HAL-9000: "Dr. Chandra, will I dream?"

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CHAOS ↔ SEPARATION ↔ SPONTANEITY ↔ DREAMING

Goal

The goal is to make a simple auto-associative memory capable of ***separating*** more then two mixed patterns and at the same time to have a module serving as a ***spontaneous*** top-down selective attention. In addition a ***dreaming*** ability is obtained. It is showed how itinerant chaos gives separation ability, separation ability spontaneity and spontaneity dreaming ability.

Network Model

Following equations define an auto-associative chaotic memory:

$$\eta_i(t+1) = k_\eta \eta_i(t) + \sum_{w_{ij} \in W_i^\eta} w_{ij} x_j(t) + e_i^\eta \quad (1)$$

$$\zeta_i(t+1) = k_\zeta \zeta_i(t) - \alpha x_i(t) + \sum_{w_{ij} \in W_i^\zeta} w_{ij} x_j(t) + \theta - e_i^\zeta \quad (2)$$

$$x_i(t+1) = f\{\eta_i(t+1) + \zeta_i(t+1)\}. \quad (3)$$

$$f(u) = \frac{1}{1+\exp(\frac{-u}{\varepsilon})}. \quad (4)$$

- $x_i(t+1)$ - an output of the ith neuron at the time $t+1$
- f - a continuous output function
- ε - a steepness parameter of the continuous output function f
- $\eta_i(t)$ - a summation of *periodic-driven* potentials
- $\zeta_i(t)$ - a summation of *chaotic-driven* potentials
- k_η - a decay parameters of the periodic-driven potentials
- k_ζ - a decay parameters of the chaotic-driven potentials
- α - a refractory scaling parameter
- θ - a threshold value independent of the serial number i of a neuron
- e_i^η - an external input to the ith neuron to the periodic-driven potentials
- e_j^ζ - an external input to the jth neuron to the chaotic-driven potentials

When an external input equal to binary "one" is applied to the ith neuron, then $e_i^\eta \neq 0$ and $e_i^\zeta = 0$, and when an input equal to binary "zero" is applied to jth neuron, then $e_j^\eta = 0$ and $e_j^\zeta \neq 0$. Moreover W_i^η and W_i^ζ are sets which consist two types of wages in order to balance the chaotic and periodic - driven potentials. They have been obtained in the following way:

$$\begin{array}{l} W_i^\eta = \{w_{ij} : \forall_{0<j\leq n} w_{ij} \geq w\} \\ W_i^\zeta = \{w_{ij} : \forall_{0<j\leq n} w_{ij} < w\} \end{array} \quad (5)$$

- w - a discriminating parameter
- w_{ij} - wages
- n - a number of neurons
- i - ith neuron

Furthermore the wages have been acquired from the Hebbian learning rule:

$$w_{ij} = \frac{1}{n}\sum_{p=1}^{m}(2x_i^p - 1)(2x_j^p - 1), \quad (6)$$

- m - a number of patterns
- n - a number of neurons
- ij - a connection between ith and jth neuron

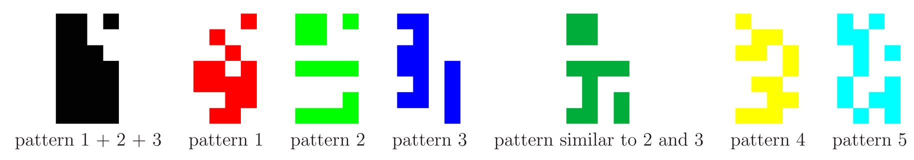
Parametric Space Search Results

The number of synchronously updated neurons in simulations is set at $n = 28$. Therefore equations 1-4 define a 56-dimensional discrete dynamical system. Only $\varepsilon = 0.015$ and $k_\eta = k_\zeta - 0.1$ were chosen arbitrarily. Rest of the parameters are results of searching various parametric spaces.

- $n = 28$
- $m = 5$
- $k_\eta = k_\zeta - 0.1 = 0.865$
- $k_\zeta = 0.965$
- $\alpha = 0.6$
- $\theta = 0.39$
- $\varepsilon = 0.015$
- $e_i^\eta = 0.125$
- $e_j^\zeta = 0.125$
- $w = -0.17$

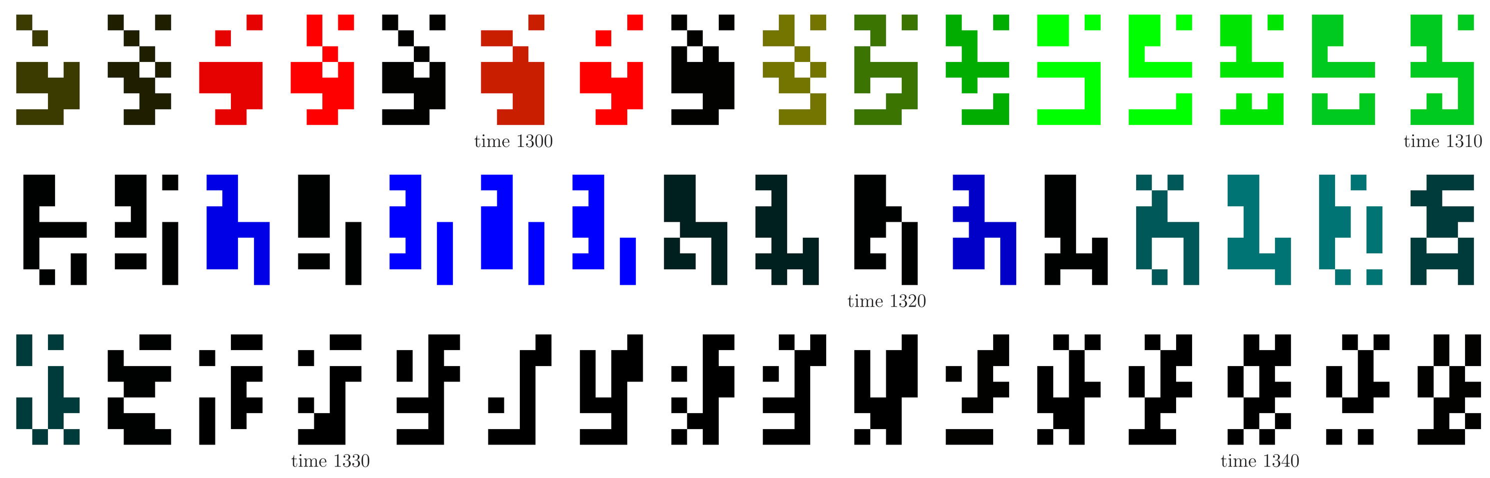
Patterns

Stored patterns are **randomly** chosen with a **load factor 0.5**. The **normalized Hamming distance** between **every two patterns** is ≈ 0.5. It is crucial for the chaotic itinerancy and the separation ability that the distance between every two patterns stored in the wages matrix is equal.



Now I see ...

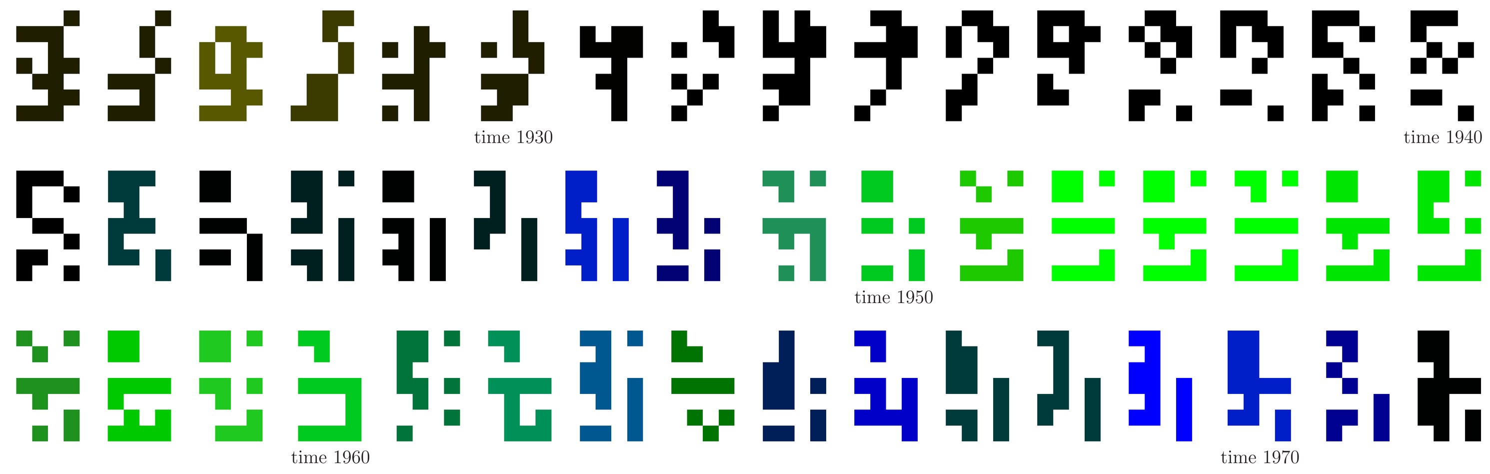
With the set of all parameters fixed at optimal values responses of the network are investigated. As an **external input** a **logical OR** mixture of **patterns 1, 2 and 3** is applied to the network.This experiment shows the **separation ability**.



Time series when external input pattern = pattern 1 + 2 + 3

I am not sure ...

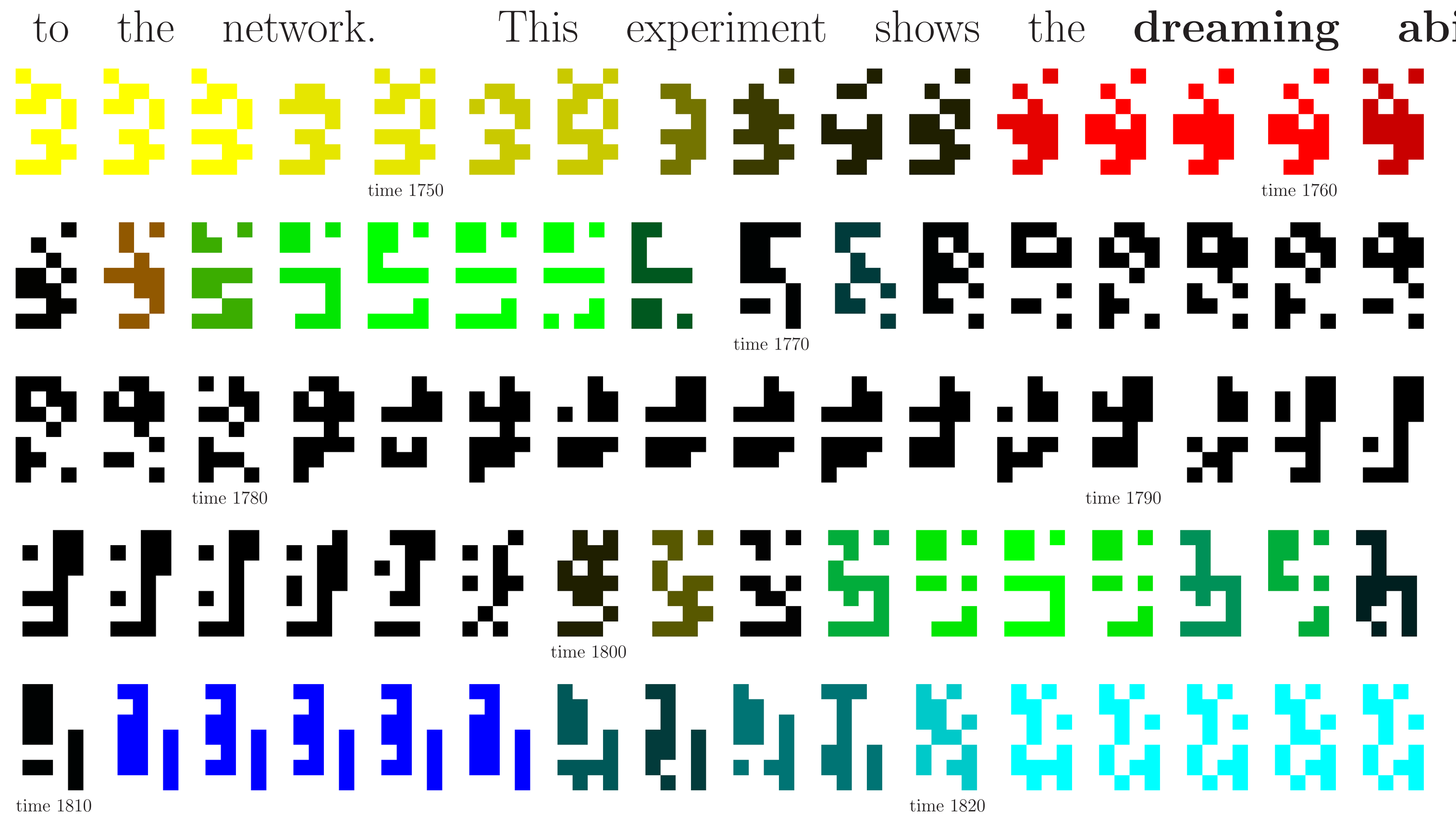
In this experiment as an **external input** a **randomly** chosen pattern, **similar** to stored **patterns 1 and 2** is applied to the network. The **normalized Hamming distance** between this **similar pattern** and **patterns 1 and 2** is ≈ 0.25 and between **the rest of the stored patterns** is ≈ 0.5. This experiment shows **the spontaneous top-down selective attention**.



Time series when external input pattern = pattern similar to pattern 1 and 2

I dream about ...

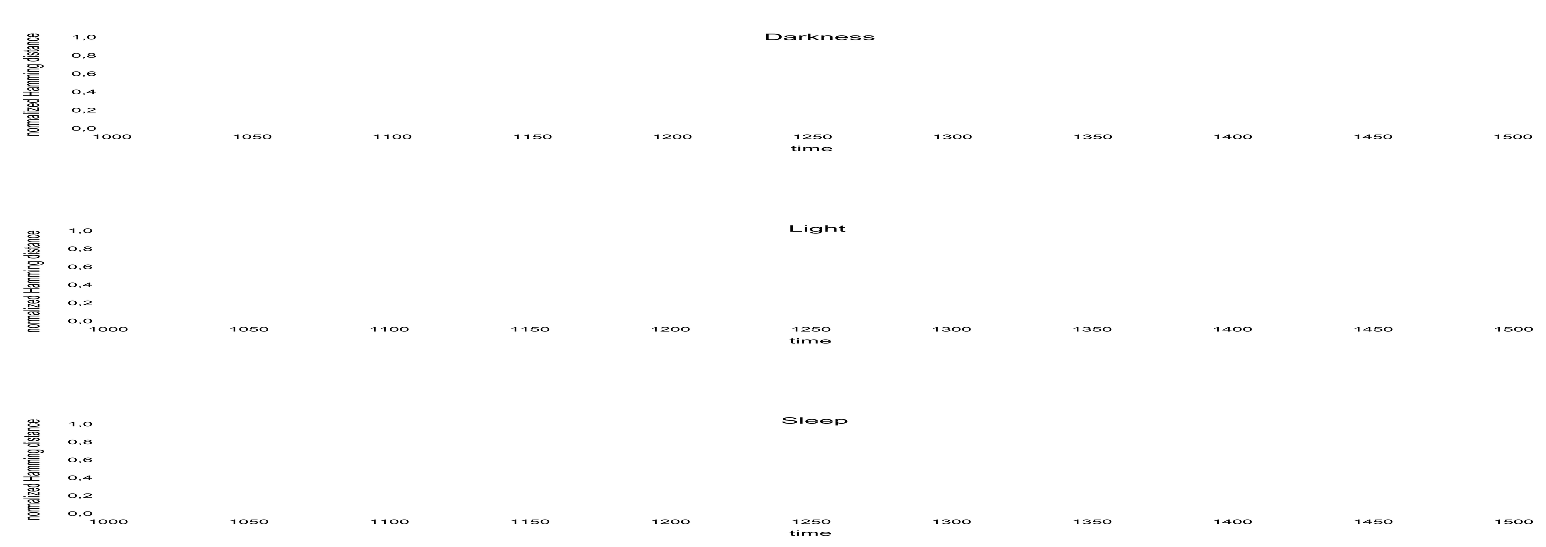
In order to simulate the **sleep** state **no external input** is applied to the network. This experiment shows the **dreaming ability**.



Time series when no external input pattern

Darkness, light and sleep

There is a significant difference when the external input vector consists of only binary **"zero"** constituents, only binary **"one"** constituents and when **no external input** is applied to the network. These cases are called **darkness**, **light** and **sleep** case, respectively. Different behavior in these three cases is noted.



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