A supervised learning approach based on STDP and polychronization in spiking neuron networks

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Plan

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Motivation

- In **Spiking Neuron Networks** (SNNs), information processing is based on the times of spike emissions.
- SNNs are a very powerful new generation of artificial neural networks but efficient learning in SNNs is not straightforward.
- A current track is to simulate the synaptic plasticity, as can be observed by neurobiologists [Bi and Poo,1998] but this method lacks supervised control of learning.

Theoretical fundations

- Theoretically, the use of **delays** increases the learning capacity of SNNs...
  [Maass, 1997] [Schmitt, 1999]

  ... but delays are rarely used in SNN models
- Recent advances in neural networks (ESN [Jaeger, 2001], LSM [Maass et al, 2002]) give interesting results
- The concept of **polychronization** emphasizes the importance of delays for explaining neural activity
  [Izhikevich, 2006]

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Problematics

A better computational power is a good point, but what about the learning algorithm ? How to take advantage of the computational power of delays ?

- We take advantage of polychronous groups activations to monitor activity in the network
- We define a supervised[1] learning mechanism to control the computational power of a SNN

Polychronization will help us monitor and understand the network activity.

[1] simplest way for us to show that polychronization can actually be a reliable information coding

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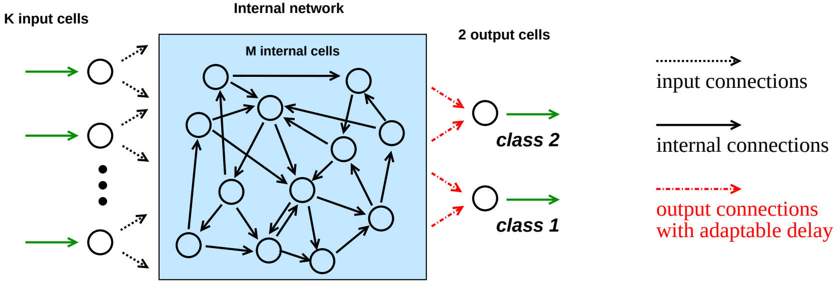
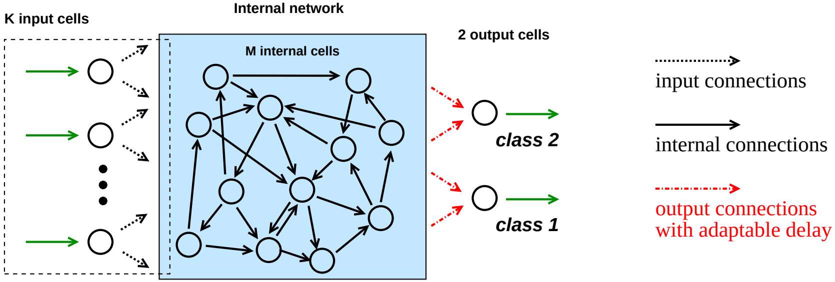
The model

- Maintains biological plausibility within the internal network
- Neuron model : Spike Response Model (SRM_0) [Gerstner 1997]
- Inspired from LSM/ESN architectures :
  - input layer of spiking neurons
  - recurrent randomly connected internal network
  - output layer which supports a supervised learning rule



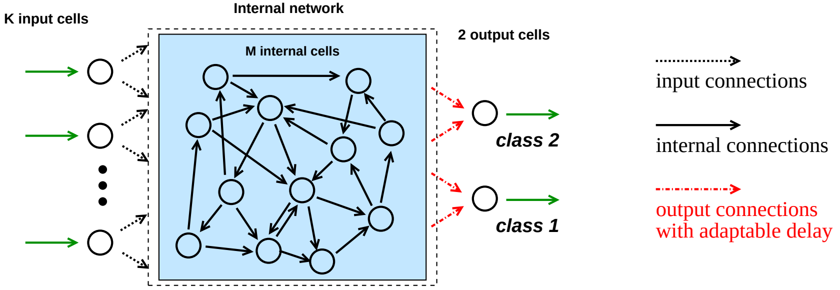
The model



Input layer (stimulation layer) :

- 10 neurons
- Input injection

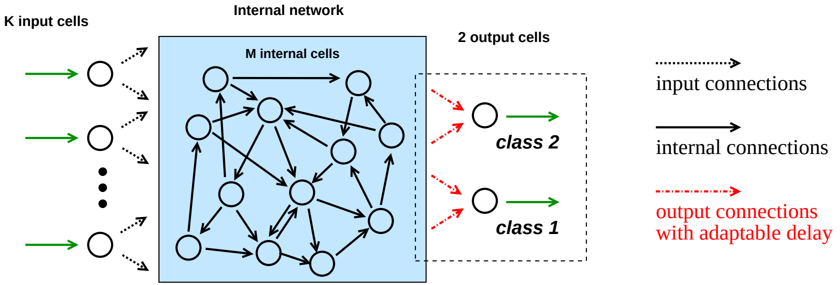
The model



Internal Network :

- 100 neurons, 80% excitatory, 20% inhibitory
- Random recurrent topology
- Connection delays fixed (but randomly chosen) between 1 and 20 ms

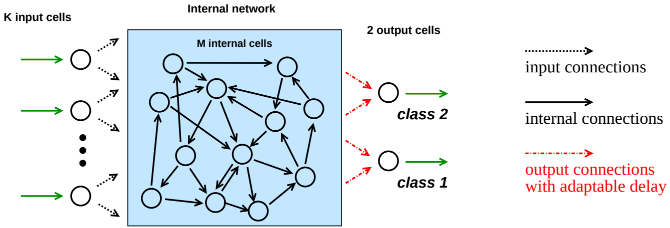
The model



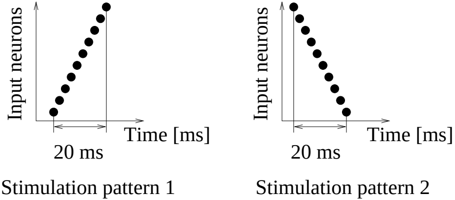
Output layer :

- 2 neurons : one for each target class
- recieves a connection from each internal neuron

The model



- Tested on a classification task
- Two input patterns :
  Target neuron must fire before non-target neuron



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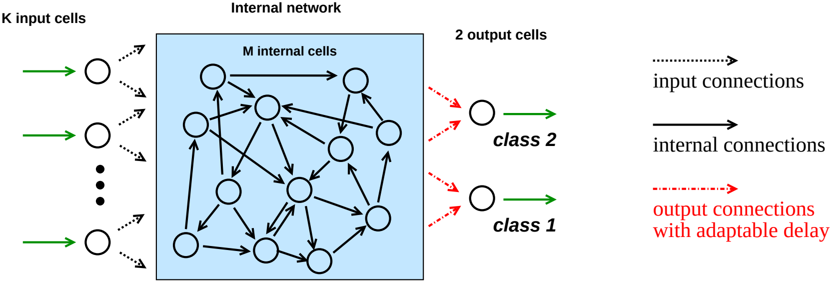
A two scale learning algorithm

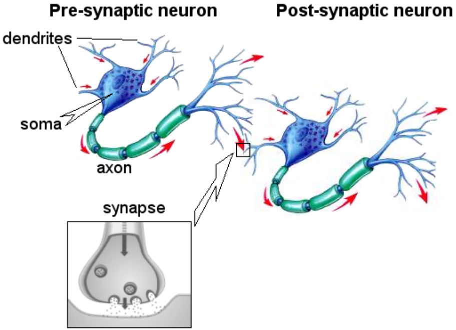


1. **Unsupervised** learning : Spike Time Dependent Plasticity (STDP) within the internal network (ms time scale) [Kempter et al., 1999]
2. **Supervised** mechanism : delay adaptation on output connections (at each input presentation) based on a margin criterion [Vapnik, 95]

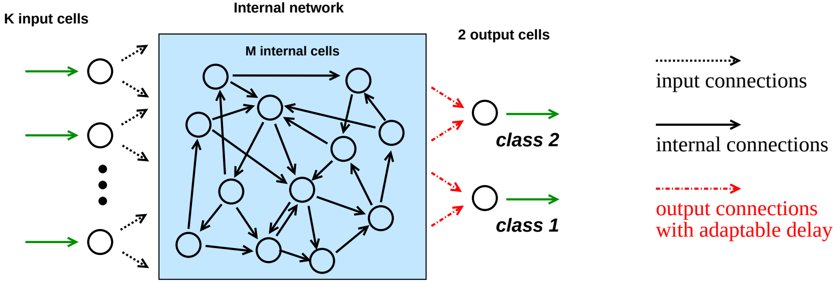
1. Unsupervised learning algorithm

Unsupervised learning : Spike Time Dependent Plasticity (STDP) within the internal network (ms time scale)

- Temporal hebbian rule, suitable for SNNs
- At the synaptic level (local mechanism)
- Depending on activity going through the synapse
- Causality based on spike emissions order



2. Supervised learning algorithm



After the presentation of a given input pattern p,
<u>If</u> target/non-target spikes order is OK
AND
<u>If</u> margin between target/non-target spikes $> \epsilon$

<u>Then</u> : pattern is well classified
<u>Otherwise</u>,

- **for target neuron : decrement the delay ($-1ms$)**
- **for non-target neuron : increment the delay ($+1ms$)**

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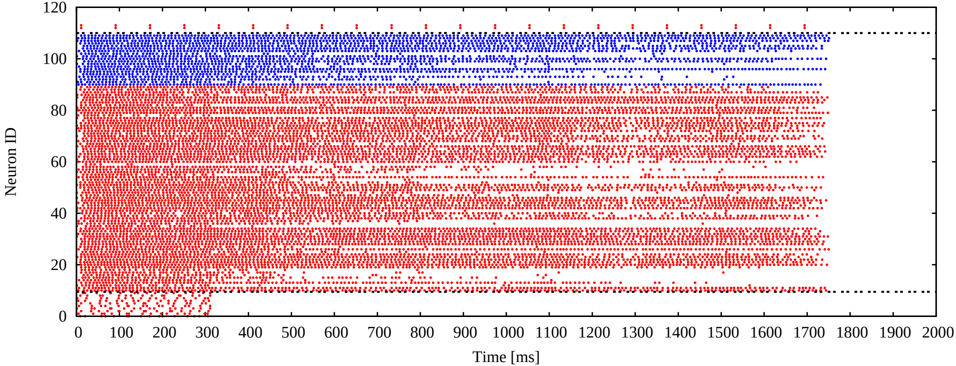
Simulation protocol

- Initial noisy stimulation : noise presented during 300 ms
- Learning phase : alternated presentation of two patterns
- Generalization phase : alternated presentation of the two noisy patterns

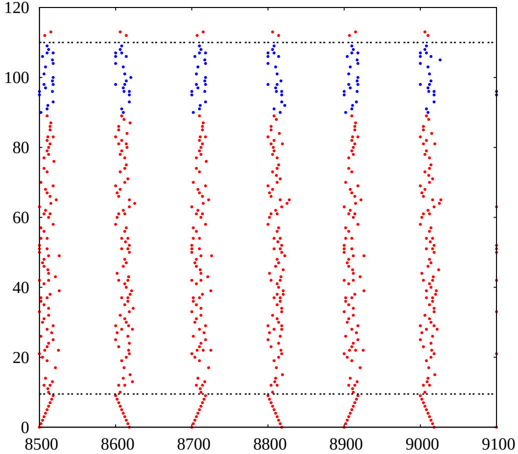
NB : One presentation every 100 ms

Initialization phase



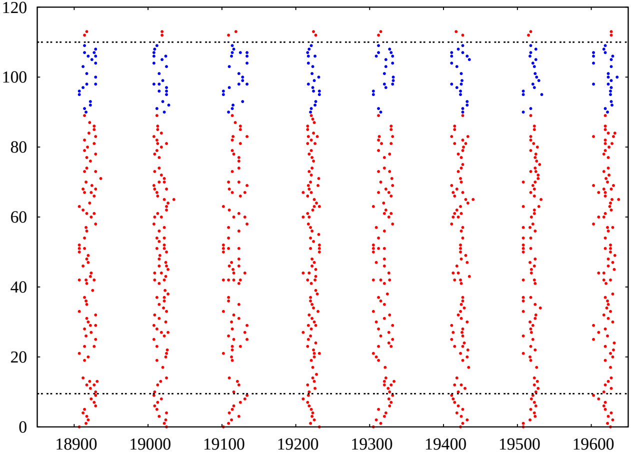
Learning phase observation

- Decreasing internal activity (STDP)
- Activity pattern different from an input to the other
- Margin evolution



Generalization performance

- Error rate with noise 4 : 4%
- Error rate with noise 8 : 19%
- Hard to discriminate by human



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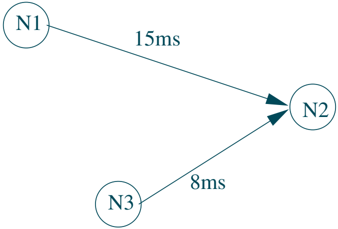
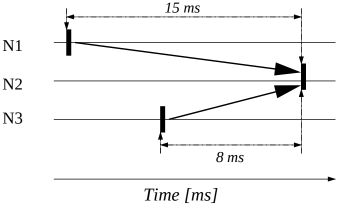
Polychronization [Izhikevich, 2006]

Definition : neuron interactions characterized by spike times following a precise temporal pattern, depending on delays.

Example :





If N_1 emits a spike at t, and N_3 at $t + 7$, then N_2 emits a spike at $t + 15$.

- A set of such interacting neurons is called a **polychronous group**.

Scanning for supported polychronous groups

Structure

Polychronous groups are supported by the topology.

- connections between neurons
- delays of the connections

- A given topology = a particular set of supported polychronous groups
- Each neuron can be involved in several polychronous groups

To find all supported polychronous groups, we use the same algorithm as [Izhikevich 2006].

Dynamics

set of **supported** polychronous groups $\neq$ set of **activated** polychronous groups

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Polychronous groups activations

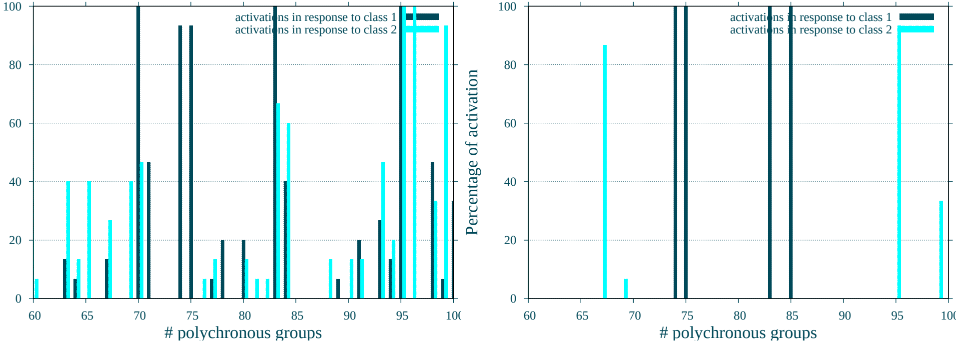

Figure: Activation ratio from 2000 to 5000 ms, and then from 8000 to 11000 ms.

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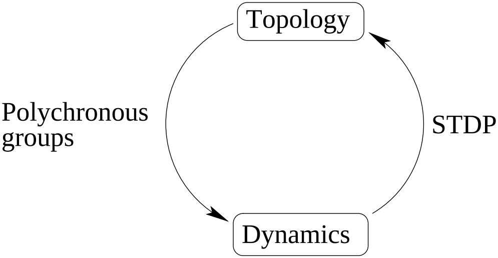
Conclusion

- Algorithm easy to implement
- The learning seems to work on a classification task
- Easily explained by polychronization
- Activity easily monitored with polychronous groups
- Internal network is no longer a black-box contrary to ESN and LSM

Perspectives



Complex network analysis :

- Are polychronous groups the (or a part of the) link between topology and dynamics
- How far ?

Thank you for listening.

Questions !

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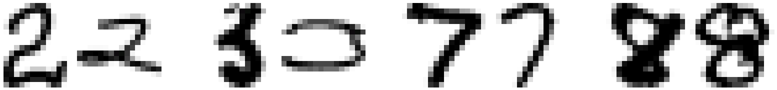
Work in progress

- Use larger inputs : encouraging tests with USPS dataset



2 versus 7 : 96% success on train set, 93% on test set
3 versus 8 : 89% success on train set, 86% on test set

- Switch to more than two classes
- Extend model with persistant activity

retour

Reservoir Computing perspectives : Open questions

Might there be links with reservoir computing. Indeed, some theoretical properties exists : point-wise separation, universal approximation, echo state properties...
But still difficulties to investigate what's going on in the reservoir (refering to special session)
Polychronous groups can be a reliable way

- to analyse dynamics of a spiking neuron reservoir
- to find optimal topologies (structures)

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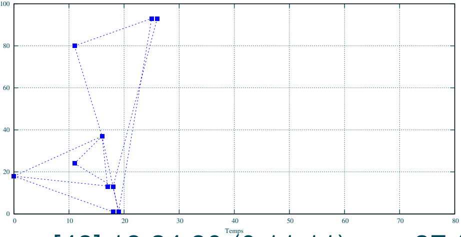
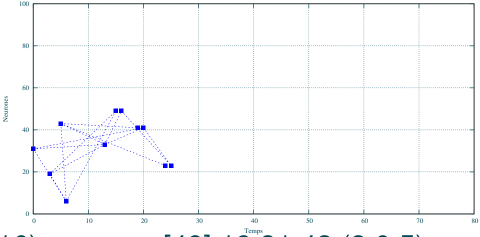
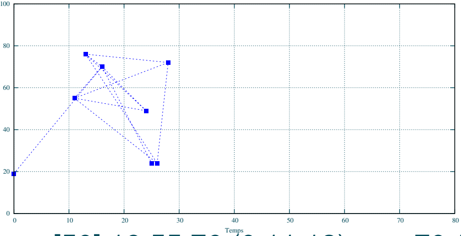
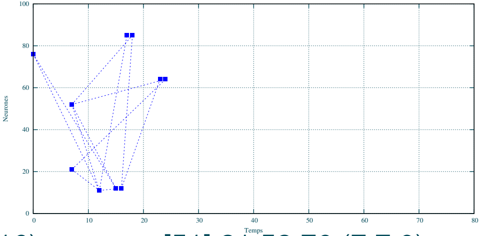
Groupes polychrones sur 100 neurones





[48] 18,24,80 (0,11,11) ==> 37 (16) — [49] 19,31,43 (3,0,5) ==> 6 (6)



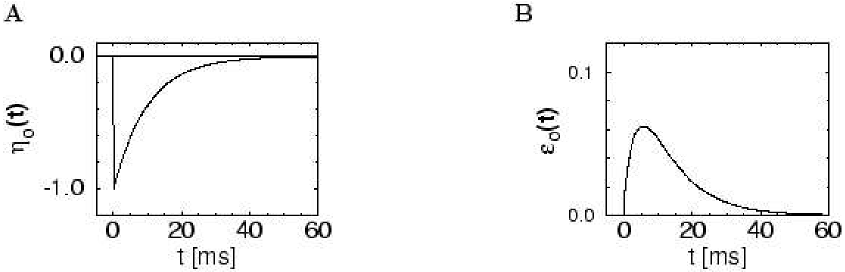


[50] 19,55,76 (0,11,13) ==> 70 (16) — [51] 21,52,76 (7,7,0) ==> 11 (12)

retour

Modèle SRM_0 (used)

$$u_j(t) = \underbrace{\eta(t - t_j^f)}_{\text{A : refractory periode}} + \sum_i w_{ij} \underbrace{\epsilon(t - t_i^f - d_{ij})}_{\text{B : excitatory potential}}$$



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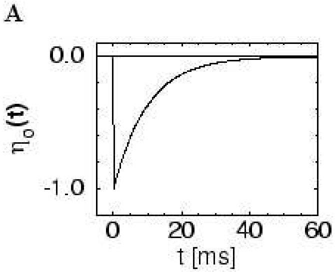
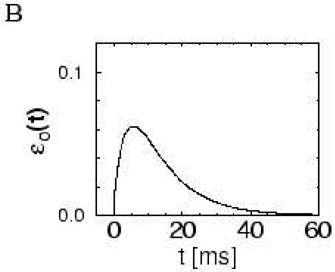
Modèle SRM_1

$$u_j(t) = \underbrace{\eta(t-t_j^f)}_{\text{A : refractory periode}} + \sum_i w_{ij} \sum_f \underbrace{\epsilon(t-t_i^f-d_{ij})}_{\text{B : excitatory potential}}$$





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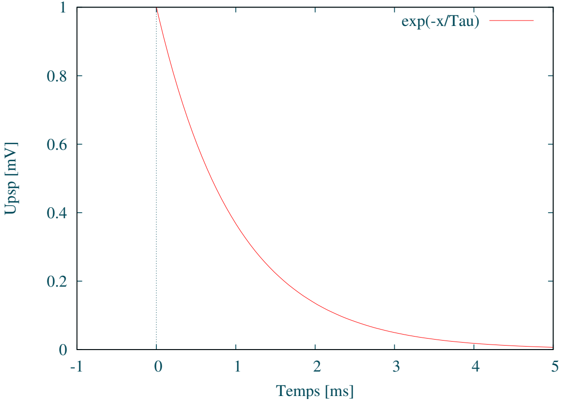
Forme d’un PPS



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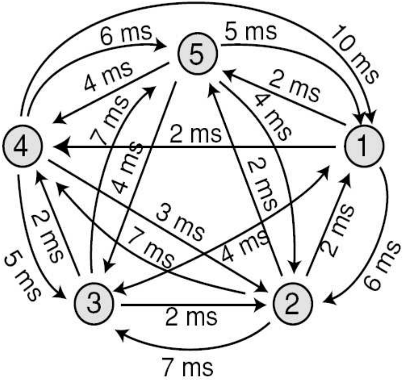
Réseau expérimental



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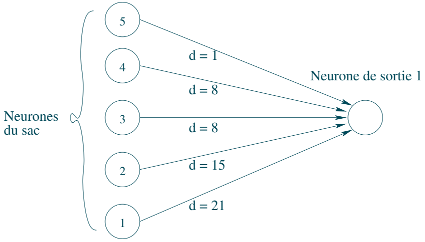
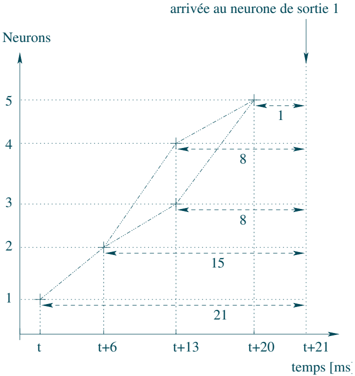
Sensibilité à un motif spécifique





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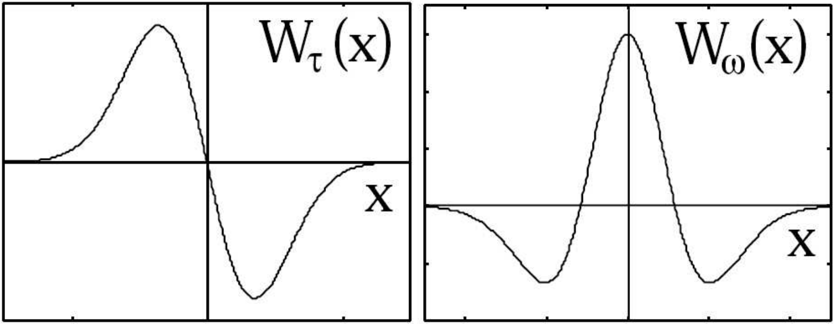
Fenêtre STDP Eurich



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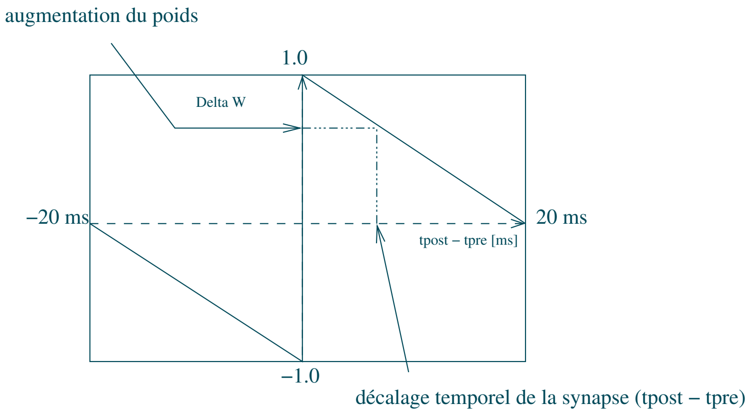
Fenêtre STDP classique



retour

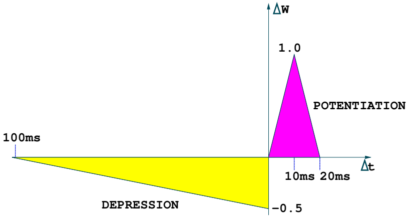
Fenêtre STDP Meunier

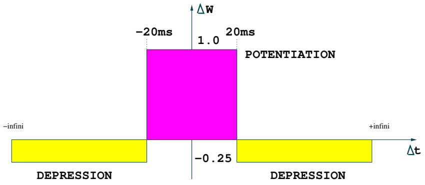
Si $\Delta W \leq 0$, le poids est augmenté :

$$w_{ij} \leftarrow w_{ij} + \alpha * (w_{ij} - w_{min}) * \Delta W$$

Si $\Delta W \geq 0$, le poids est diminué :

$$w_{ij} \leftarrow w_{ij} + \alpha * (w_{max} - w_{ij}) * \Delta W$$





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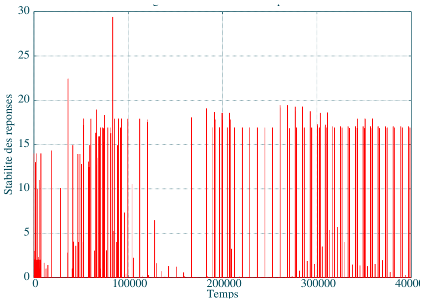
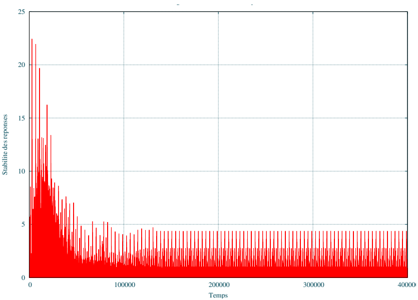
Stabilité du classifieur





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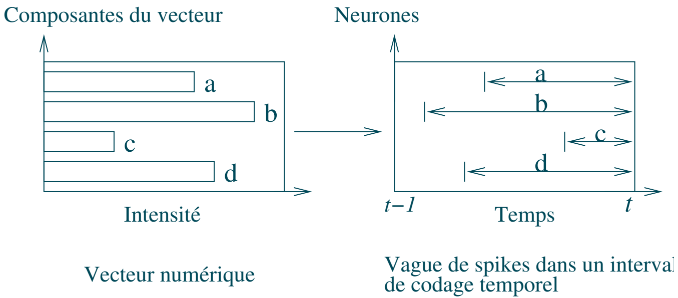
Codage temporel



Codage en intensité

Codage temporel

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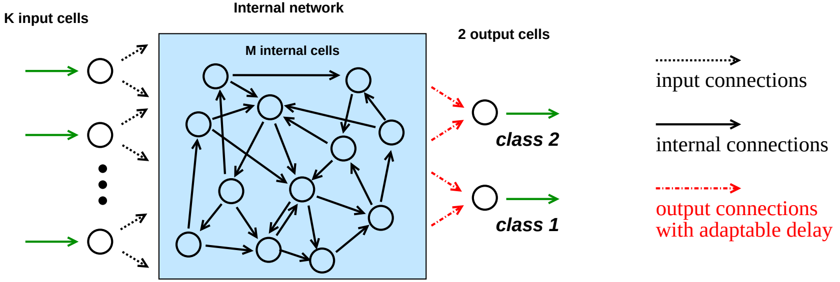
Architecture



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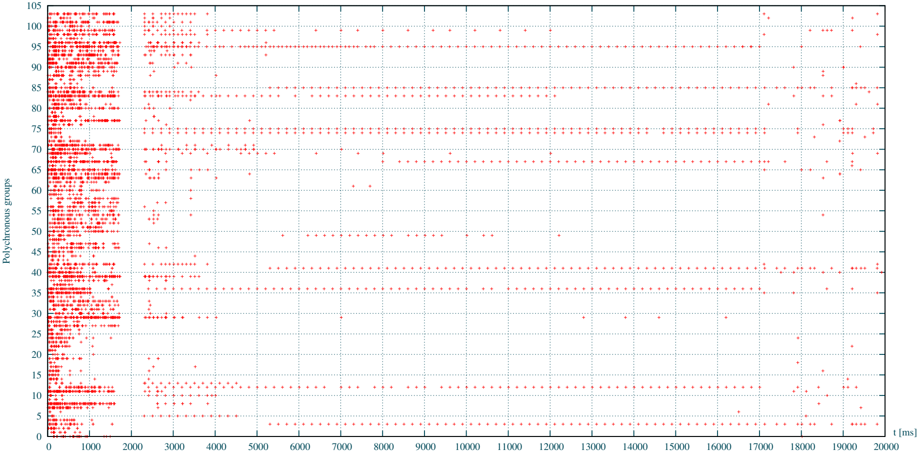
Activation des groupes polychrones



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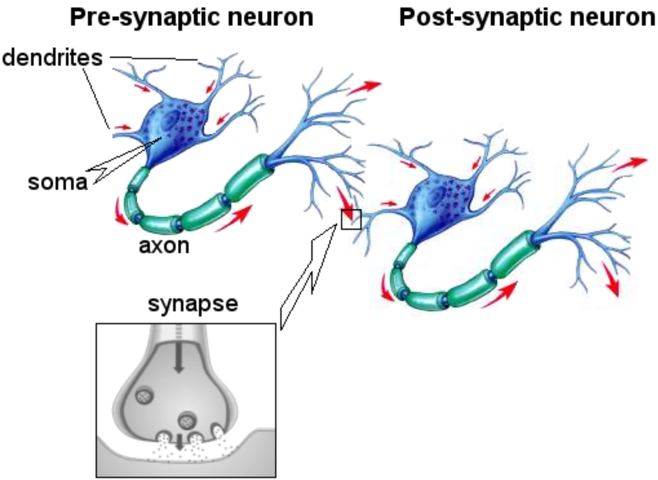
Activité neuronale



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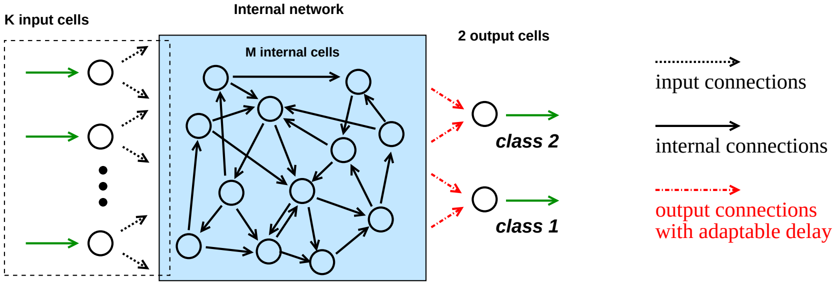
PG detection

To find all supported polychronous groups, we use the same algorithm as [Izhikevitch 2006]. It consists in scanning for spike time combination of all groups possible of 3 neurons (i.e. combinatorial quiestions), so that the spikes would trigger the firing of one or more impacted neurons, taking axonal delays into account.

Il est possible de procéder de même en cherchant plus de déclencheurs, mais la complexité est accrue: $O(n^p)$, avec p nombre de déclencheurs. retour

The model proposed



Input layer (stimulation layer) :

- 10 neurons
- Outgoing connection probability : 0.1
- Delay to central assembly : 0 ms

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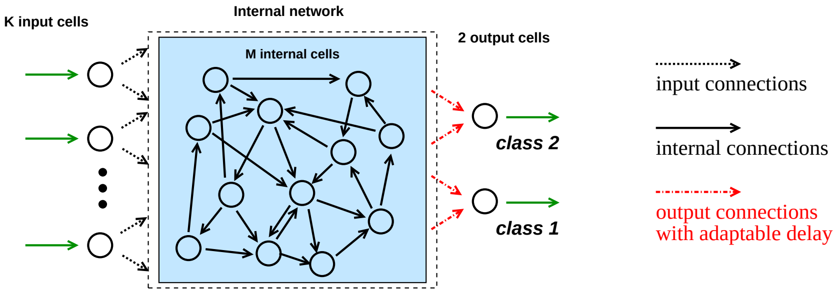
The model proposed



Central assembly :

- 100 neurons, 80% excitators, 20% inhibitors
- Random topology
- Reccurent connection probability : 0.3
- Recurrent connections delay from 1 to 20 ms
- Spike Time Dependent Plasticity (STDP)

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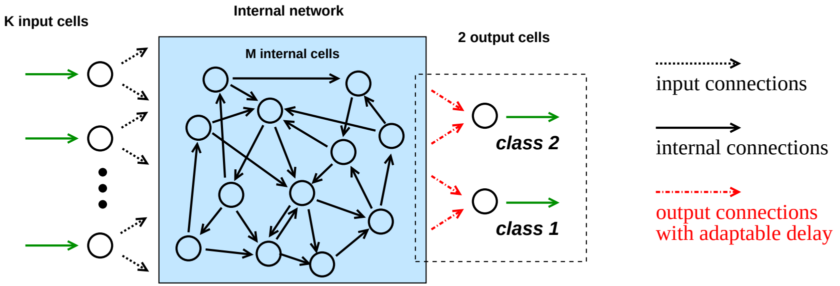
The model proposed



Output layer :

- 2 neurons : one for each target class
- Incoming connection probability : 1 (central assembly completely projected)
- Adaptable delays of input connections (all initialized to 10 ms)

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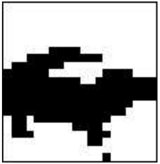
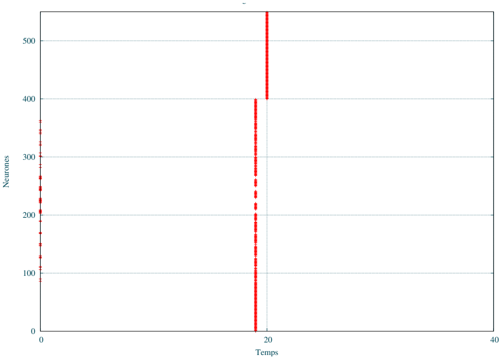
Initial work

- Originally : problem for learning binary patterns
- Spike responses : all or nothing
- Solution : allow diversity in axonal delays





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Difference with synfire chain

in **Synfire Chains and Catastrophic Interference** – J. Sougné and R. French (2001) :

> *when an initial neuron, A, fired, a second neuron, B, would fire 151ms later, followed by a third neuron, C, that would fire 289ms later with a precision across trials of 1 ms*

in **Polychronization : computation with spikes** – E. Izhikevich (2006) :

> *Synfire chains describe pools of neurons firing synchronously, not polychronously. Synfire activity relies on synaptic connections having equal delays or no delays at all. Though easy to implement, networks without delays are finite-dimensional and do not have rich dynamics to support persistent polychronous spiking.*

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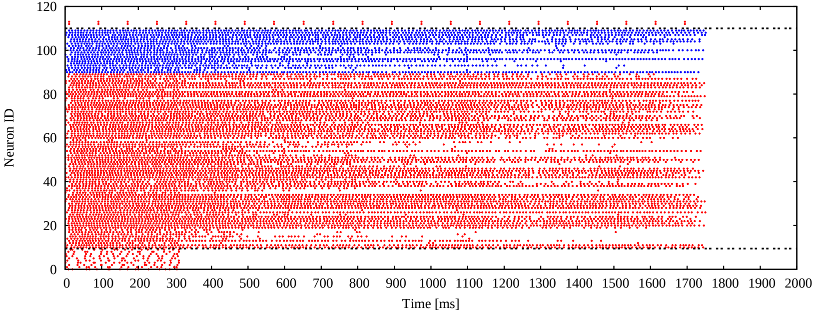
Initialization phase



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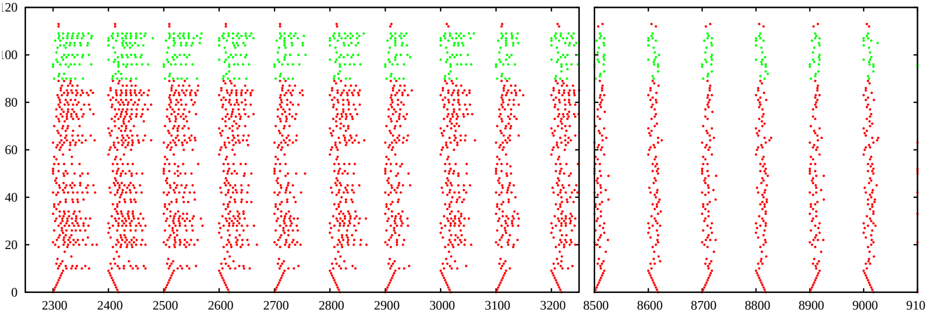
- Margin evolution



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Generalization performance

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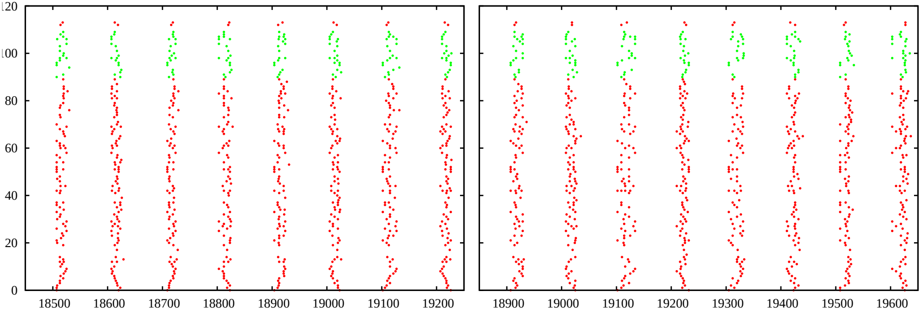

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