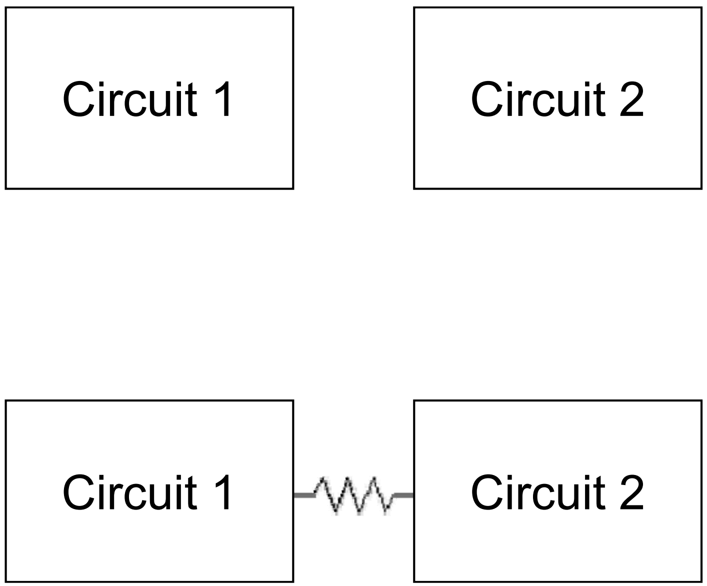


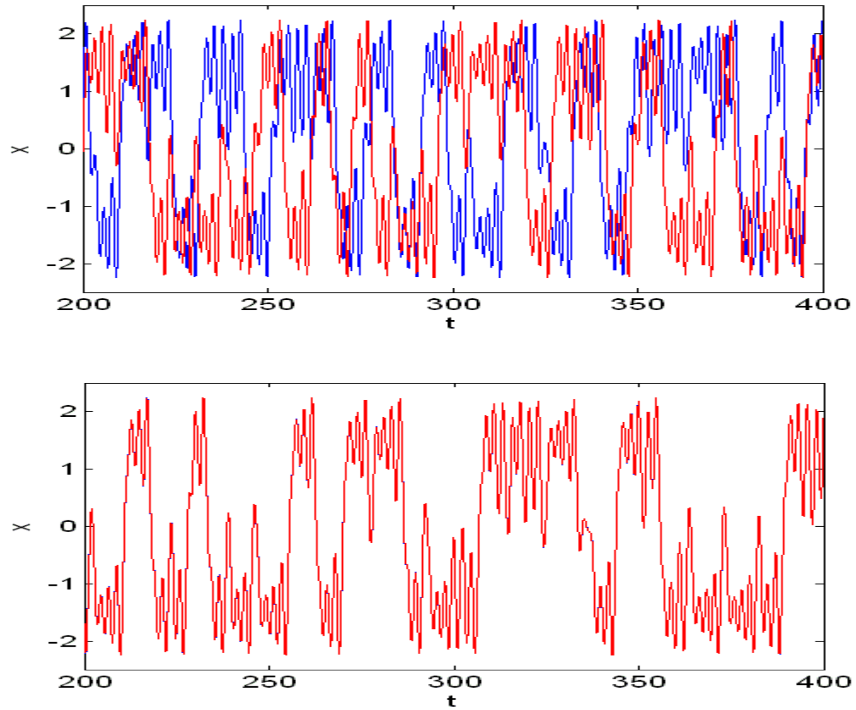
Trajectories of interacting robots:
1. obstacle avoidance





Trajectories of interacting robots:
2. synchronization

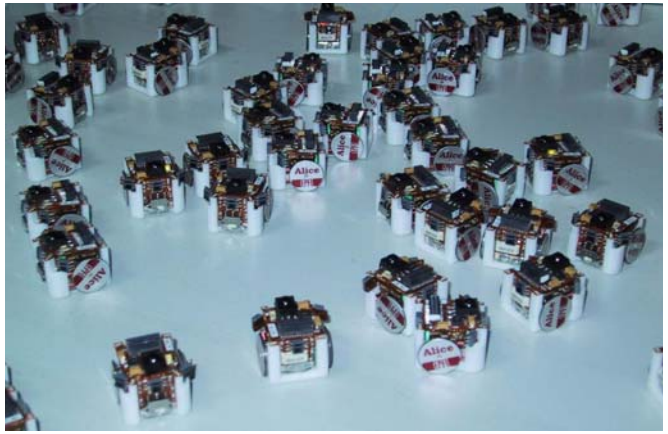




Trajectories of interacting robots: 2. synchronization

chaos → irregular trajectories

synchronization → coordination

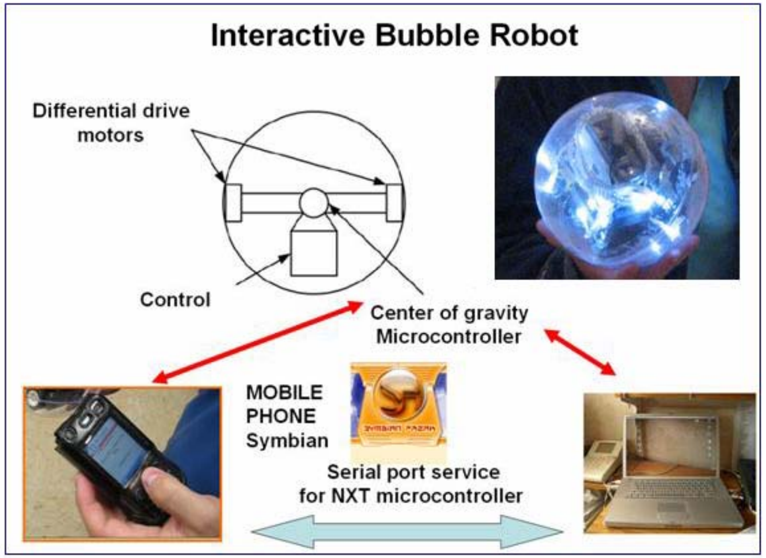


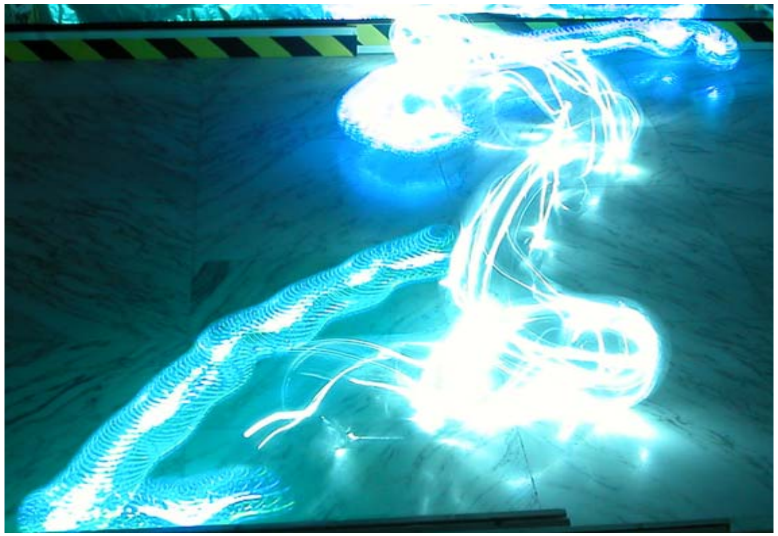
Robot team for exploration (irregular, but coordinated trajectories)

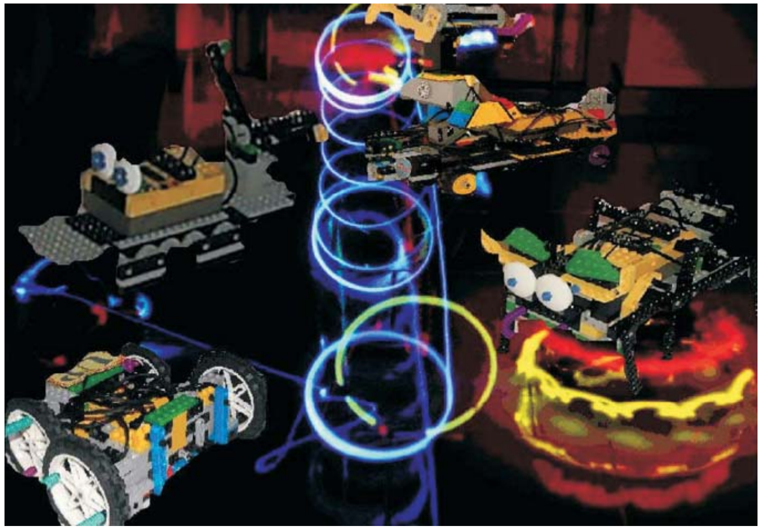
A. Buscarino, C. Camerano, L. Fortuna, M. Frasca, “Chaotic Mimic Robots”, *Phil. Trans. R. Soc. A*, vol. 368, pp. 2179-2187, 2010.

P. Belluomo, C. Camerano, L. Fortuna, M. Frasca, “From kinetic art to immaterial art through chaotic synchronization”, *International Journal Bifurcations and Chaos*, vol. 20, no. 10, pp. 3379–3390, 2010.

Towards Immaterial Art



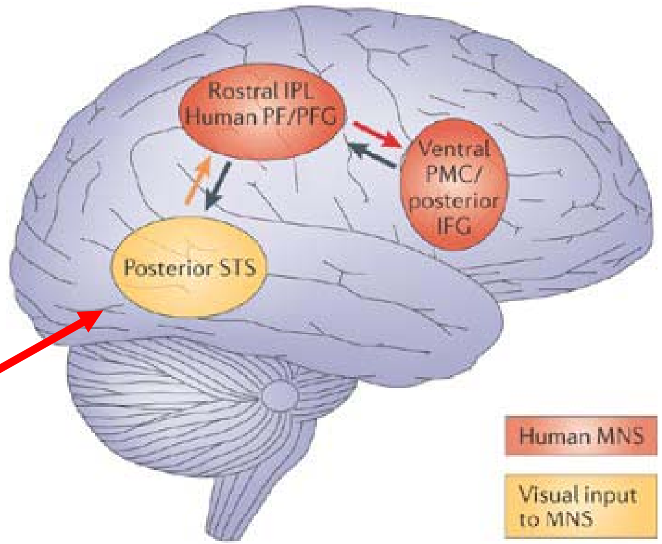




Chaotic Mimic Robots: learning synchronization

Mirror neurons are active cells in the macaque brain, located in the ventral premotor Area (Area F5) of the brain (Gallese, V. and Goldman, A. ,1998).

The study of these neurons revealed that they have motor and visual properties, they are cells emitting information when the monkey performs a specific action and when it observes someone else performing similar actions.



Area F5: Mirror Neurons

Chaotic Mimic Robots: learning synchronization

STEP 1:

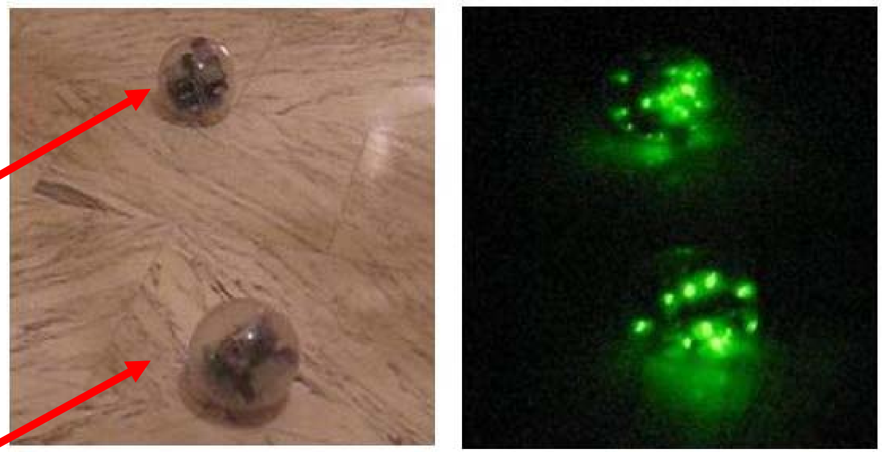
Two identical Bubble Robots were designed: one robot is controlled by a chaotic law and the other is guided by a system of Mirror Neurons.

STEP 2-3:

Through the Bubble Robot approach, the concept of robot-to-robot interaction and the concept of “hanging by imitation” through the Mirror Neurons are implemented.

STEP 4:

In this experiment the user is able to interact with the twins mirror robots and create art through the lighting patterns generated by the robots during the process of synchronization.



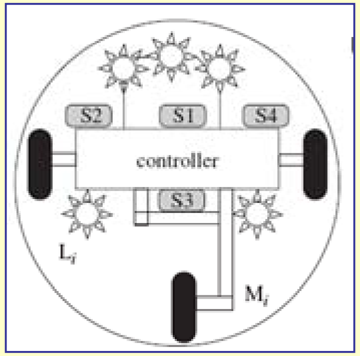
Observed Robot (A)

Observer Robot (B)

Chaotic Mimic Robots and Immaterial Art

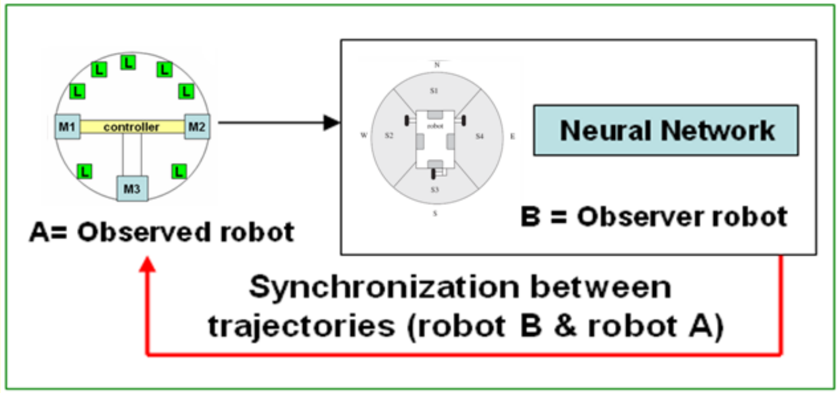
step1
Design of two innovative Bubble Robots

The Bubble Robot

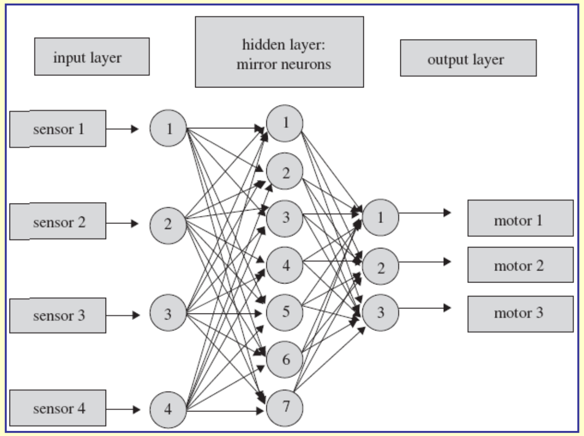


Architecture of Robot

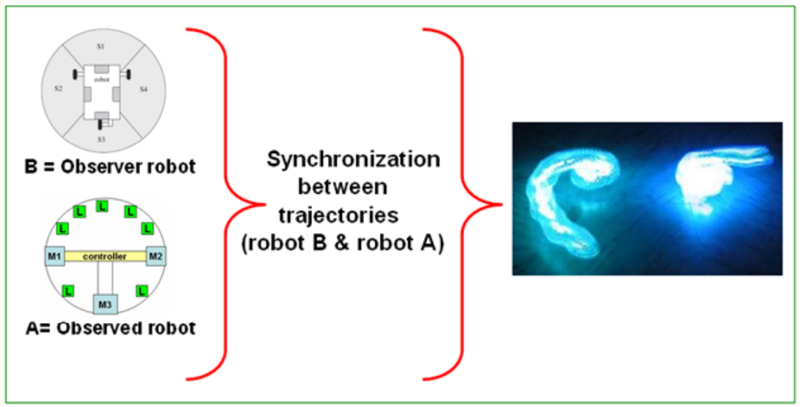
step2 → step3
Control System and Mirror Neurons



step3
Neural Network for Learning Mechanism

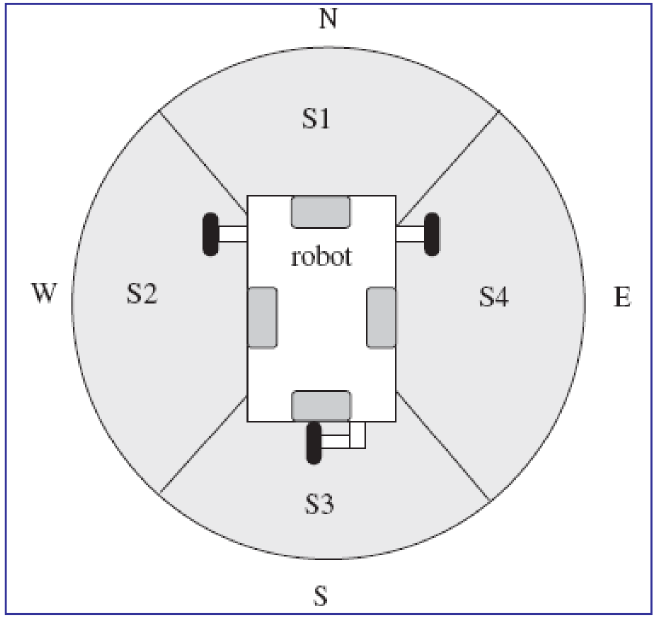


step4
Interaction of Bubble Robots for art



Architecture of the Bubble Robot

The two robots have the same mechanical structure, but differ in terms of the control law. While one is driven by a chaotic one, the second is controlled by a mirror neuron-like structure.

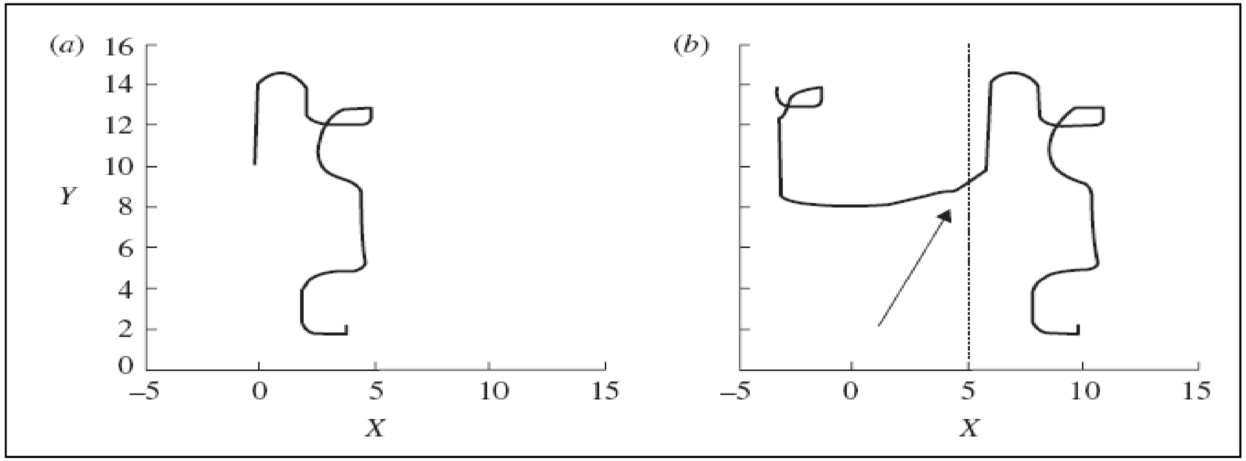


S1, S2, S3, S4, IR sensors; Li , light-emitting diode lights (i = 1, . . . , 21); Mi , motors (i =1, 2, 3).

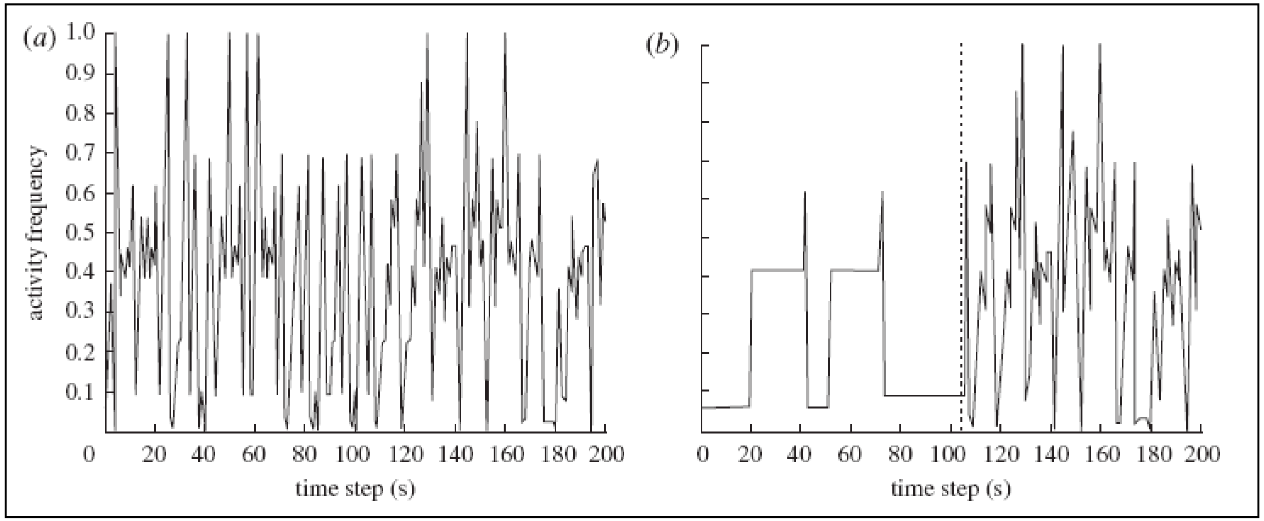
Main features:

- The three motors are all 9 V/0.55A DC motors.
- The core of the robot is the microcontroller ARM7/32 bit Atmel (AT91SAM7256) with 256 kB of FLASH memory and 64 kB of RAM memory.
- The chassis of the robot is realized with the mechanical parts of the Mindstorms Robotics Kit.

Experimental Results: Imitation through Mirror Neurons

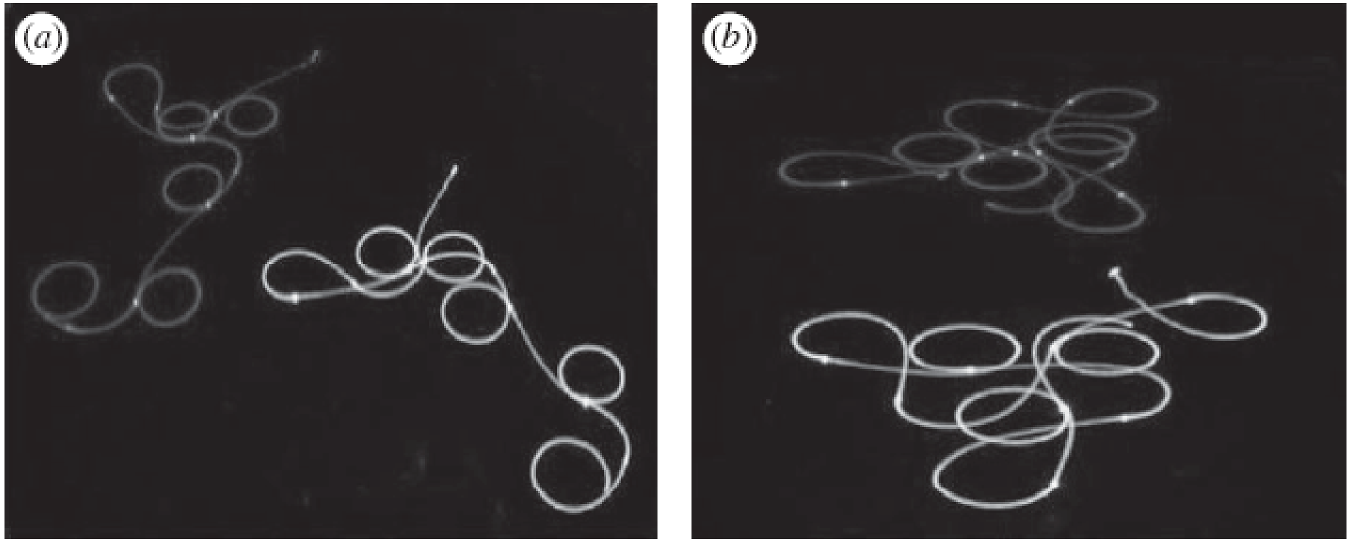


(a) Trajectory of the observer robot in the **presence** of the observed robot.
(b) Trajectory of the observer robot in the **absence** of the observed robot.

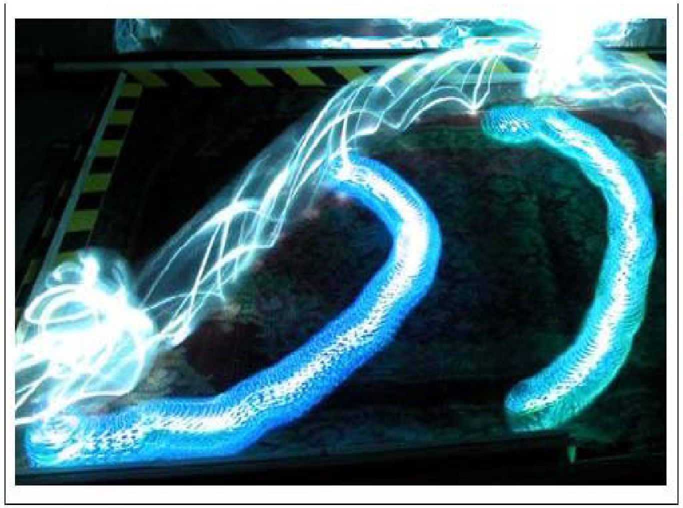


Activation of neuron 1 when the observed robot is visible (a) and when it is not (b).

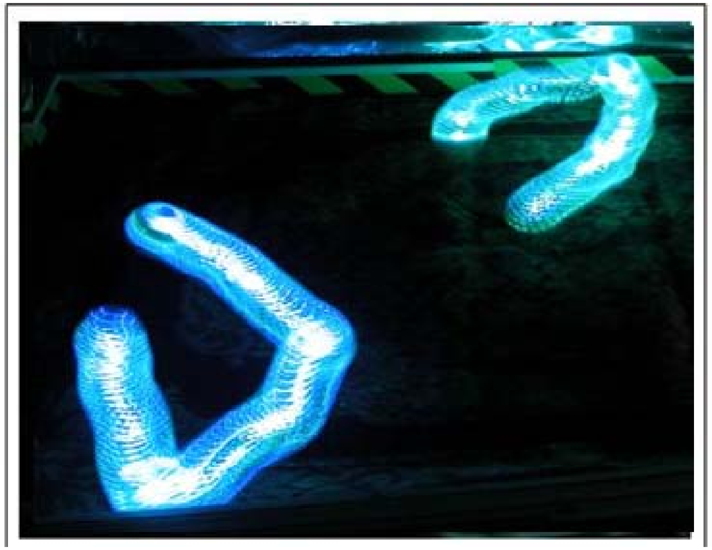
Experimental Results: Imitation through Mirror Neurons

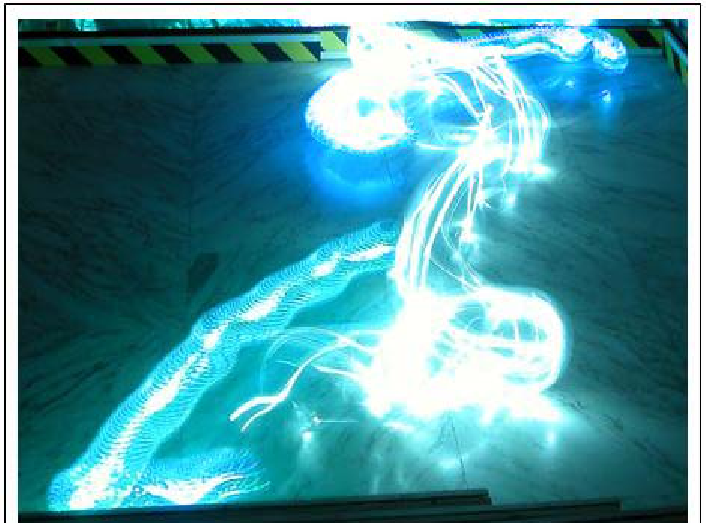


Synchronization between robot trajectories.
Each frame represents a trajectory lasting about 8 s.

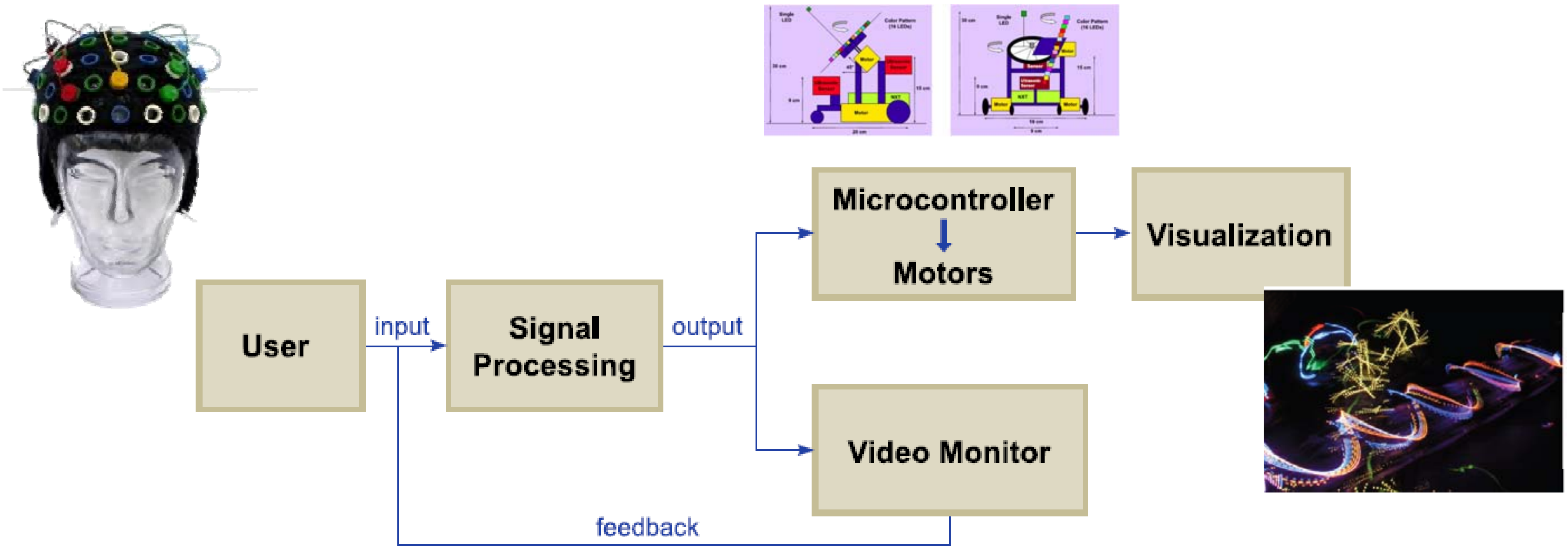


Experimental Results: Imitation through Mirror Neurons





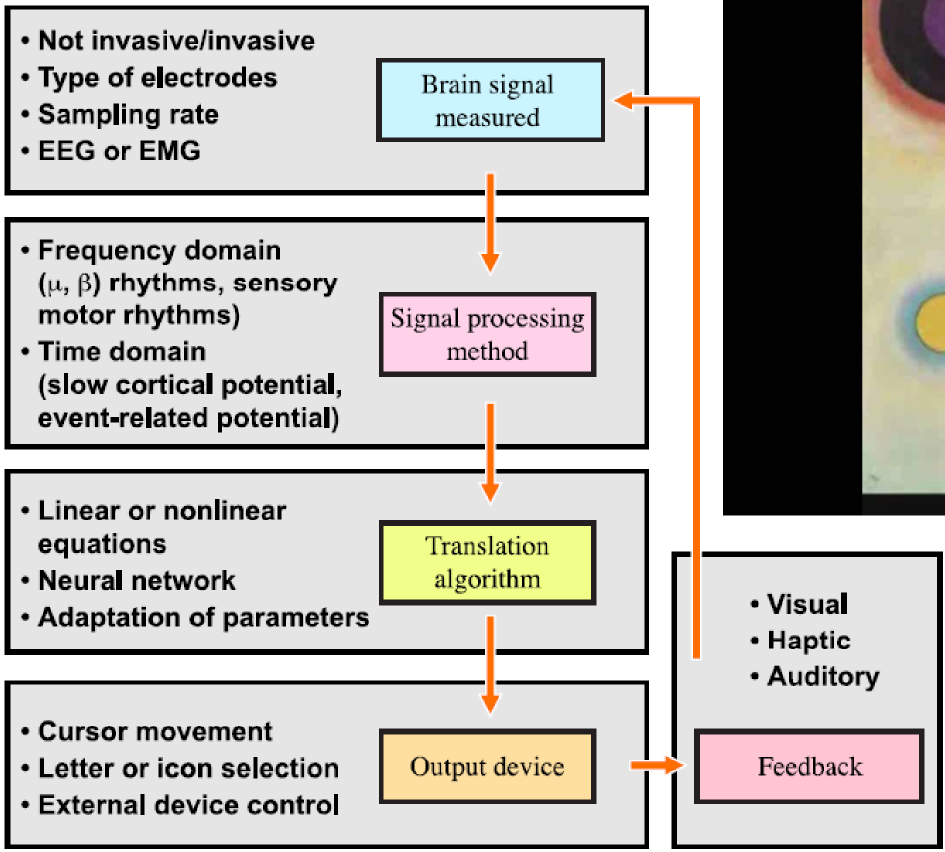

Brain Computer Interfaces to drive robots to create art

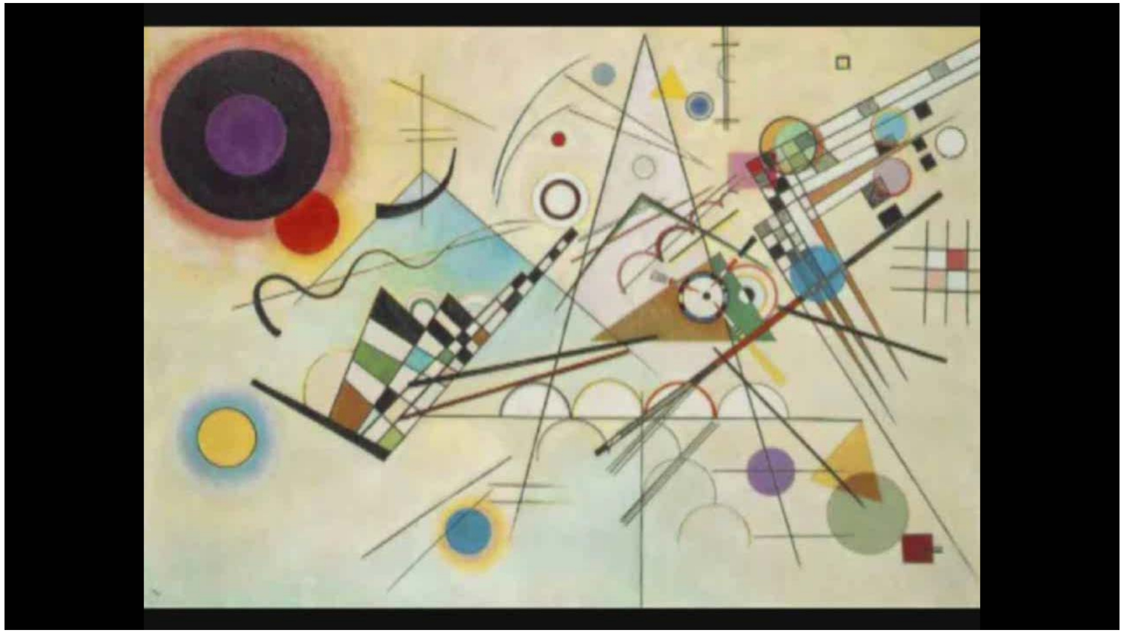


http://www.youtube.com/watch?v=AmfAynGhVaE

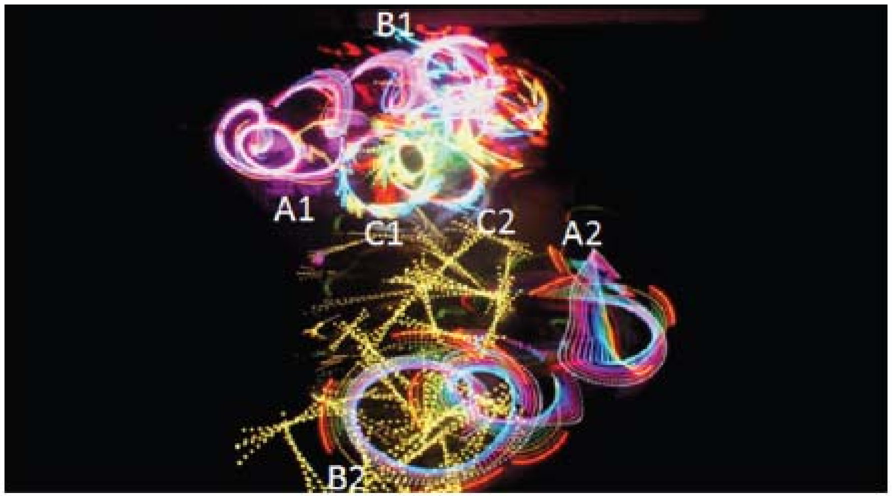
P. Belluomo, M. Bucolo, L. Fortuna, M. Frasca, “Robot Control Through Brain Computer Interface For Patterns Generation”, *Complex Systems*, vol. 20, no. 3, pp. 243-251, 2012.

Brain Computer Interfaces to drive robots to create art

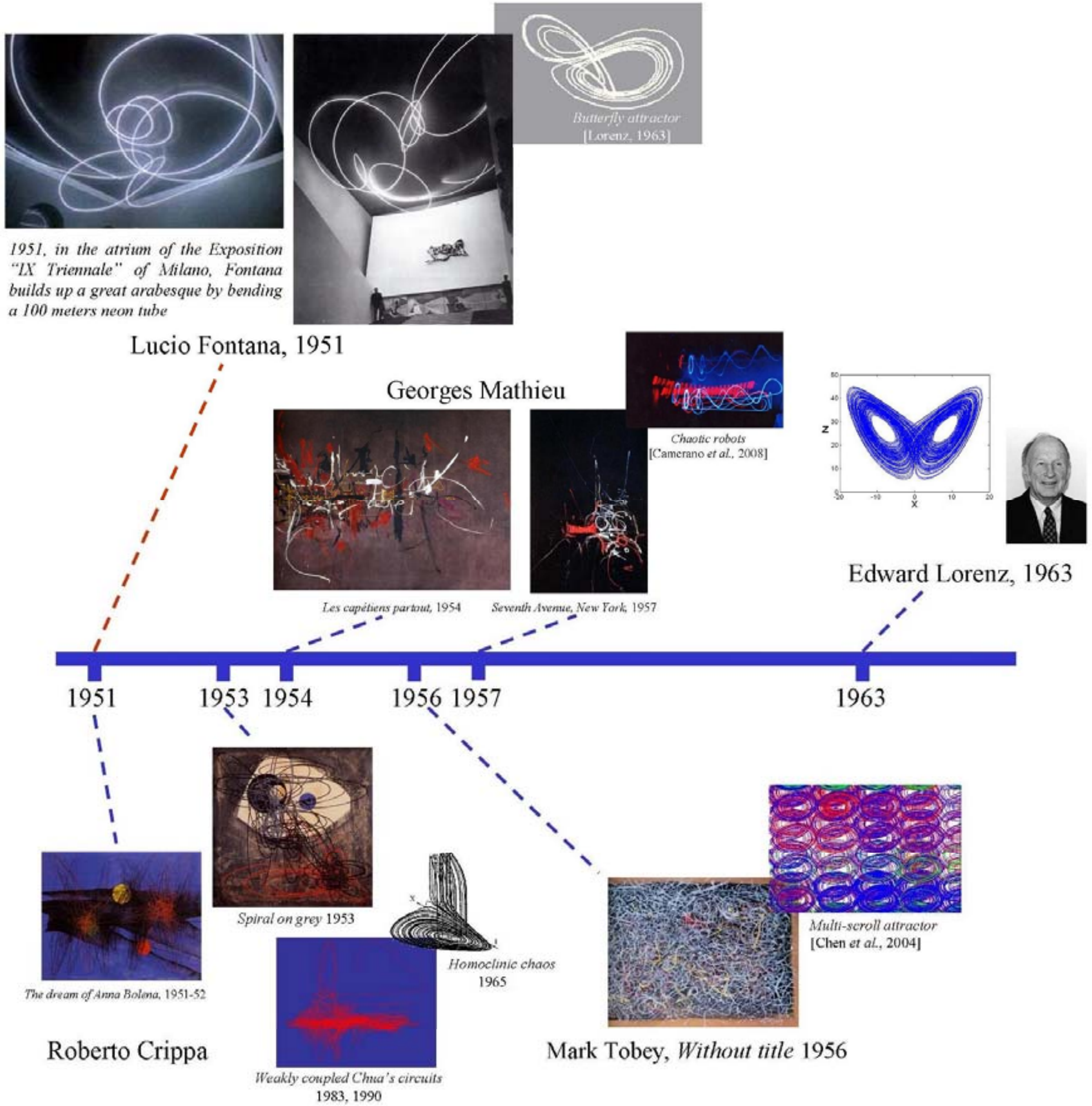




Brain Computer Interfaces to drive robots to create art



Did artists discover chaos before scientists?”



L. Fortuna, M. Frasca, “Did artists discover chaos before scientists?”, *International Journal of Bifurcation and Chaos*, vol. 20, no. 4, pp. 973-978, 2010.

Chaos and Bergson's Time

- Bergson refused the idea of a homogeneous and reversible, quantitative and measurable time

- In his conception the time interval has not physical meaning, but *it is the single consciousness which registers the real duration of time*, which is therefore *qualitative* and *heterogeneous*, *not measurable* and *irreversible*

- According to Bergson, *time is a continuous flow of unique states of consciousness*

- Duration is the *continuous progress and growth of the past*, which preserves itself entirely and is always present in the consciousness

Recurrences and recurrence times

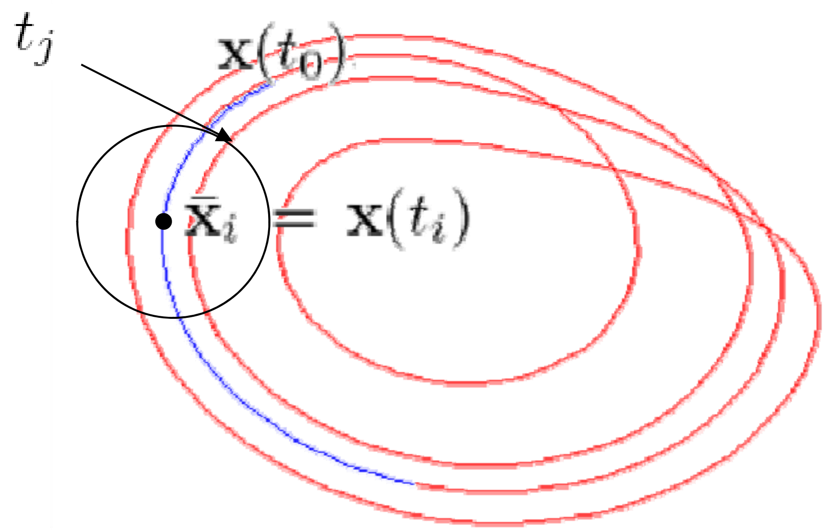
Let us consider a chaotic dynamical system defined by

$$\dot{\mathbf{x}} = f(\mathbf{x}) \qquad \begin{array}{c} \mathbf{x} \in \mathbb{R}^n \\ f : \mathbb{R}^n \to \mathbb{R}^n \end{array}$$

and a time series $\mathbf{x}(t_i)\ (i = 1, \ldots, N)$ extracted by the solution of this system with initial conditions $\mathbf{x}(t_0)$

Let us now consider a generic point $\bar{\mathbf{x}}_i = \mathbf{x}(t_i)$ and look when the trajectory comes sufficiently close to this point:

$$||\mathbf{x}(t_j) - \bar{\mathbf{x}}_i|| < r$$



Average recurrence time

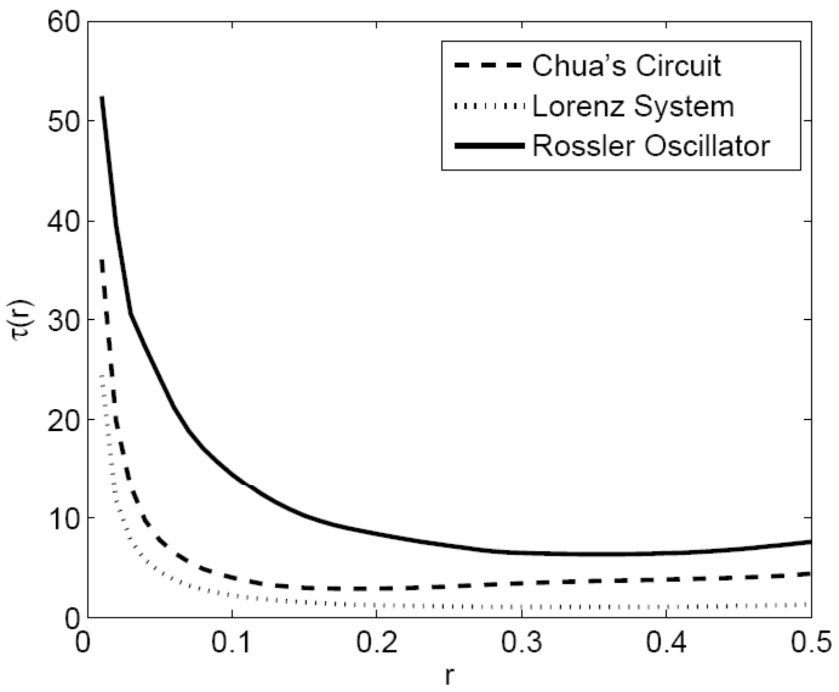
Recurrences and recurrences times:

$$||\mathbf{x}(t_j) - \bar{\mathbf{x}}_i|| < r \quad \Rightarrow \quad \tau_{ij}(r) = \begin{cases} t_j - t_i & \texttt{if } j = 1 \\ t_j - t_{j-1} & \texttt{if } j = 2, \ldots, M \end{cases}$$

Average recurrence time:

$$\boxed{\tau(r) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{M} \sum_{j=1}^{M} \tau_{ij}(r)}$$

Average recurrence time



A. Buscarino, L. Fortuna, M. Frasca, "Bergson's time and strange attractors", *19th International Symposium on Mathematical Theory of Networks and Systems*, Budapest, Hungary, 5-9 luglio 2010, pp. 231-234.

- The consequence of the Bergson's conception of the past is that *the consciousness cannot pass two times through the same identical state*

- Even if the external circumstances are the same, the person which experiences them is not the same, since he/she is in continuous evolution thanks to the irreversibility of the duration and the continuous growth of the experience

- The idea of Bergson about time is therefore that it is *dynamic* and *not static*

Conclusions

A route that we started some years ago with no particular aims has been presented. A route to study, to observe, to understand. A strange route, a strange attractor route. A route among many disciplines: from control technology to dynamical systems, from electronic systems to arts, from arts to robotics, from robotics to phylosophy.

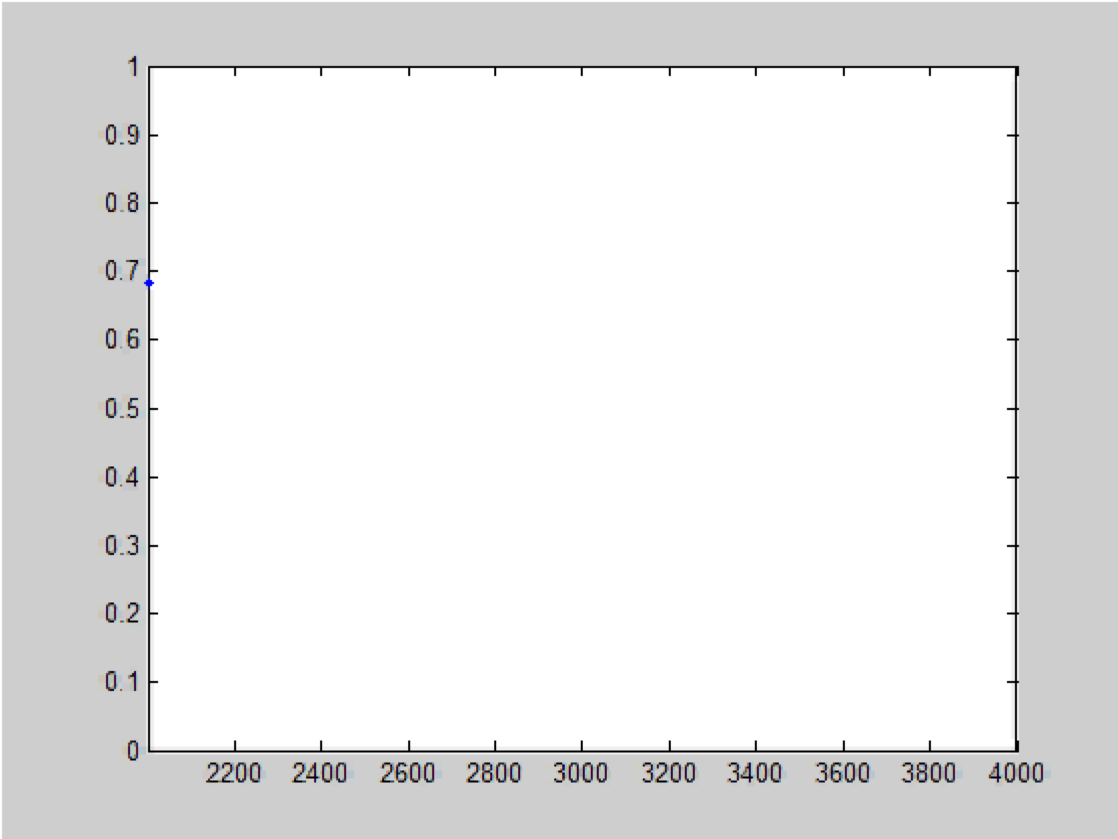
The route is still in progress and we are convinced that arts should inspire science and technology, and viceversa.

J. Saramago

As Intermitências da Morte

F. Knhopff, Maschera con tenda blu

Transient Chaos: Intermittency



The end