Sciences cognitives et robotique: le défi de l'apprentissage autonome

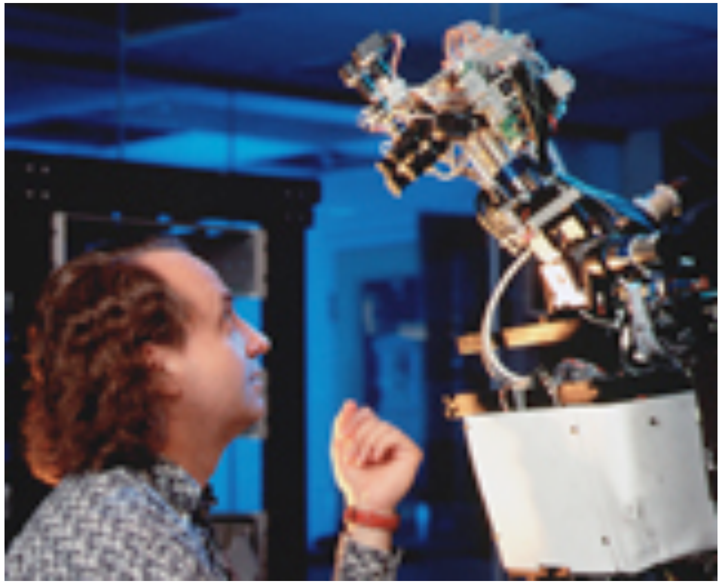
P. Gaussier

ETIS, UMR 8051

ENSEA, Université Cergy Pontoise, CNRS

IUF

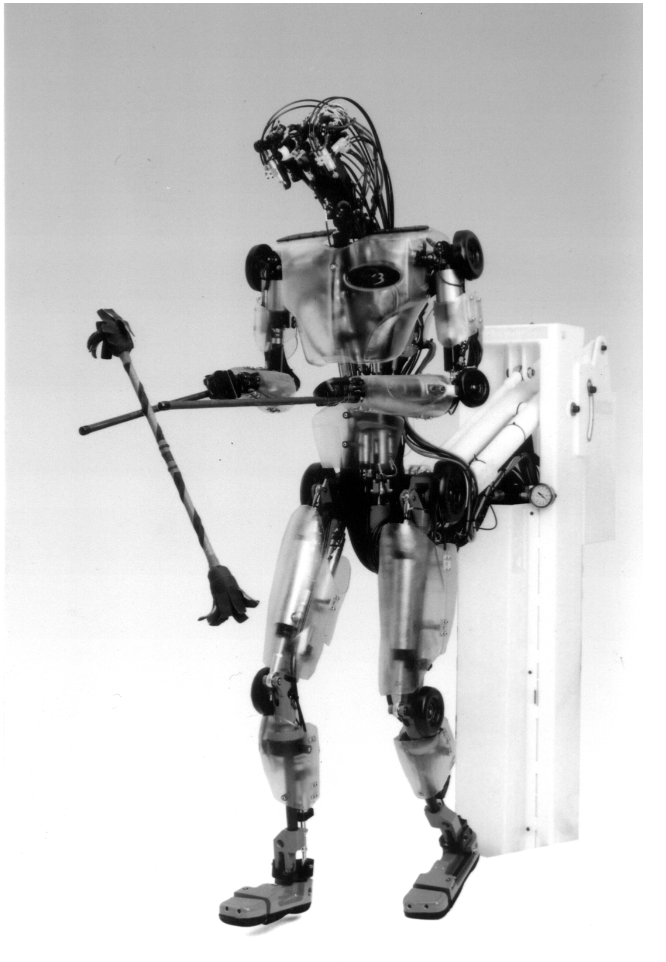
Les robots humanoides

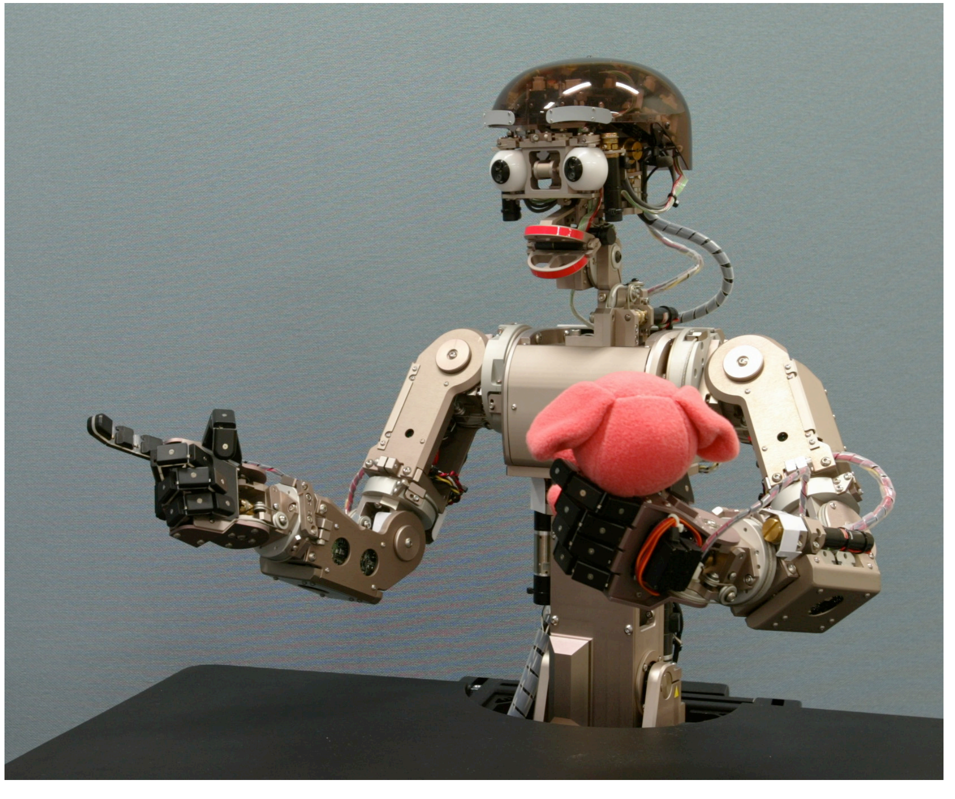


Cog

(R. Brooks MIT)

(G. Chen ATR)





Infanoid

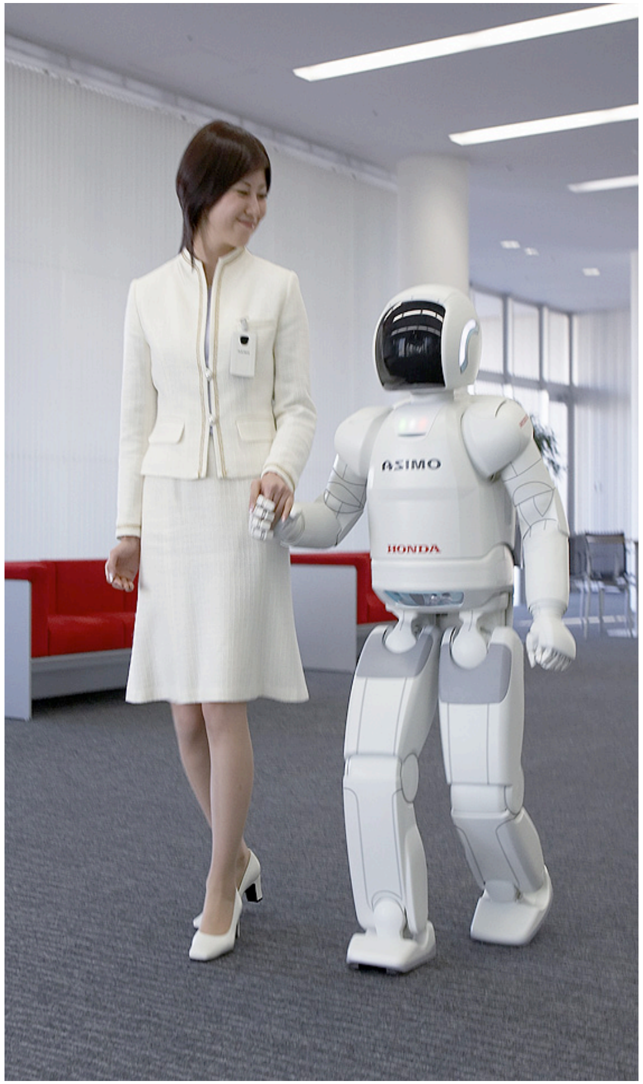
(I. Kosima

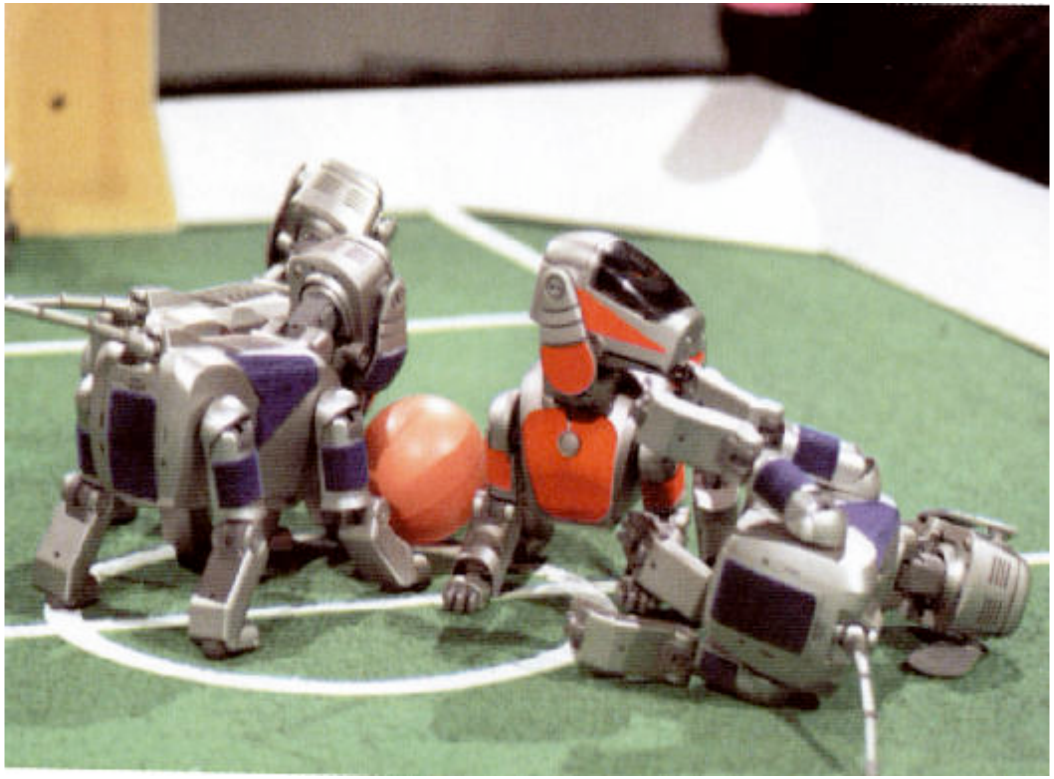
NICT)

(Scasselatti, Schall, Billard,

Kedar, Laumond, Metta, …)

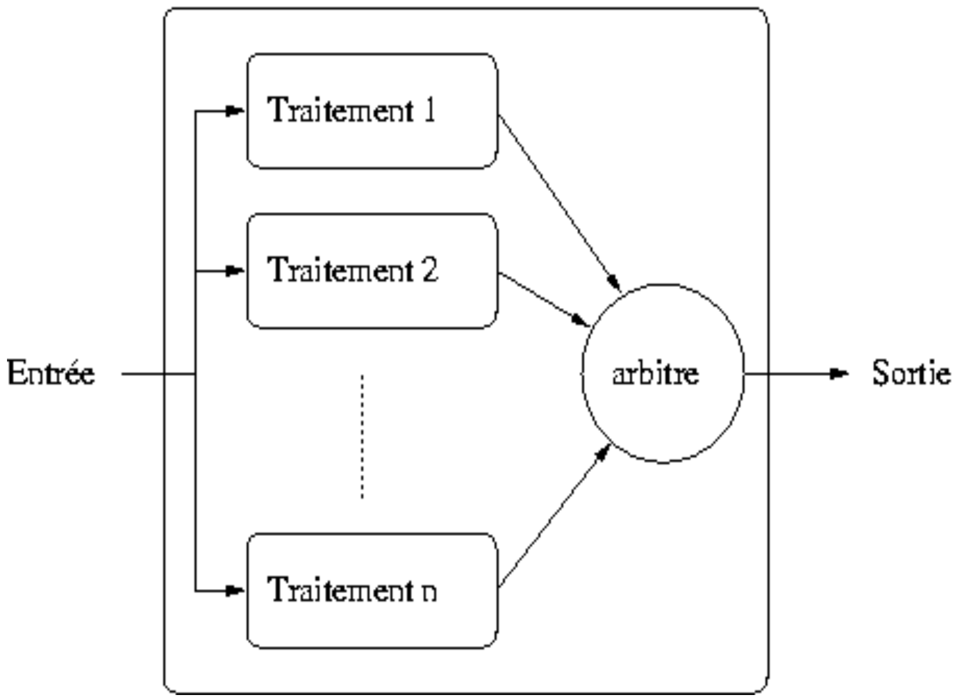
Les robots : outil et/ou modèle





Des ordinateurs champions d'échecs
Mais des robots qui ne savent pas très bien tenir debout ni mettre la table !!

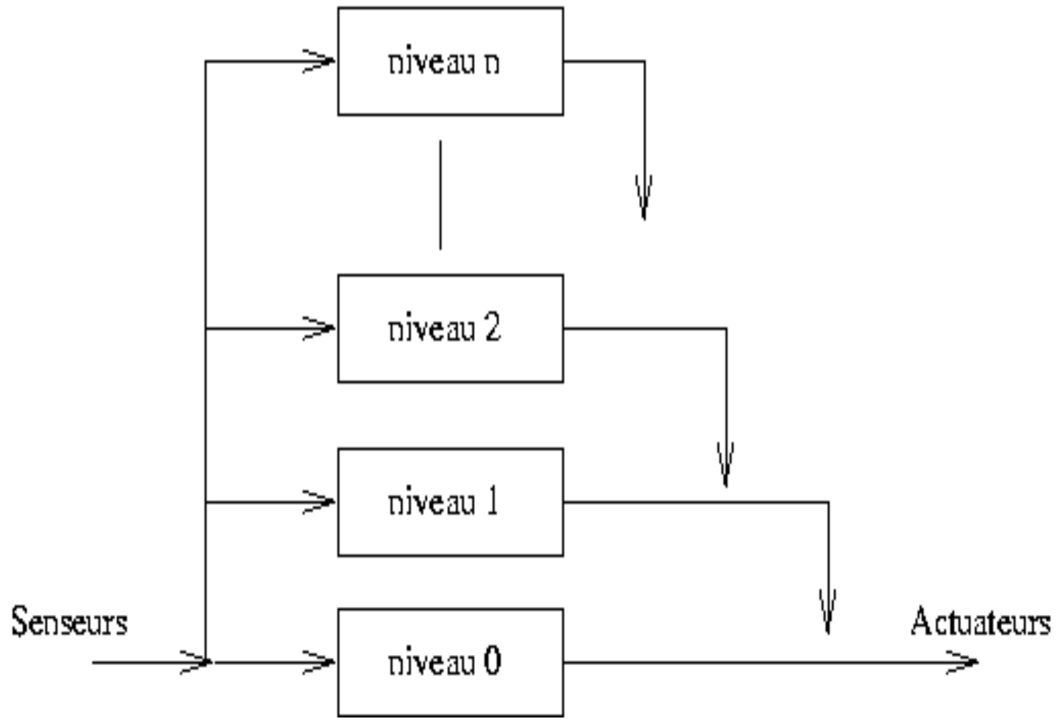
Approche comportementale



Arbitrage:
- Somme
- Max
- Modulation / motivation

Importance de la stratégie d'arbitrage :
- comportements indépendants
 (simple sommation de champs de potentiel, R. Arkins, O. Khatib, P. Maes, L. Steels...)
- comportements interdépendants (R. Brooks, Tyrrel...)

Approche subsumption



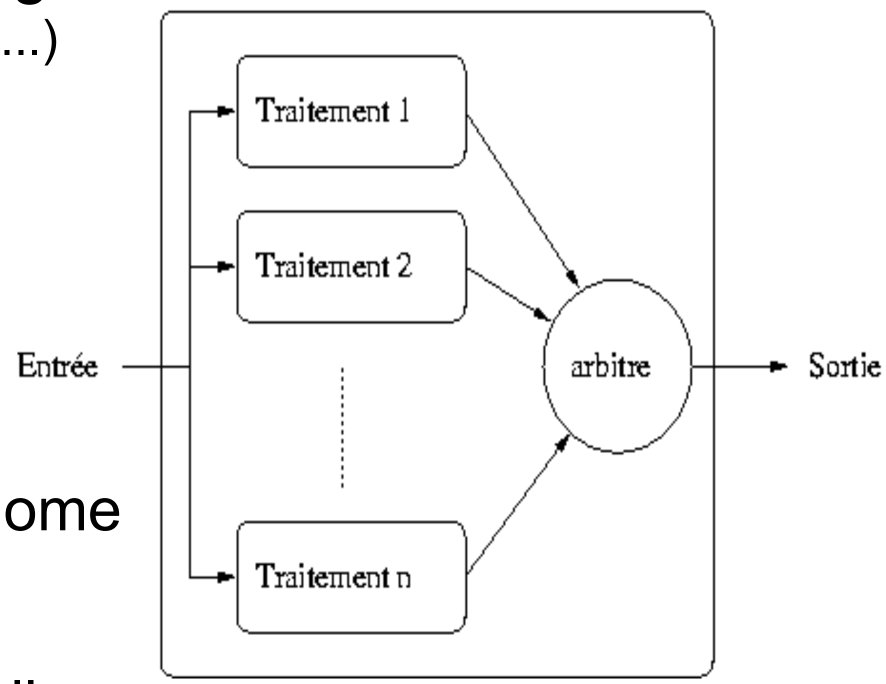
(Brooks 86)

Système préemptif en strates:

- Les couches de plus haut niveau peuvent subsumer le rôle des couches de plus bas niveau (notion de priorité).
- Bas niveau exécution rapide (temps réel)
- Haut niveau (mise à jour plus lente)

Problèmes:

Importance de la stratégie d'arbitrage :
(R. Arkins, O. Khatib, P. Maes, L. Stells, Tyrrel...)



Possibilités d'apprentissage simple (coefficients multiplicatifs , apprentissage par renforcement)

Mais pas de réel apprentissage autonome

- fonctions et comportements sont elles parfaitement superposables?
- 1 comportement = 1 fonction

➔ Explosion du travail à faire si l'on veut obtenir une capacité à avoir des comportements complexes (+ risque d'échec cf Aibo)

Les défis de demain

-Apprentissage **autonome** et en **temps réel** de comportements complexes (développement de compétences)
- Adaptation à des environnements a priori inconnus
- Interactions homme/ machine « non verbales »

Neurosciences et robotique (IA)

Différents points de vue:

- aucun intéret...
- source d'inspiration
- Comprendre des mécanismes cognitifs (niveau global)

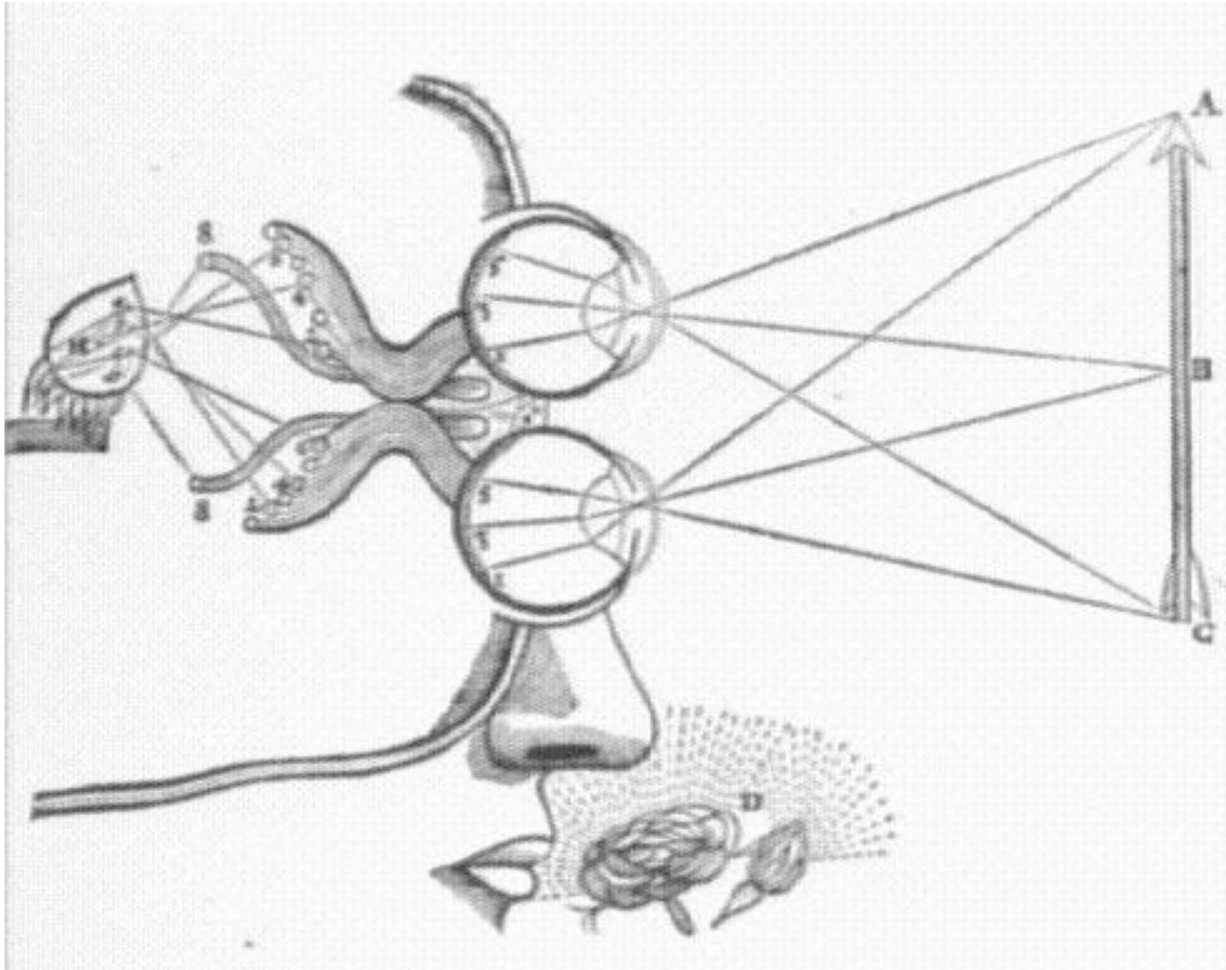
Actroid (Yshiguro)

Cognition située (Dennet91)

Embodied cognition (Varela93)

Le problème de l'homoncule

Descartes



Système visuel des primates

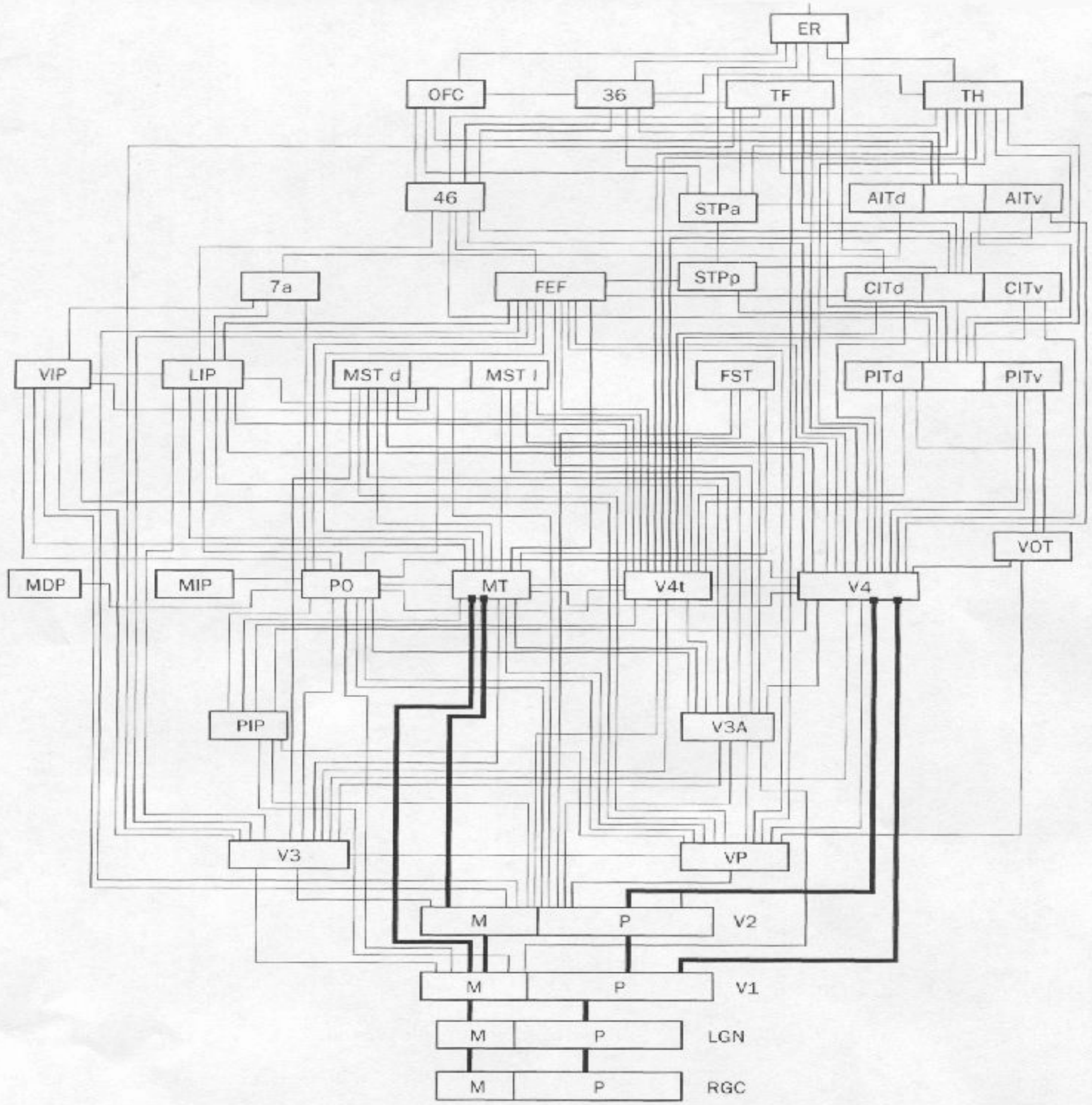


FIGURE 4.15 Diagram showing the hierarchical arrangement of visual processing stages, starting with the retina (bottom of diagram) and moving up through the multiple visual areas of the brain. The bold lines show the P and M pathways discussed in the text. (Adapted from Felleman and Van Essen, 1991.)

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(Van Essen 91)

Problème:

Connaître l'activité d'un neurone n'aide pas forcement à comprendre le processus cognitif !

Solution:

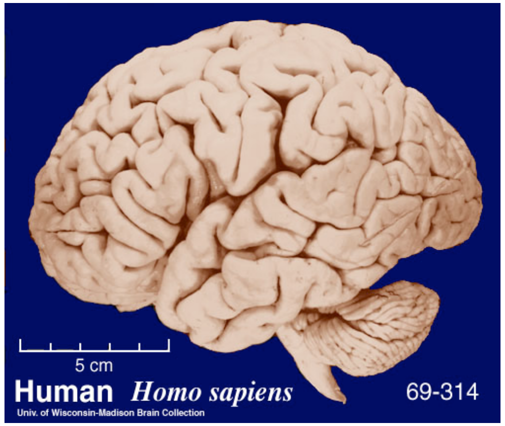
Comprendre le lien entre activité neuronale et dynamique comportementale.

Notre approche

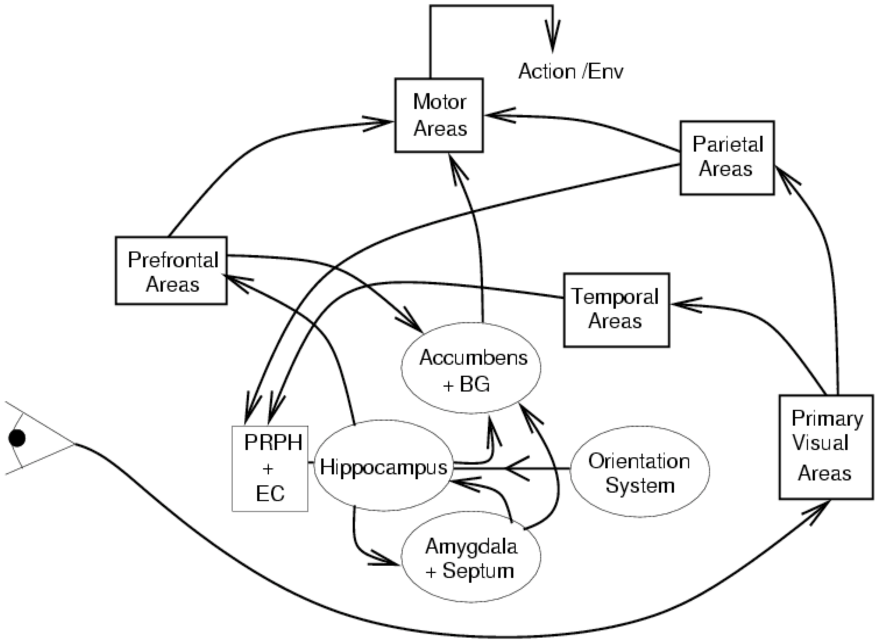
Trouver un modèle minimal justifié par des arguments théoriques forts:

- Prendre en compte un **minimum** de structures biologiques,
- Essayer de comprendre ce qu'apporte une entrée ou structure donnée pour un comportement global (sinon pas pris en compte),
- Utiliser les robots pour tester les implications comportementales d'un modèle (preuve par l'échec!)

Cognition, cerveau, neurones...



-Developpement
-Interactions sociales



Limites d'une approche réductionniste….

« Virtual » Laboratory

Joint works with:

- Jean Paul Banquet : neurobiological modelling
- Bruno Poucet (Marseille 3C): exp. neurobiology

- Jacqueline Nadel: developmental psycho pathology
  (+ inter-lab. association CNRS)
- Yann Coello, Yvonne Delevoye (URECA-Lilles),
  F. Ben Ouezdou (LISV-Versailles)
  ANR INTERACT / SESAME TINO
- Lola Cañamero (**Feelix growing** UE STREP project)
  Adaptive Systems Research Group, U. of Hertfordshire, UK
- ANR Neurobot (S. Wiener, B. Poucet…)

Plan:

- Point de vue sciences cognitives de l’apprentissage
- Apprentissage sensori-moteur et « perception »
- Impact du contexte social sur l’apprentissage: le cas de l’imitation
- Emotions et apprentissage

PARTIE 1

Point de vue “sciences cognitives” sur les différentes formes “d’apprentissage”

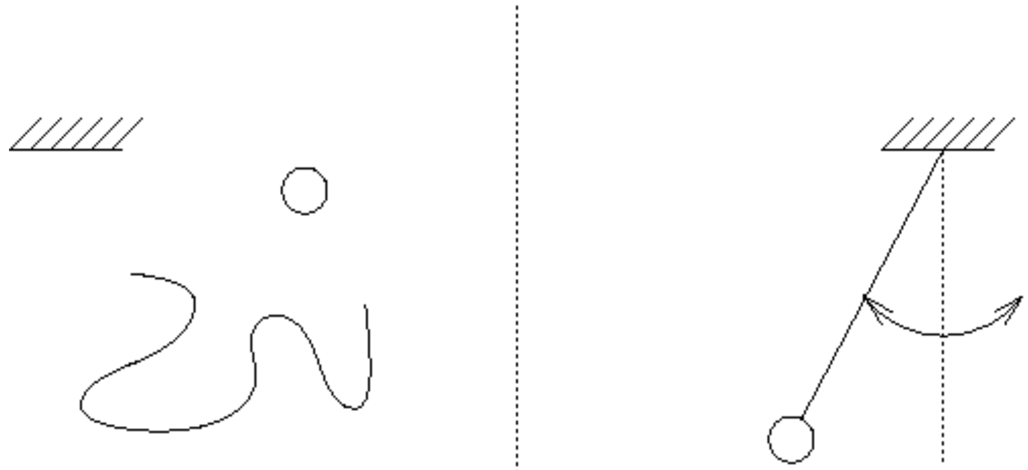
« Les sciences cognitive regroupent un ensemble de disciplines scientifiques dédiées à l'étude et la compréhension des mécanismes de la pensée humaine ou animale, et plus généralement de tout système cognitif, c'est-à-dire tout système complexe de traitement de l'information capable d'**acquérir**, **conserver**, **utiliser** et **transmettre** des connaissances… ».

(wikipédia)

Propriété émergente

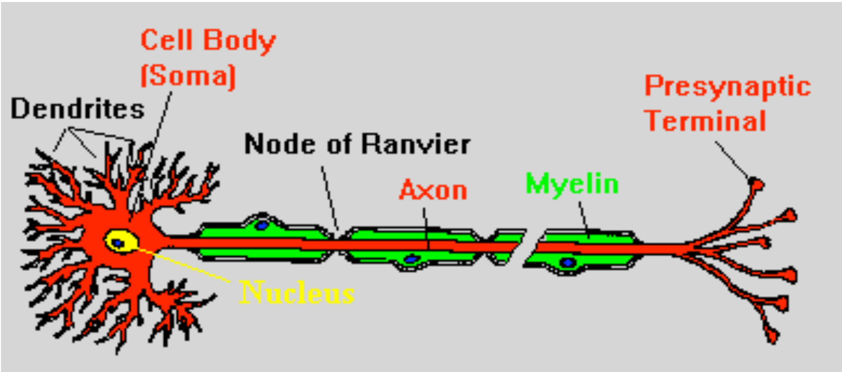
« Le tout est plus que la somme de ses parties »

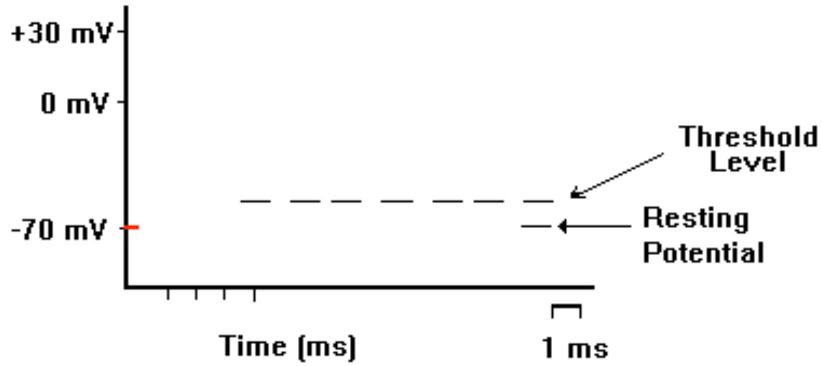
Effet constitutif lié la dynamique
(propriété « émergente », Gestalt)



(K. Lorenz 75)
Autopoïèse (Maturana et Varela 80)
Vie = cognition (Stewart 94)

L'activité du neurone

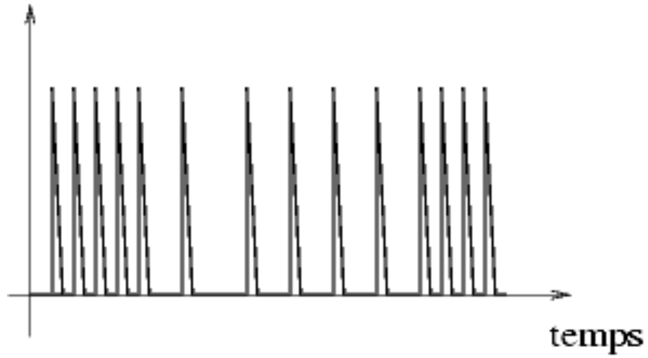


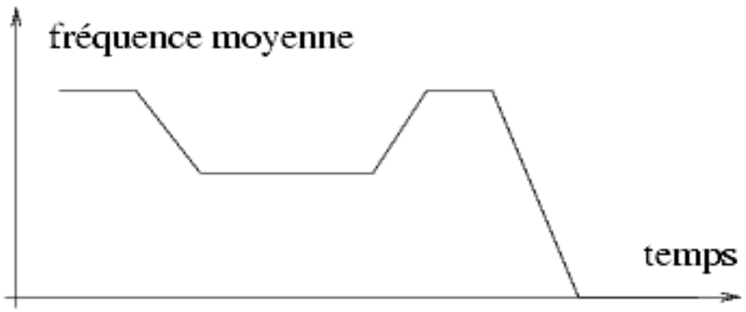


Potentiel (interne) P(t) du neurone et freq. décharge y :

$$\begin{cases} \dfrac{dP}{dt} = -\lambda\left(P(t) - P_{\min}\right) - \left(P(t) - P_{\min}\right) \displaystyle\sum_{k=1\ldots p^-} w_k^- \, x_k + \left(P_{\max} - P(t)\right) \sum_{k=1\ldots p^+} w_k^+ \, x_k \\ y = f(P,\theta) \text{ avec } f(P,\theta) = 0 \text{ si } P < \theta \text{ et } f(P,\theta) > 0 \text{ et croissante sinon} \end{cases}$$

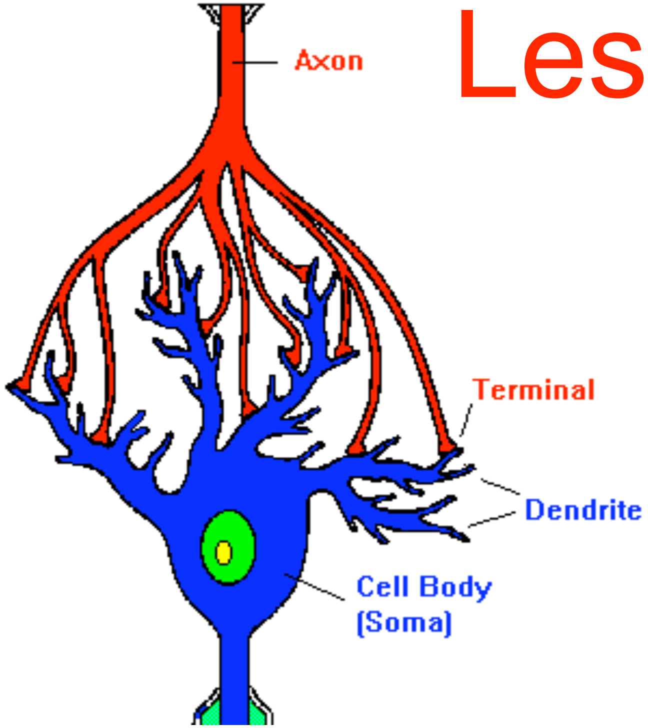
➔ dyn. Interne du neurone (effet mémoire à court terme)

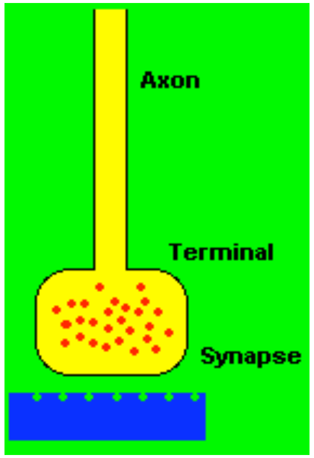


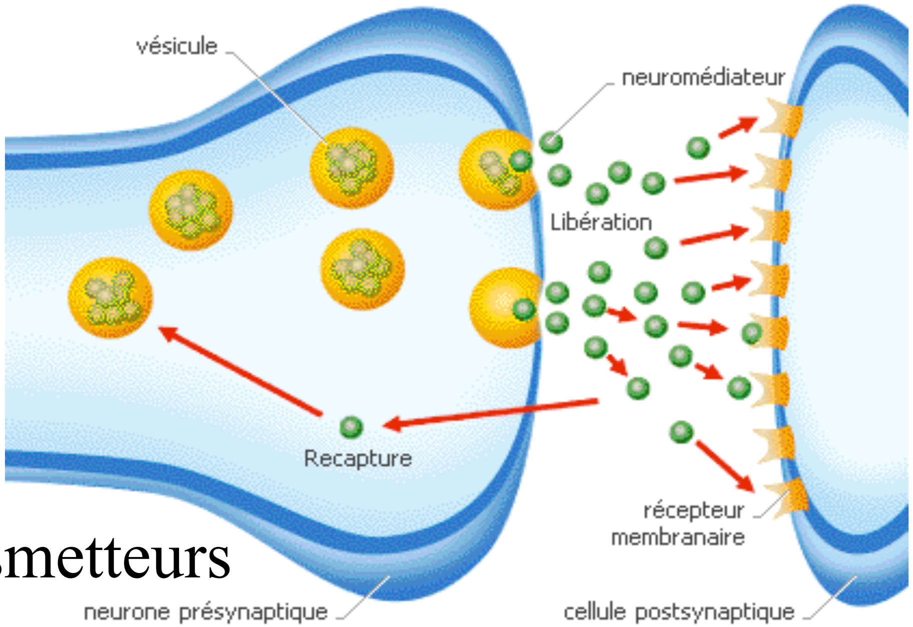


Souvent ajout param. habituation/sensibilisation
(au niveau du corps cellulaire ou des synapses)

Les synapses





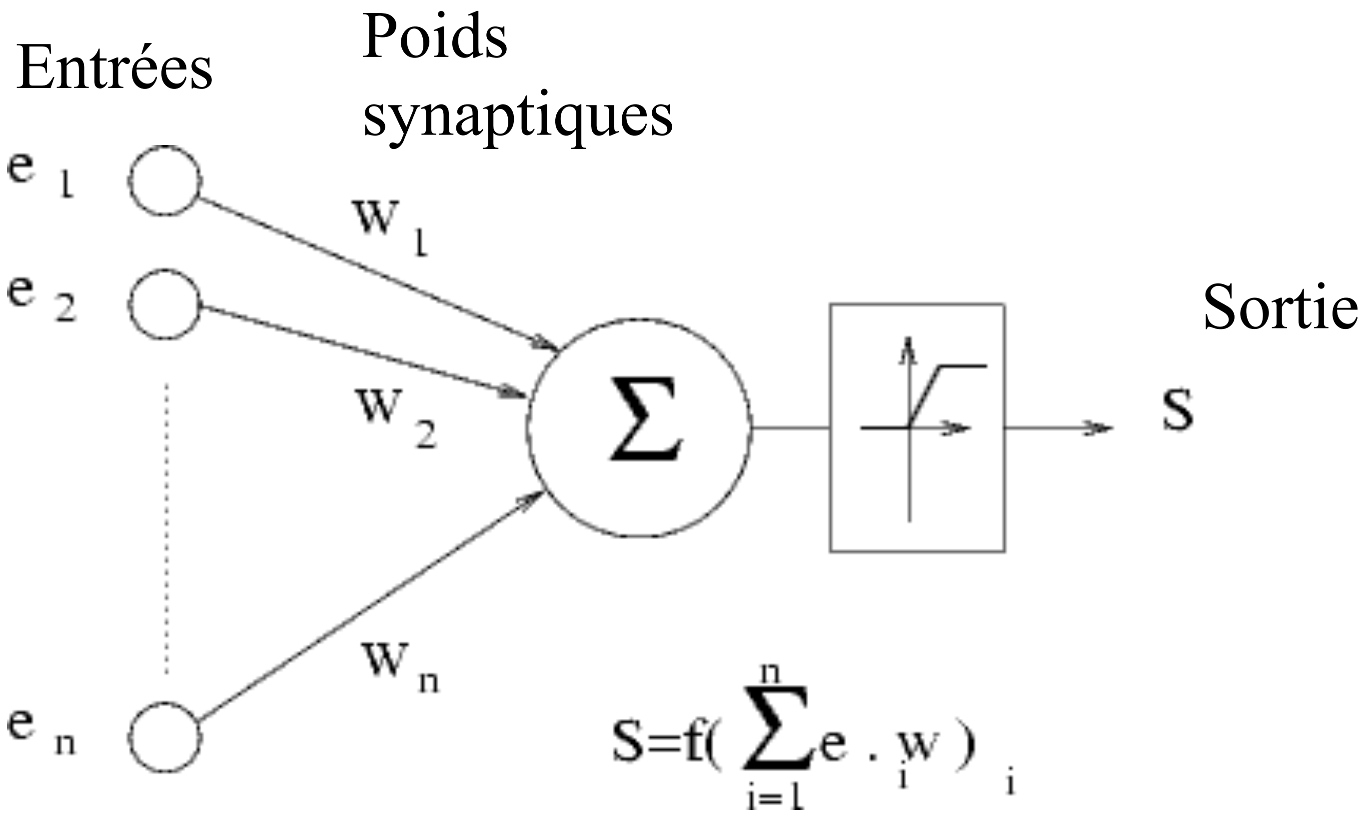


Transmission
de l'information

Attention:

≠ types de synapses/neurotransmetteurs
≠ types de neurones
≠ types de neuromodulateurs

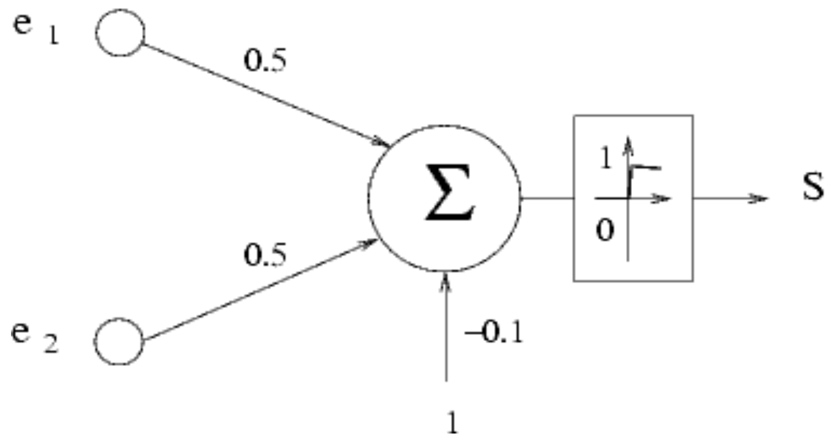
Modèle de neurone formel



(Fréquence moyenne de décharge)

Modèle de neurone formel

Exemple 1:



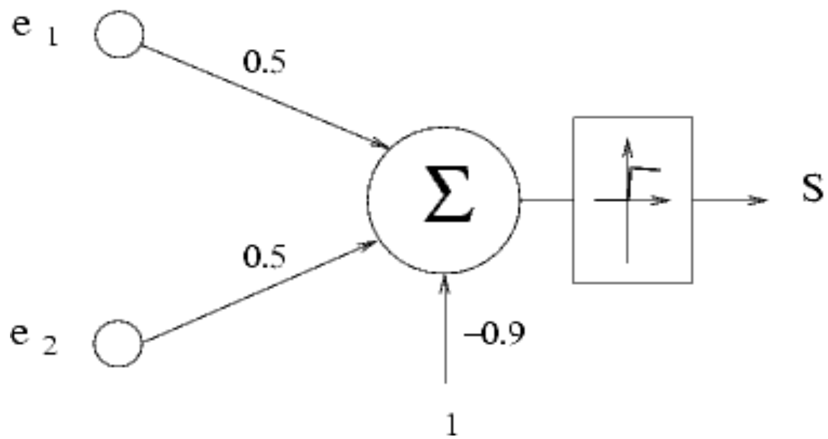
e_1	e_2	S
0	0	0
0	1	1
1	0	1
1	1	1

0=FAUX
1=VRAI

OU logique

Modèle de neurone formel

Exemple 2:



e_1	e_2	S
0	0	0
0	1	0
1	0	0
1	1	1

0=FAUX
1=VRAI

ET logique

Modèle de neurone formel

En connectant correctement ces neurones formels, il est possible de réaliser n'importe quelle fonction logique.

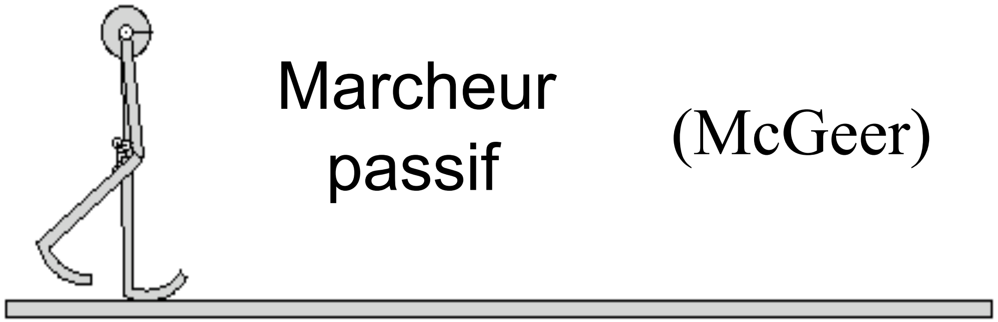
Capacité de calculateur universel...

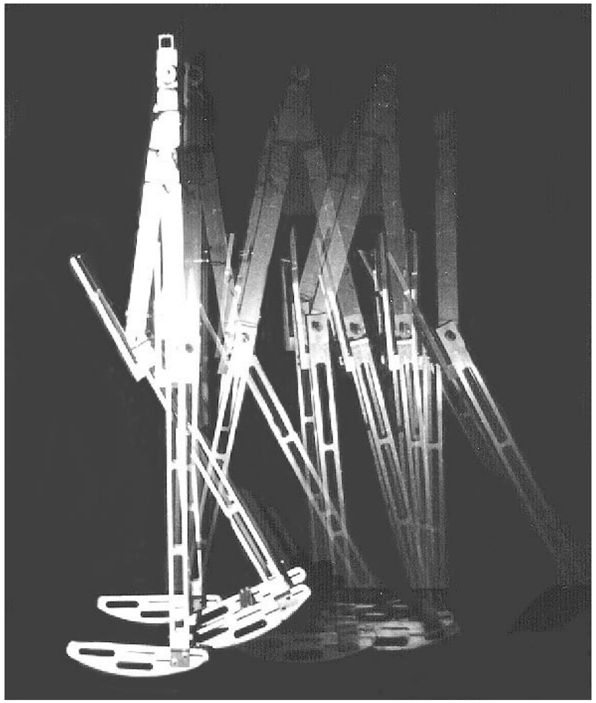
+ réseaux récurrents:

possibilités de dynamiques complexes

➔ bifurcations, chaos

Importance interactions physiques (embodiement)





Véhicules de Braitenberg

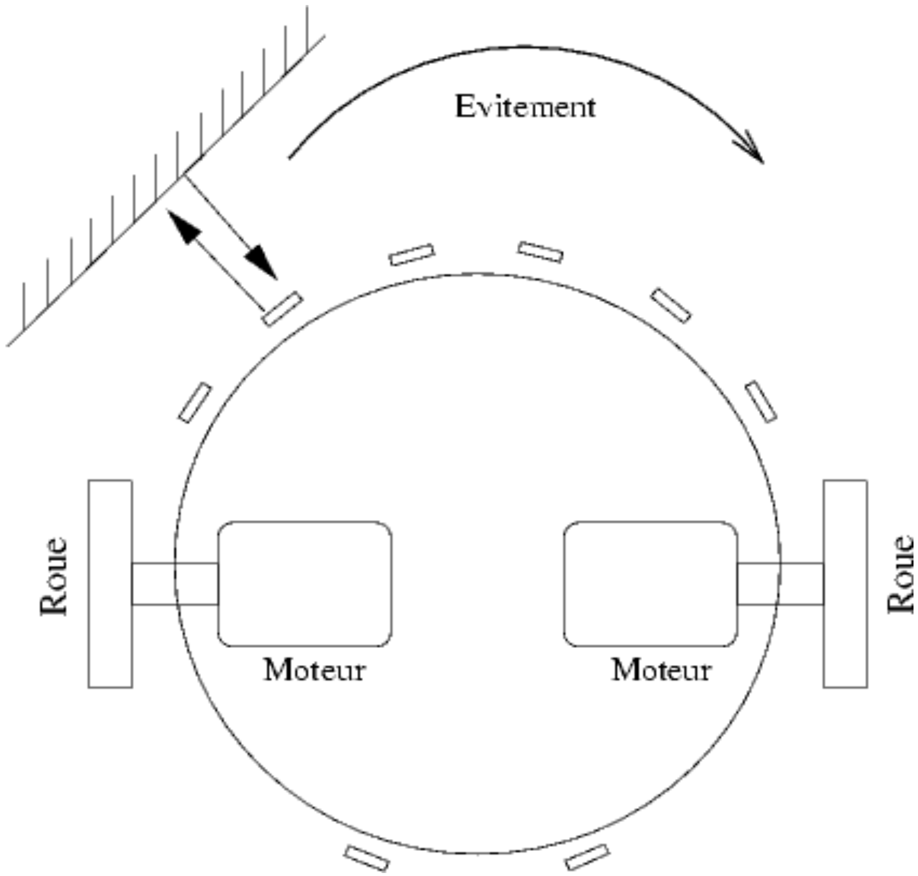
- Phototaxie: attraction par la lumière
- Evitement d'obstacles
- ...

Un réseau de neurones minimal:

- N capteurs
- 2 moteurs

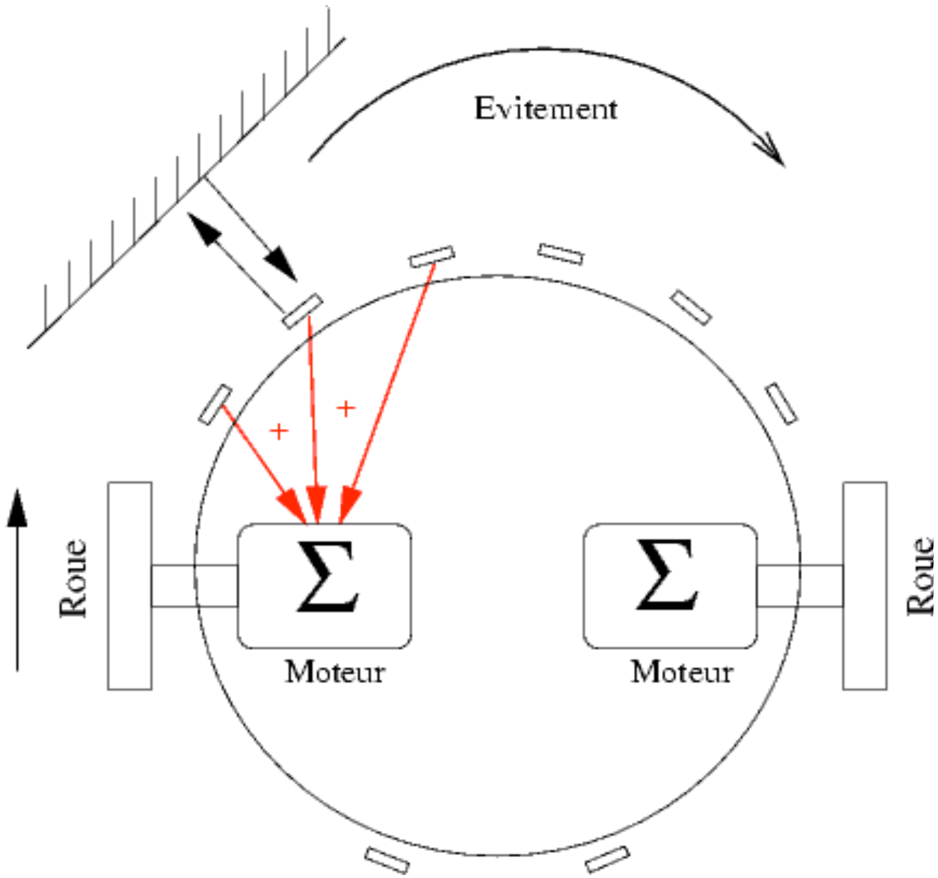
Véhicules de Braitenberg

Evitement d'obstacle (Braitenberg84)



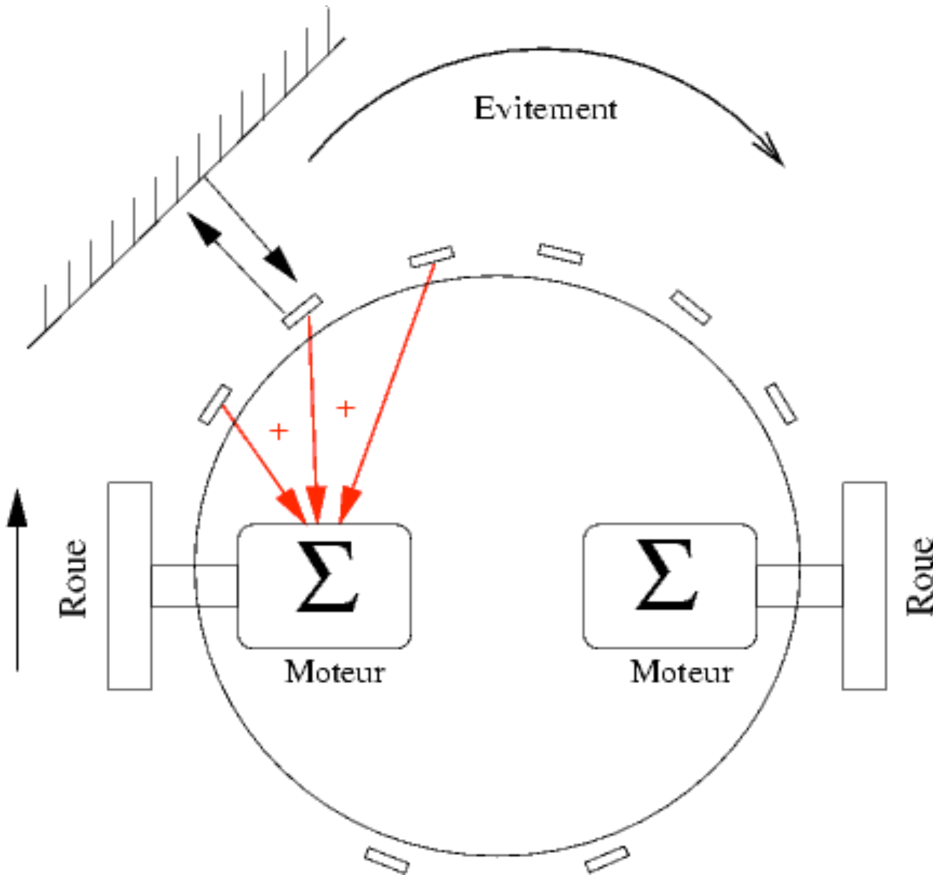
Véhicules de Braitenberg

Evitement d'obstacle



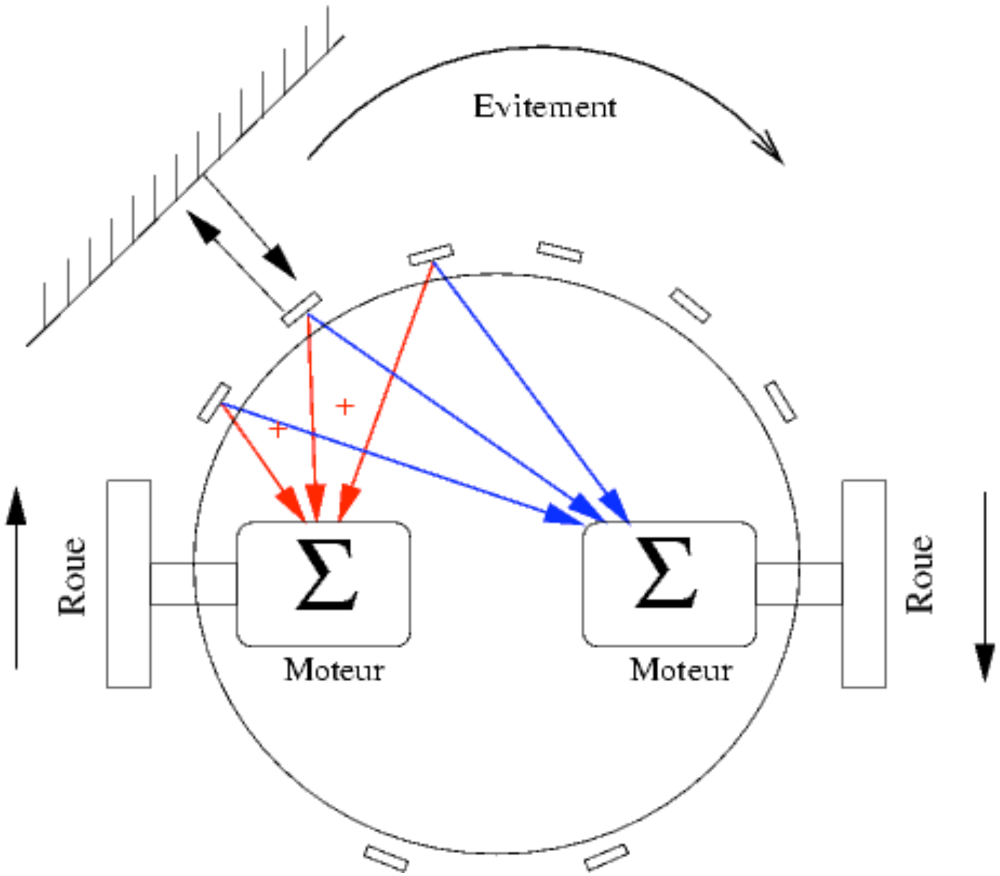
Véhicules de Braitenberg

Evitement d'obstacle



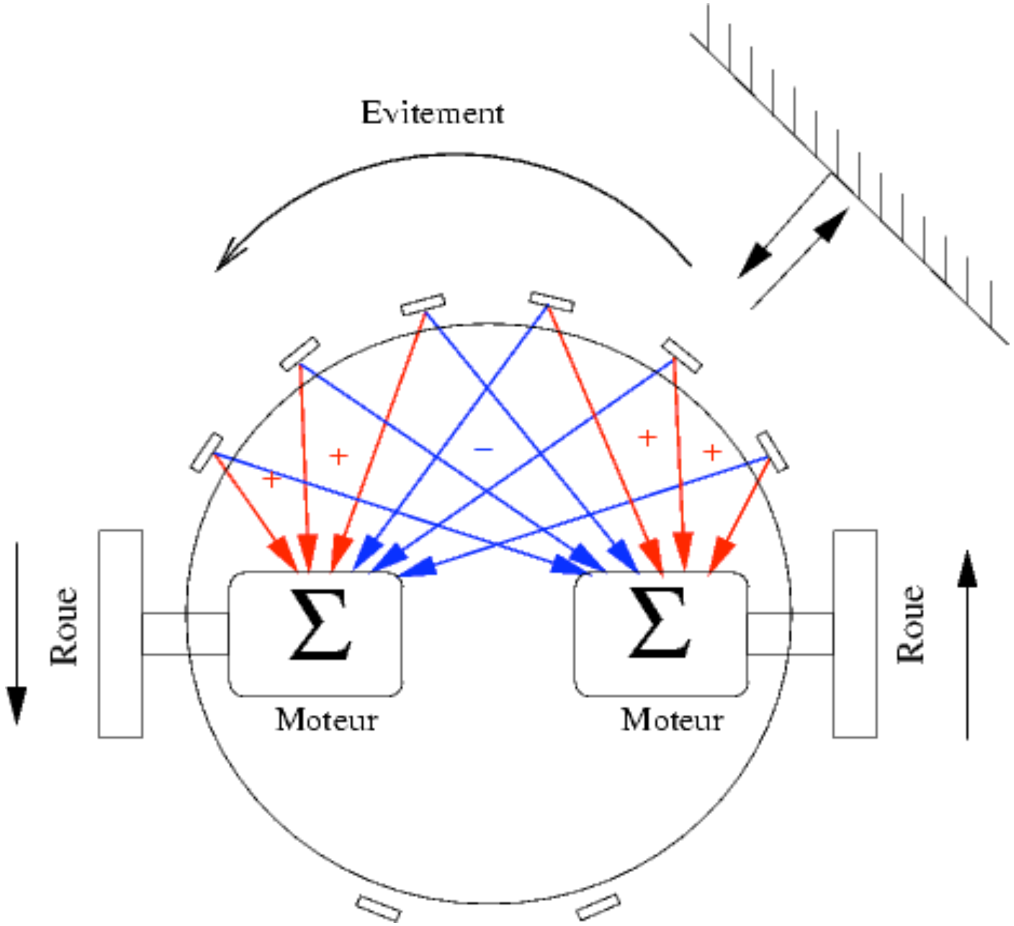
Véhicules de Braitenberg

Evitement d'obstacle



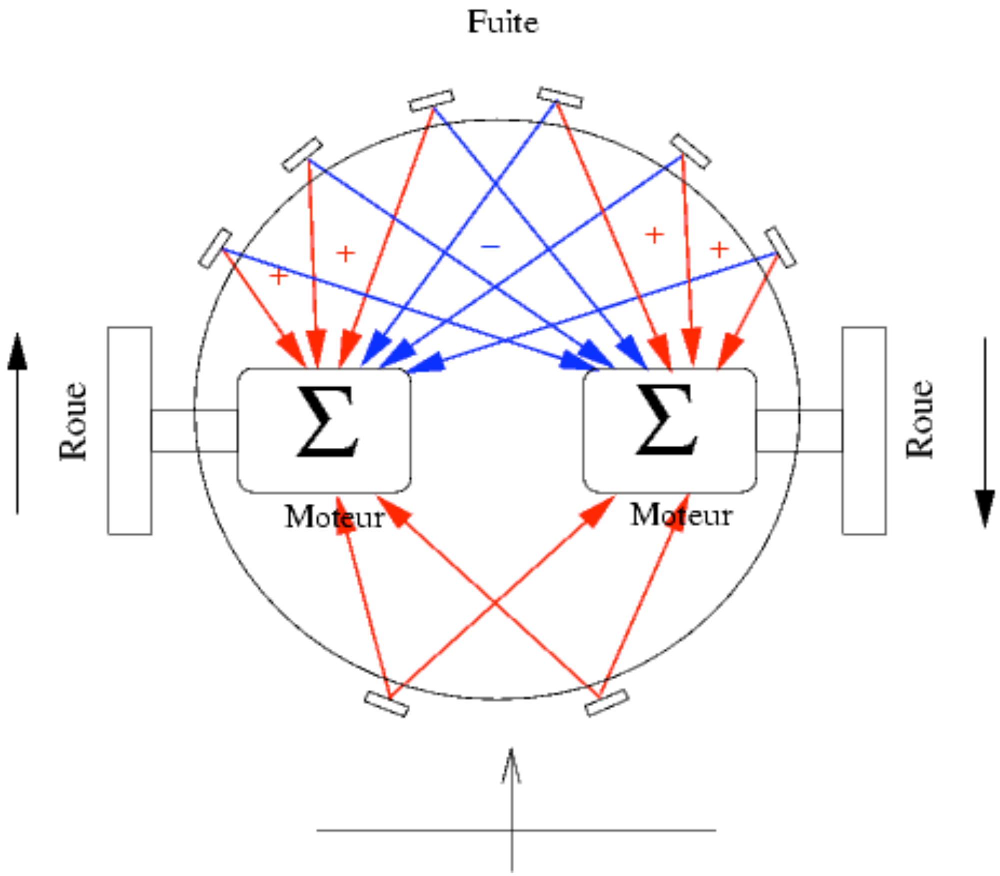
Véhicules de Braitenberg

Evitement d'obstacle



Véhicules de Braitenberg

Ajout d'une capacité à fuir



Véhicules de Braitenberg

Le réseau se construit comme étant un attracteur d'un comportement dynamique particulier

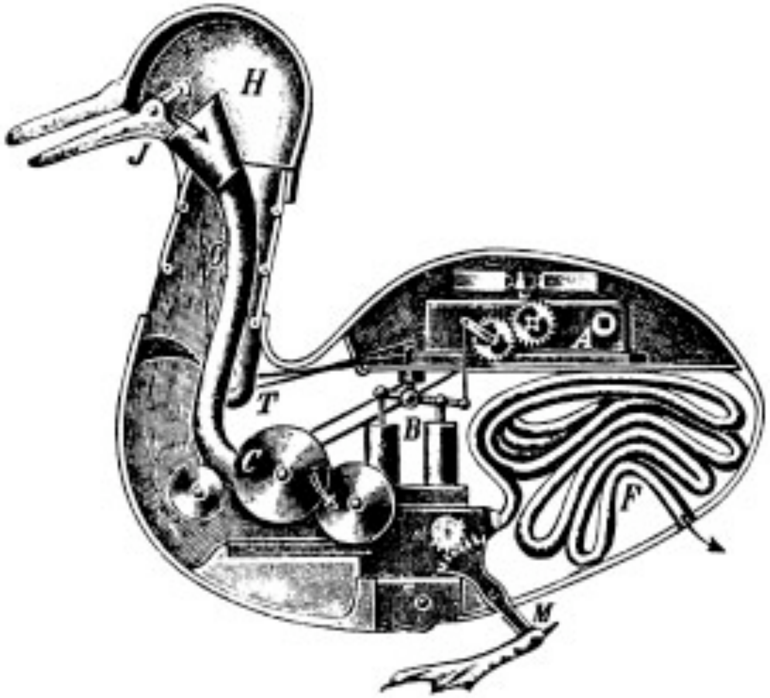
(idée: revenir dans l'état d'équilibre si l'on subit une perturbation et faire telle ou telle action)

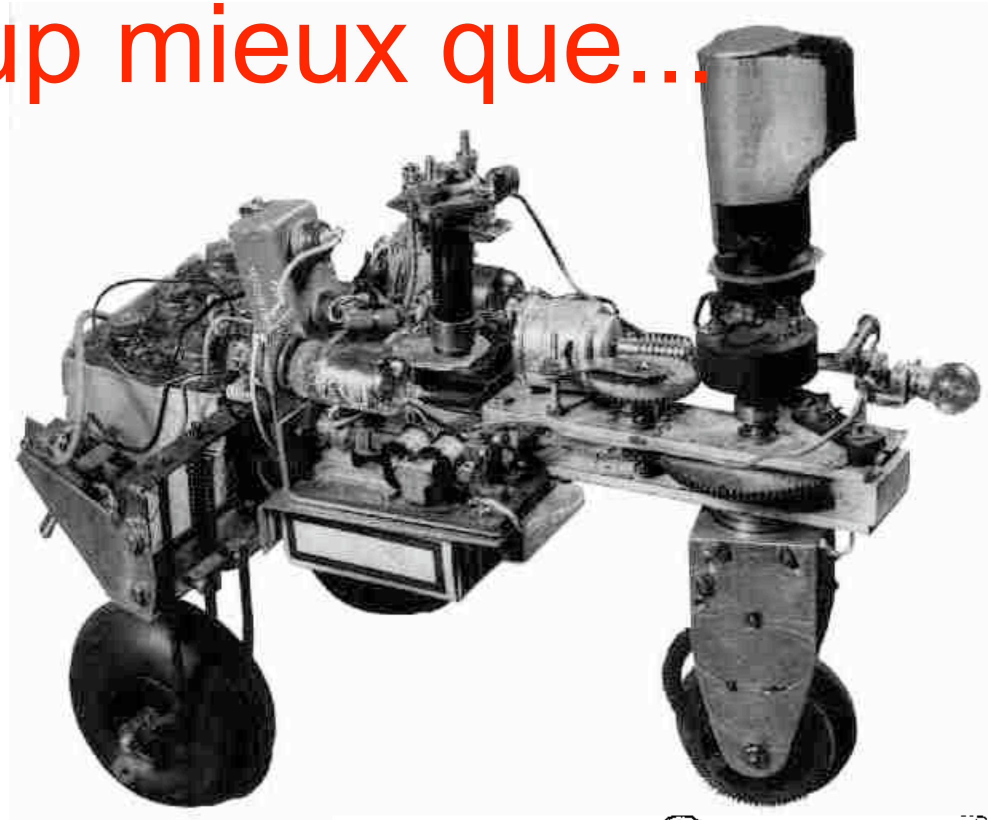
1 comportement

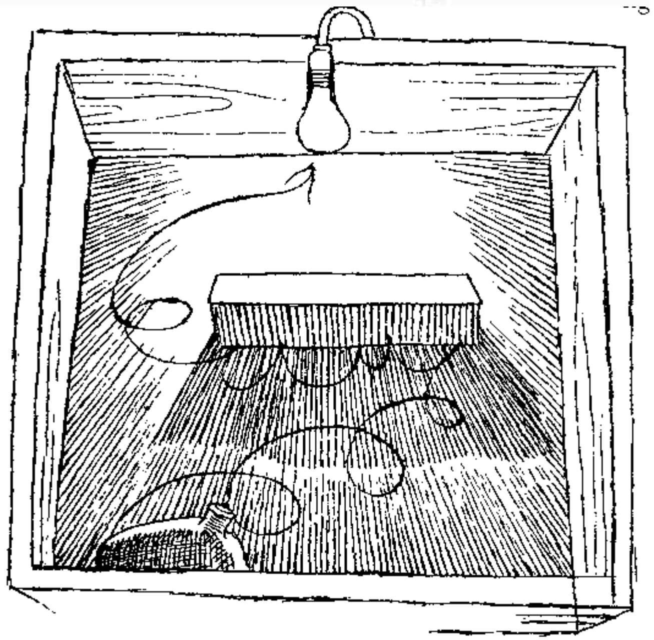
=

1 état d'équilibre dynamique

Pas beaucoup mieux que...







Digesting duck

Vaucanson 1739

Electronics turtle

G Walter 1950

Pas si loin des robots d’aujourd’hui…

(même en performances!)

Quels modèles d'apprentissage?

Quelles mémoires?

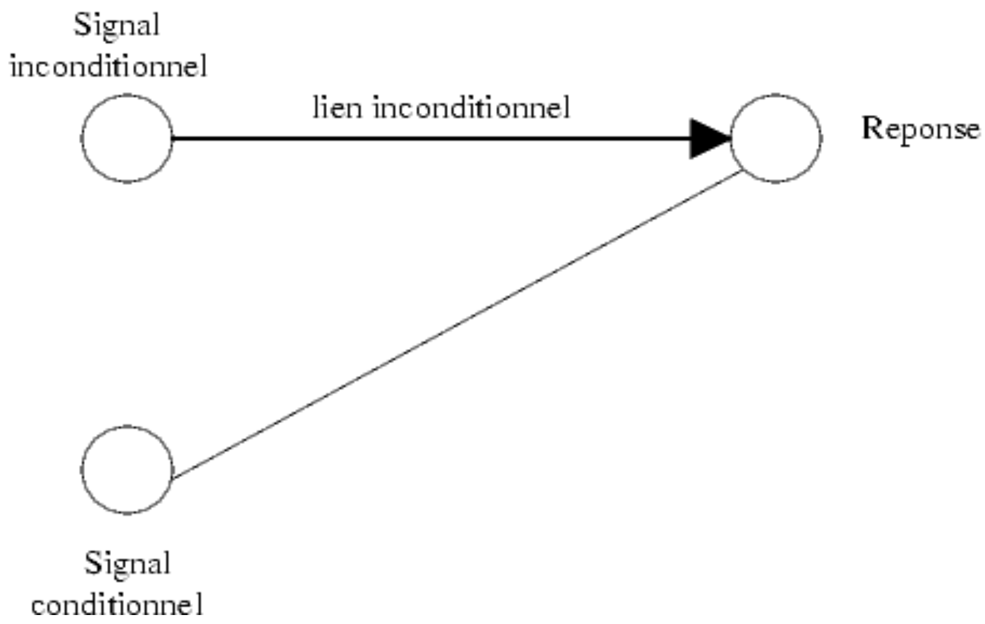
- Procédurales (habitude, habileté: y=f(x) a été optimisée)
- Déclaratives (« je sais que je sais », « je viens de voir x »
  Mémoire d'items spécifiques très limitée (< 7 ?)
- Dynamiques

Adaptation ou apprentissage ?

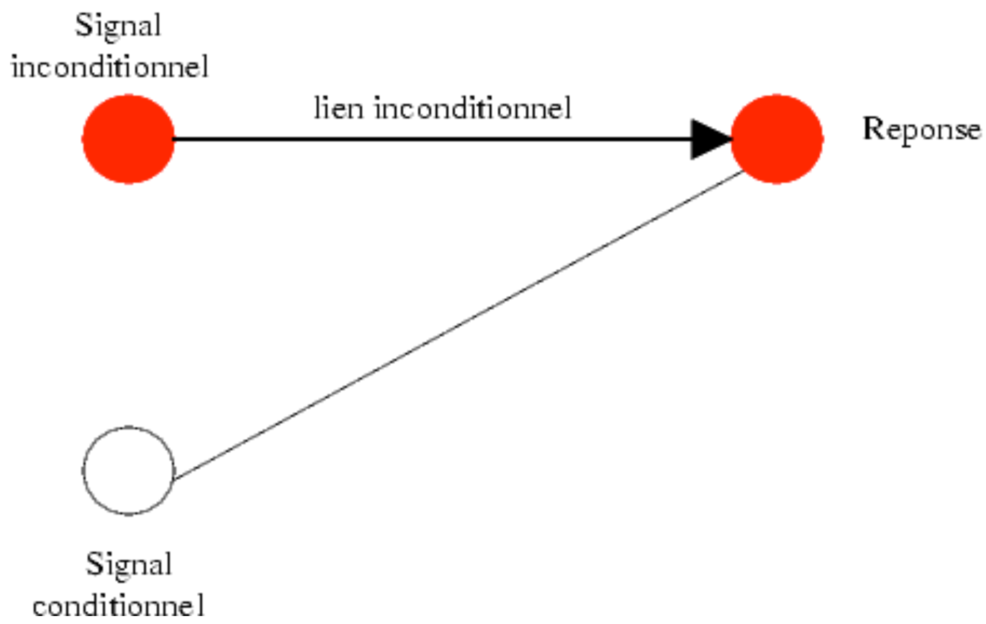
- Adaptation ➔ graduel et réversible
- Apprentissage ➔ rapide et irréversible (effets de seuil)

Les combinaisons sont possibles !

Conditionnement pavlovien

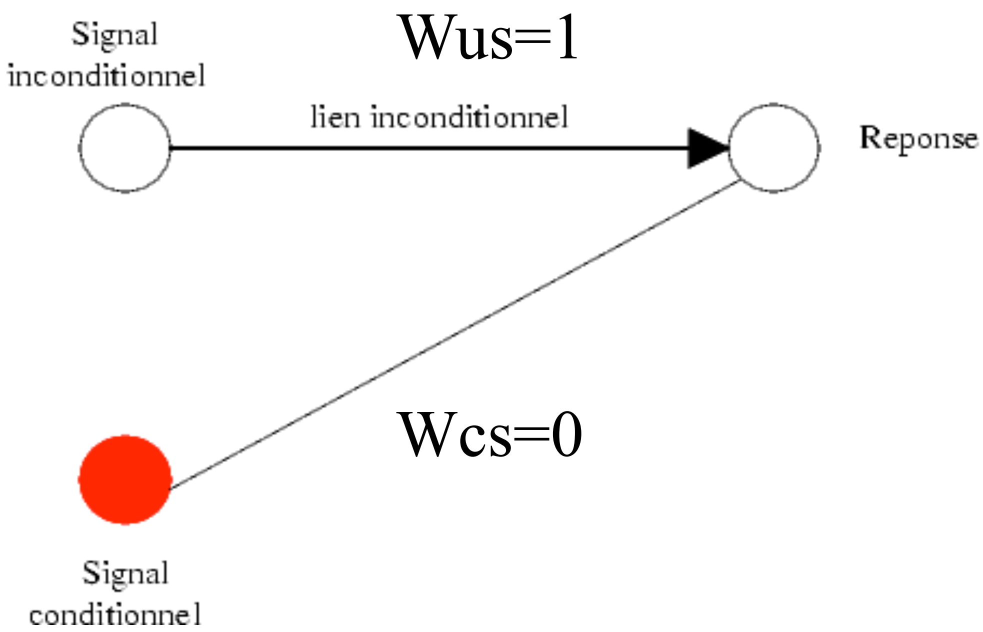


Conditionnement pavlovien



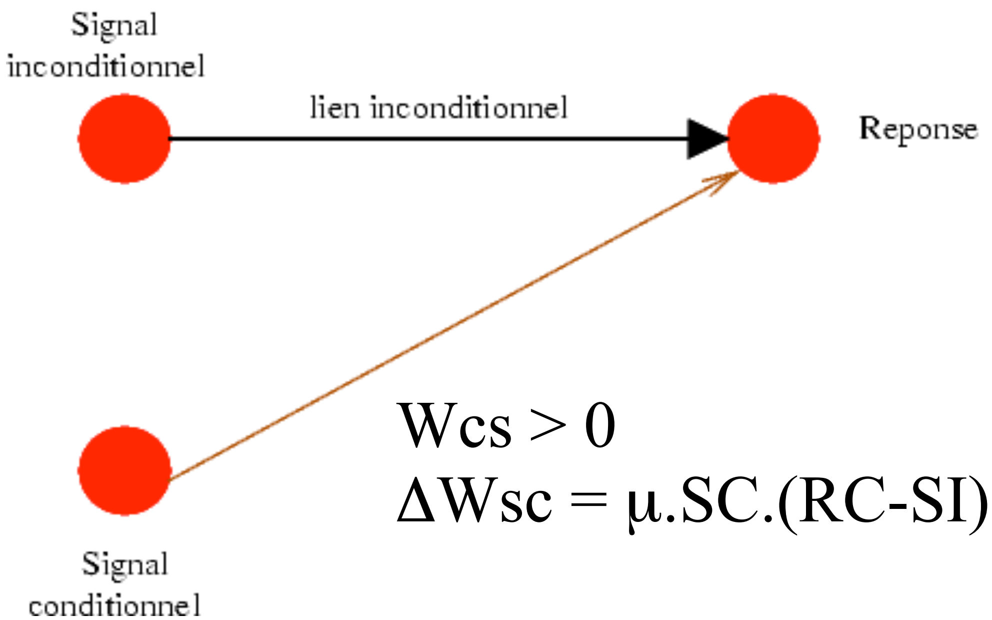
signal inconditionnel => toujours la même réponse

Conditionnement pavlovien



Signal conditionnel seul => pas de réponse

Conditionnement pavlovien

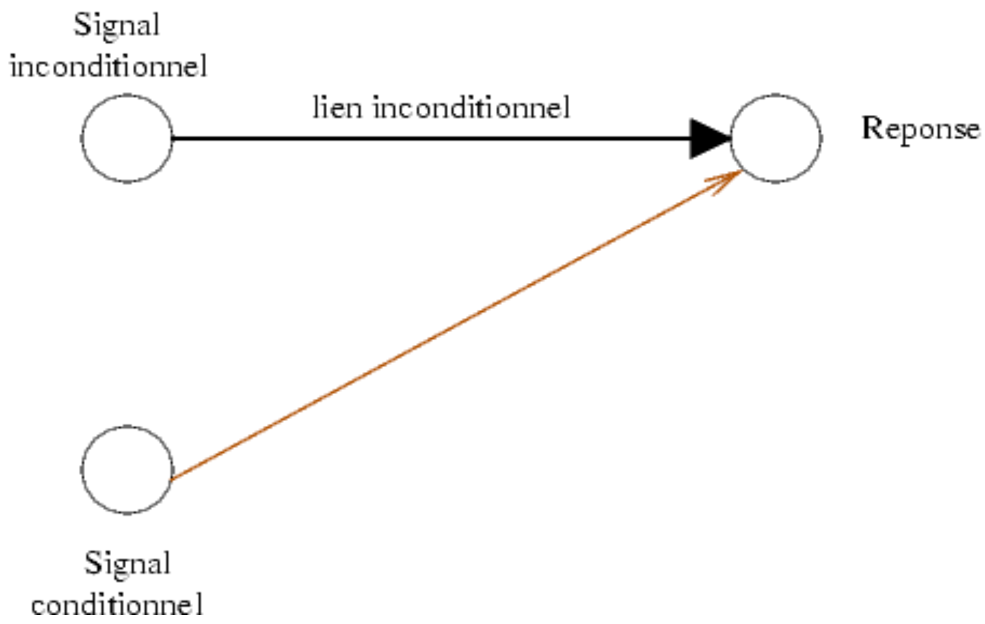


$Wcs > 0$

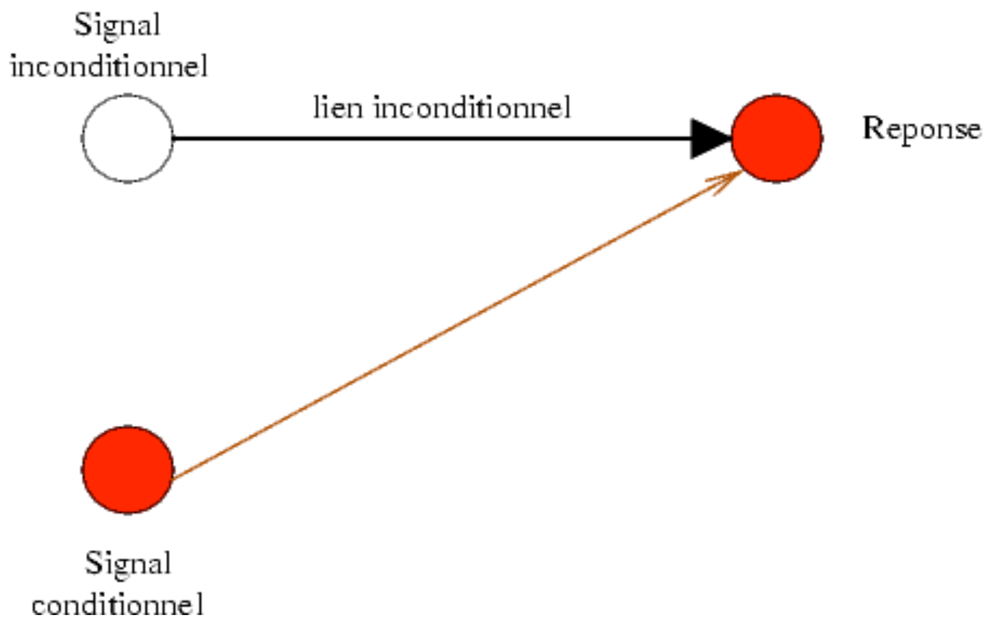
$\Delta Wsc = \mu.SC.(RC\text{-}SI)$

Signal cond. + Reponse active => renforcement

Conditionnement pavlovien



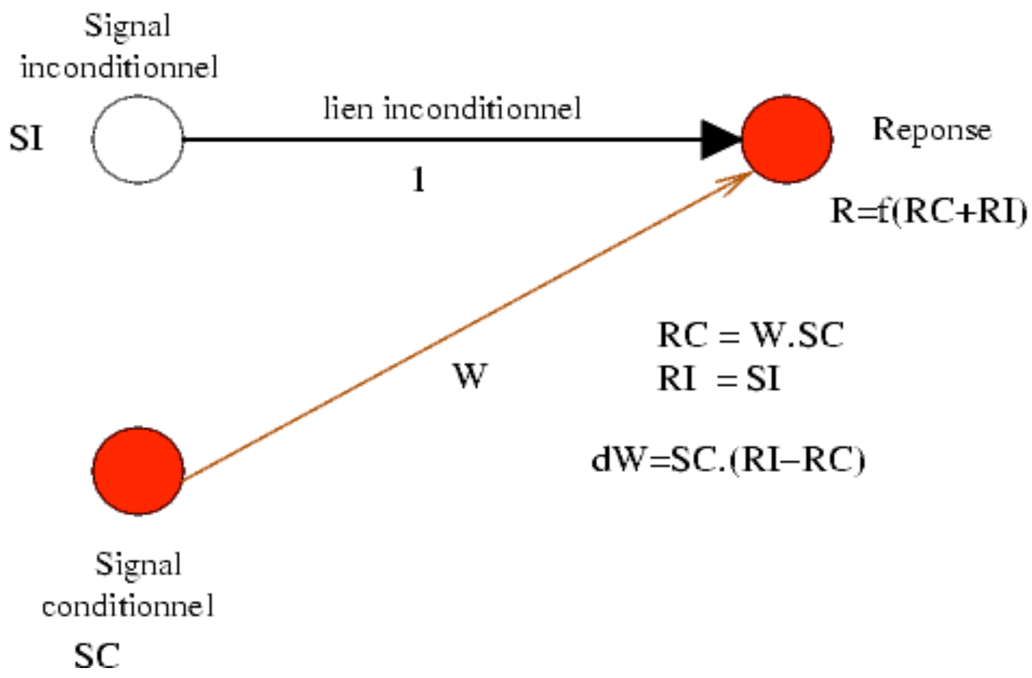
Conditionnement pavlovien



Après apprentissage:
Le signal conditionnel suffit à déclencher la réponse

Conditionnement pavlovien

Eq. de (Rescorla et Wagner 72) (psycho)
Eq. de (Widrow et Hoff 60) (traitement du signal)



Capacité d'oubli, possibilité ajout renforcement

Différentes formes d'apprentissage

$$Y_i = f(W\ X_i) \quad avec\ X_i \in R^p, Y_i \in R^q, W \in R^{p\times q}, i = 1 \ldots n$$

- Associatif $\quad W = \mu \sum_{i=1\ldots n} Y_i\ X_i^T \quad \text{avec} \quad 0 < \mu < 1$ (règle de Hebb 49 / Hopfield 82)

Pb divergence ➔ $\dfrac{dw_{k,l}}{dt} = -\lambda_1 w_{k,l}(t)(\lambda_0 + x_l(t)) + \mu(w_{\max} - w_{k,l}(t))y_k(t)x_l(t)$

- Conditionnement pavlovien (Widrow 60, Rescorla 72, Schmajuk 91…) $\quad W = \mu \sum_{i=1\ldots n} (Y_i^d - Y_i\ )X_i^T$

Pb données non stochastiques ➔ modulation apprentissage $\quad \alpha(t) \geq 0$
(effet niveau de vigilance, ou randomisation des données)

$$\frac{dw_{k,l}}{dt} = \mu\,\alpha(t)\,(y_k^d(t) - y_k(t))x_l(t)$$

Différentes formes d'apprentissage

. Cartes auto-organisatrices

$$z_j = g\left(\left\|W_j - X\right\|\right) \quad et \quad Y \quad \text{tel que } y_j = \begin{cases} z_j & si\ j = \underset{k}{ArgMax}\ z_k \\ 0 & \text{sinon} \end{cases}$$

$$W_k(n+1) = W_k(n) + \mu\, h(d)\left(X_n - W_k(n)\right) \quad avec\ d = \left\|k - j\right\|$$

$h(d)$ une fct de type chapeau mexicain (topologie)

$g(x)$: Radial Basis Function

Différentes formes d'apprentissage

. Conditionnement instrumental (renforcement)

$$\frac{dW}{dt} = \varepsilon \frac{dR}{dt} X_i^T(t - dt) \frac{dY_i}{dt}$$

(Klopf 82, Barto et Sutton 81, Schultz 98, Dayan 94, Doya…)

Apprentissage par renforcement:

- TD(λ) (Barto et Sutton 89)
- Qlearning (Watkins 92)

Différentes formes d'apprentissage

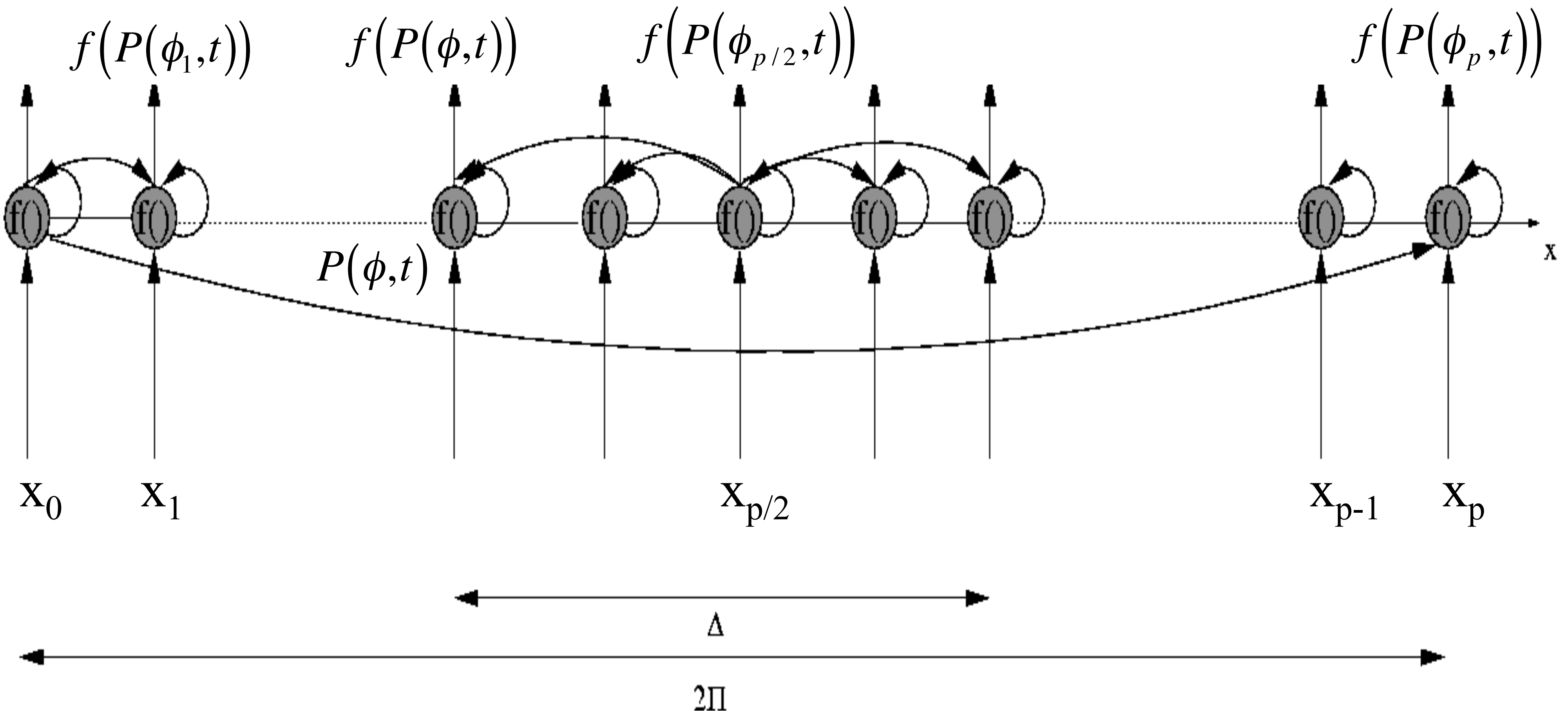
Autres contraintes:

- Sorties neurones: positives ou nulles
- Les poids ne peuvent changer de signe
  (les liens inhibiteurs ne semblent pas être modifiables)
- Dissymétrie entre excitation et inhibition
- Codage « sparse » et distribué (robustesse)

➔Mécanismes de rehaussement de « contraste »

➔Importance de la structure du réseau

Neural Fields (Amari 77)

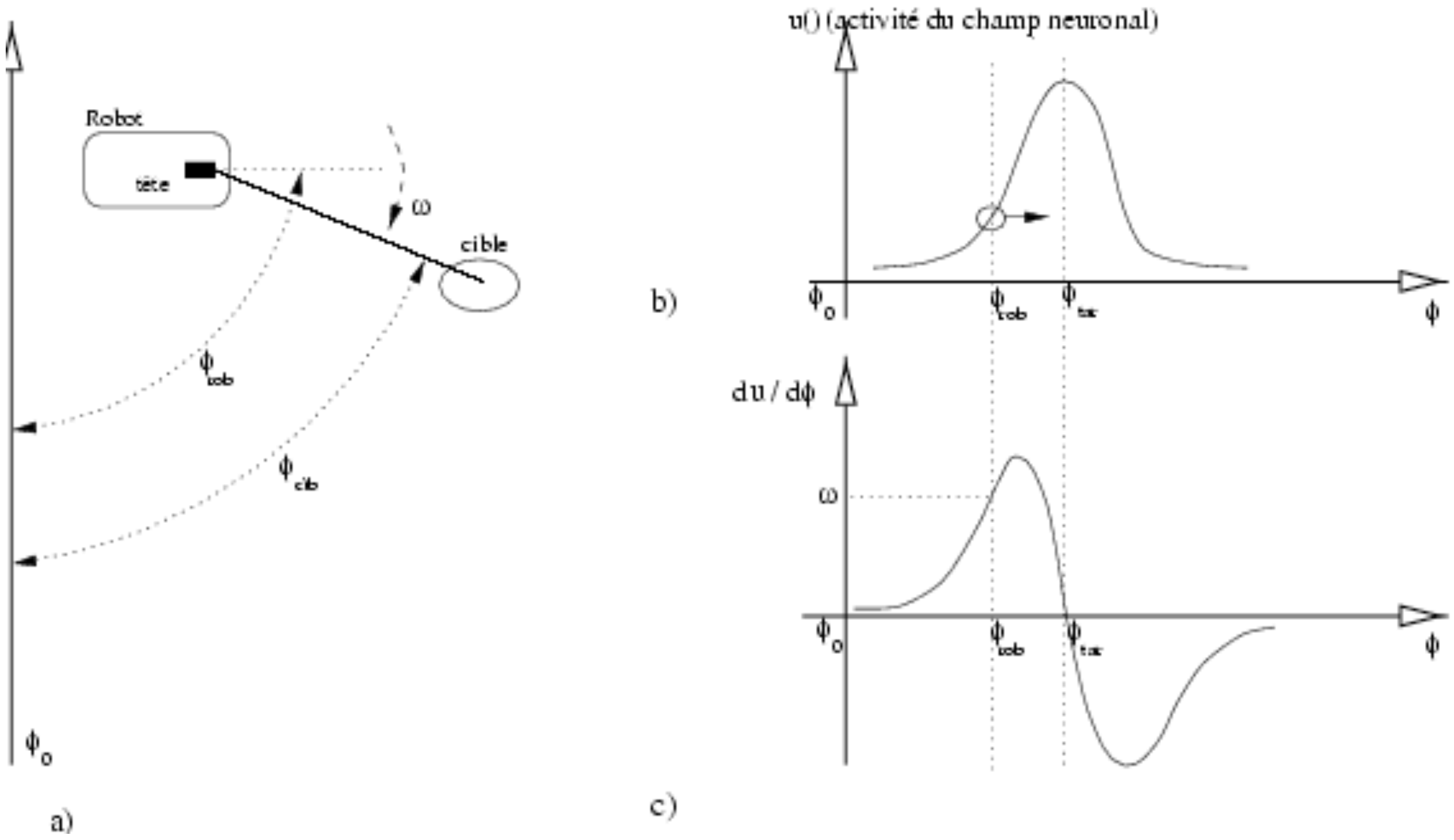


$$\tau \frac{\partial P(\phi,t)}{\partial t} = -P(\phi,t) + h + x(\phi,t) + \int_{\Delta} \omega(\phi-\theta) f(P(\phi,t)) d\theta$$

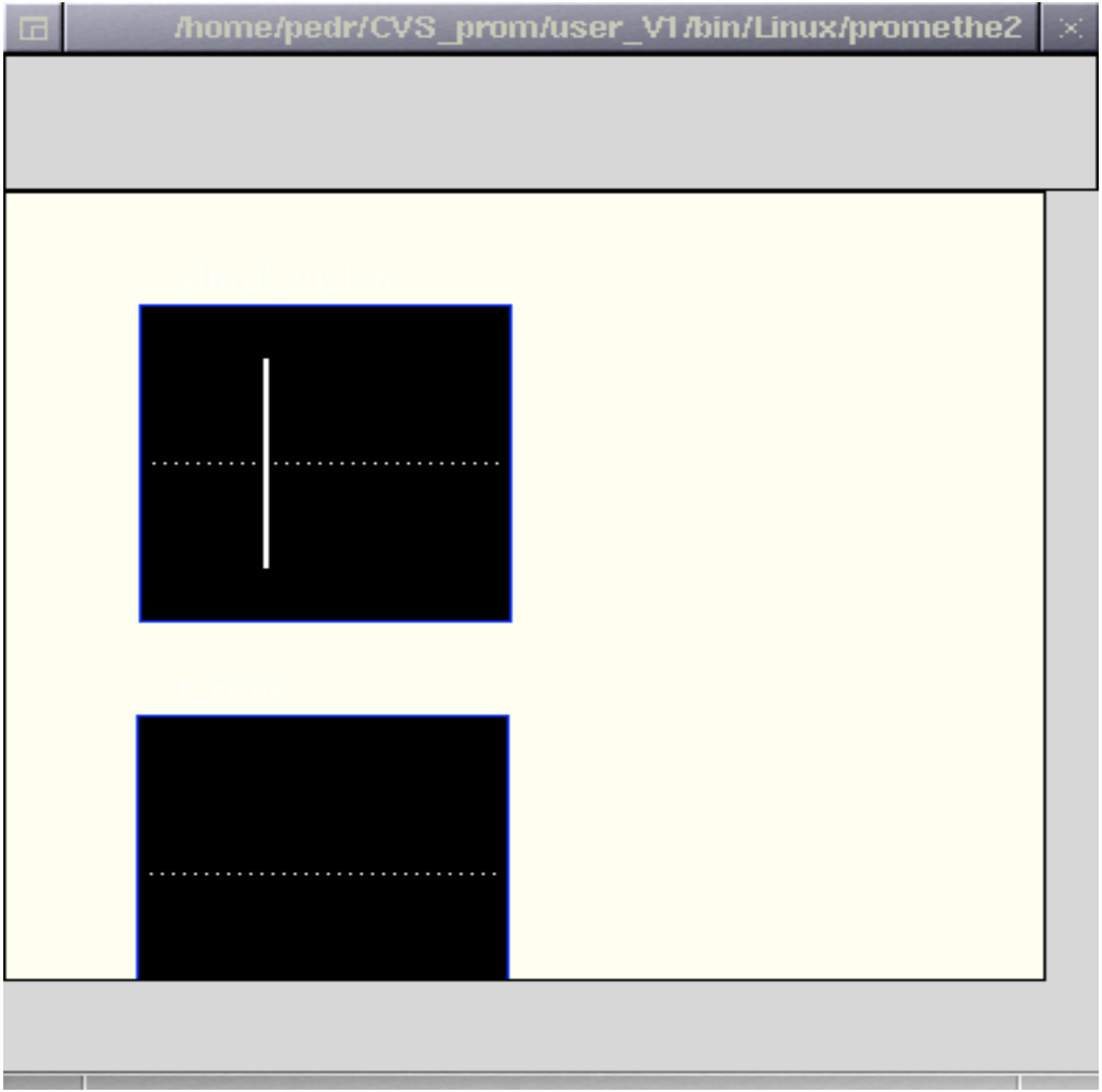
$h < 0$, $\omega(\ )$ kernel (mexican hat), $0 < \tau << 1$ time constant

Neural Fields

(Schoner et al 94)



Bell curve: probabilistic interpretation
(Georgopoulos 88, Pouget et al 99, Pouget et al 02)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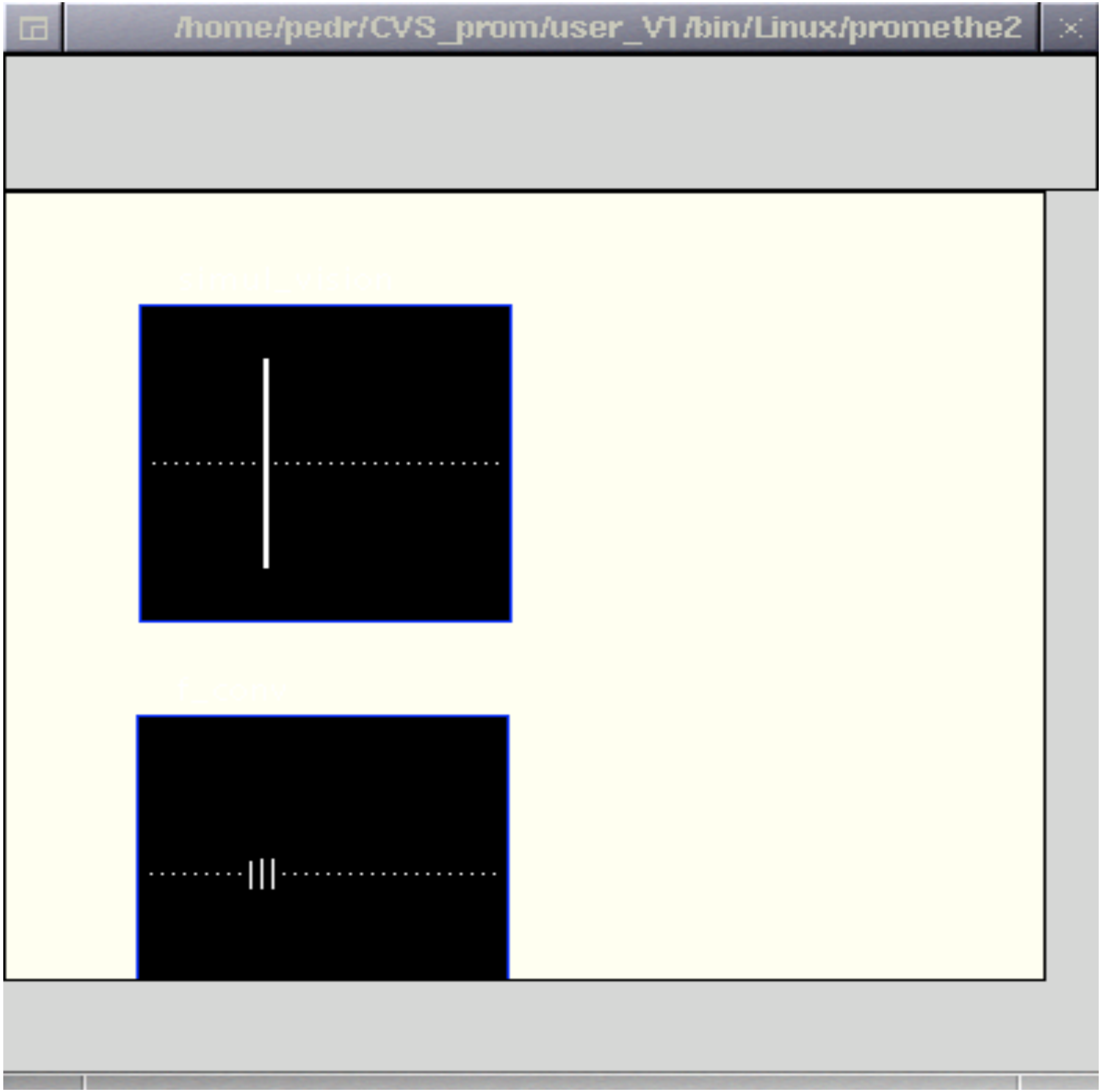
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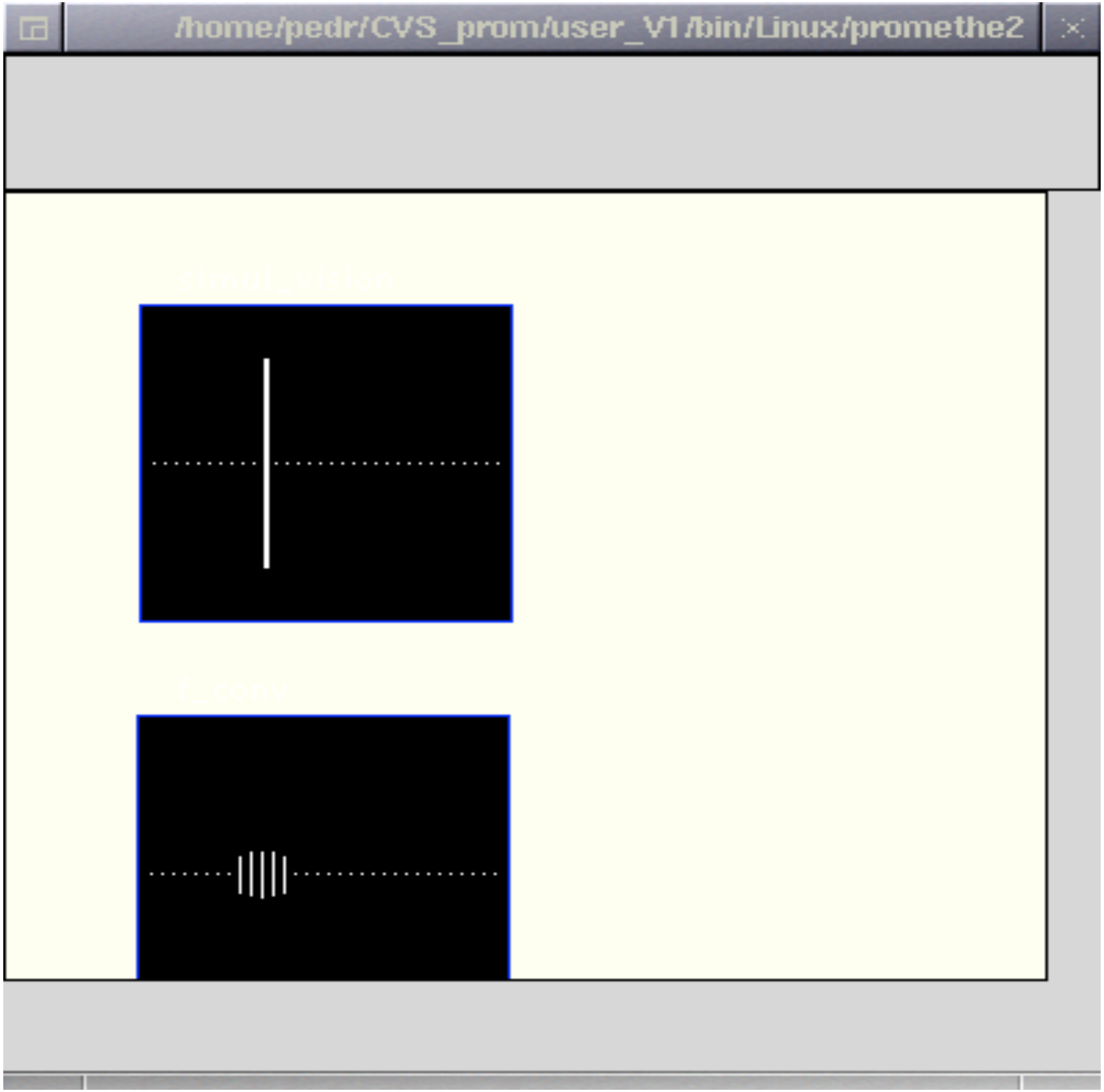
simul_vision
f_conv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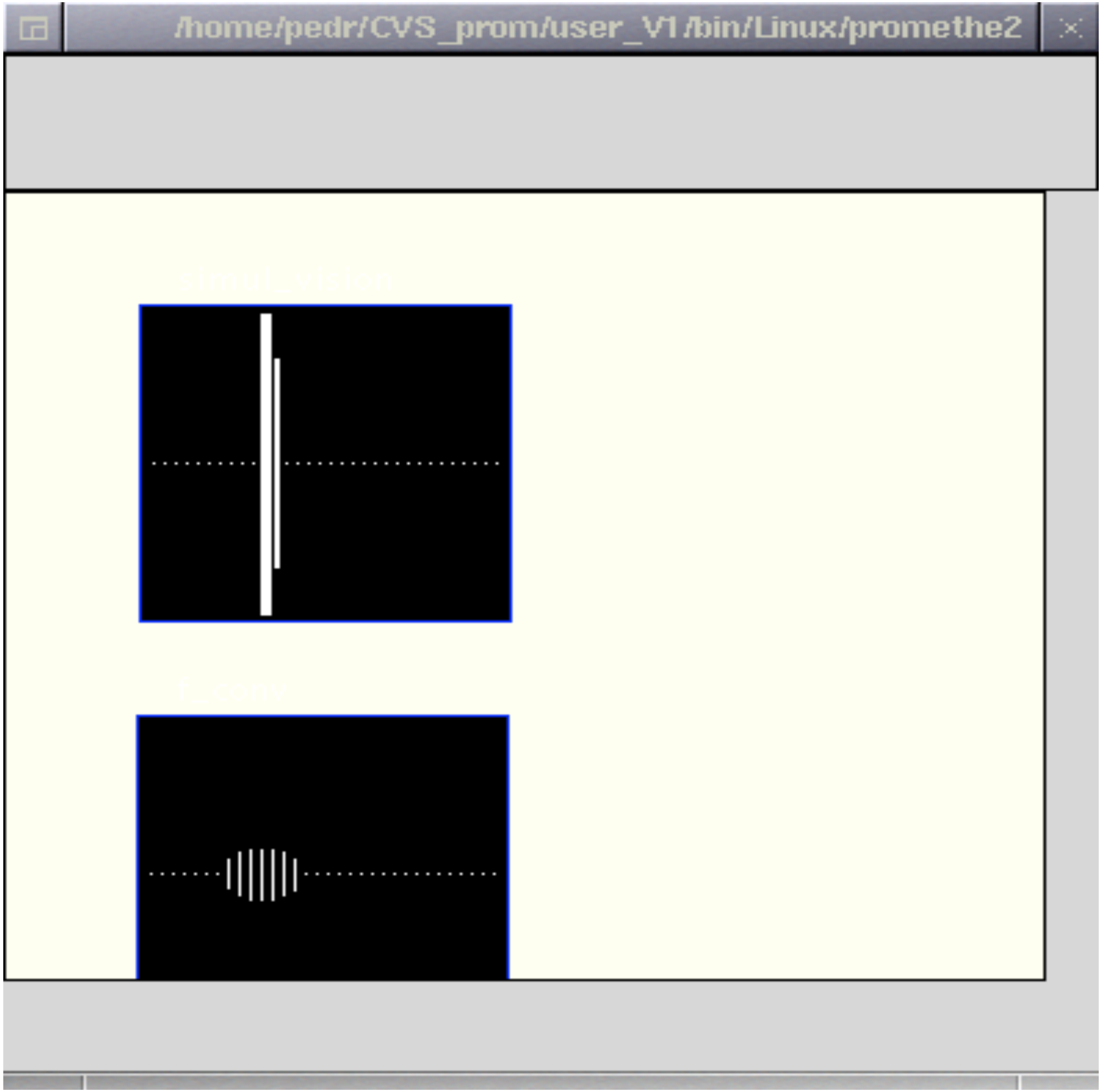
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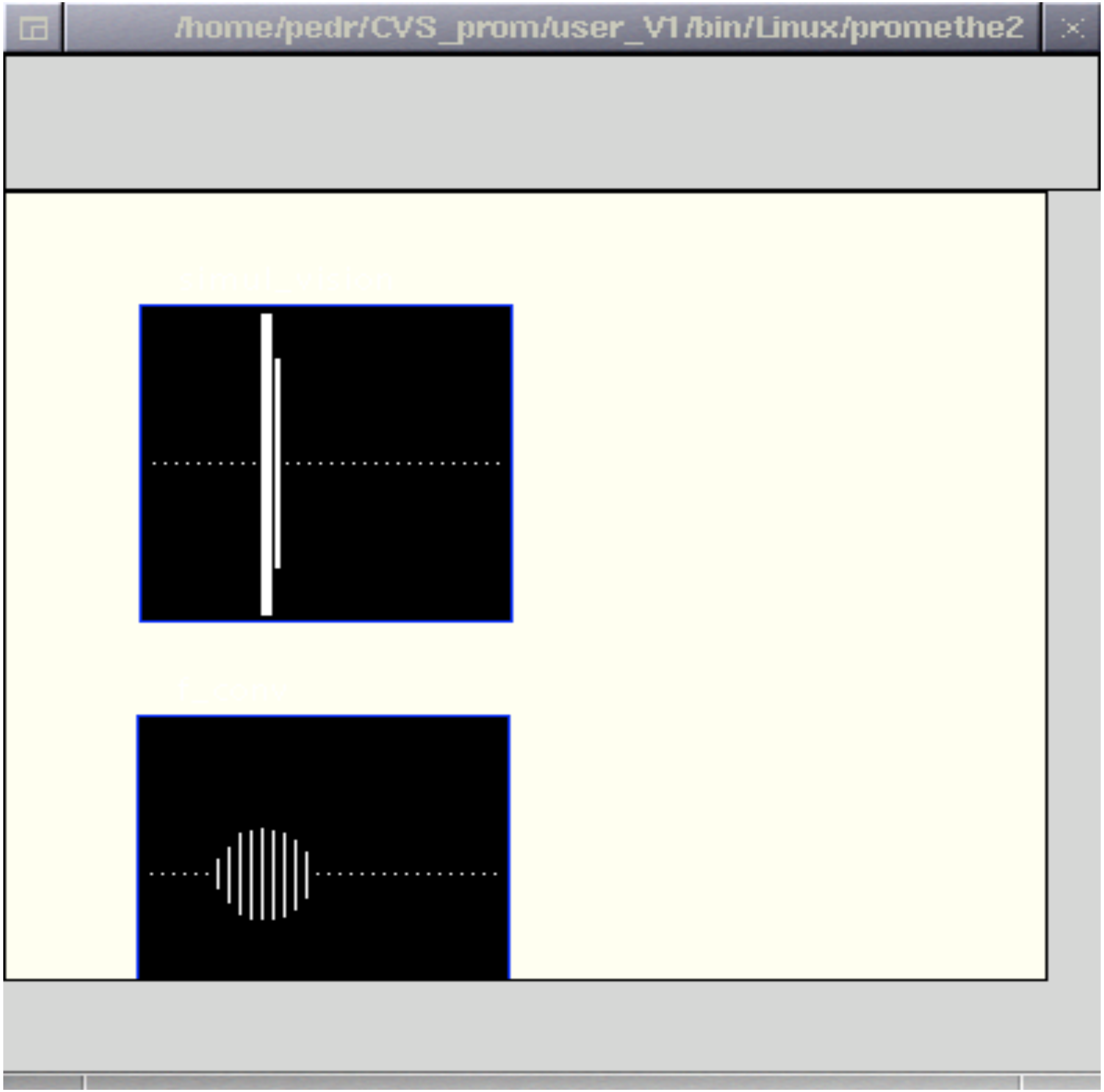
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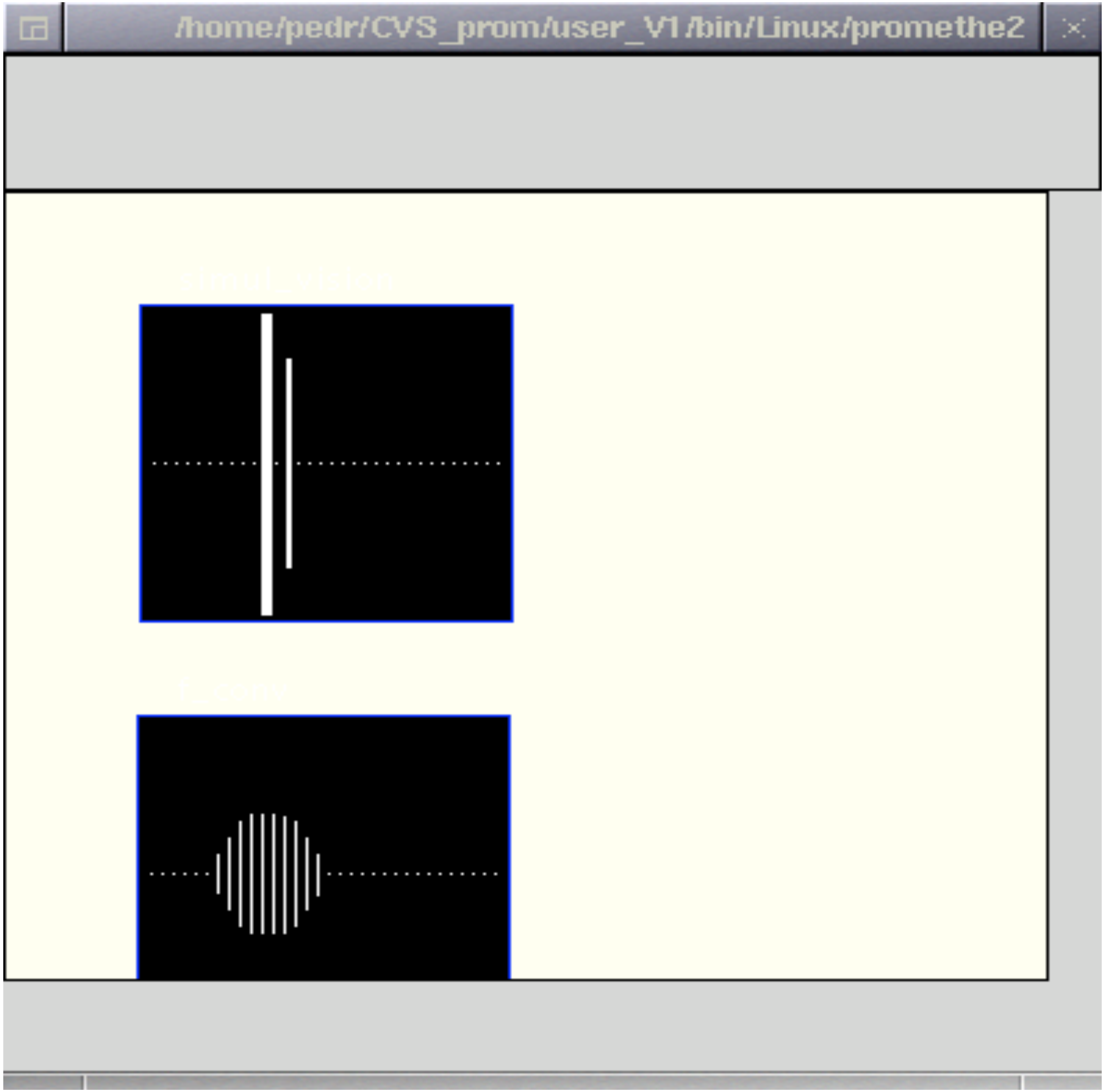
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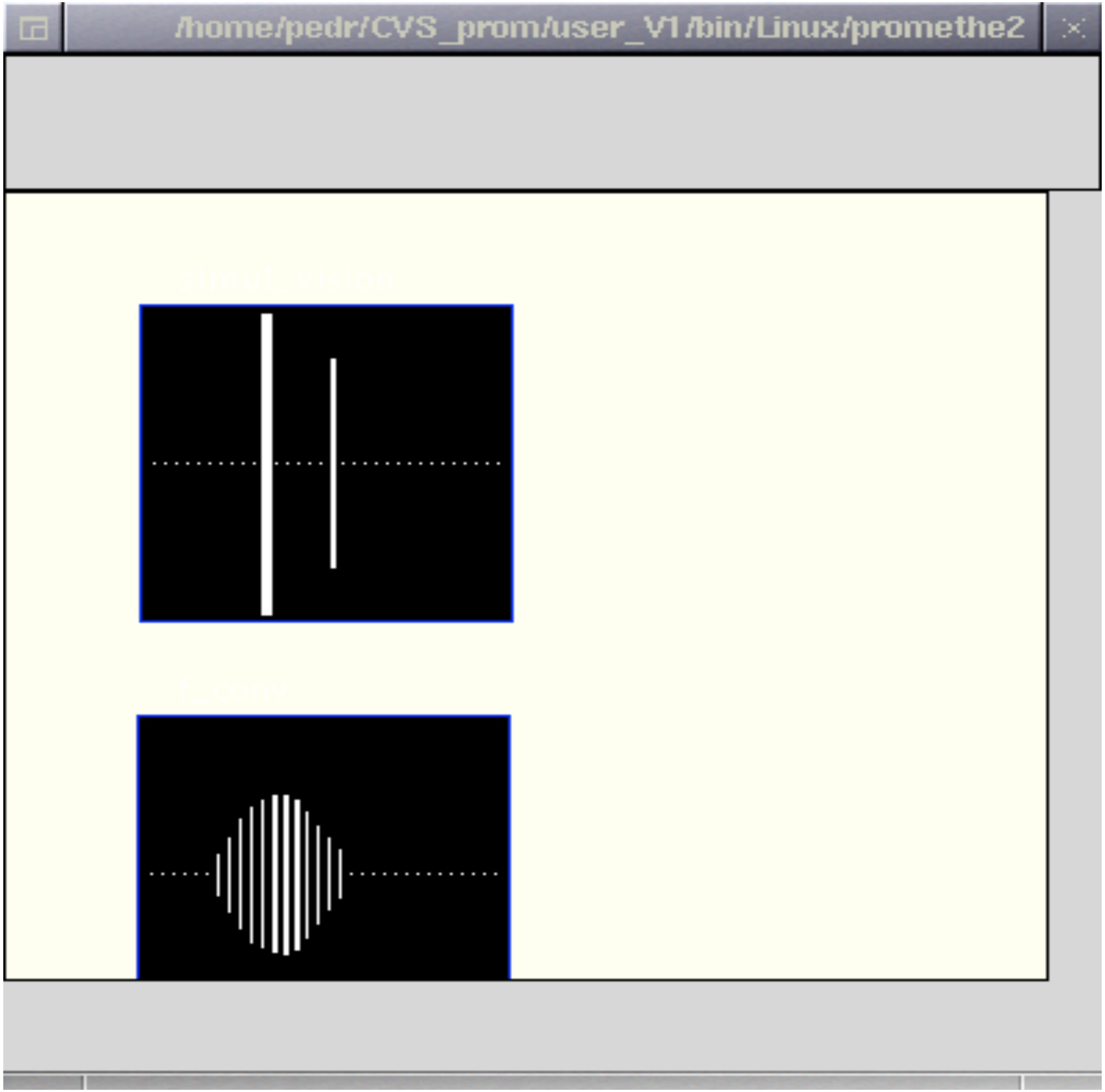
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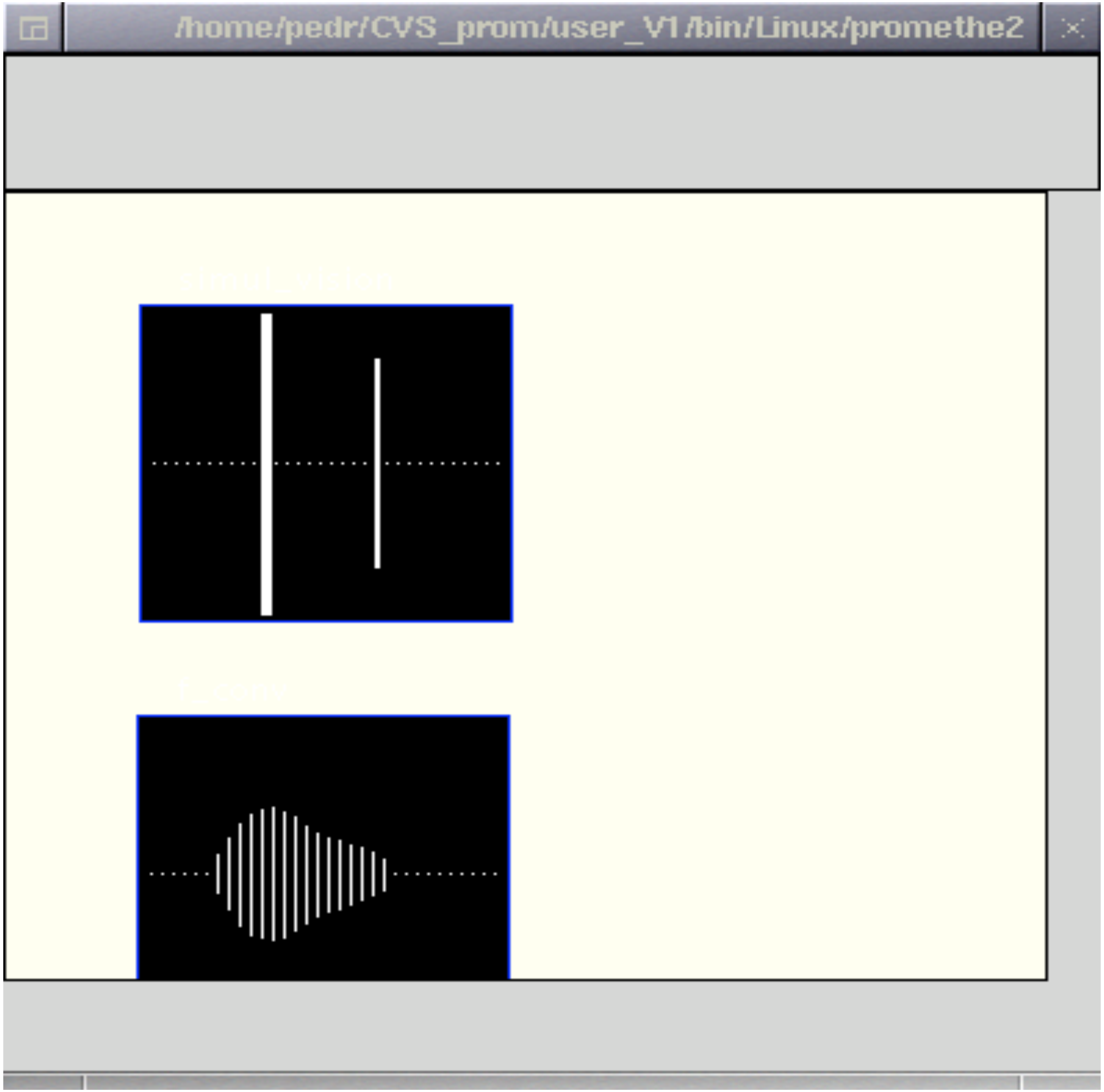
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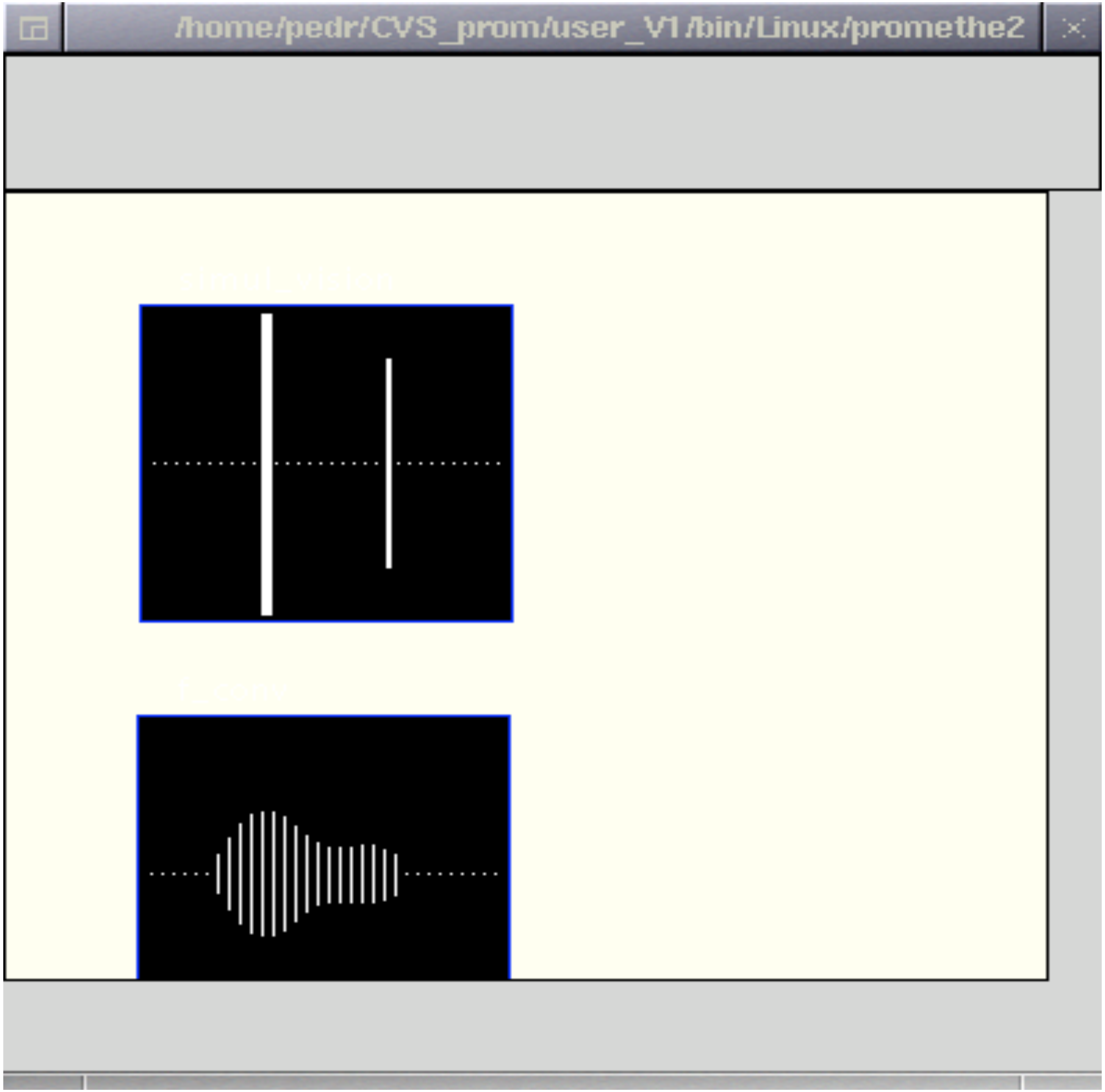
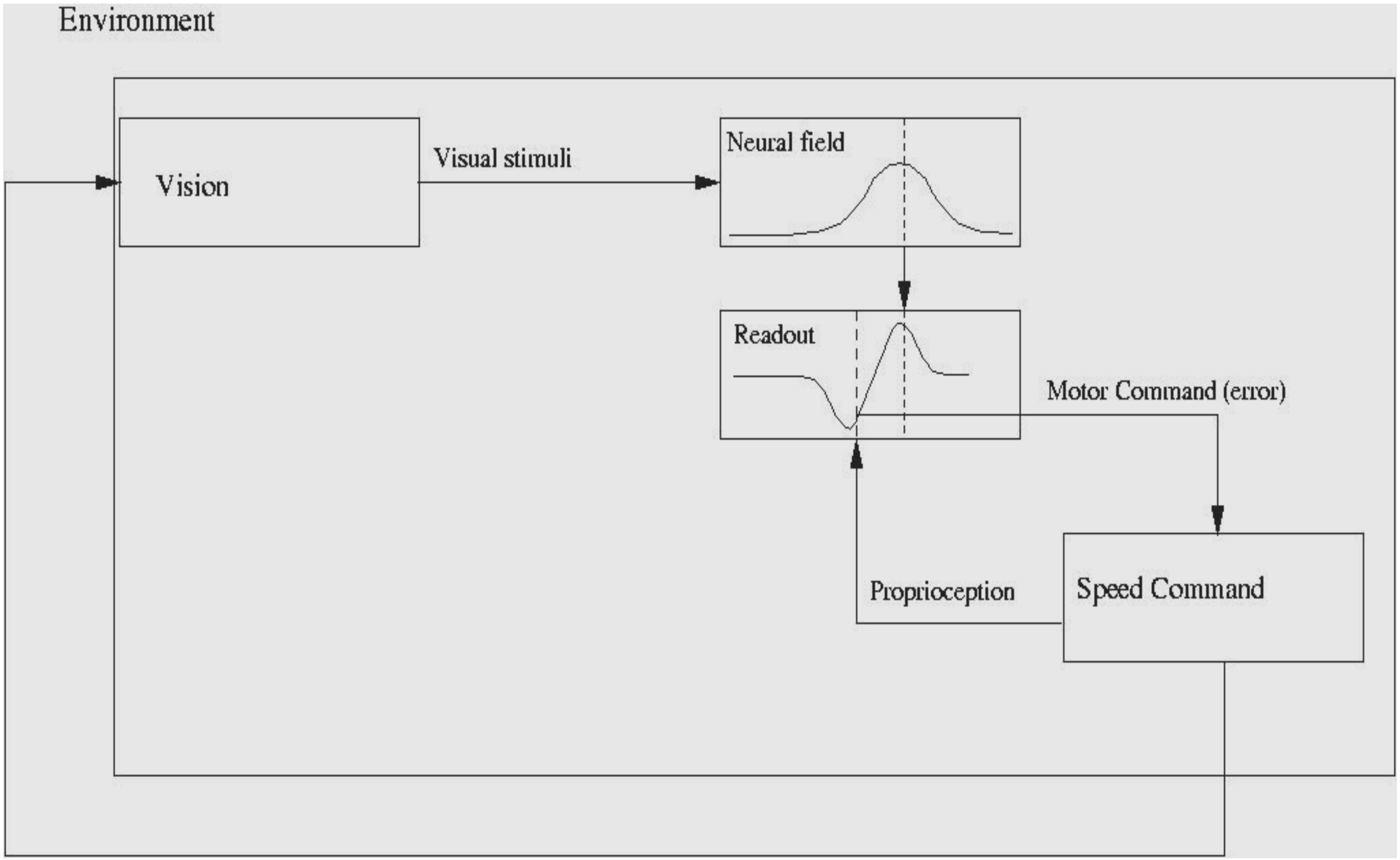
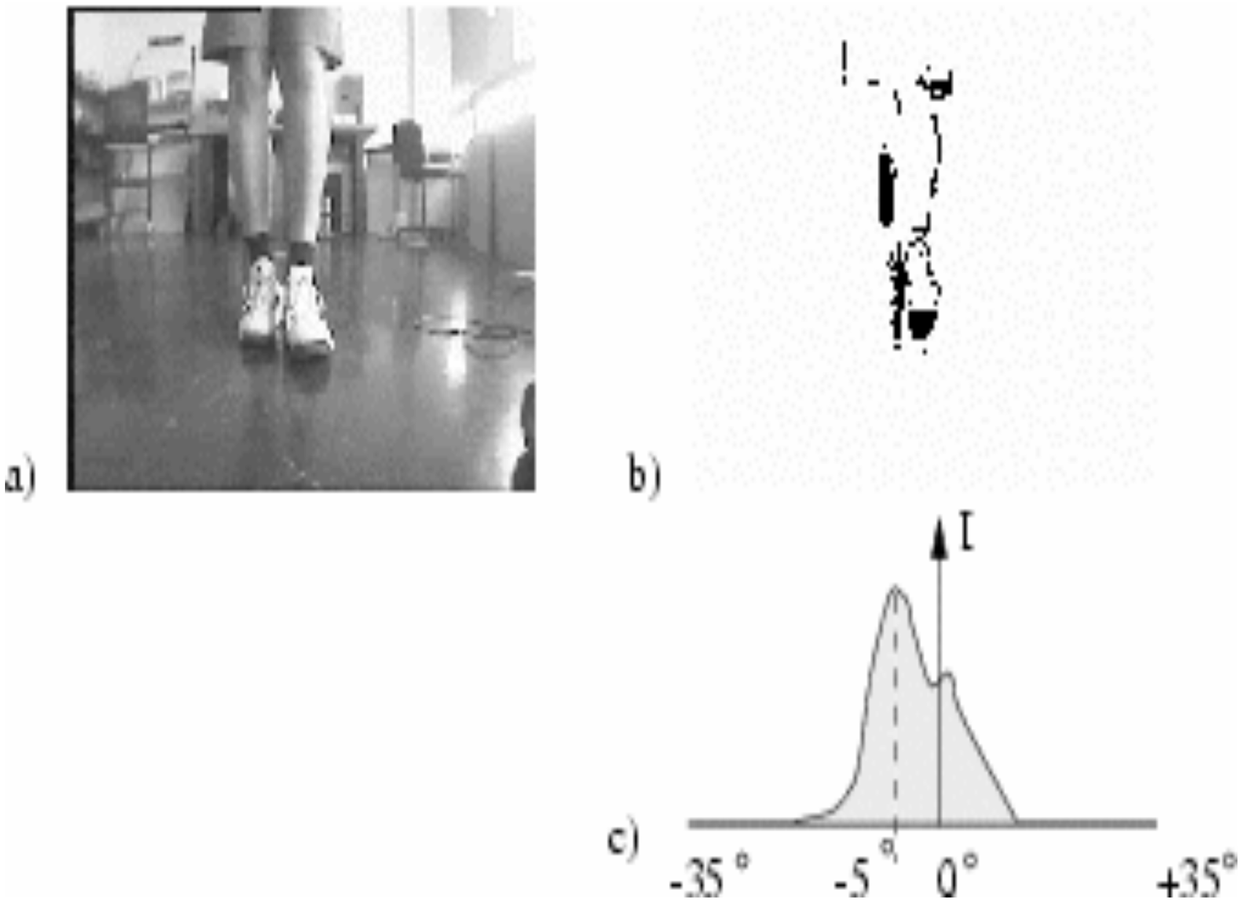

/home/pedr/CVS_prom/user_V1/bin/Linux/promethe2
simul_vision
f_conv

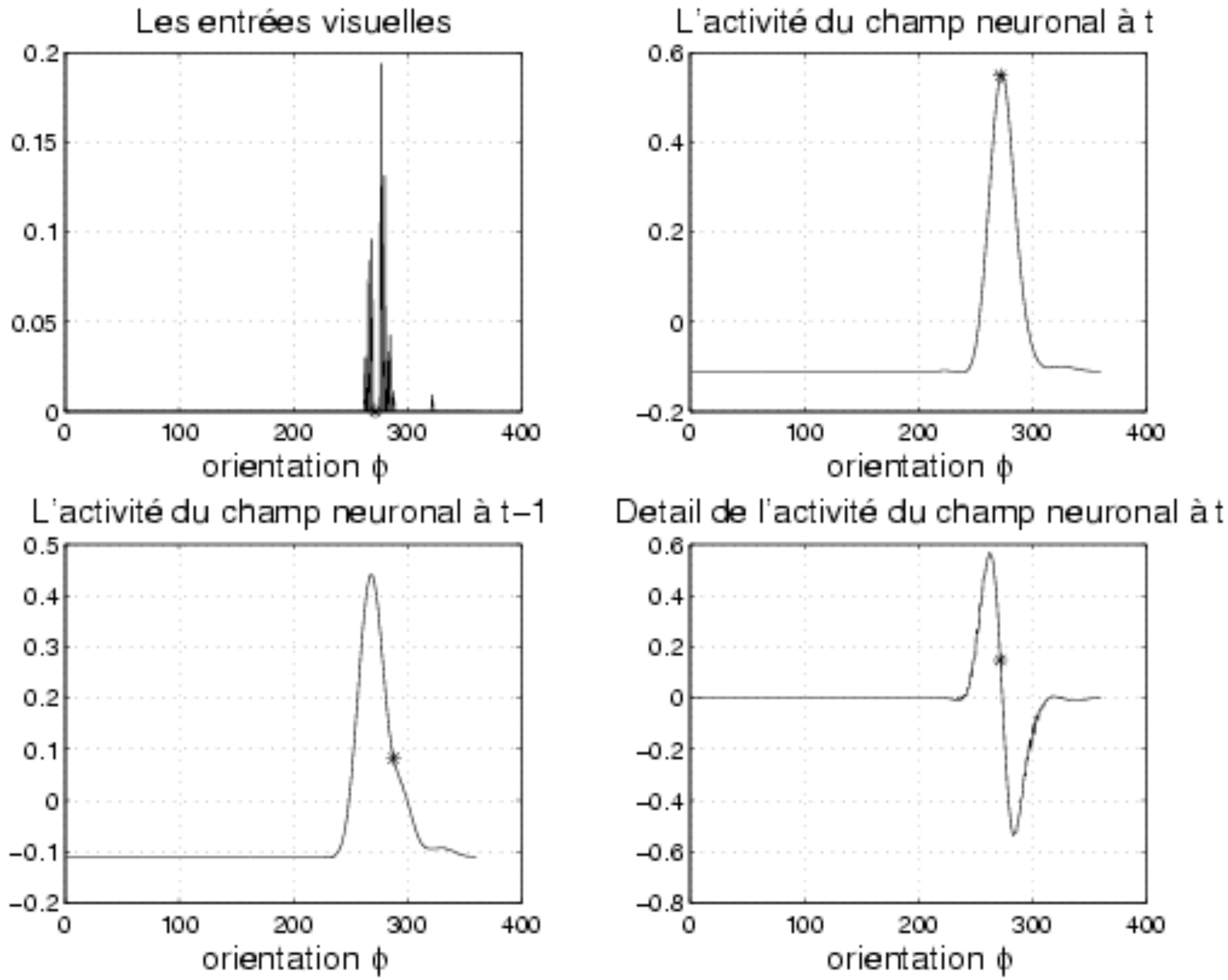
NF readout for speed control



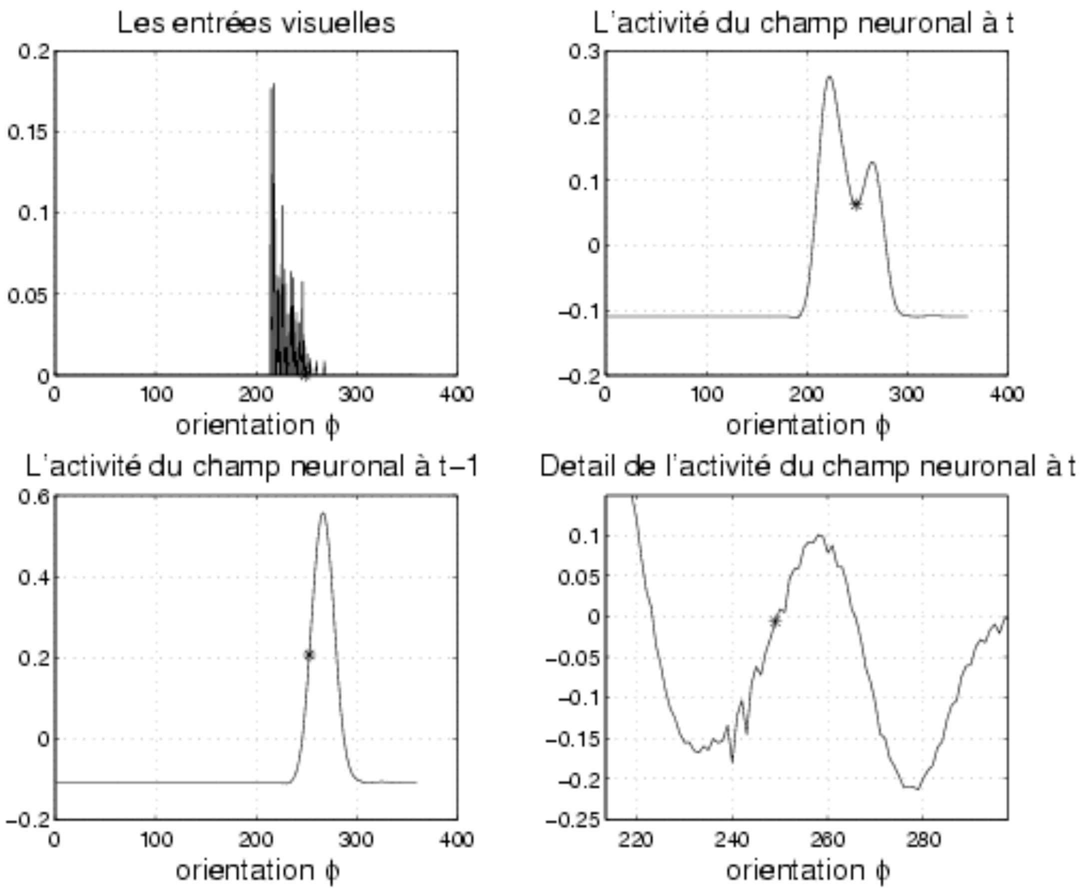
Application: mvt following



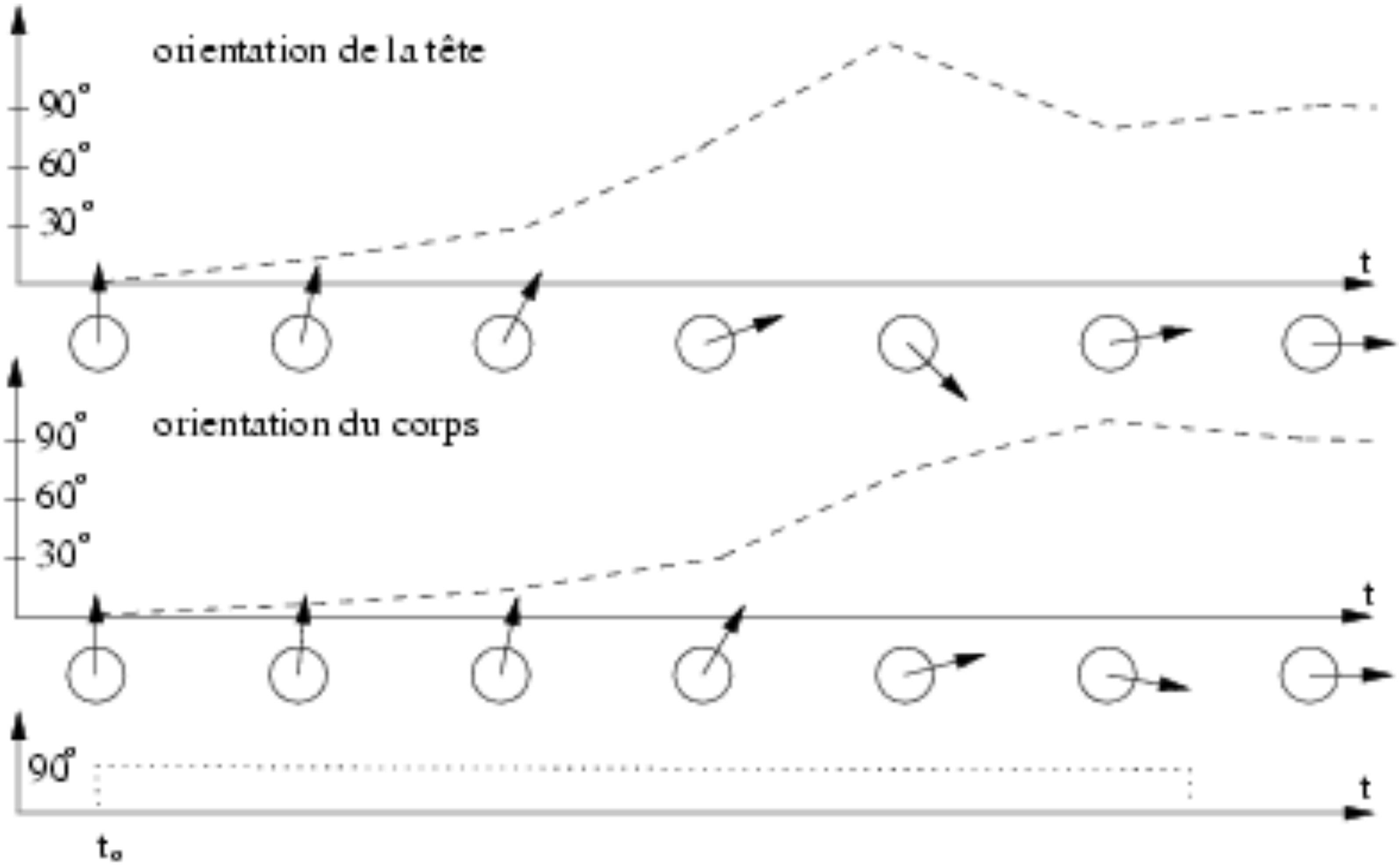
Exemple (neural field)



Example (neural field)



Control 2 DOF (head and body)



Maitriser des RNs complexes

- Comment évaluer les performances d’un système de reconnaissance?
- Dépendance par rapport aux traitements de « bas niveau »
- Comment éviter le piège de la « vérité terrain »?
(ce n’est pas parce que l’on croit que c’est comme ça qu’il faut classifier que c’est comme cela que notre cerveau fait…)

- Qu'est ce que percevoir et reconnaitre?
- Pourquoi a t’on besoin de percevoir?

2eme partie

Apprentissage sensori-moteur
et
“perception”

Qu'est ce que la Perception ?

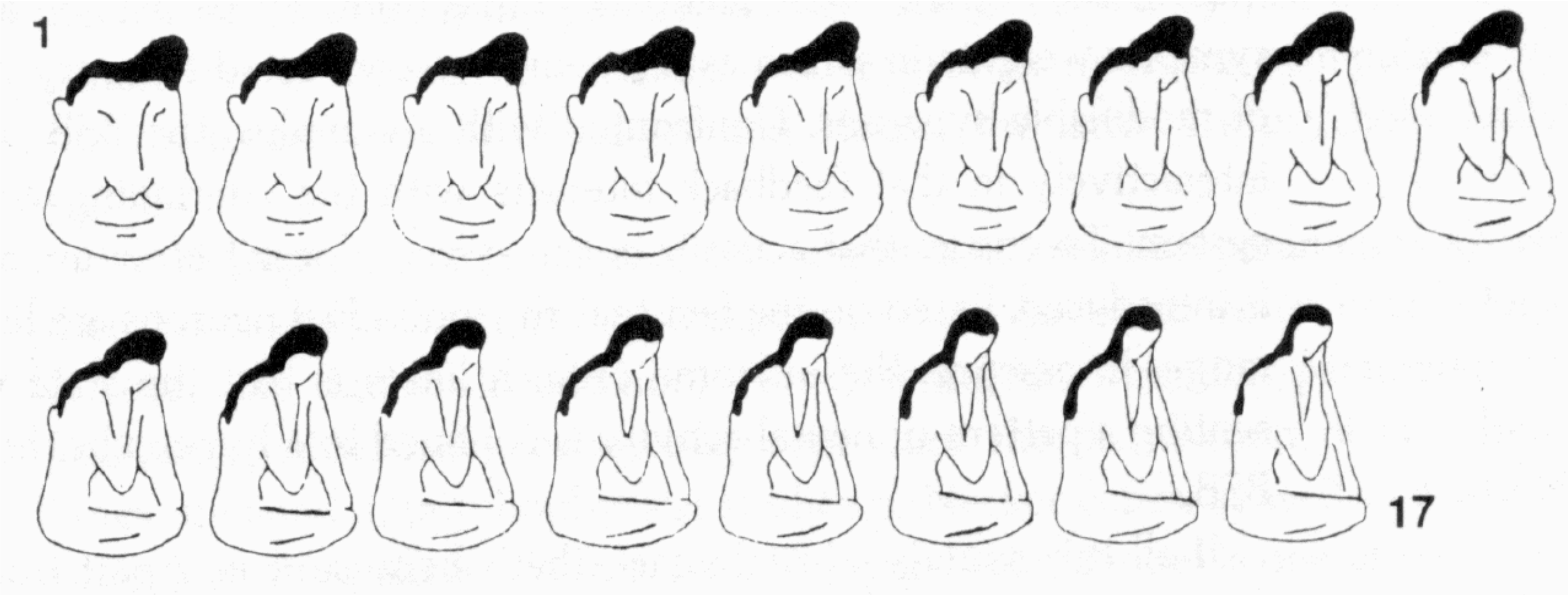
Perception

$$\approx$$

Sensations

?

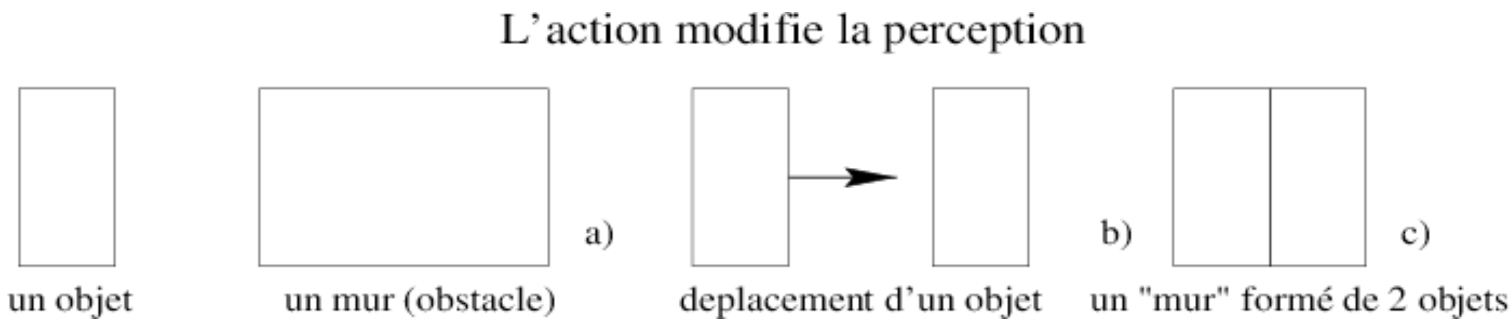
Qu'est ce que la Perception ?



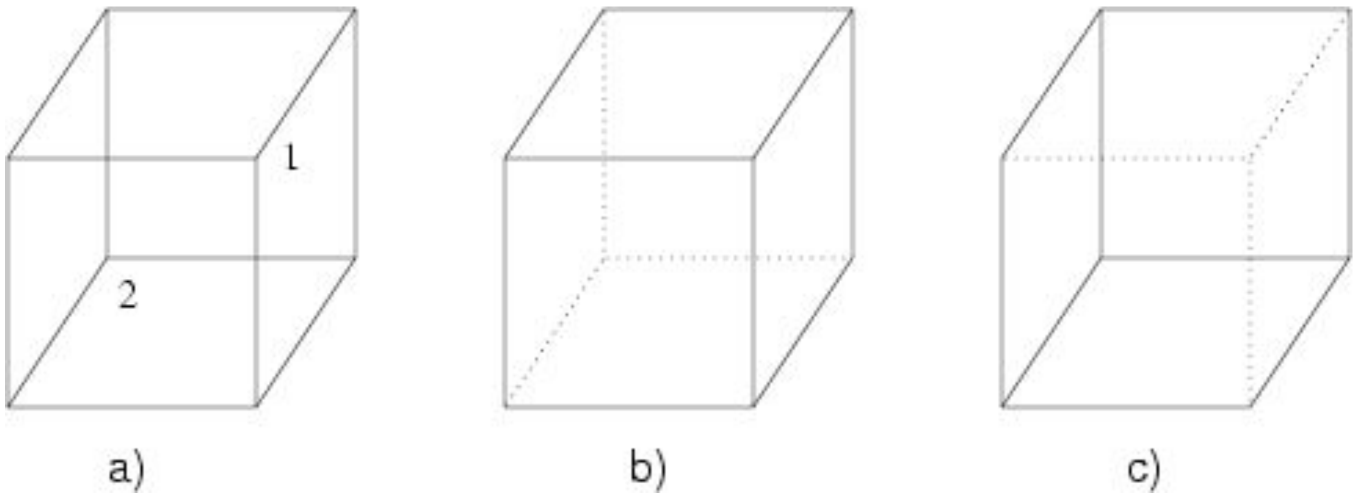
Perception ➔ reconnaissance / catégorisation?
Signal ➔ symbole : (Harnad90) «symbol grounding problem »

Hystérésis, bistabilité
Kelso, « Dynamical patterns »

Ambigüité fondamentale de la perception



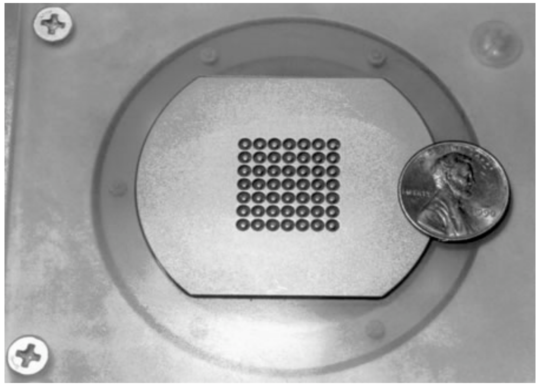
(Gaussier94)



Cubes de Necker

Qu'est ce que la Perception ?

- Experiences en psychologie : Bach-y-Rita 1972



JRRD

Bach-y-Rita

http://www.vard.org/jour/98/35/4/bachr354.htm

-> Très mauvaises performances sans action

-> Extériorisation de la perception si action

Qu'est ce que la Perception ?

~~Perception~~

~~$\approx$~~

~~Sensations~~

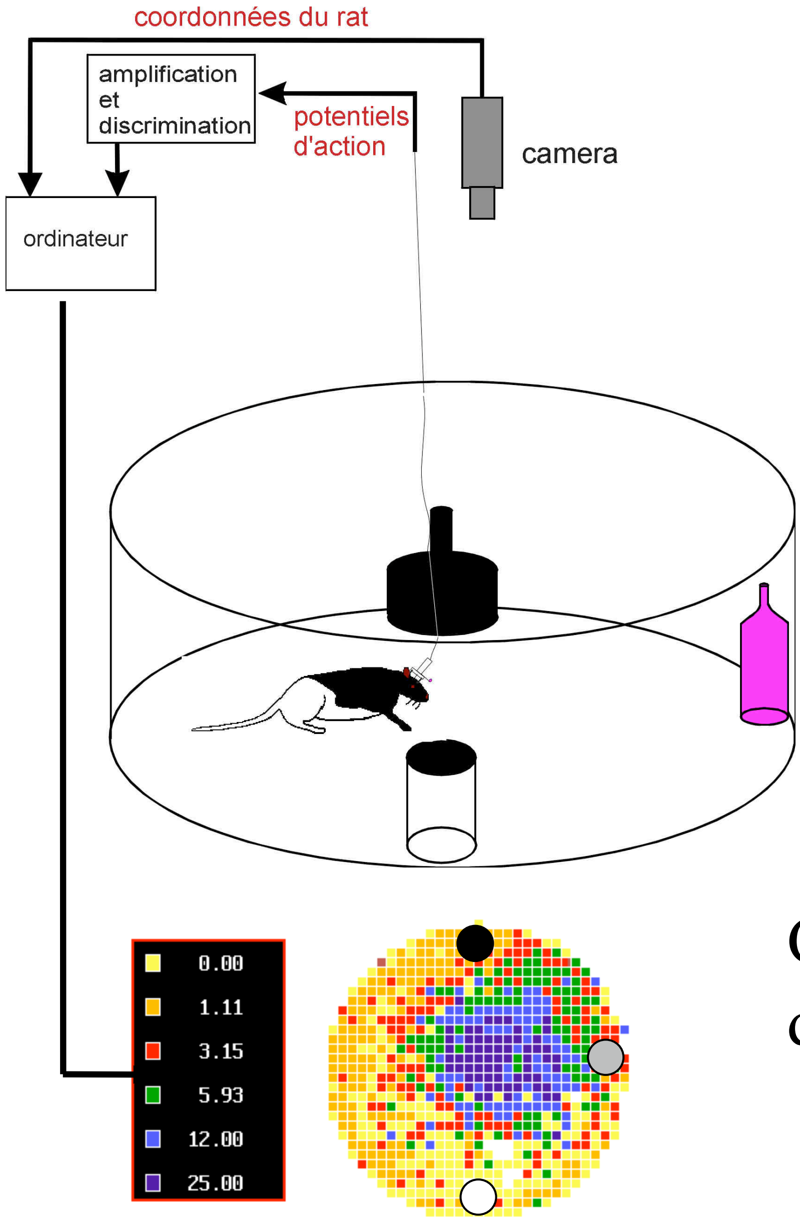
Importance du couplage sensori-moteur

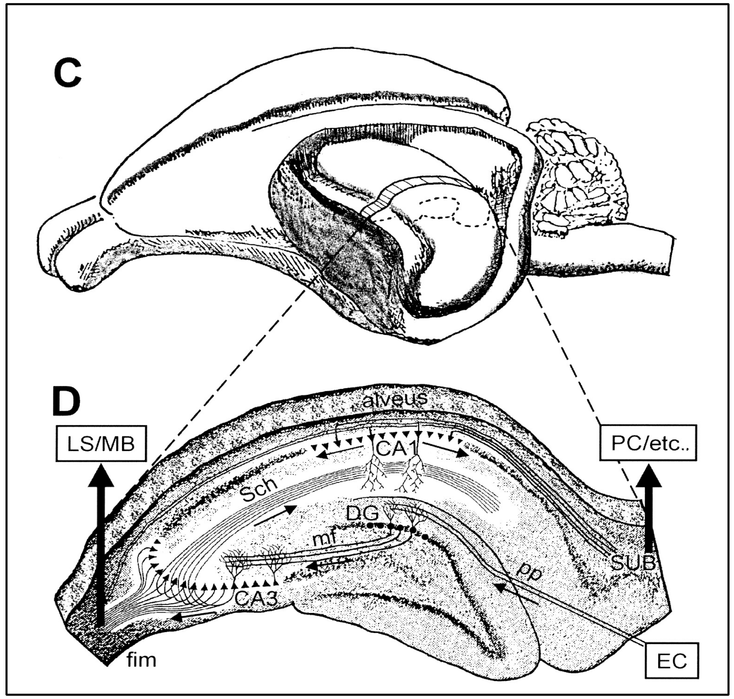
(Varela 93, Lenay 01, O’Regan 01,…)

Qu'est ce que la Perception ?

"Our Perception of the World Is a Fantasy That Coincides with Reality » (C. Frith 2007)

Reconnaissance de lieux (rat)





[O'keefe78]

Cellules de lieu dans l'hippocampe du rat (Lab. B. Poucet – Marseille)

L'hippocampe (HS)

Une des rares structures cérébrales connectée à toutes les aires corticales associatrices (capacité de fusion multimodale et détection/enregistrement d'événements complexes...)

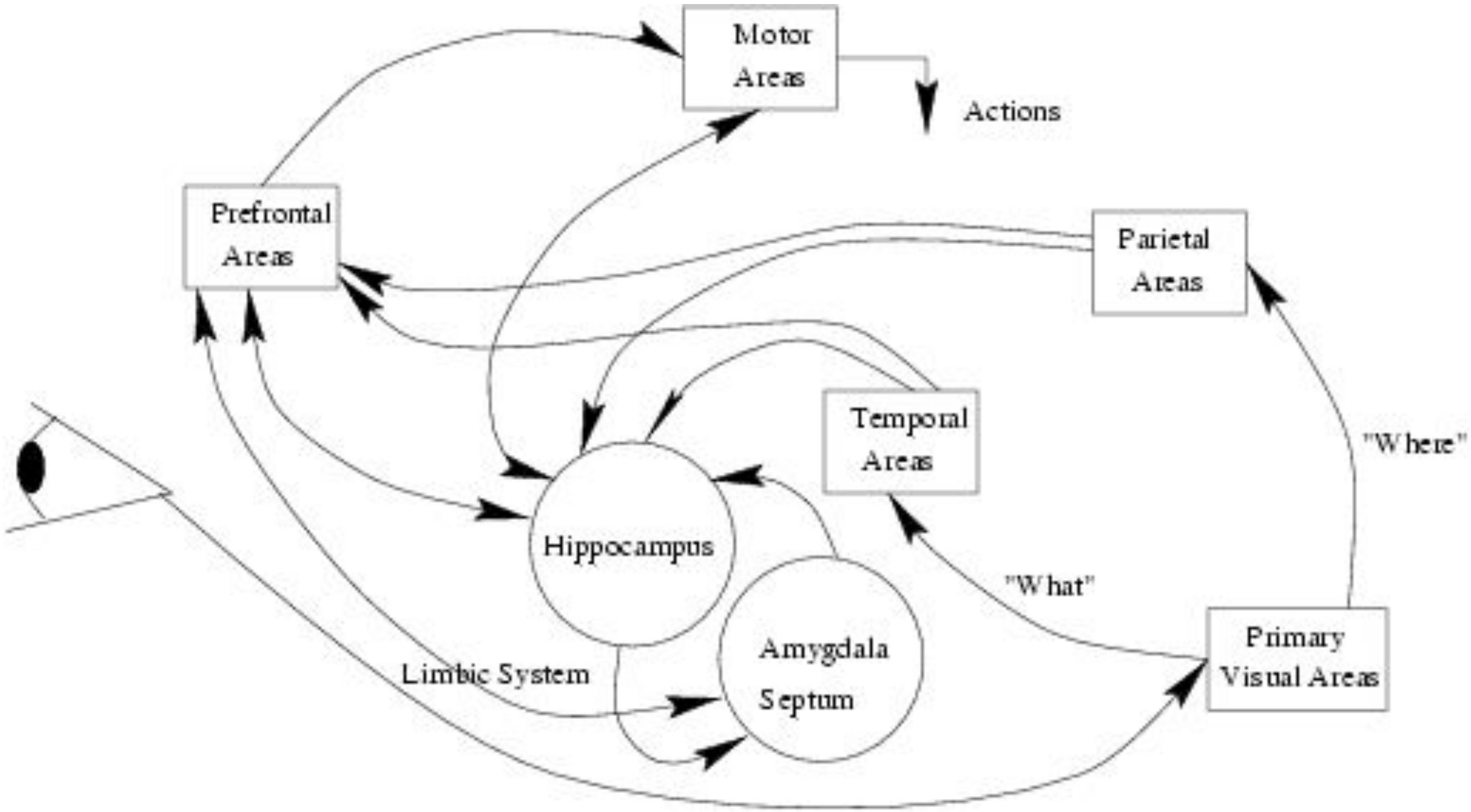
- Carte spatiale chez les rongeurs [O'Keefe78]

- Sévère amnésie antérograde après une ablation de l'hippocampe [Scoville57]
  (à la suite de crises d'épilepsie)

=> HS mémoire épisodique

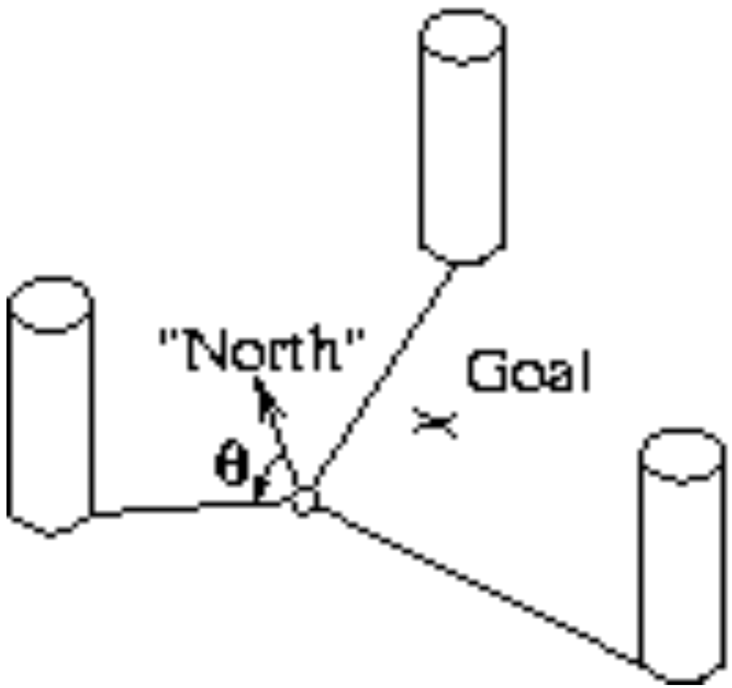
(HS aussi impliqué dans Alzheimer, l'autisme,
la schizophrénie / boucle PFC-HS-BG ...)

Architecture simulée

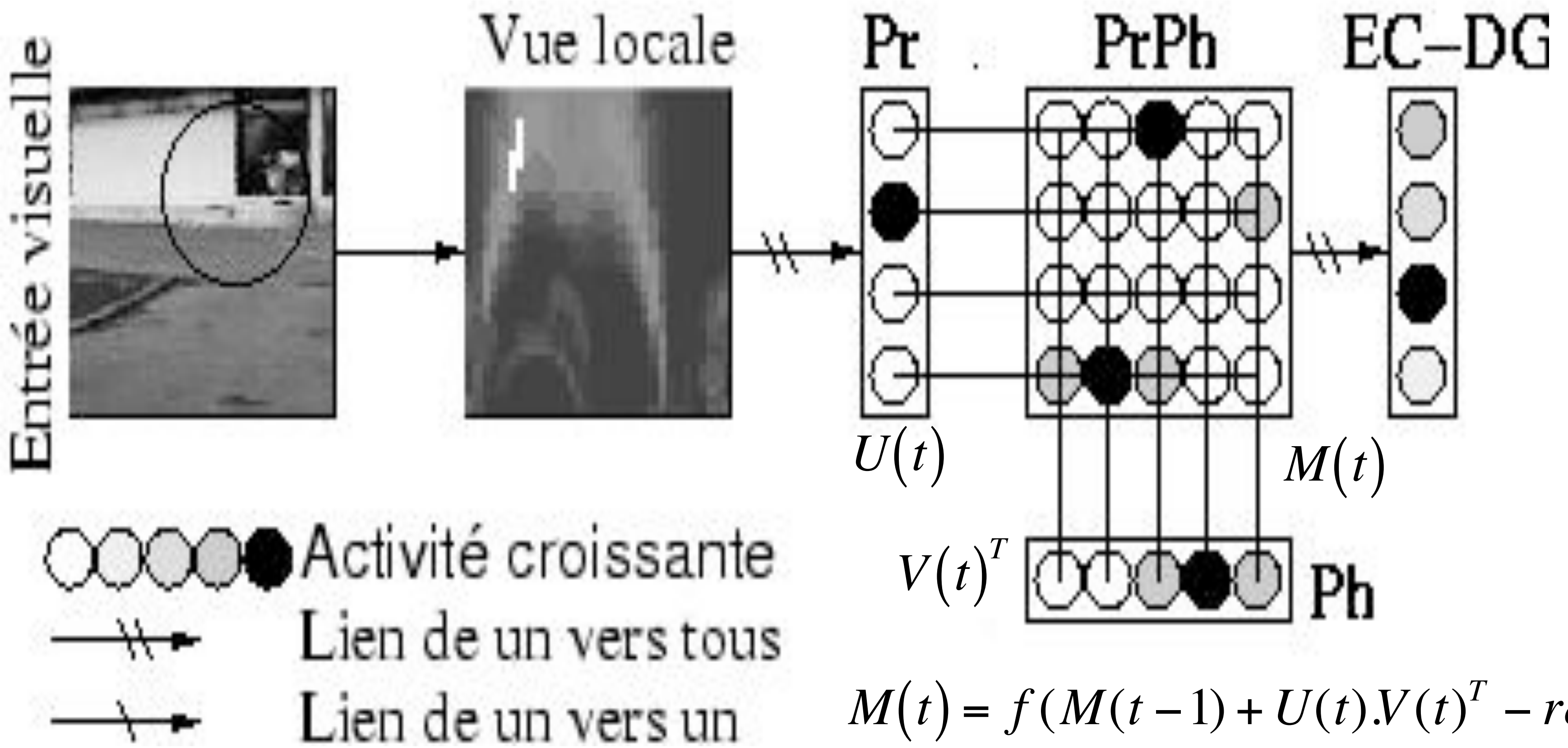


Comportement de retour au nid

- Un lieu peut être caractérisé par :
- - l'identité des amers/landmarks
- - leur azimuth et/ou distance
- ...



Reconnaissance de lieux (robot)

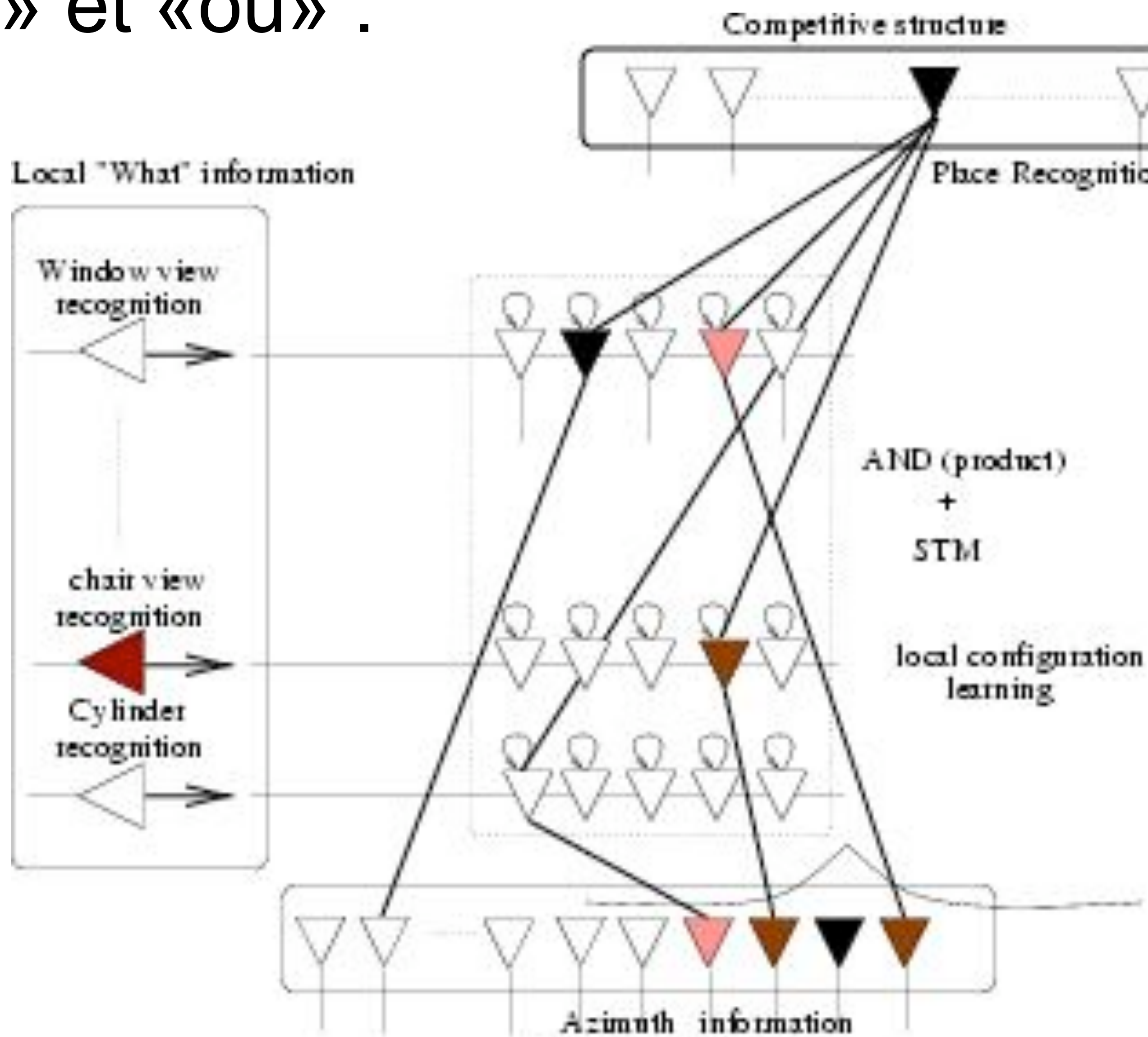


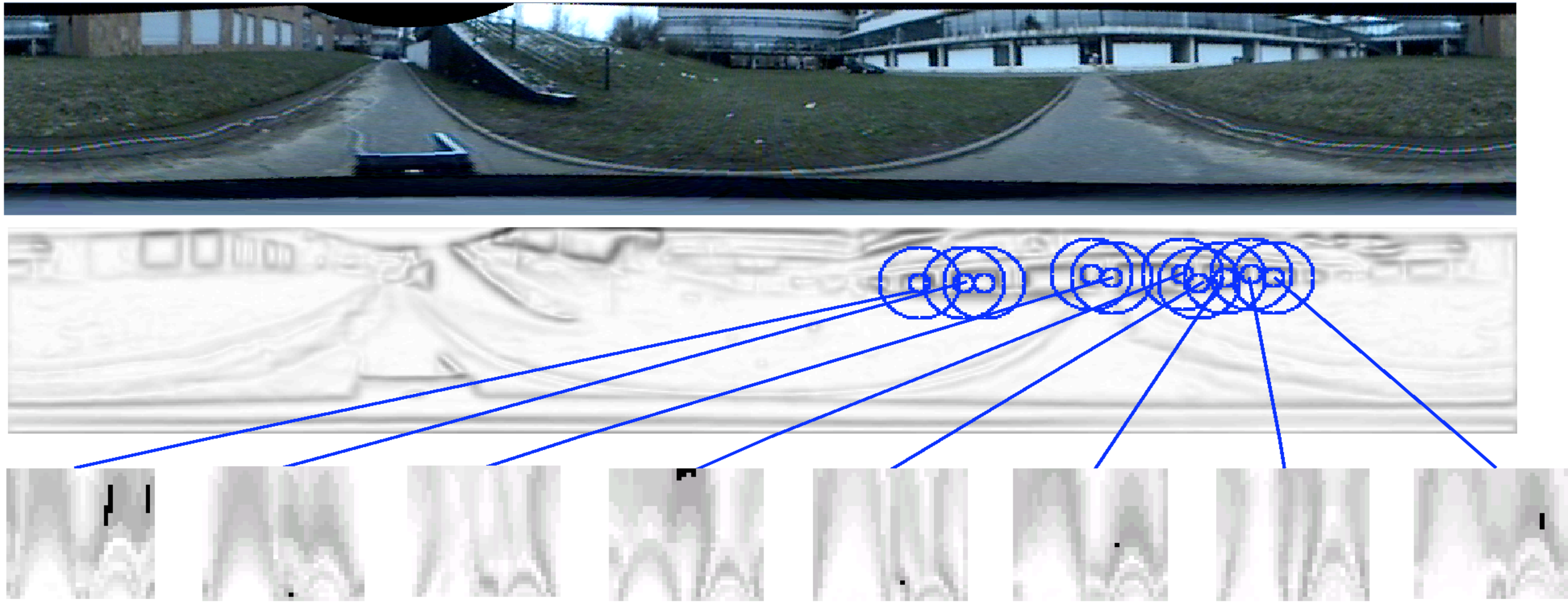
$$M(t) = f(M(t-1) + U(t).V(t)^T - reset)$$

extraction/apprentissage autonome des amers

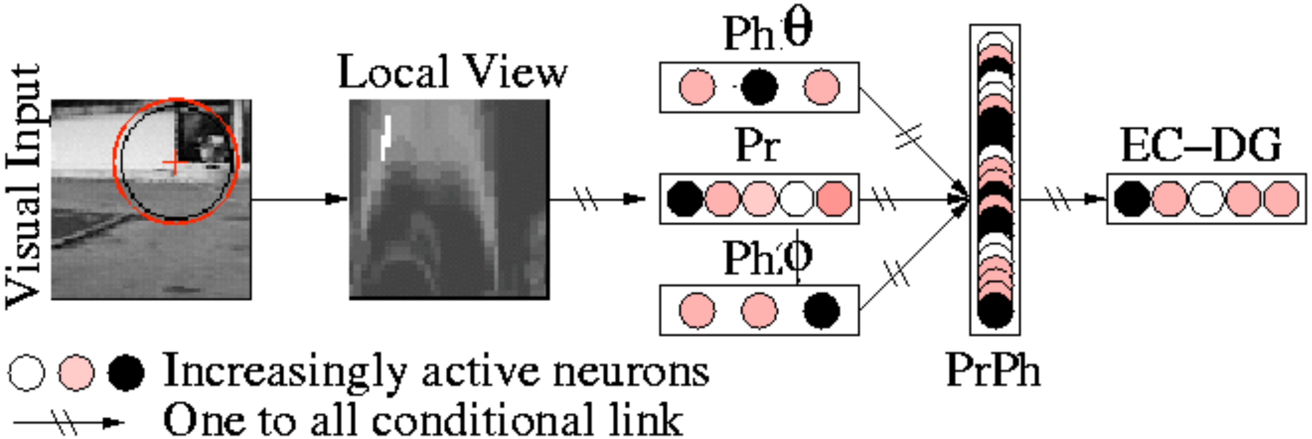
Modèle neuronal

- Apprentissage de la fusion des info. «quoi» et «où» :

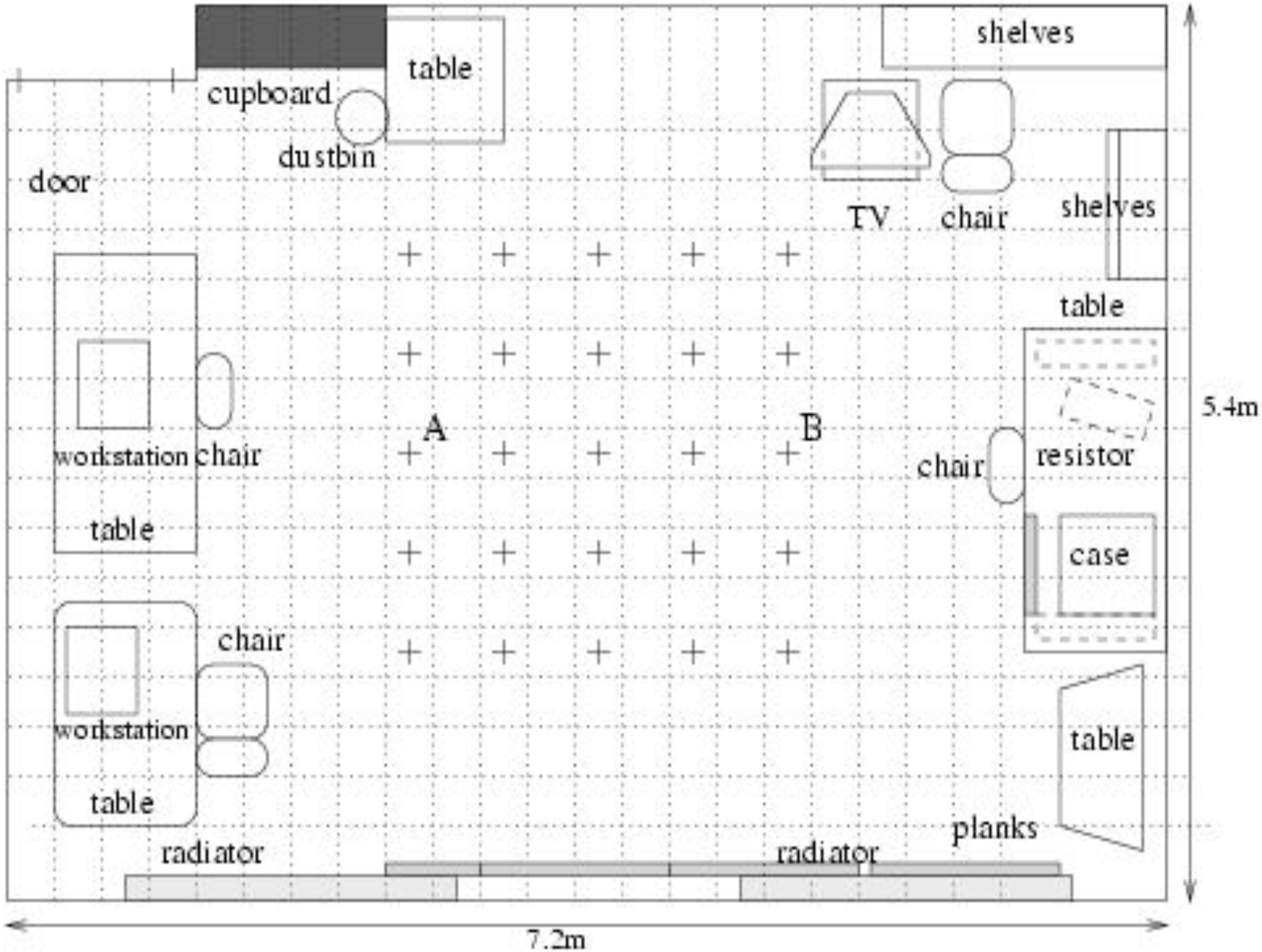




θ = 37°	θ = 49°	θ = 87°	θ = 106°	θ = 109°	θ = 113°	θ = 121°	θ = 128°
1 : 0.9615	3 : 0.9589	24 : 0.9096	4 : 0.9130	9 : 0.9358	10 : 0.9151	15 : 0.9033	0 : 0.9382
10 : 0.9246	5 : 0.9249	17 : 0.9089	21 : 0.9114	16 : 0.9304	19 : 0.9146	0 : 0.8934	2 : 0.9166
25 : 0.9221	6 : 0.9190	7 : 0.9073	32 : 0.9059	29 : 0.9301	25 : 0.9040	26 : 0.8934	22 : 0.9116
11 : 0.9056	2 : 0.8937	37 : 0.8830	13 : 0.9022	14 : 0.8980	2 : 0.9029	12 : 0.8912	12 : 0.9096

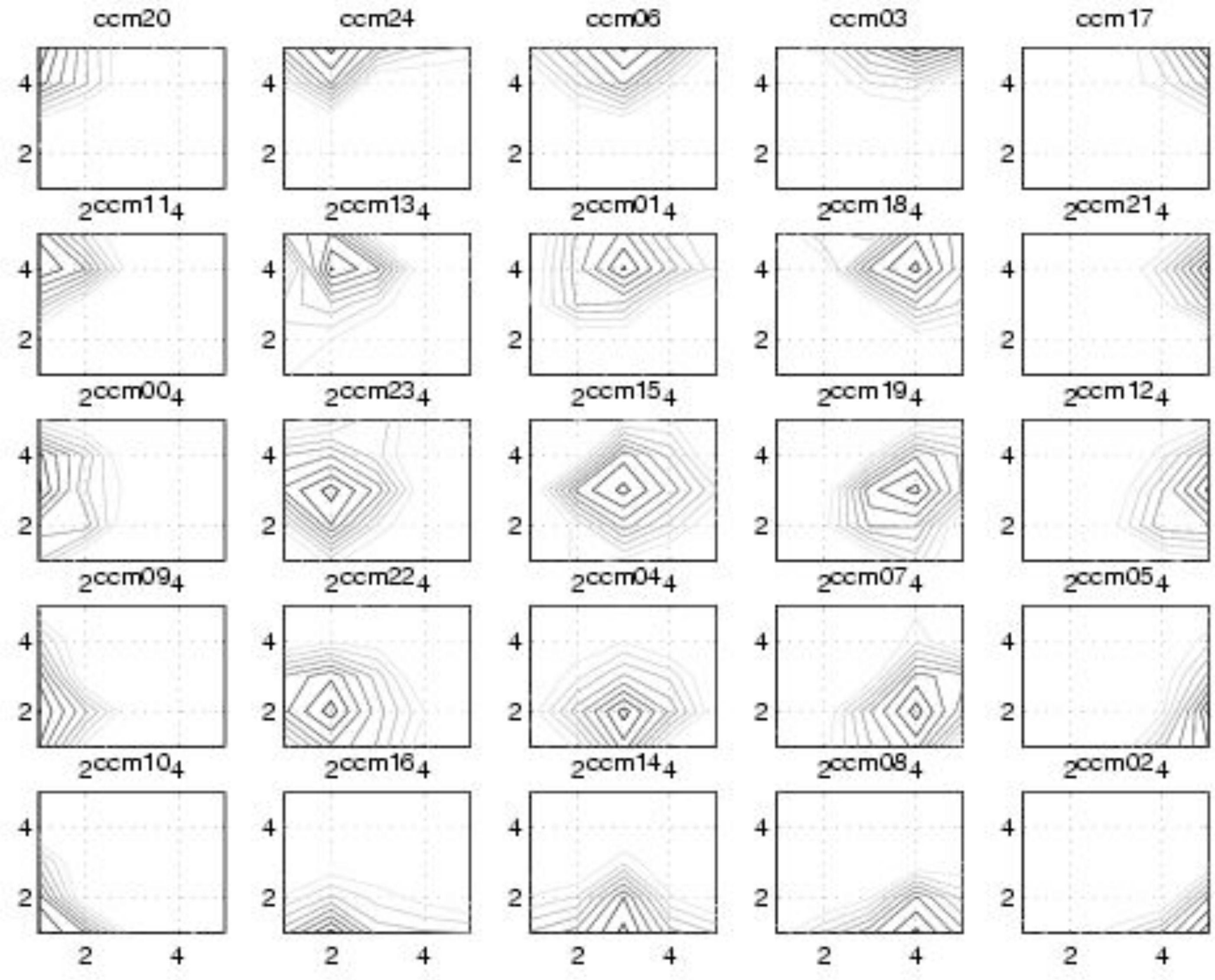


Experimental setup



Interest of robots: better learning control than animals

Primary neuronal activity



Problem !

The rat hippocampal place cells are very narrow compared to our robot place cells:

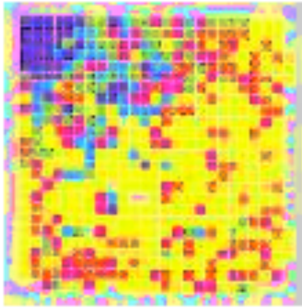
typically 3m instead of 30 cm !

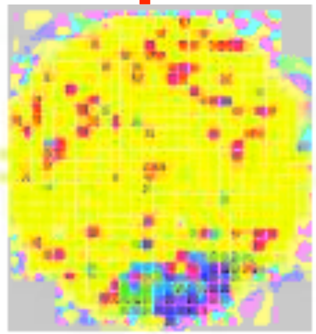
But rat should be able to access the same kind of Information [Kolb & Tees 90] !

So why does the rat seems not to use this powerful and large gradient information?

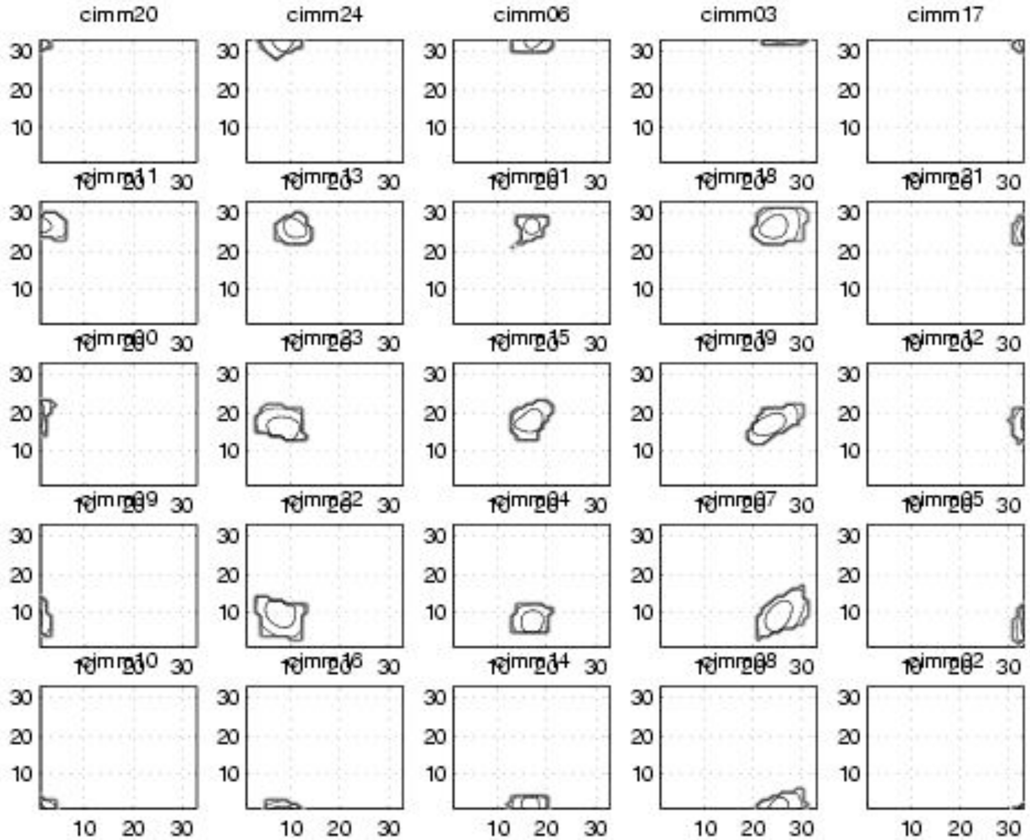
Activité après competition

rat:



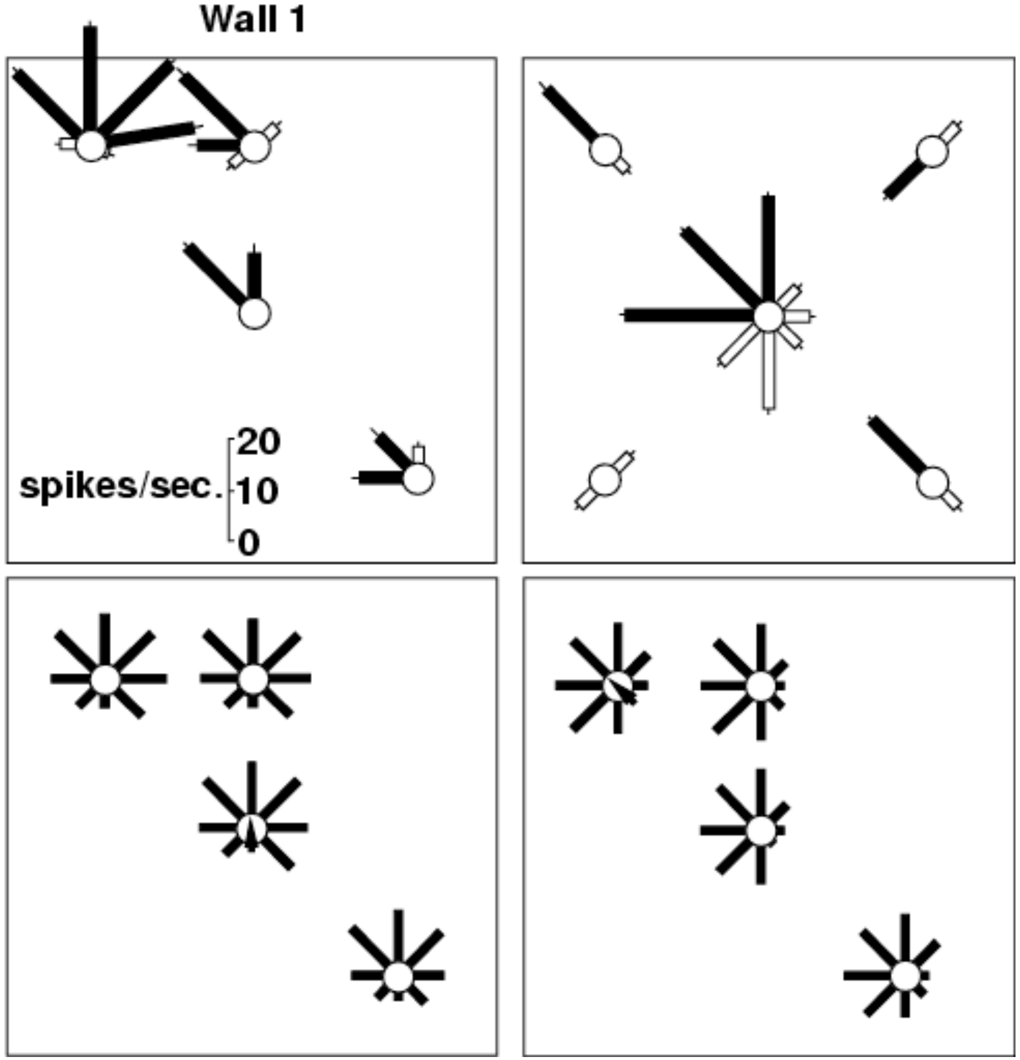


robot:



Activité de type "View cell"

- Champ de vision limité à

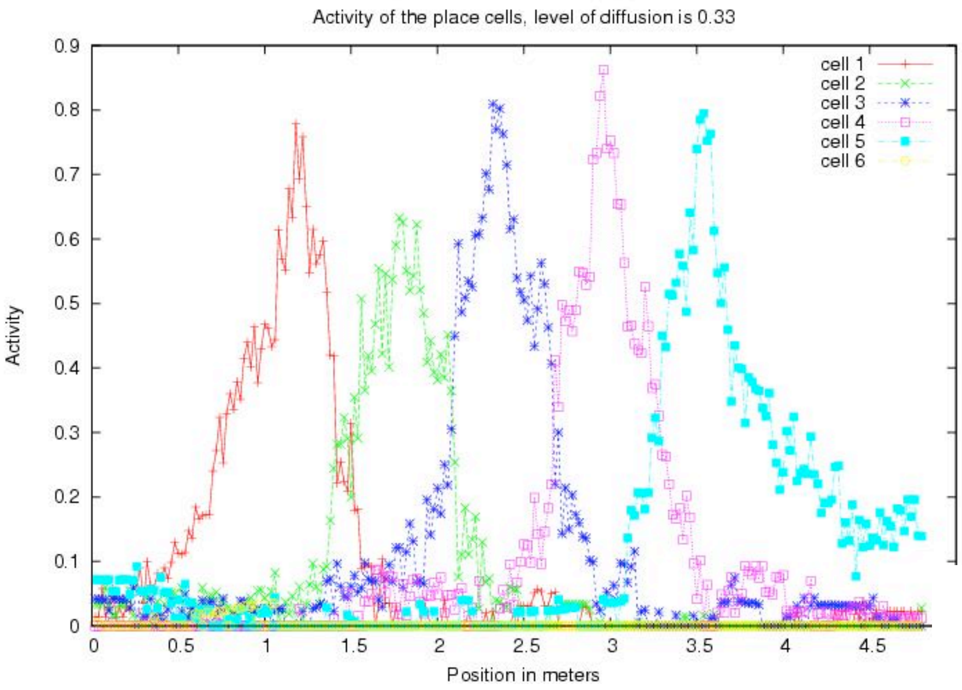


Monkey
[Rolls95]

Robot
[Gaussier98]

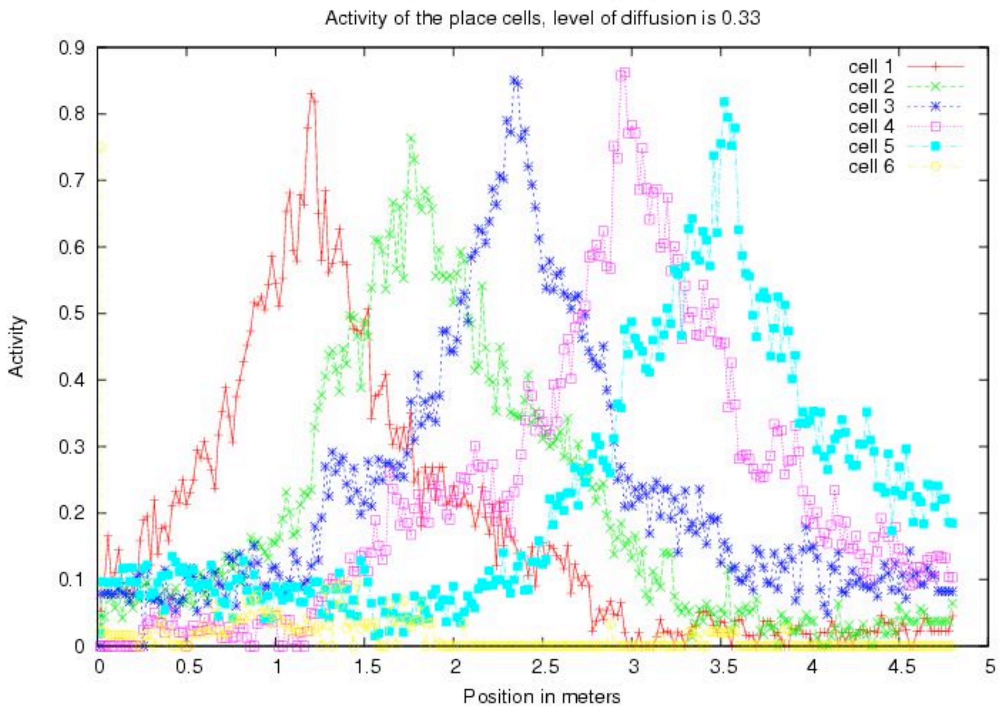
Look like primate HS

Reconnaissance de lieux (robot)

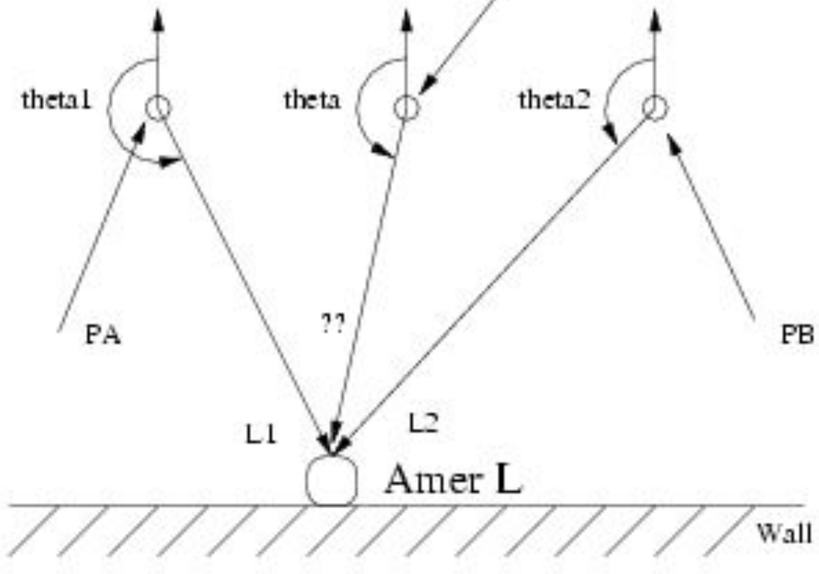


1 amer reconnu
par pt de focalisation
(WTA strict)

Compétition « souple »:
4 « gagnants » par pt
=> meilleure généralisation

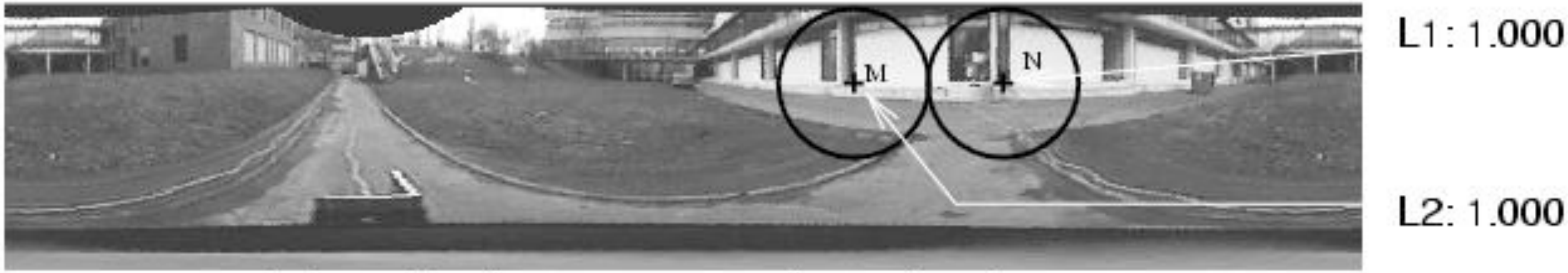


Reconnaissance de lieux (robot)

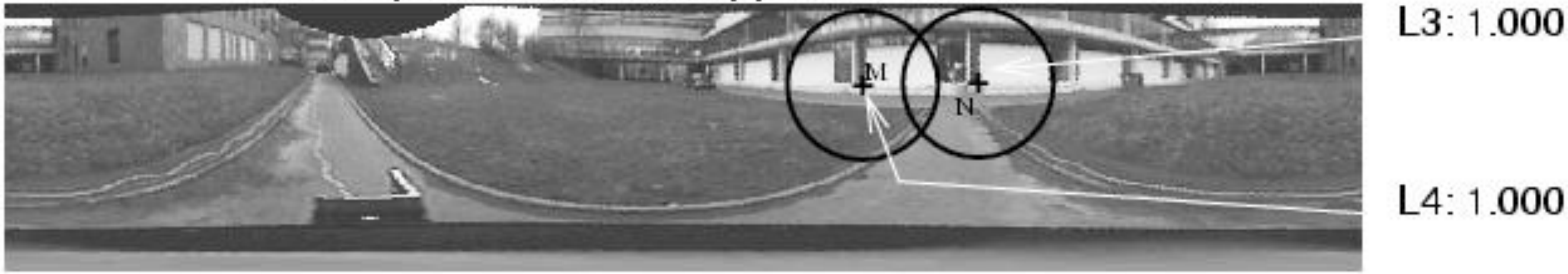


Le système focalise
sur un amer.
Est ce L1 ou est ce L2 ?

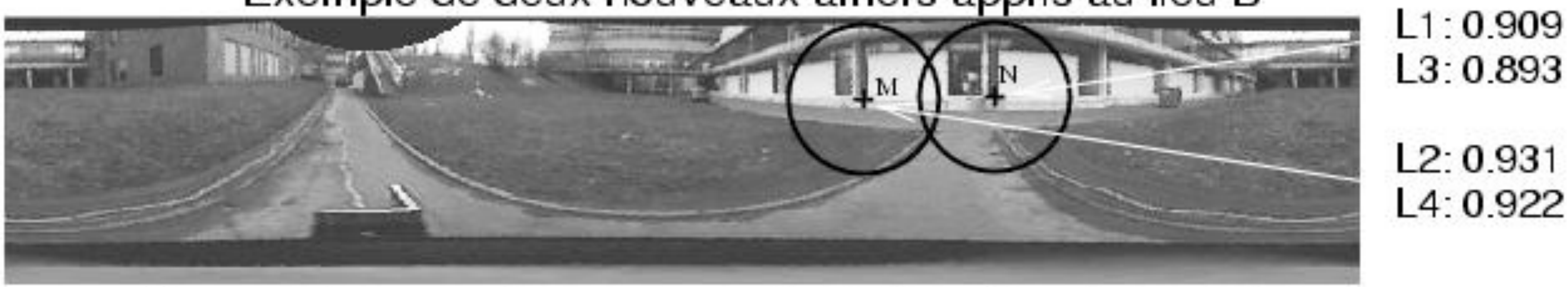
Importance d'une compétition souple



Exemple de 2 amers appris au lieu A

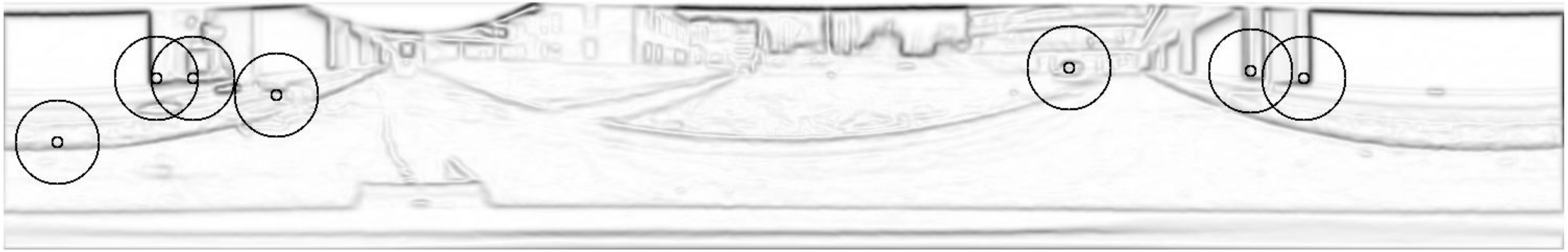


Exemple de deux nouveaux amers appris au lieu B



Reconnaissance des amers au lieu C (position intermédiaire)

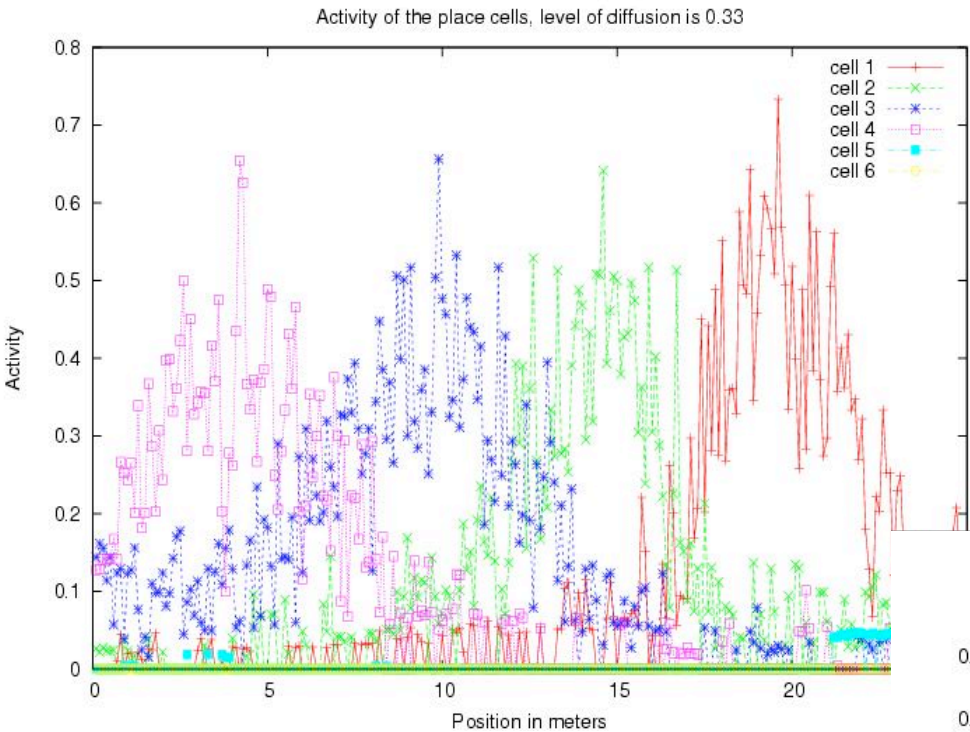
Reconnaissance de lieux (robot)



Les 7 zones les plus pertinentes

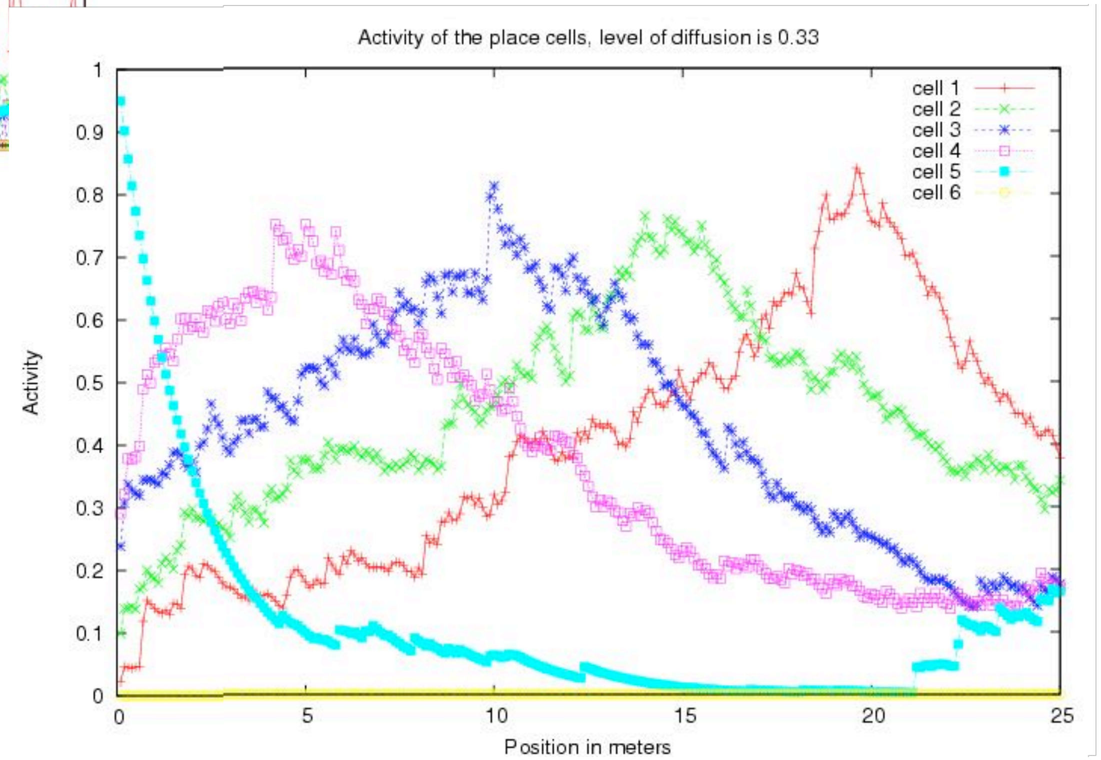
Les 15 premiers points: tout n'est pas pertinent!

Reconnaissance de lieux (robot)



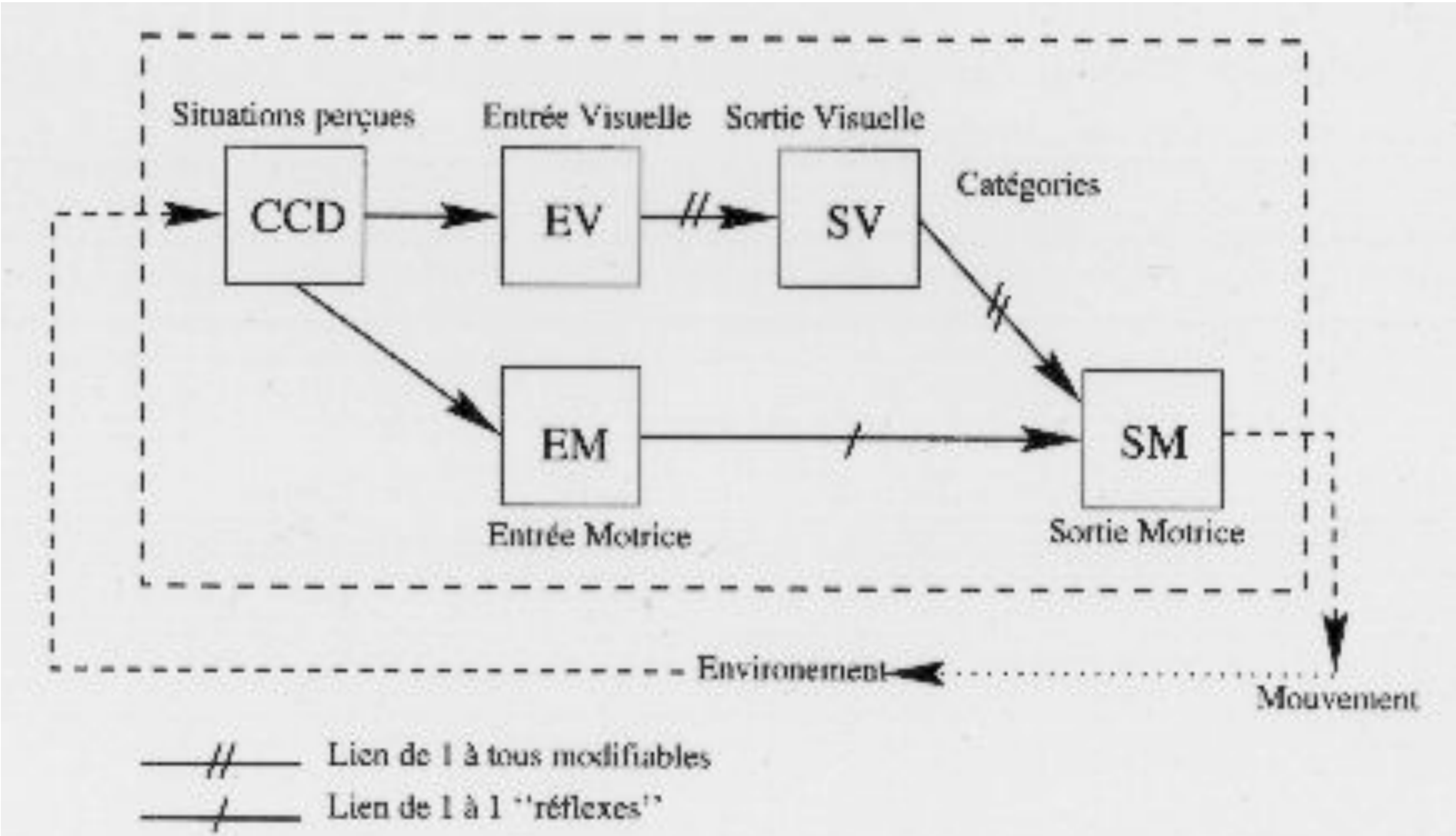
Calcul instantané
de l'activité des cellules
(4 gagnants)

Avec mémoire
du passé



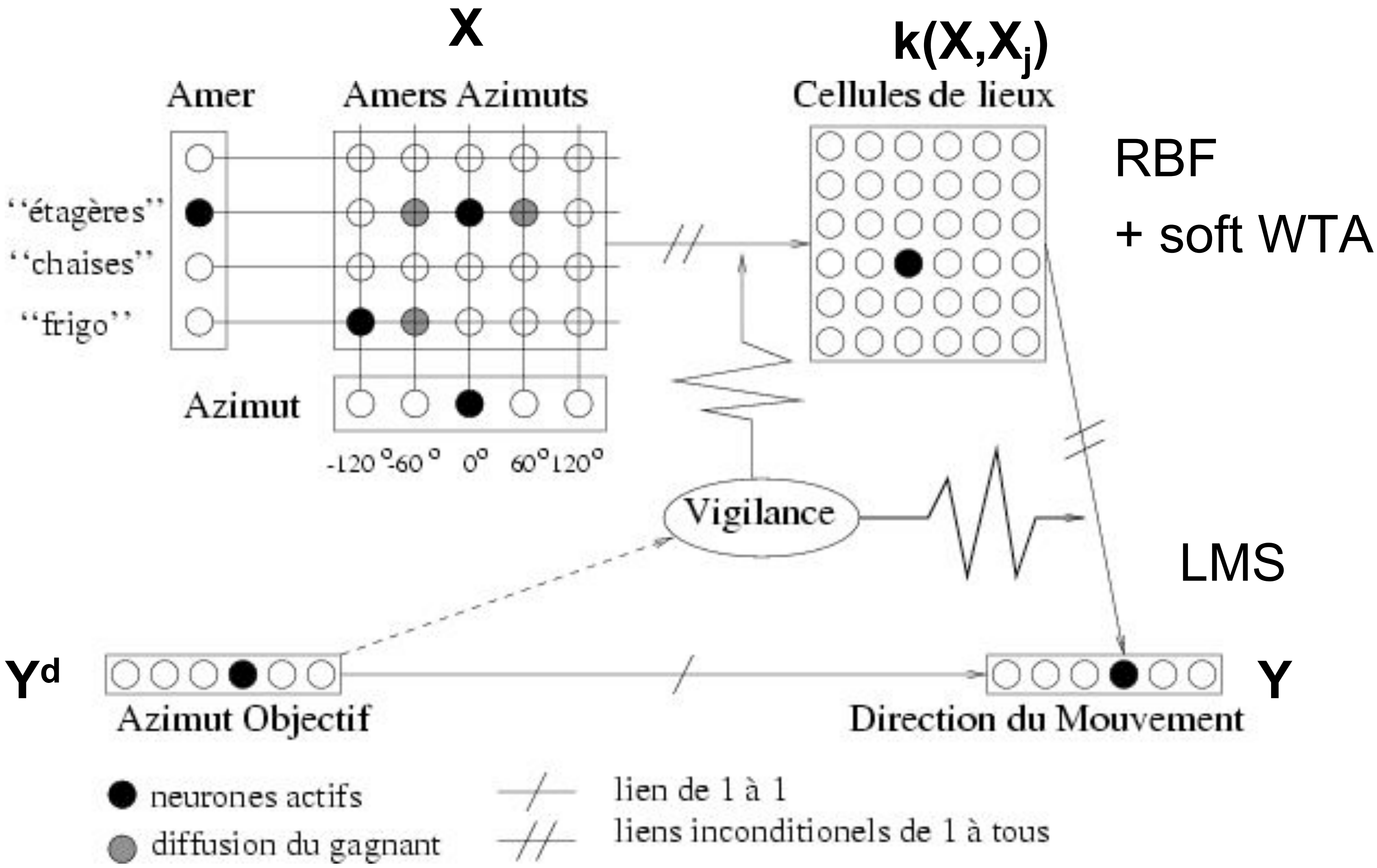
Architecture PerAc

apprentissage associations Sensation/Action pour constituer une perception



Counter propagation network (Hecht-Nielsen87) (Gaussier 94)

Architecture PerAc



Architecture PerAc

Etapes de l'algo:

$$\begin{cases} W = (W_1, W_2, \ldots, W_p) \\ q < p, \quad init : q = 0 \end{cases}$$

1) Catégoriser les signaux sensoriels "riches" X (kmeans, seuil variable, g RBF)

$$z_j = \begin{cases} g\left(\left\| W_j - X \right\|\right) & pour \quad j = \underset{i=1\ldots q}{ArgMax} \quad g\left(\left\| W_i - X \right\|\right) \\ 0 & \text{sin}on \end{cases}$$

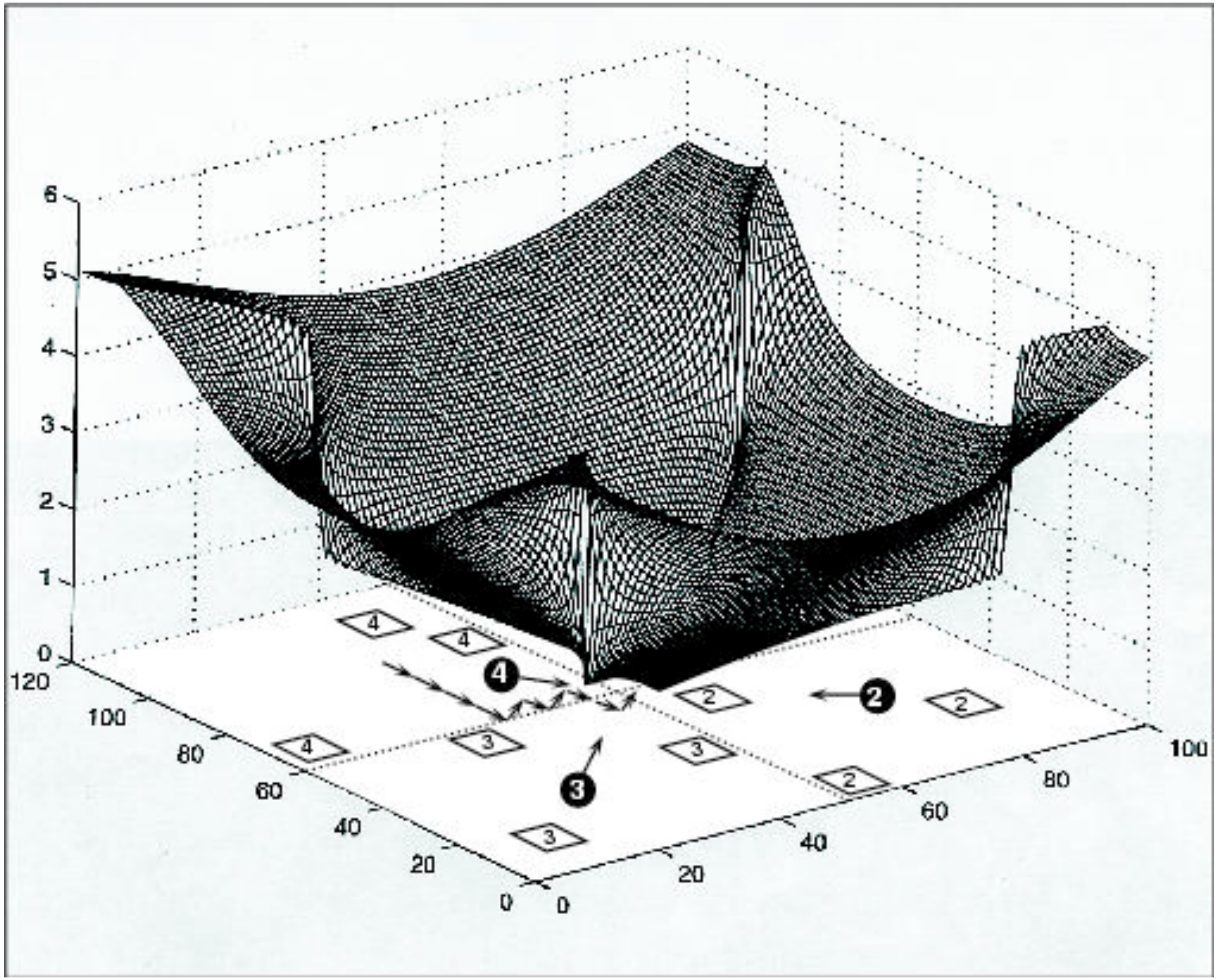
$$si \quad \underset{j=1..q}{Max}\left(z_j \leq b_1\right) \quad \Rightarrow recrutement : \; w^1_{q+1} = X(t)\,; q \leftarrow q+1$$

2) LMS pour associer les signaux classifiés aux signaux "frustres" (Y^d)

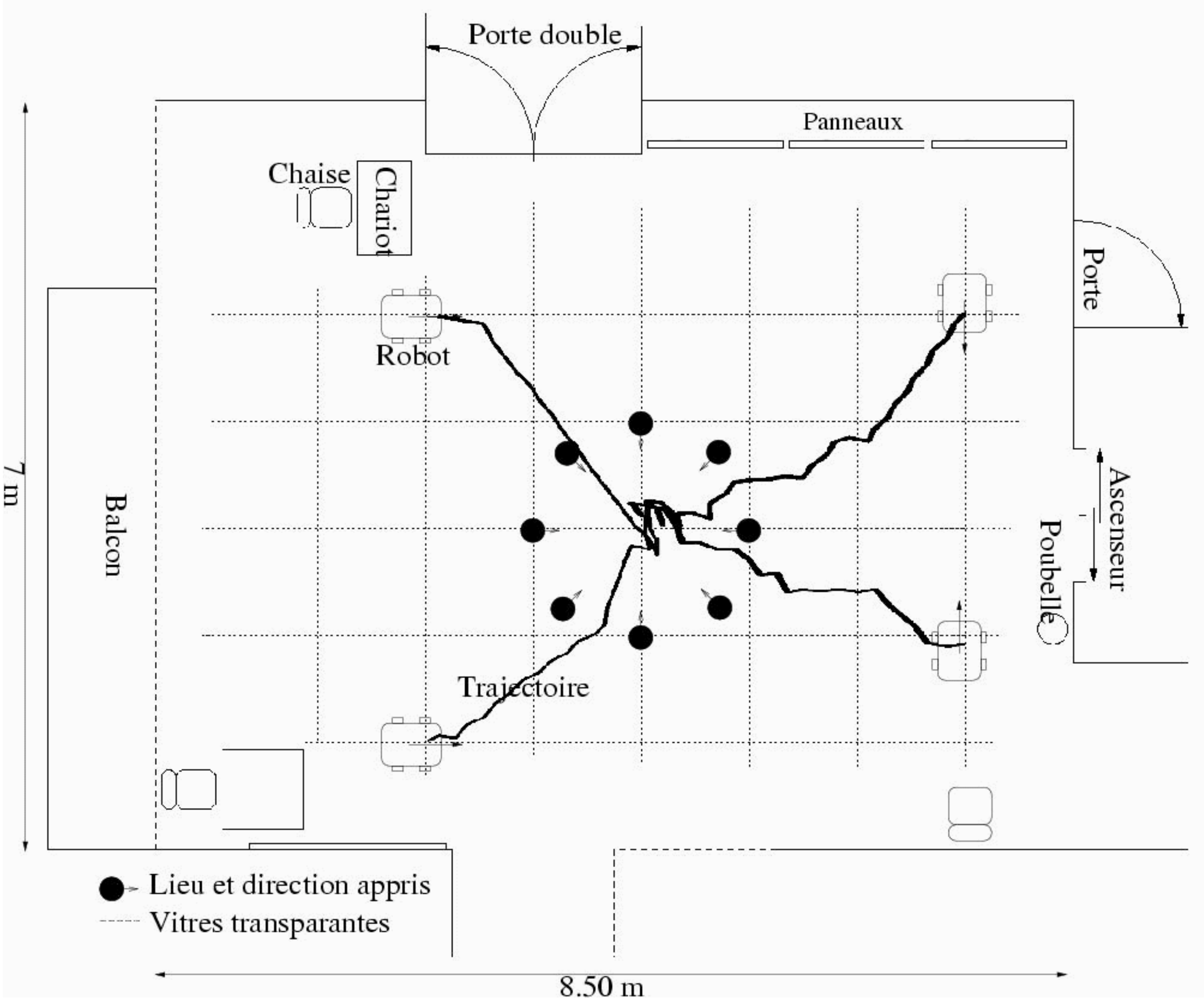
$$Y = W^{'} Z + b_2 \quad et \quad dW_2 = \varepsilon\, \alpha(t)\, (Y^d - Y)\, Z$$

$$\varepsilon > 0 \quad et \quad \alpha(t) \geq 0 \text{ neuro modulation}$$

Effet de l'apprentissage sensori-moteur



Reconnaissance de lieux (robot)



Video (suivi de chemin)

Mobile robot task specification by human–robot interaction

C. Giovannangeli
P. Gaussier

équipe Neurocybernétique
Laboratoire ETIS

Architecture PerAc

Etapes de l'algo:

$$\begin{cases} W = (W_1, W_2, \ldots, W_p) \\ q < p, \quad init : q = 0 \end{cases}$$

1) Catégoriser les signaux sensoriels "riches" X (kmeans, seuil variable, g RBF)

$$z_j = \begin{cases} s_i = g\left(\left\|W_j - X\right\|\right) & pour \ \mathrm{s_i}/z_{\max} > T \ \text{avec} \quad z_{\max} = \underset{i=1\ldots q}{Max} \quad g\left(\left\|W_i - X\right\|\right) \\ 0 & \text{sinon} \end{cases}$$

$$si \quad \underset{j=1..q}{Max}\left(z_j \leq b_1\right) \quad \Rightarrow recrutement : W_{q+1} = X\left(t\right); q \leftarrow q+1$$

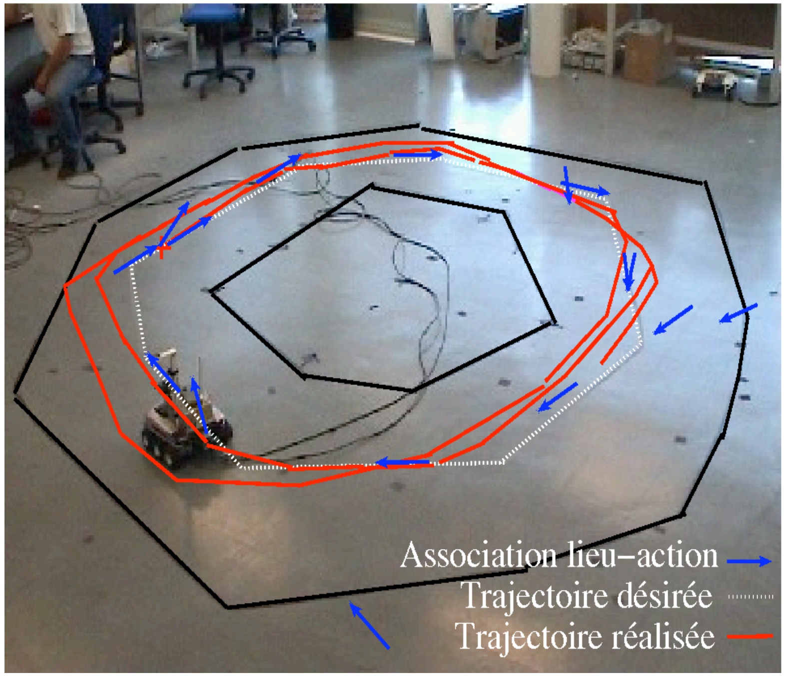
2) LMS pour associer les signaux classifiés aux signaux "frustres" (Y^d)

$$Y = W' Z \quad et \quad dW_2 = \varepsilon\, \alpha\left(t\right) (Y^d - Y)\, Z$$

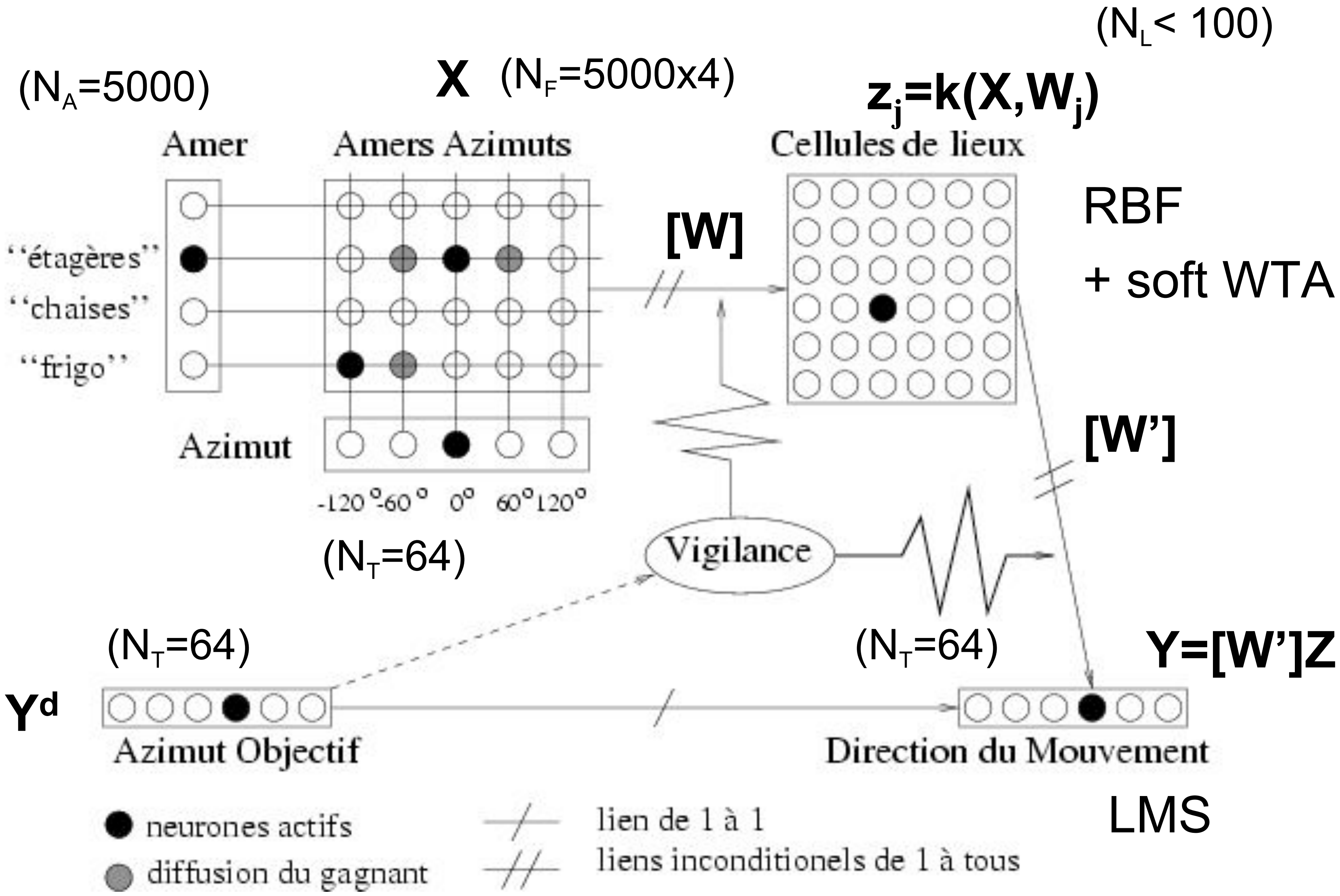
$$\varepsilon > 0 \quad et \quad \alpha\left(t\right) \geq 0 \text{ neuro modulation}$$

Apprendre une trajectoire

- [Giovannangeli05,06]



Architecture PerAc



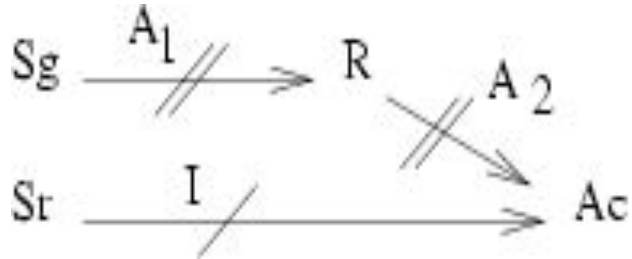
Définition de la Perception

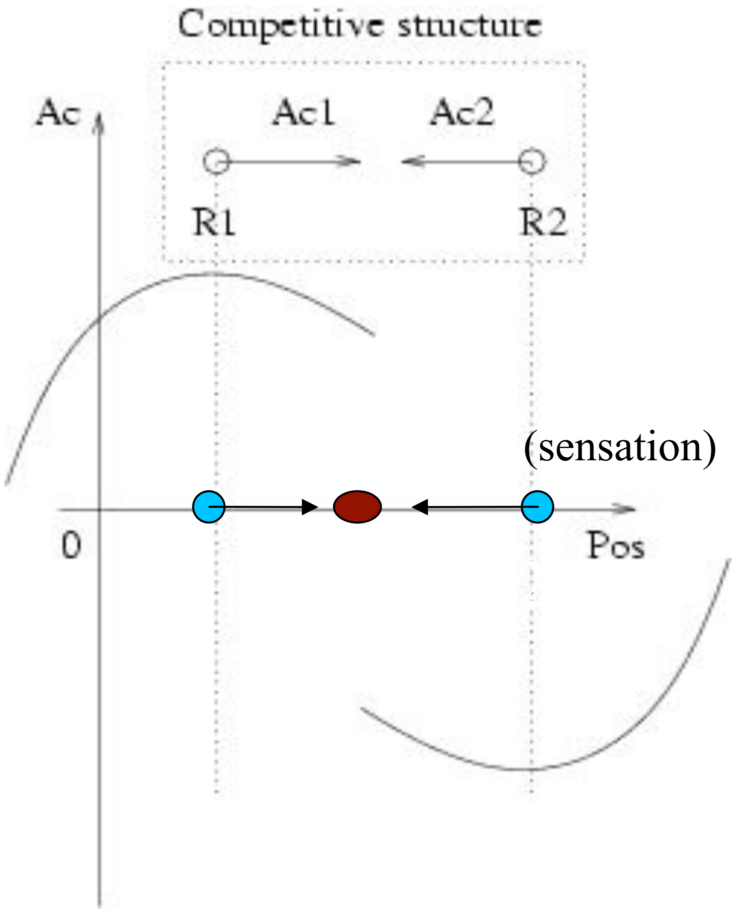
La perception est considérée comme un attracteur dynamique permettant un ensemble cohérent d'actions en fonction des sensations (attracteur sensori-moteur)

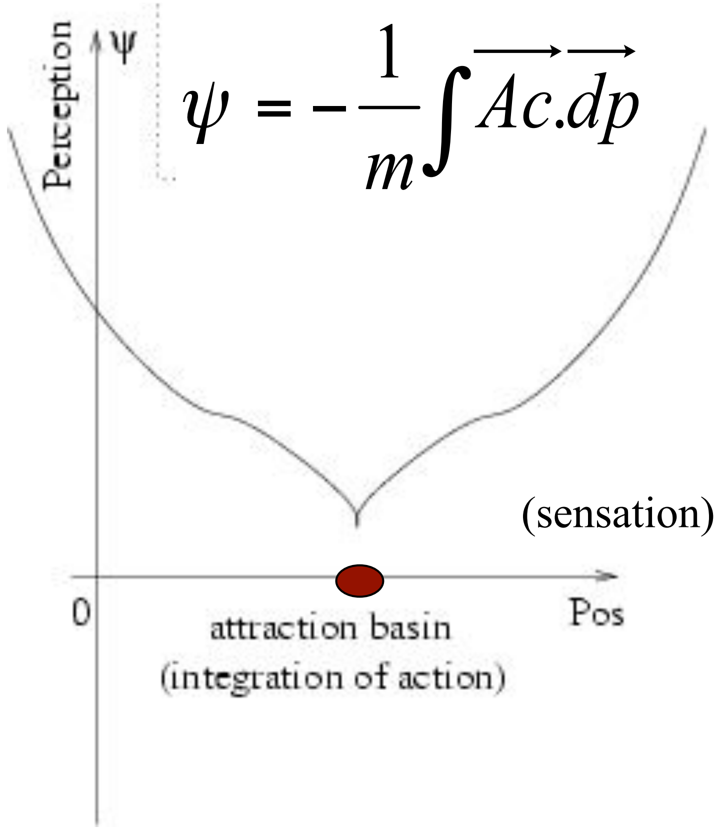
Nous définissons la Perception *Per* comme une fonction scalaire telle que :

$$\boxed{\mathrm{Ac} = -m\,\overrightarrow{grad}\,Per(\mathrm{p})}$$

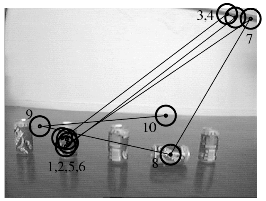
The PerAc architecture

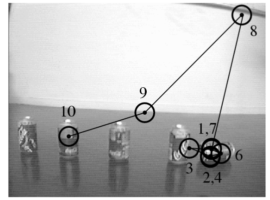






Perception

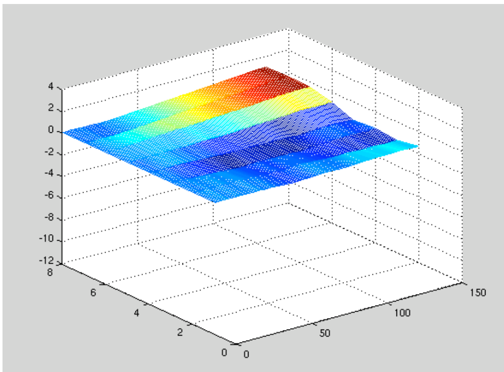


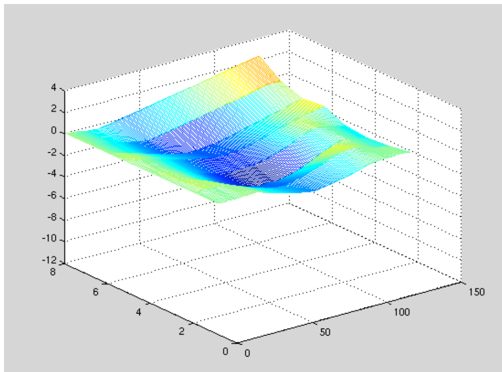


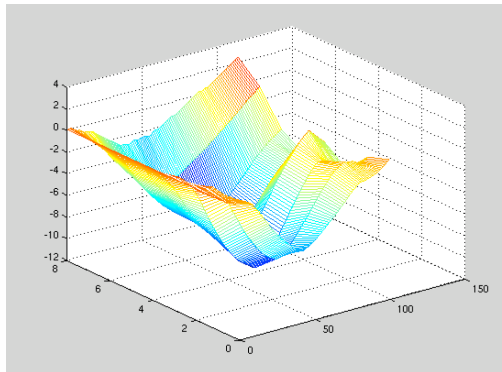
Perception : behavioral attraction basin
Learning sensori-motor invariants
(affordances/recognition)

Ac=-m.grad(Per)

(Maillard05)

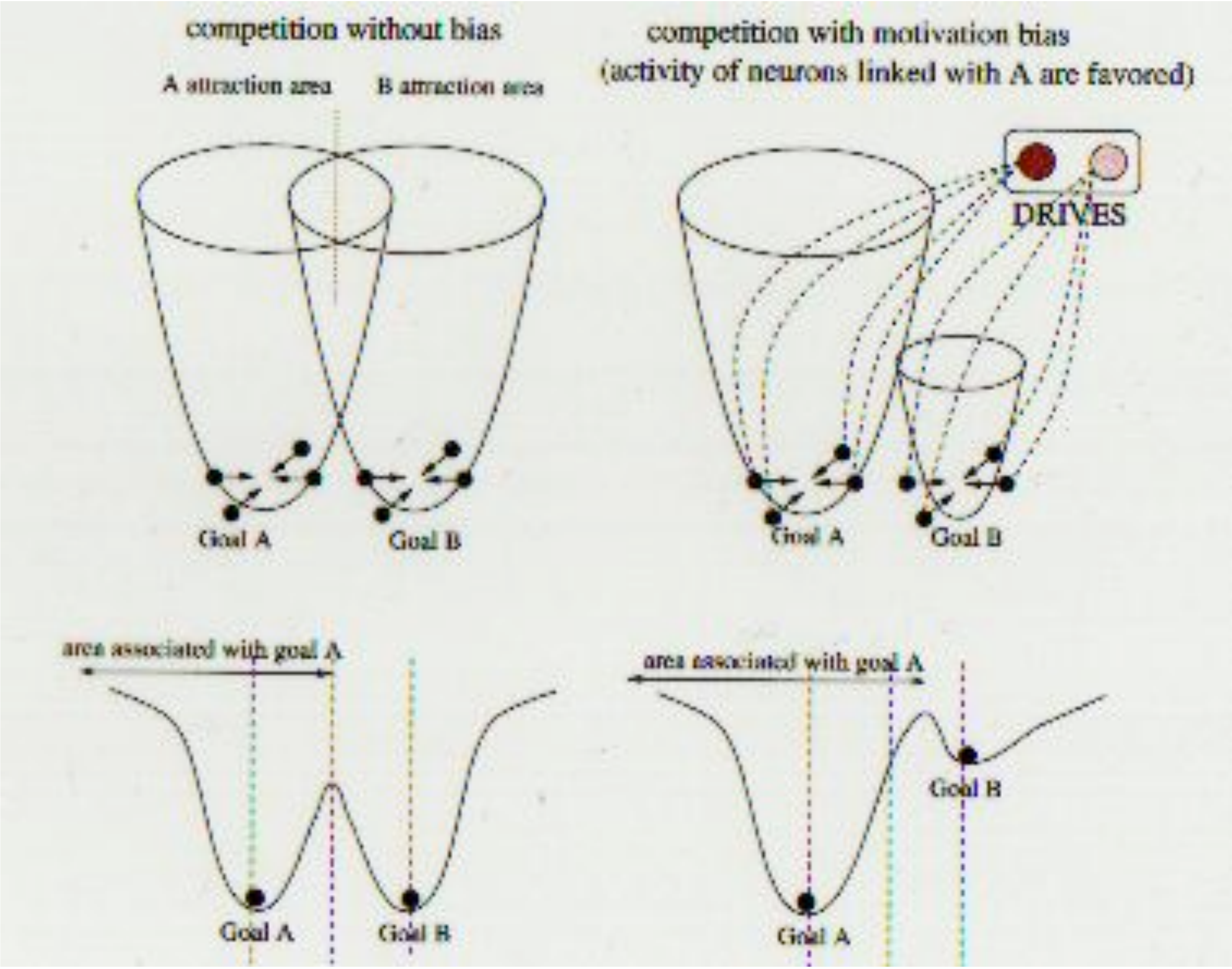




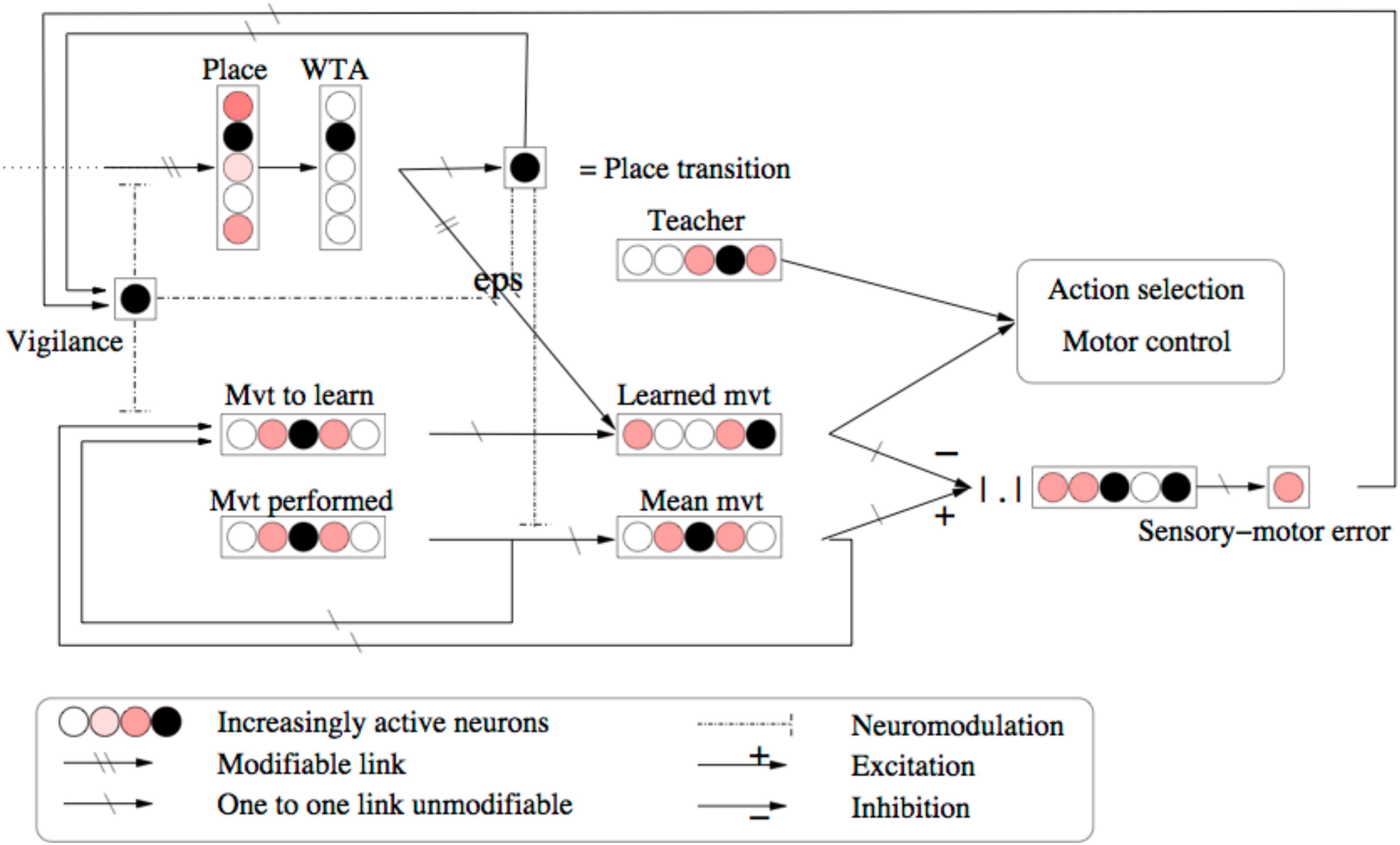


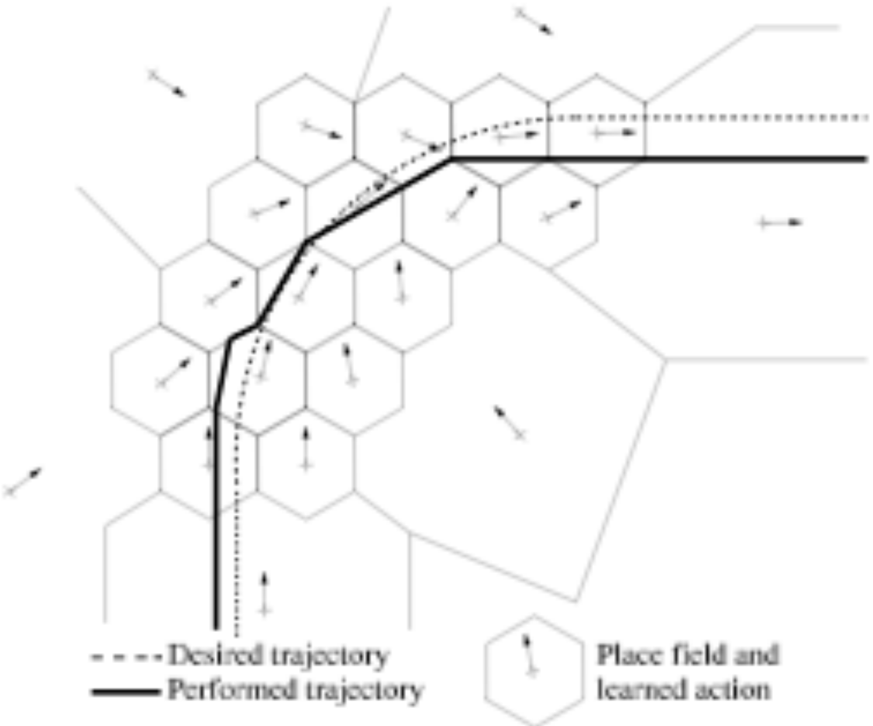
Considered as recognition for the observer ?

Motivational Bias



Interactive learning

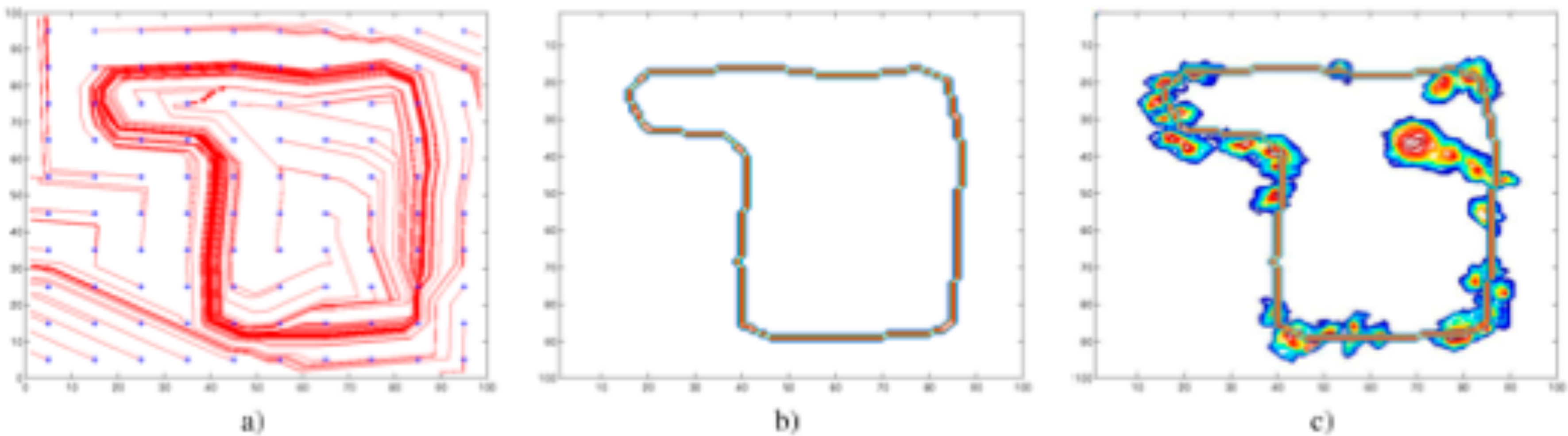




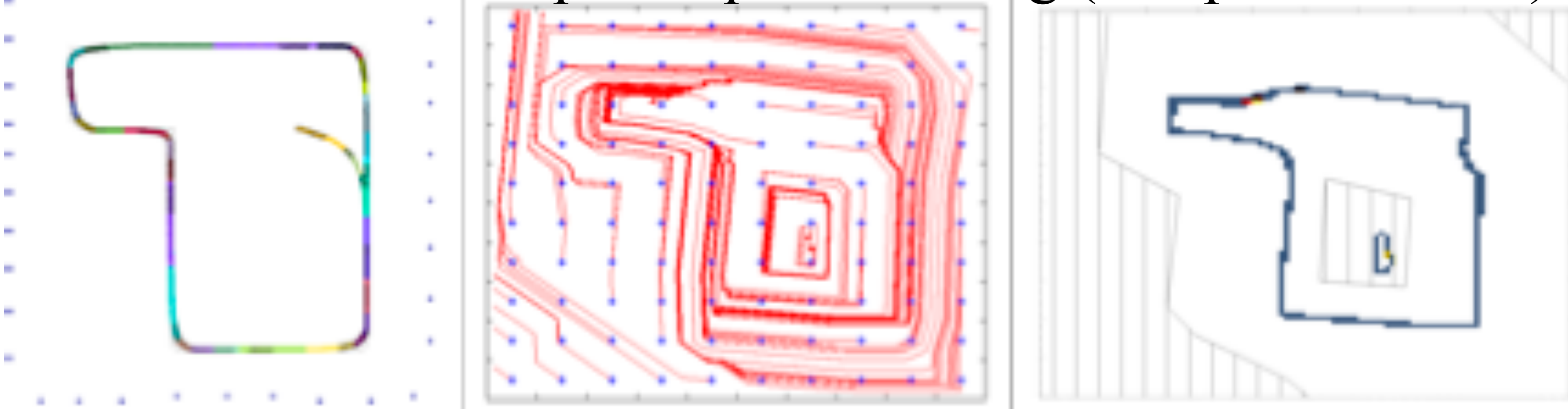
Adaptive clustering
from motor errors

(Giovannangeli 05)

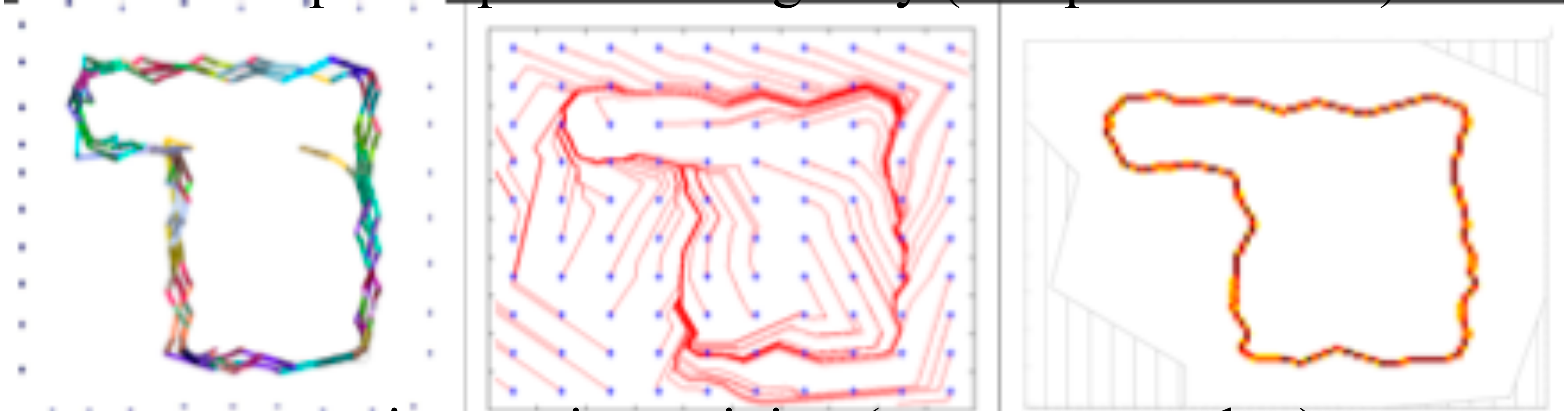
interactive training (human teacher)



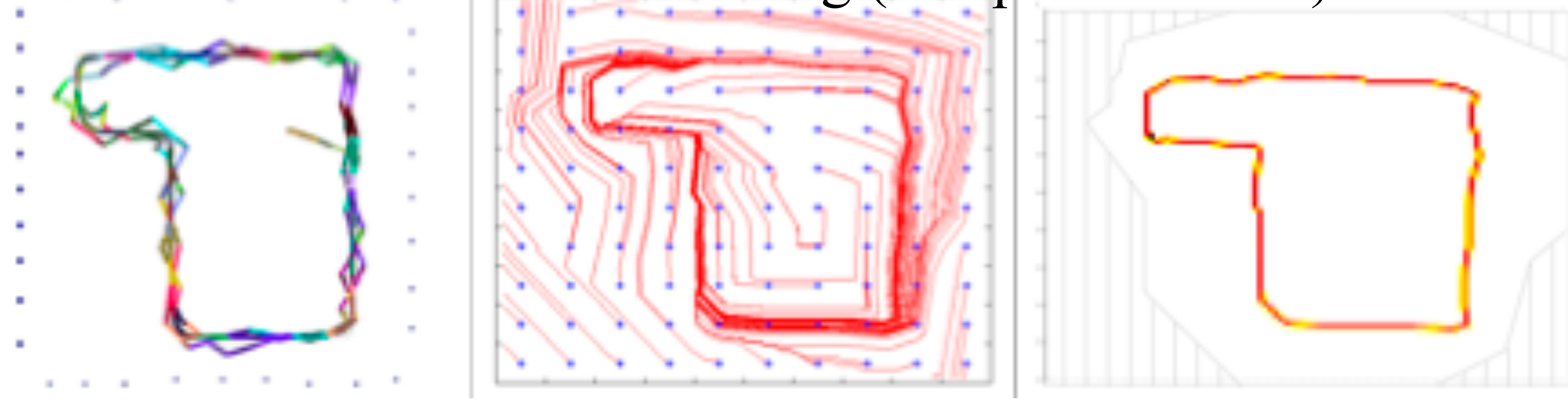
“Perfect” prescriptive training (computer teacher)



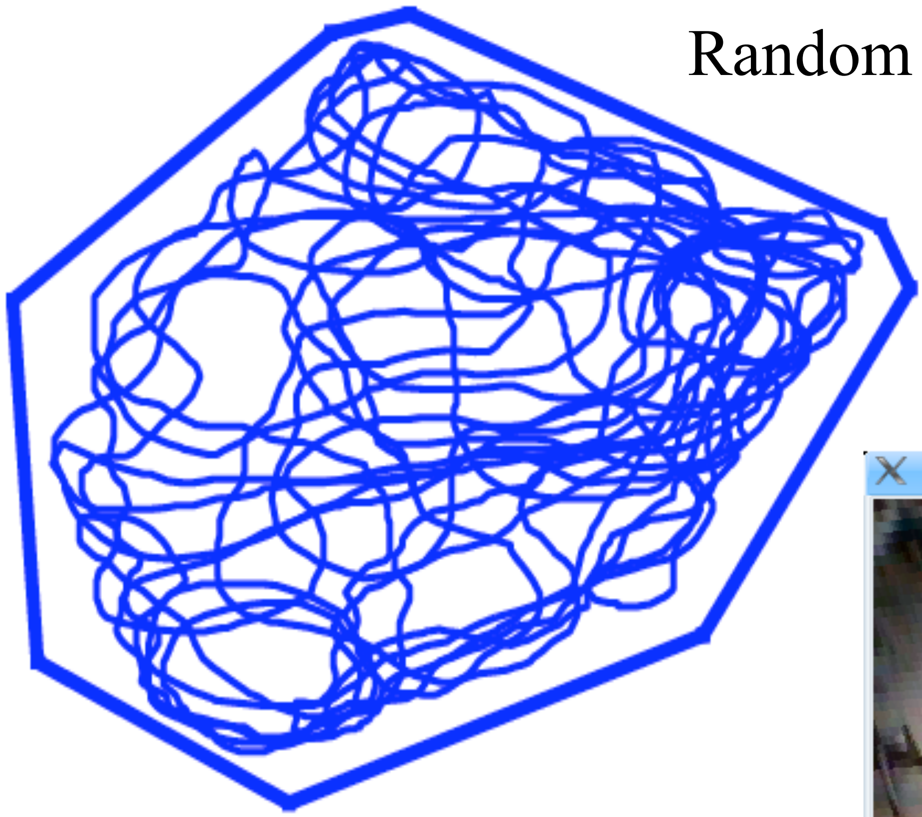
proscriptive training only (computer teacher)



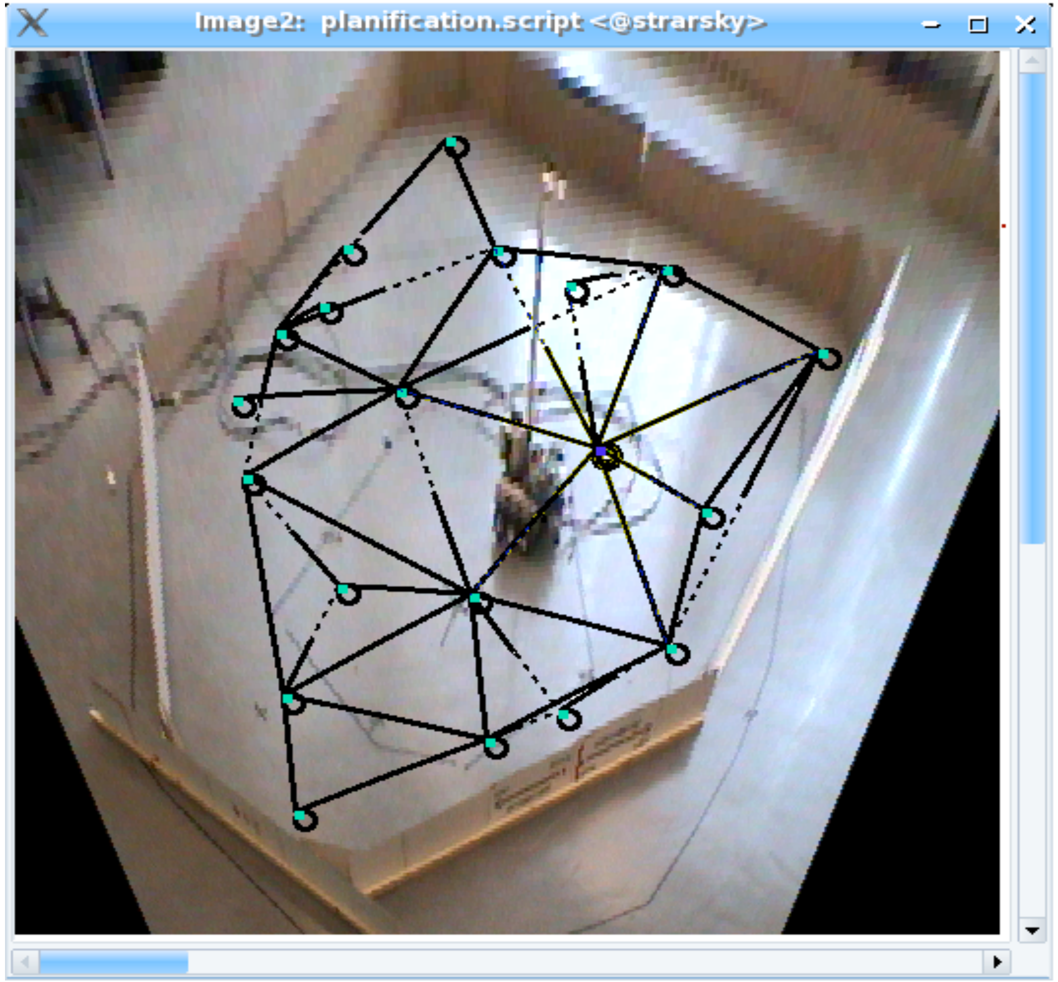
interactive training (computer teacher)

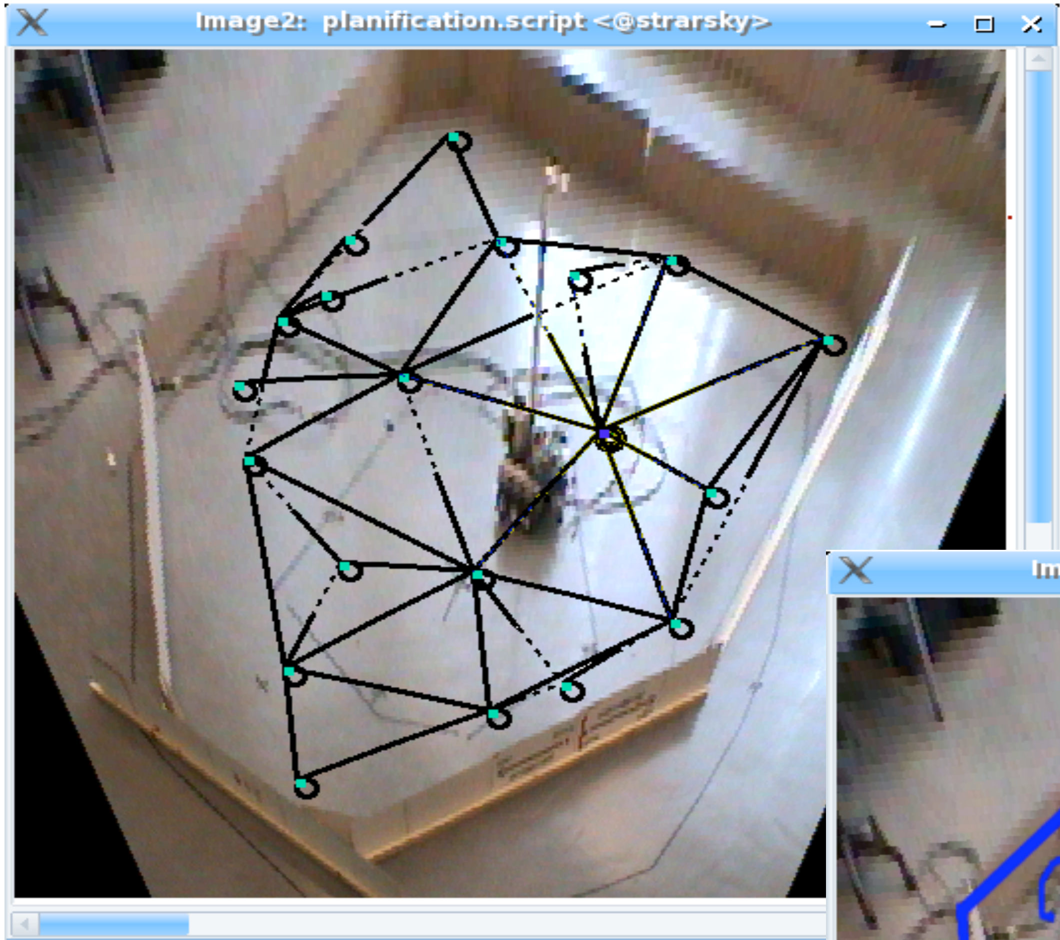


Random exploration



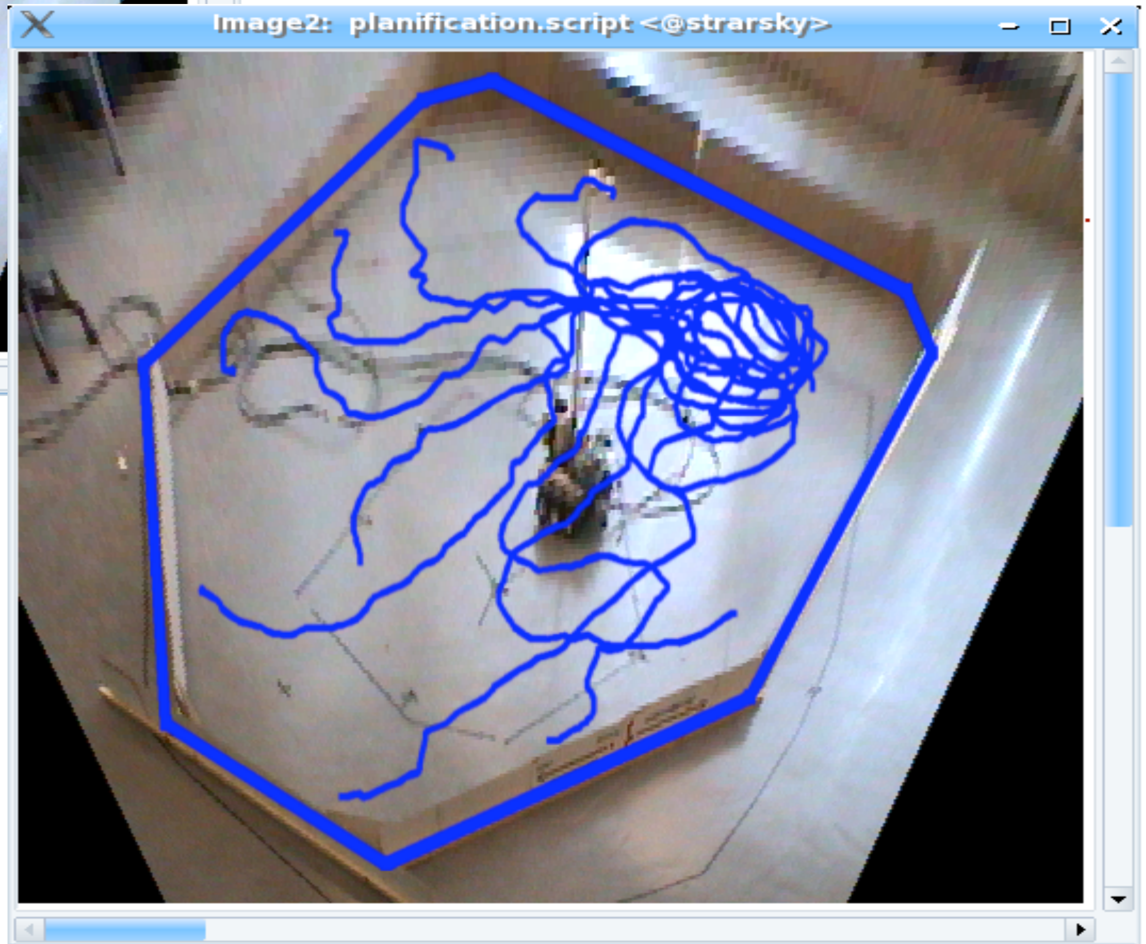
Cognitive map (associative learning)



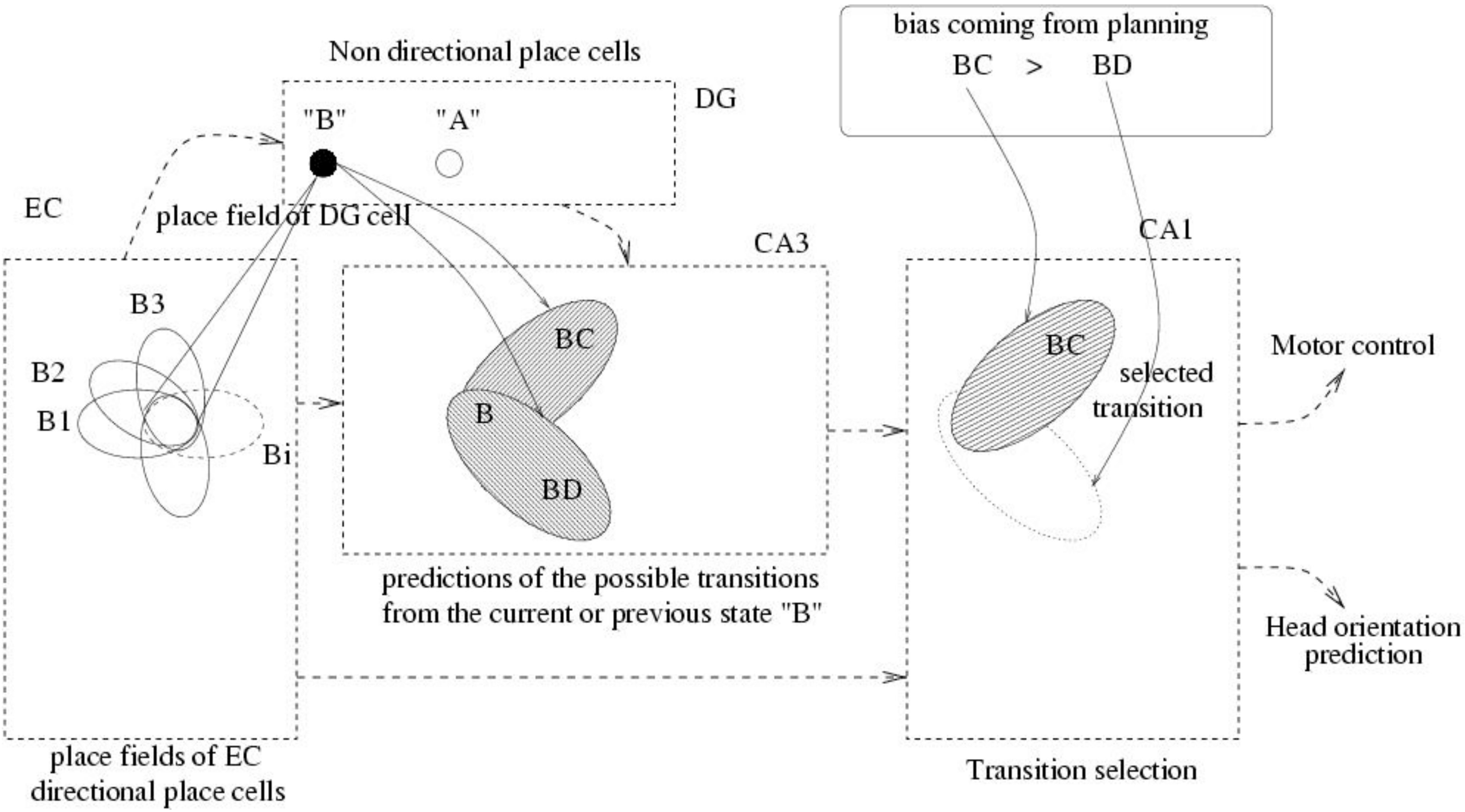


Cognitive map
of transition cells

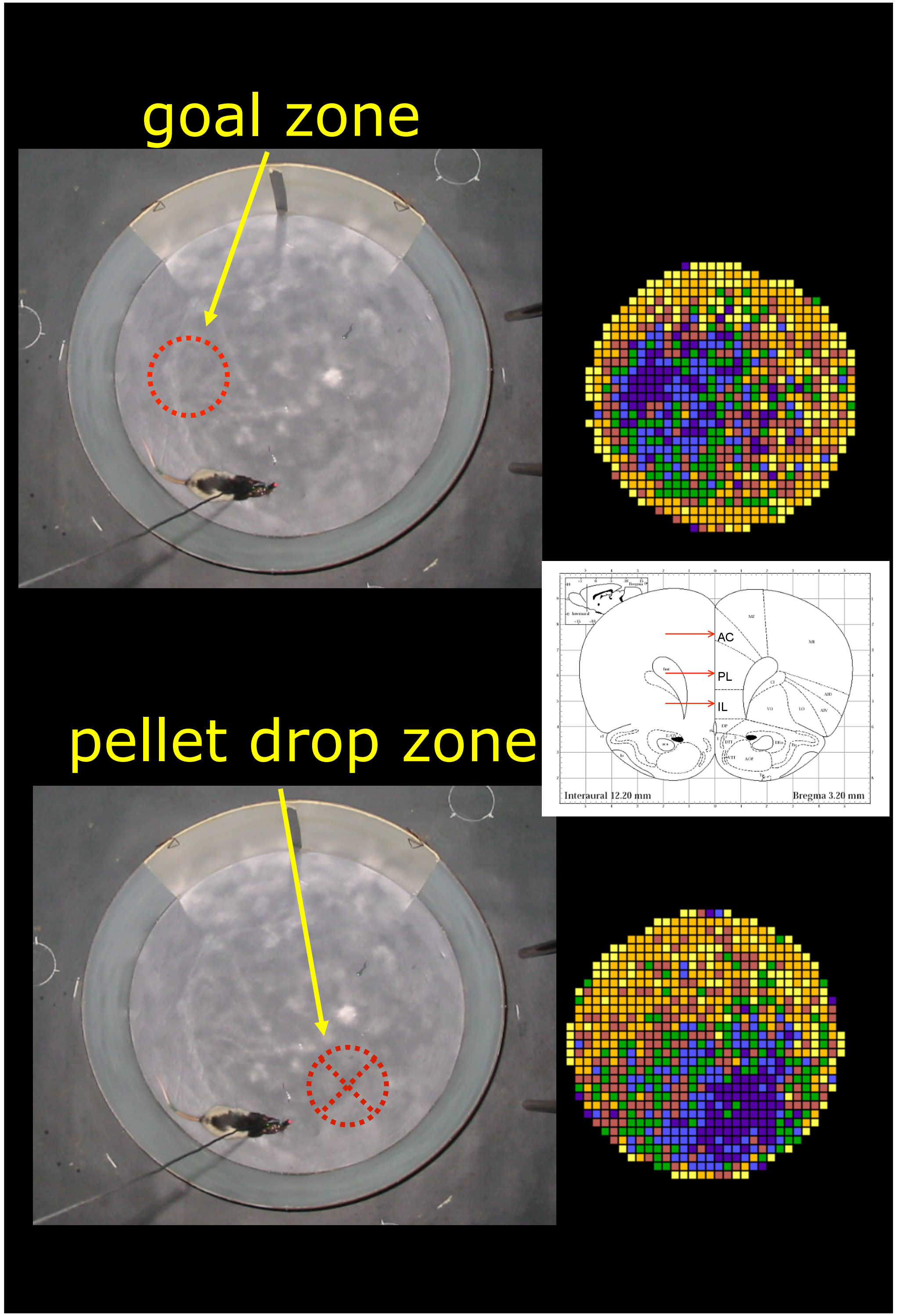
Goal in the upper right corner



Prédictions du modèle



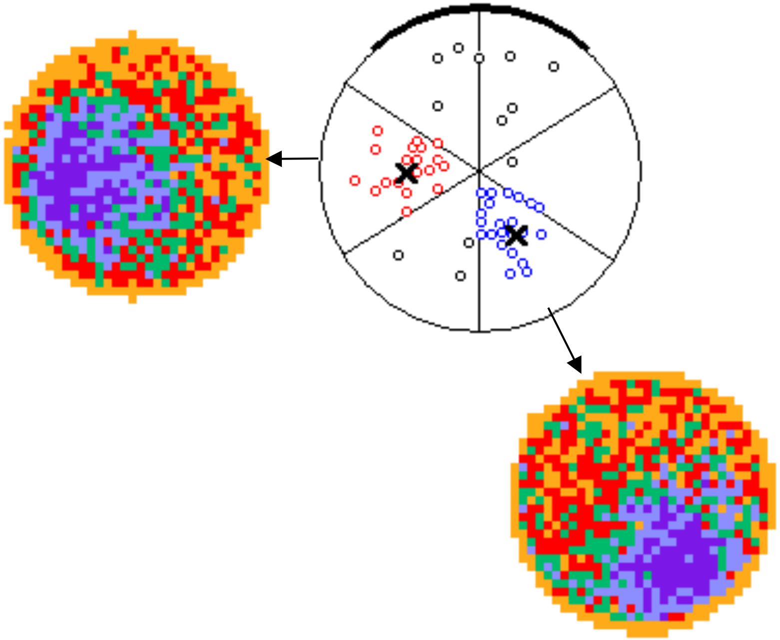
[Gaussier et al 01]



Les cellules de PL/IL ne montrent une activité spatiale sélective que lorsque l'animal est engagé dans une tâche de navigation spatiale

Deux zones du dispositif sont sur-représentées par les neurones frontaux. Ces zones représentent les buts de la navigation pour l'animal.

Distribution des champs d'activité des neurones frontaux



Hok et al. (2005)

3eme partie

Impact du contexte social sur l'apprentissage :

le cas de l'imitation

Modèle du développement

ETIS, UMR 8051
(Cergy)
Neurocybernetics team
P. Gaussier

⟺

Development and psychopathology
UMR 7593 **(Paris)**
J. Nadel

- Apprentissage de comportements moteurs complexes
- Modéliser le développement cognitif d'un bébé (< à 9 mois)
- Architectures neuronales pour l'imitation
  - ➔mécanisme de bootstrap

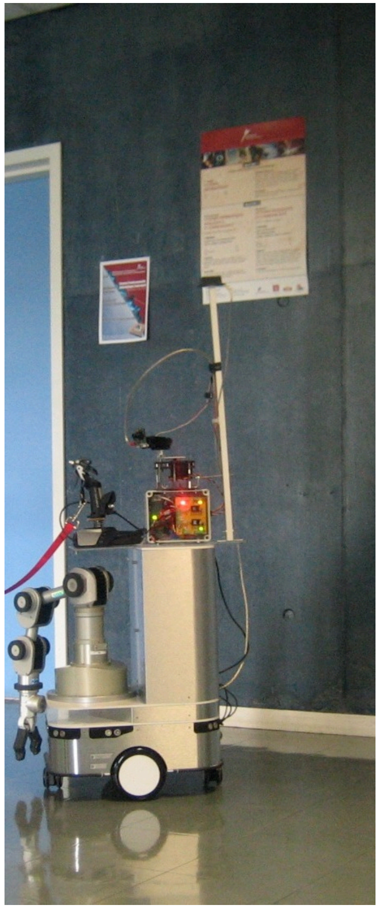
Développement autonome

- Contrôle moteur :
  le bras , les roues…
  Quel espace de travail?

- Quelles informations traiter ? fusion?

- Référentiel ?

- Dynamique du système?
  mouvements du bras,
  de la tête ?



- "one body psychology" : étude du système seul dans son environnement physique

Développement autonome

- Comment Apprendre de l’autre ? Démonstration, observation, imitation..

- Comment interagir ? Turn taking ? quels signaux ?

Développement autonome

[IROS 07,
IEEE SMC 09]

- “two body psychology” : l’interaction est une dynamique composée de deux systèmes, eux-mêmes dynamiques. Rôle important de l’imitation et des emotions.

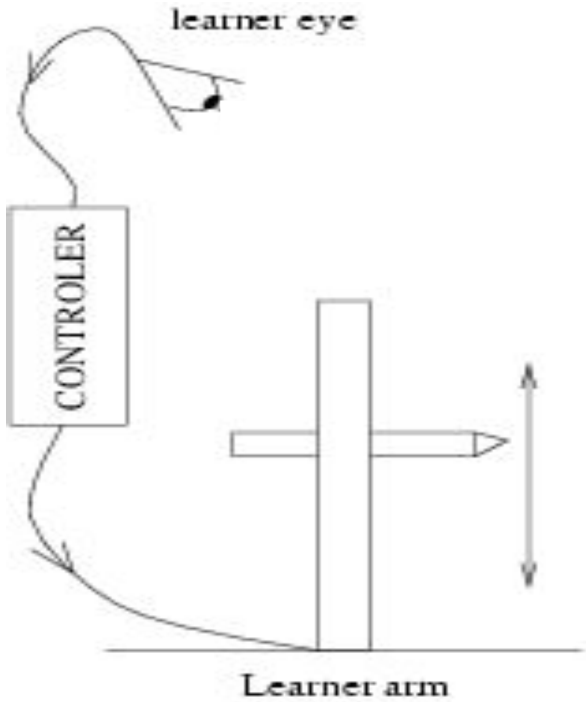
Developmental psychology hints

Imitation is present from birth on !
[Meltzoff,Trevarthen,Kugiumuzakis]

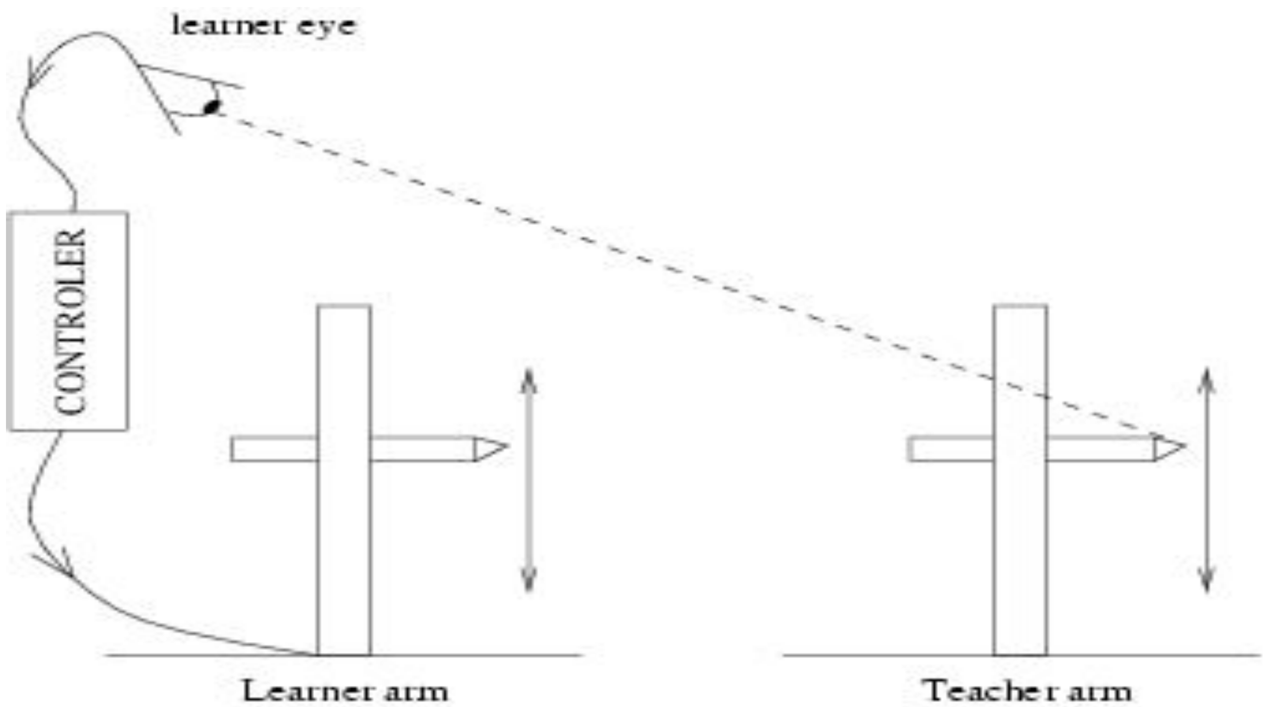
At a given sensory-motor stage, does the imitative behavior require much more than other basic sensory-motor behaviors?

i.e: What is the minimal thing we have to add to a generic control architecture to obtain low-level imitations ?

Bootstrap for low-level imitation

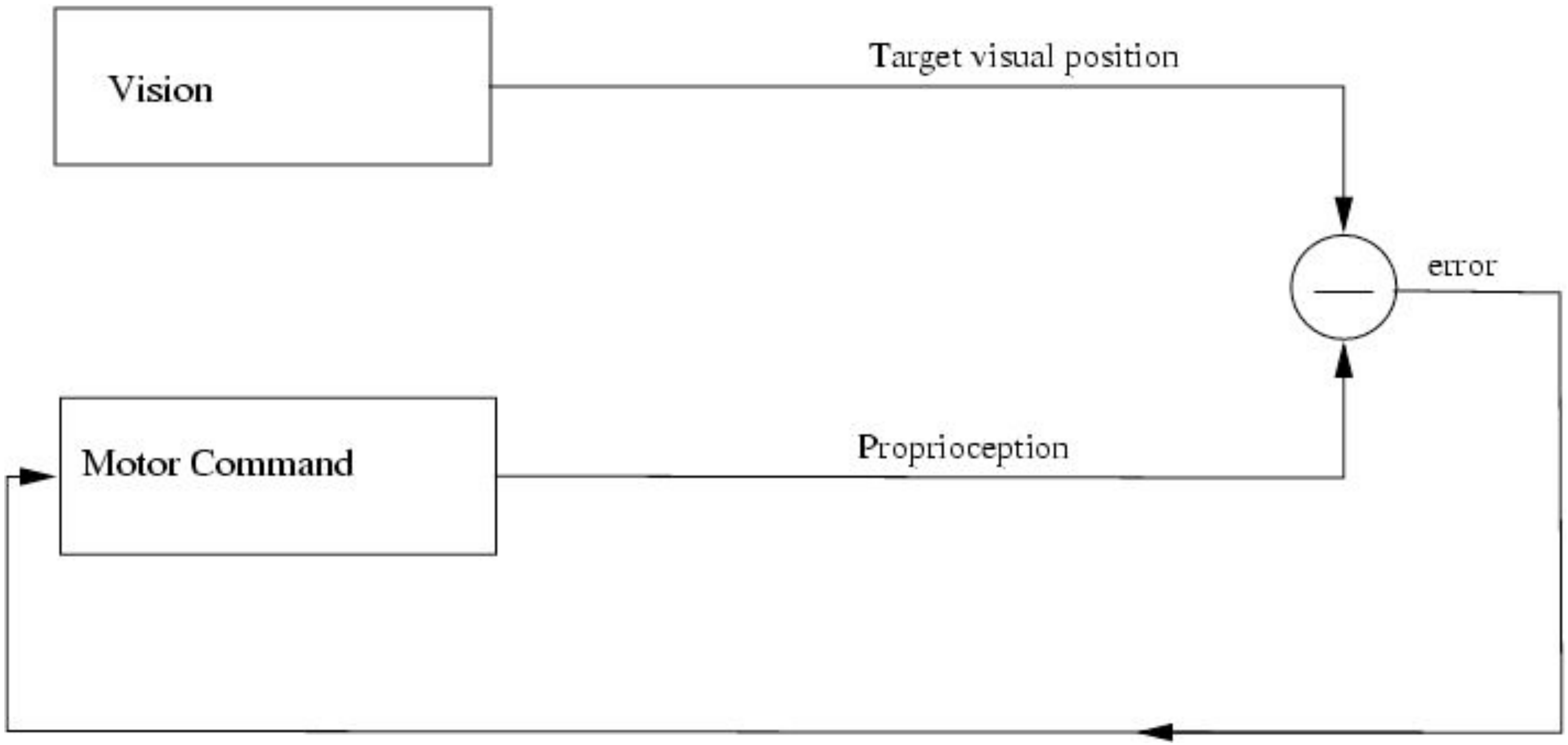


Bootstrap for low-level imitation



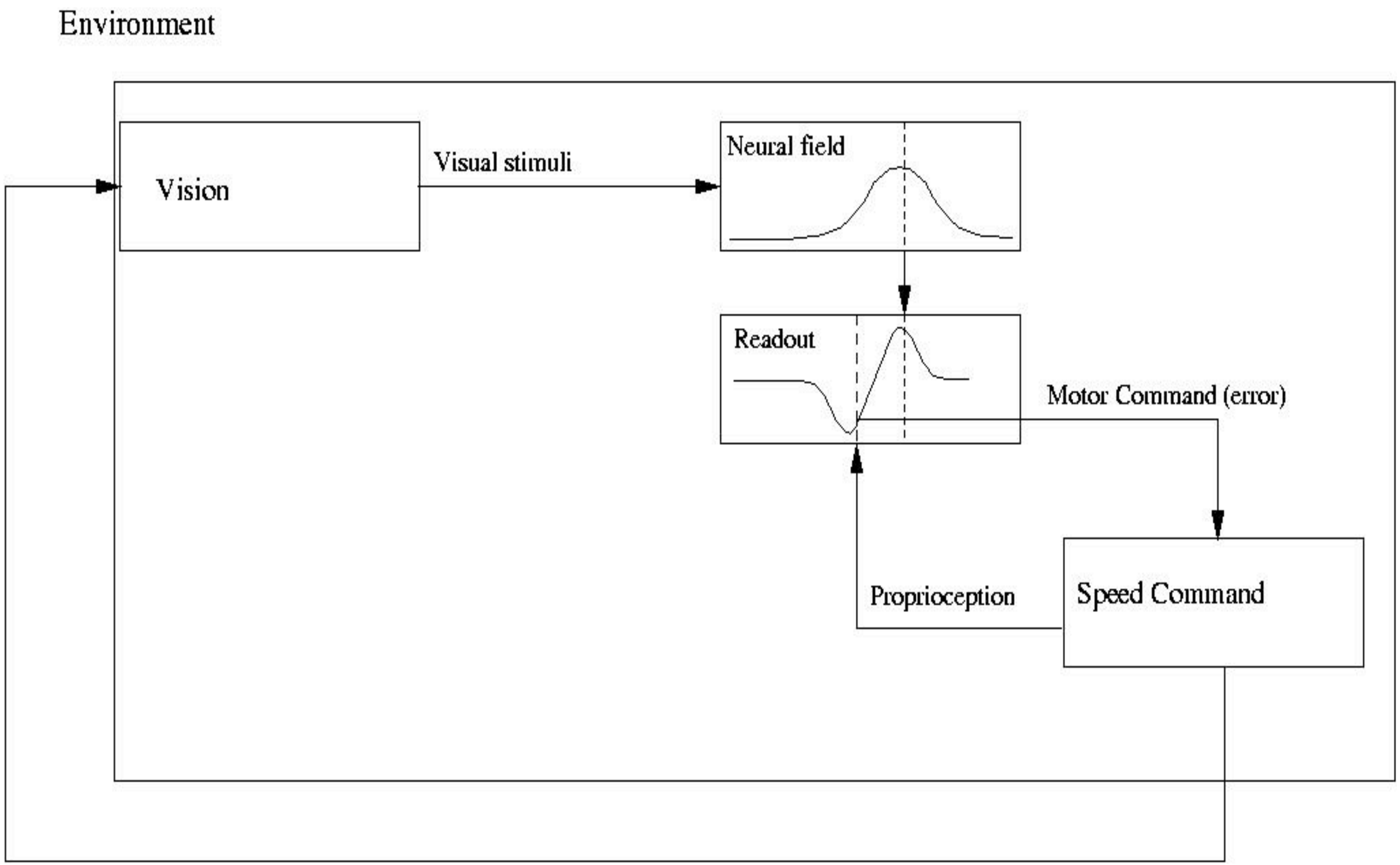
- Proto-imitation as a side effect of a homeostatic system (perception ambiguity)
- No need of a special imitation "module"

Architecture: the homeostatic principle



[Ashby52]

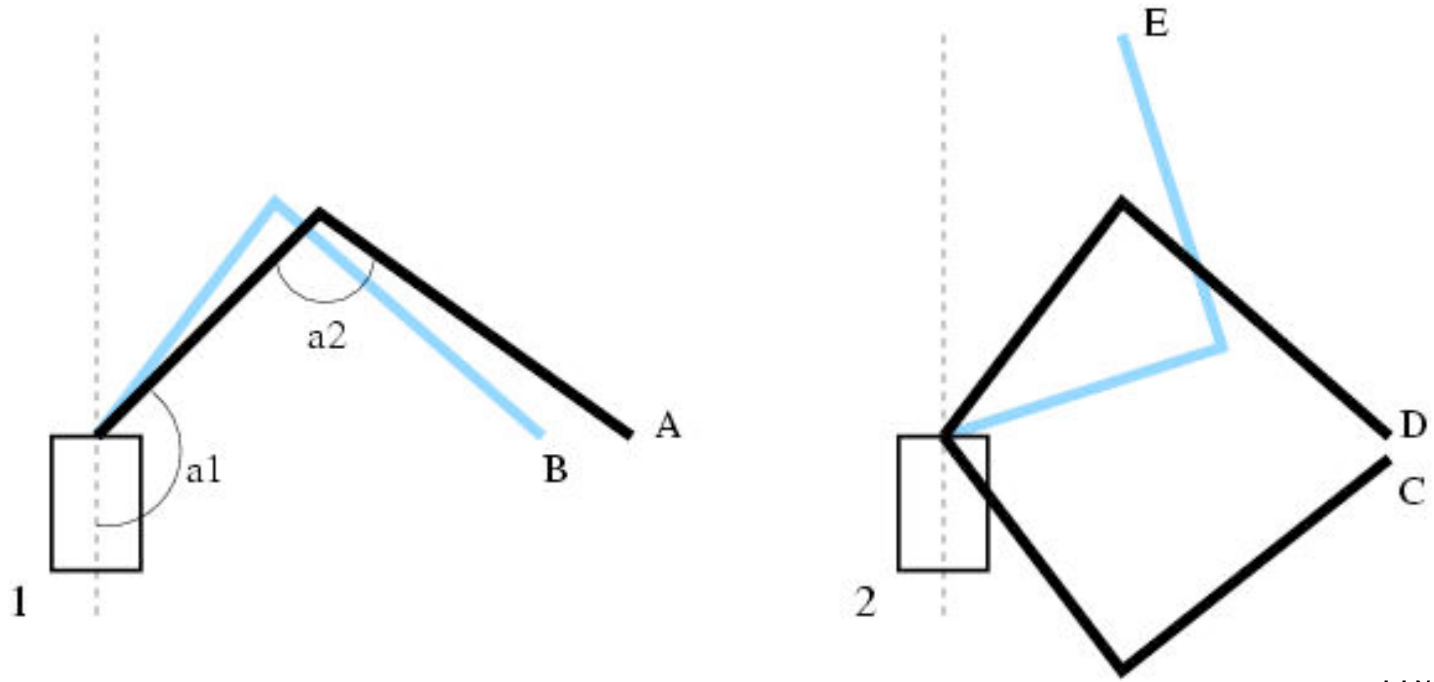
Architecture: Dynamical principle



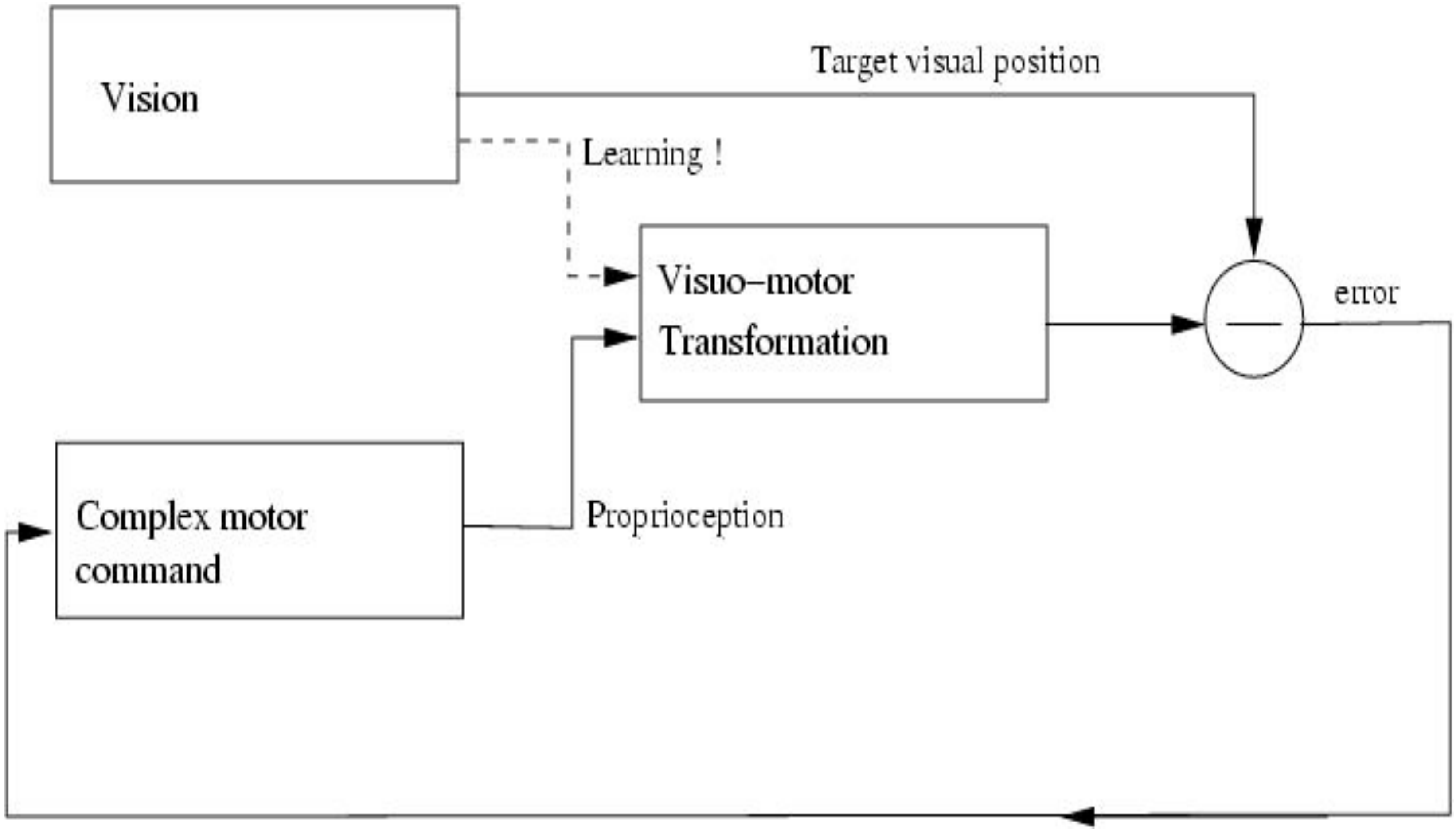
Learning visuo-motor associations

•Des positions très éloignées dans l’espace articulaires peuvent coder des positions très proches dans l’espace visuel (pour l’extrémité).

•Des positions voisines dans l’espace articulaire peuvent être associées à des positions très éloignées dans l’espace visuel.

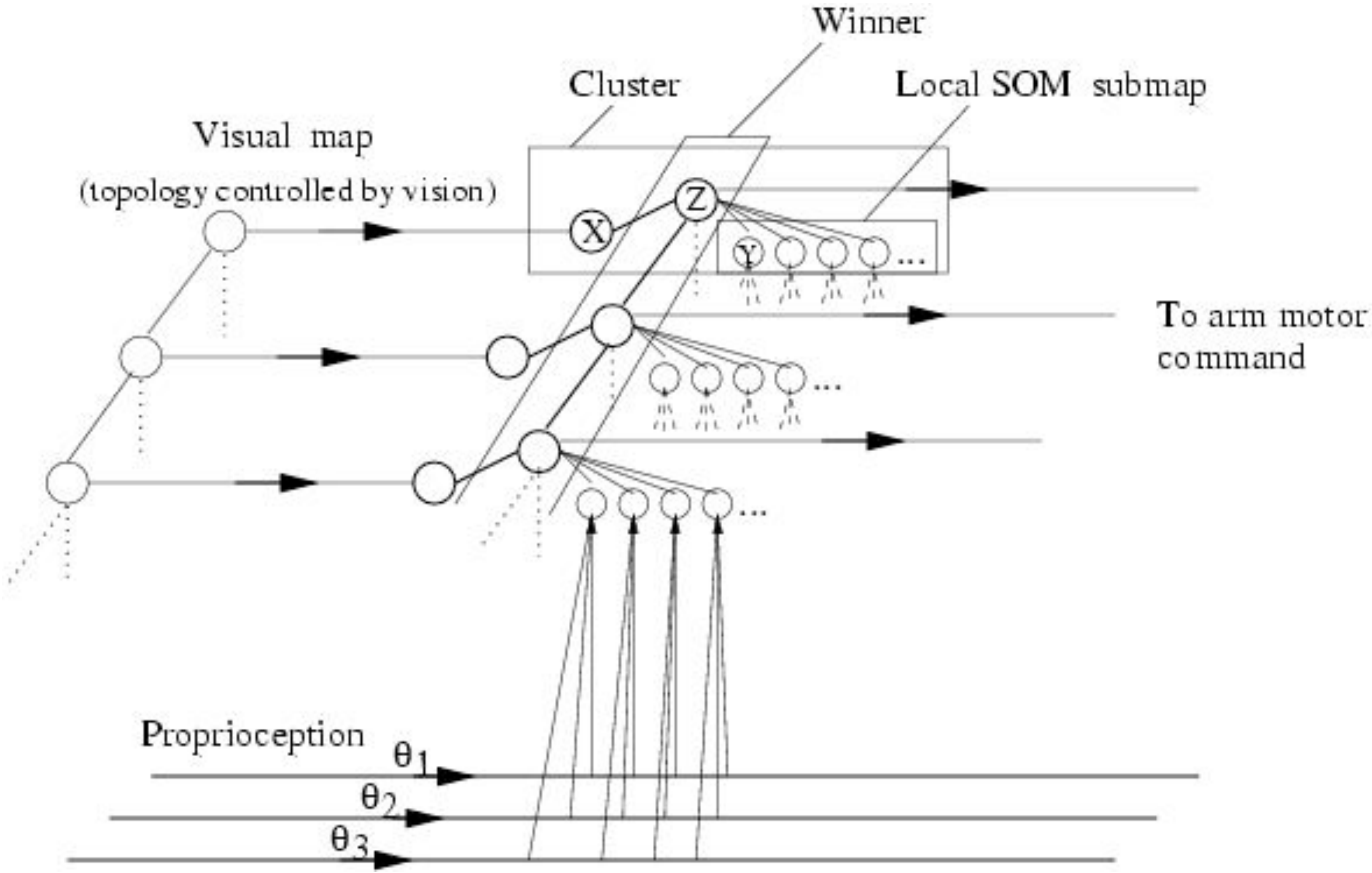


Learning visuo-motor associations

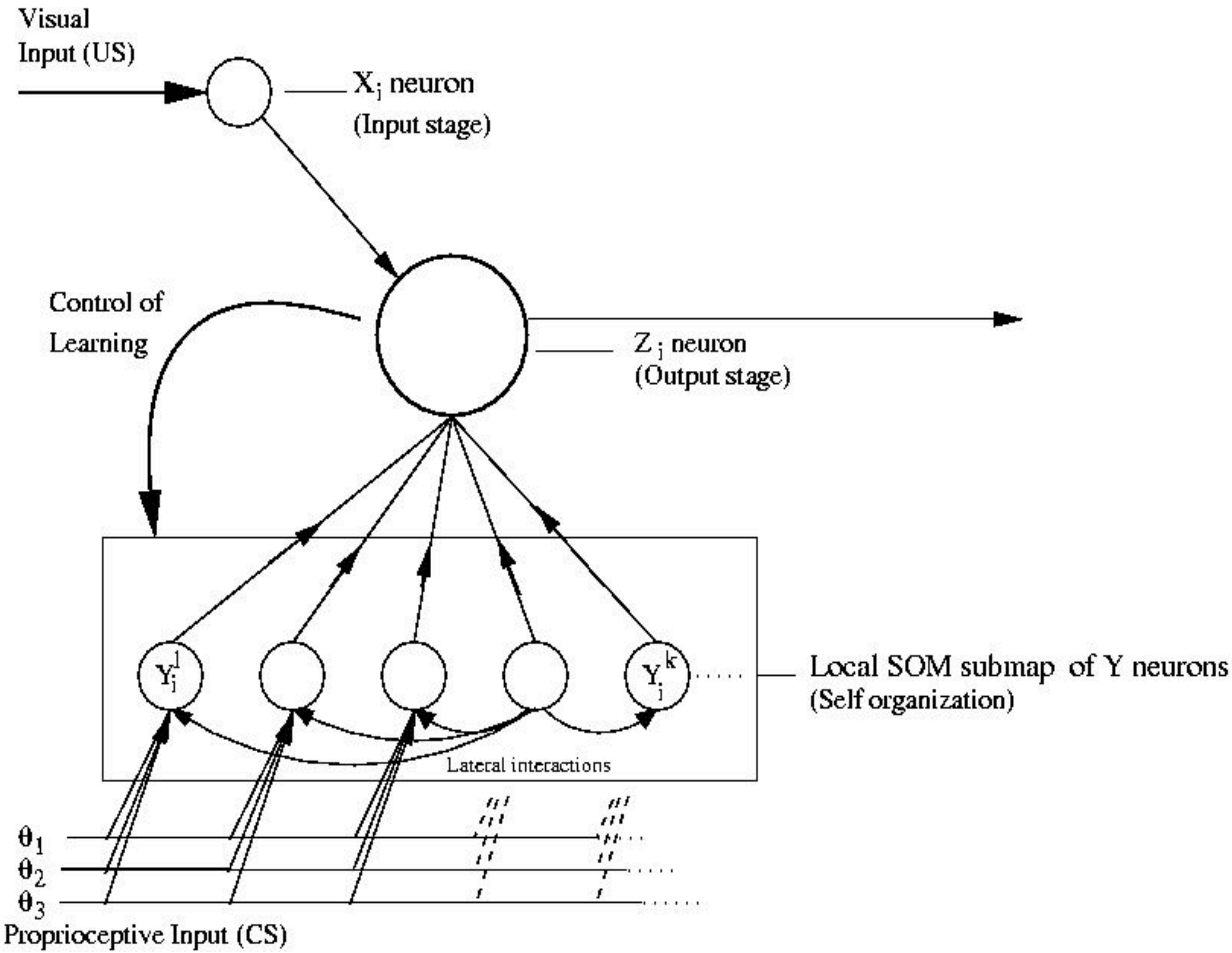


The visual space is used as a commune representation

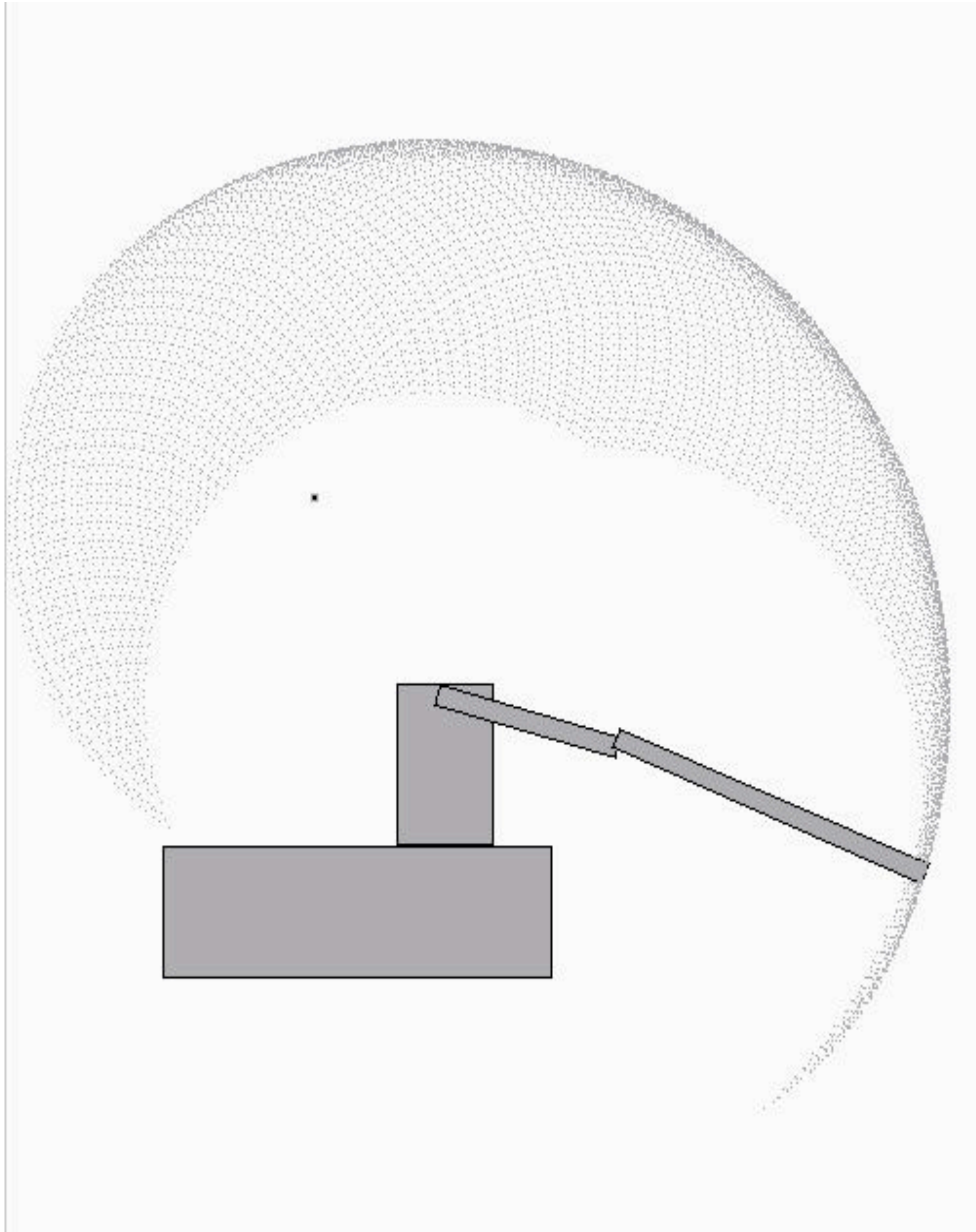
Learning a visuo-motor map



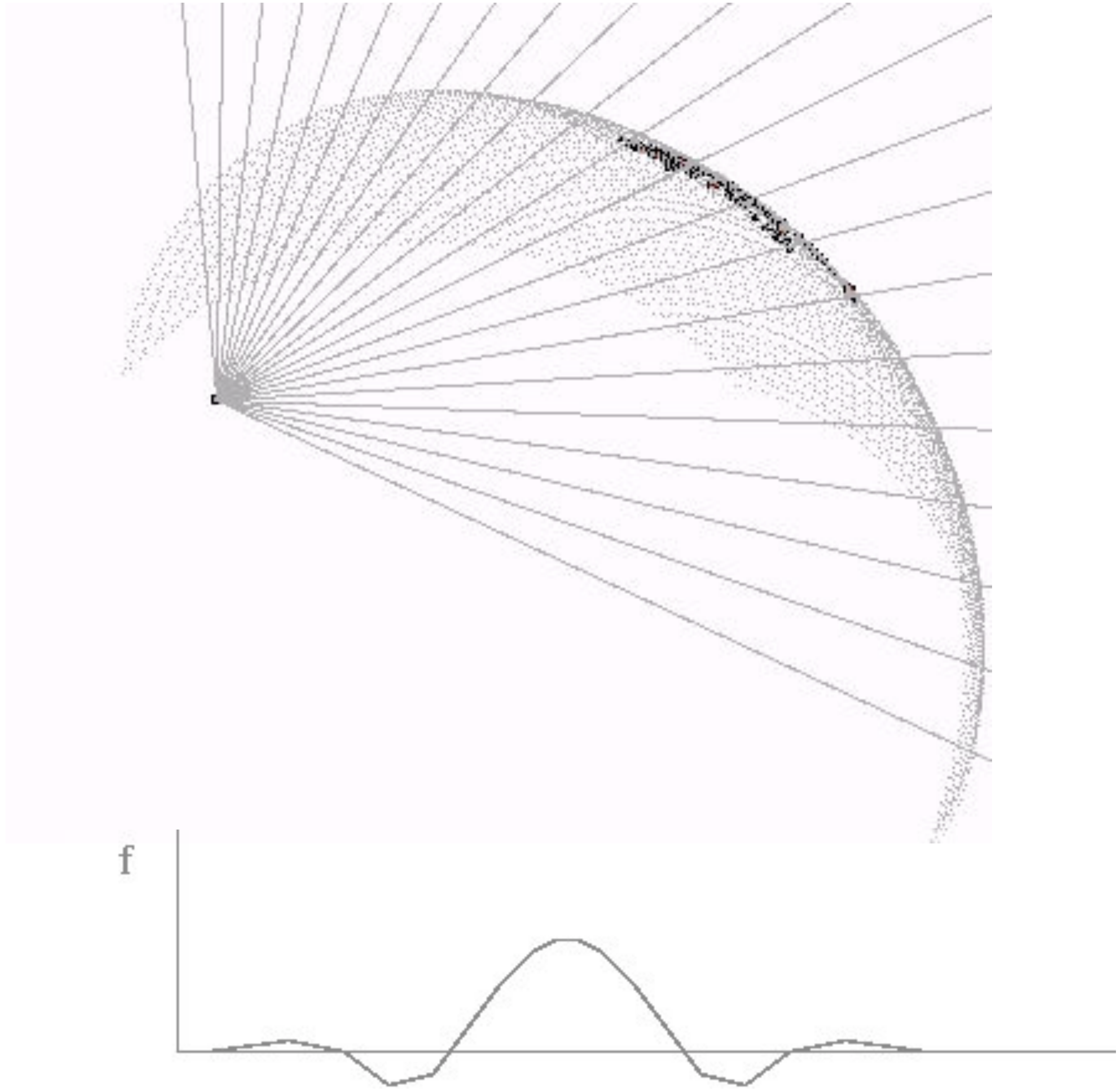
Learning a visuo-motor map



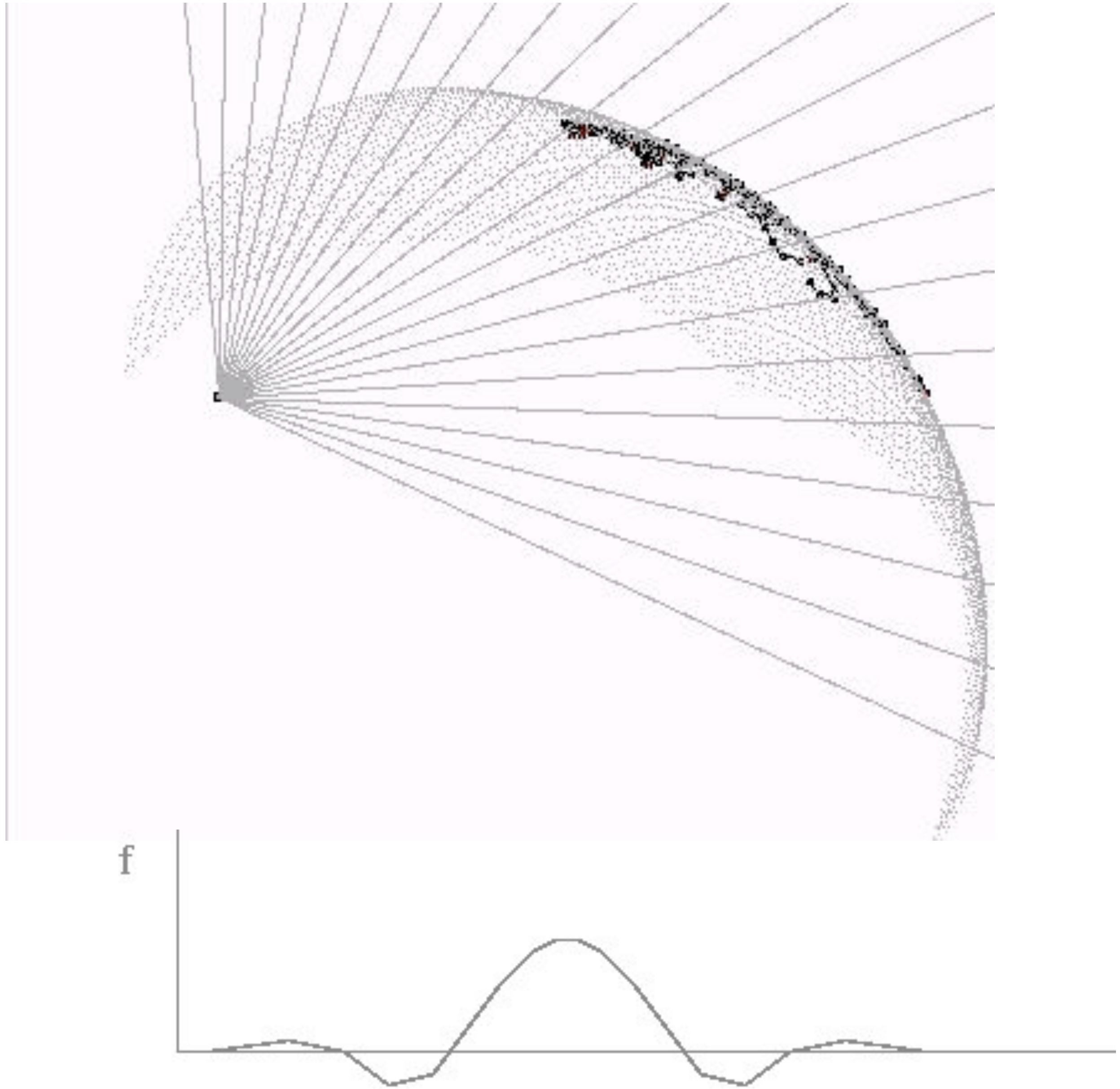
Learning: simulation results



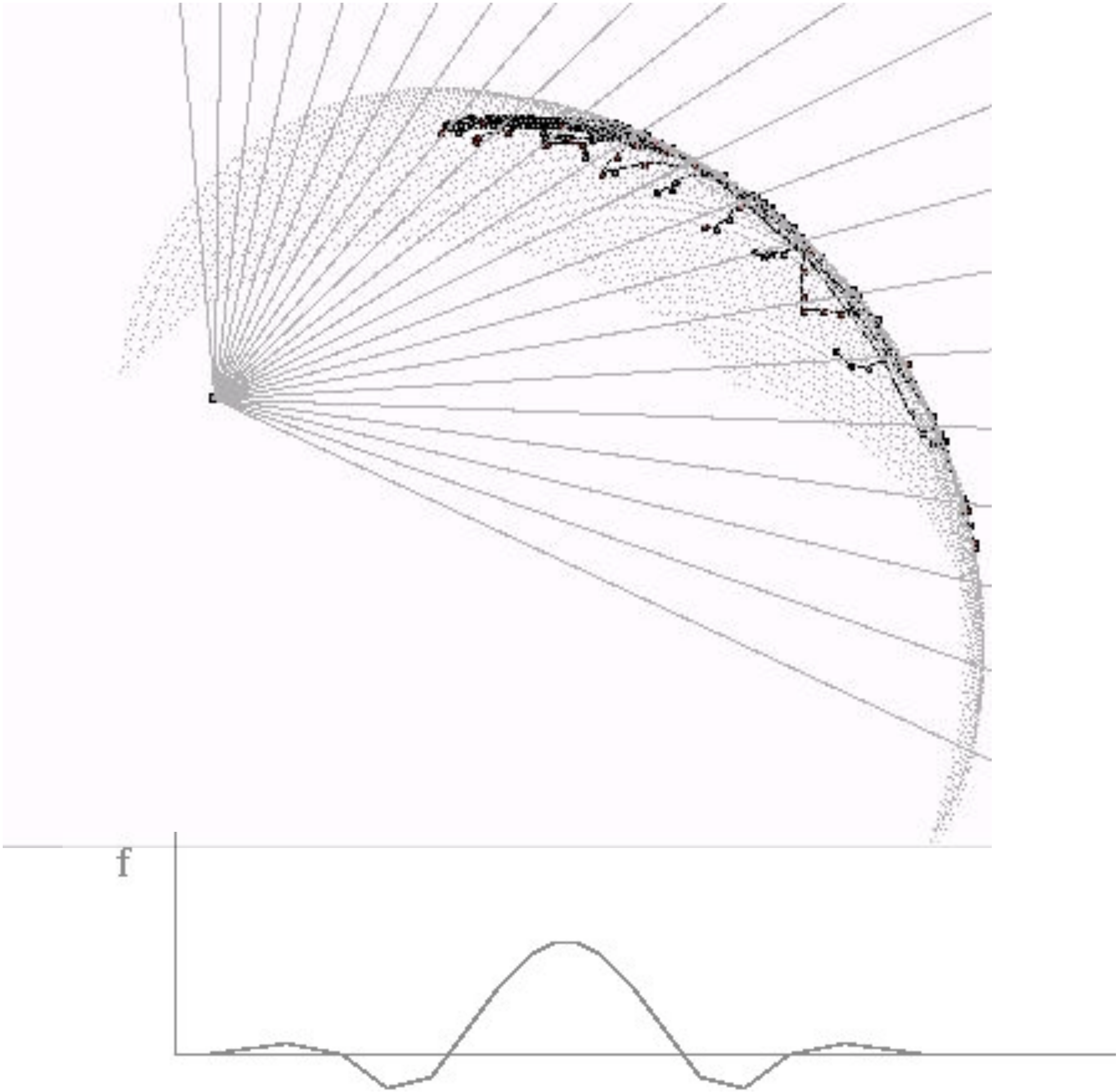
Learning: simulation results



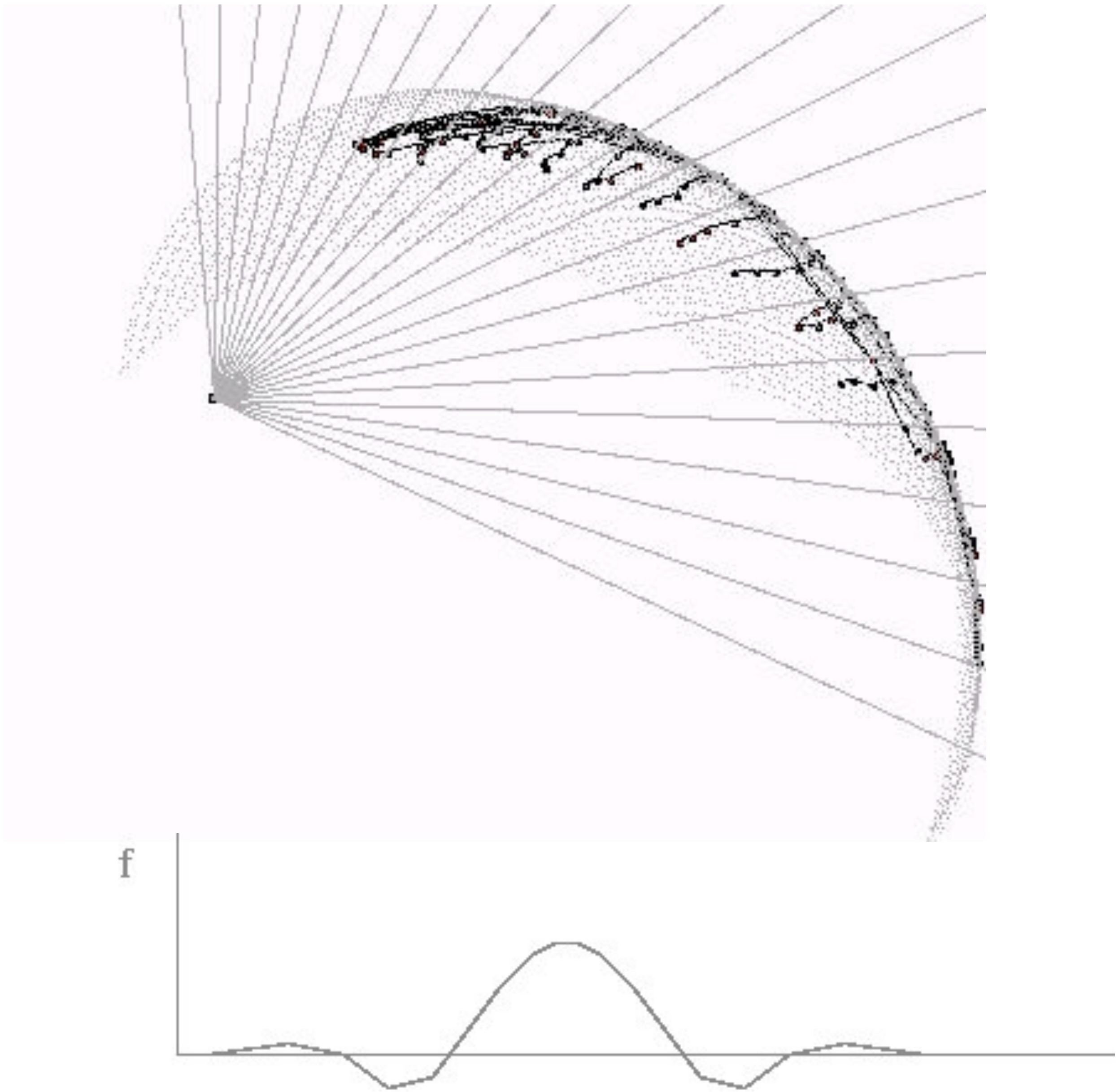
Learning: simulation results



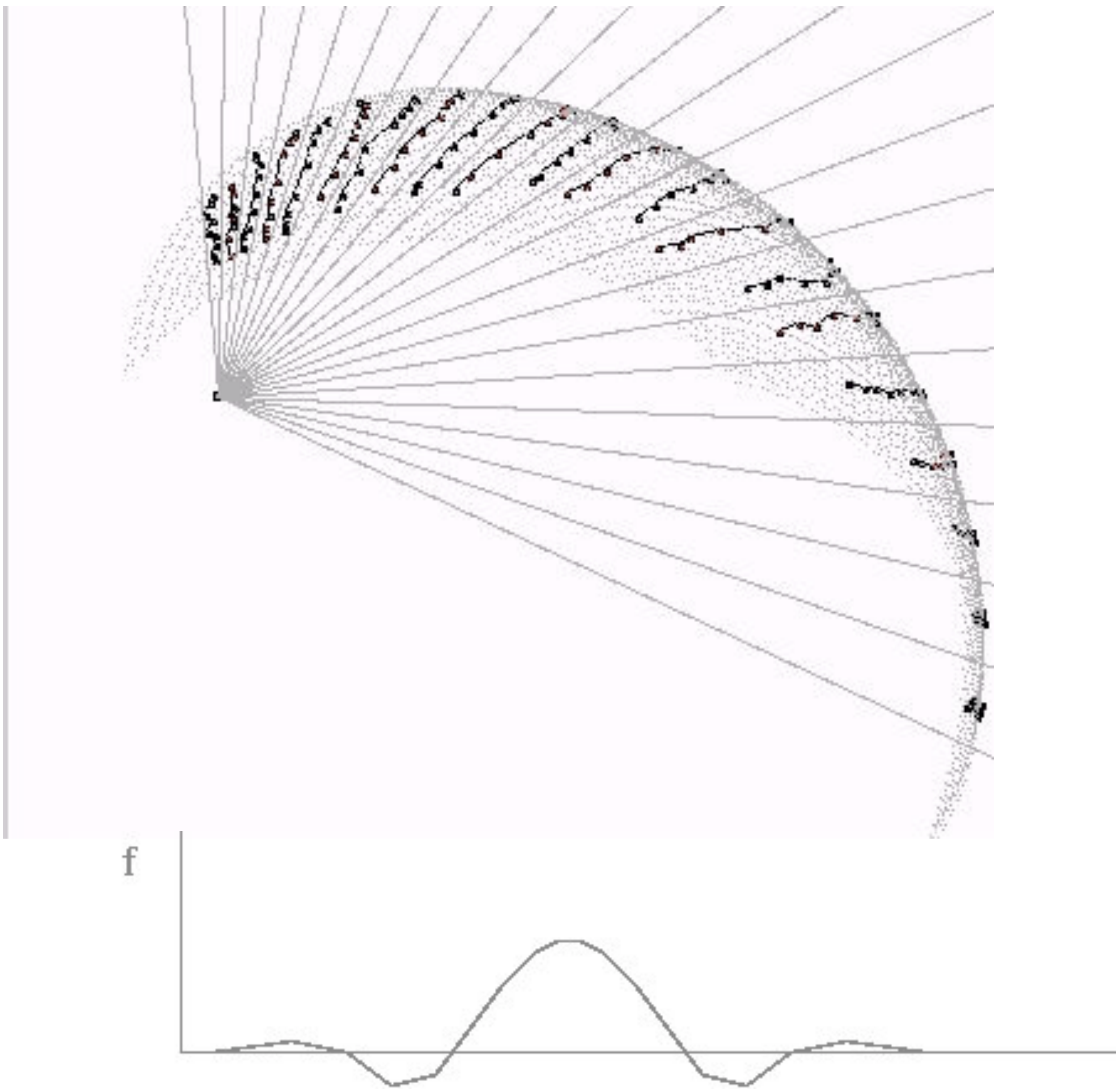
Learning: simulation results



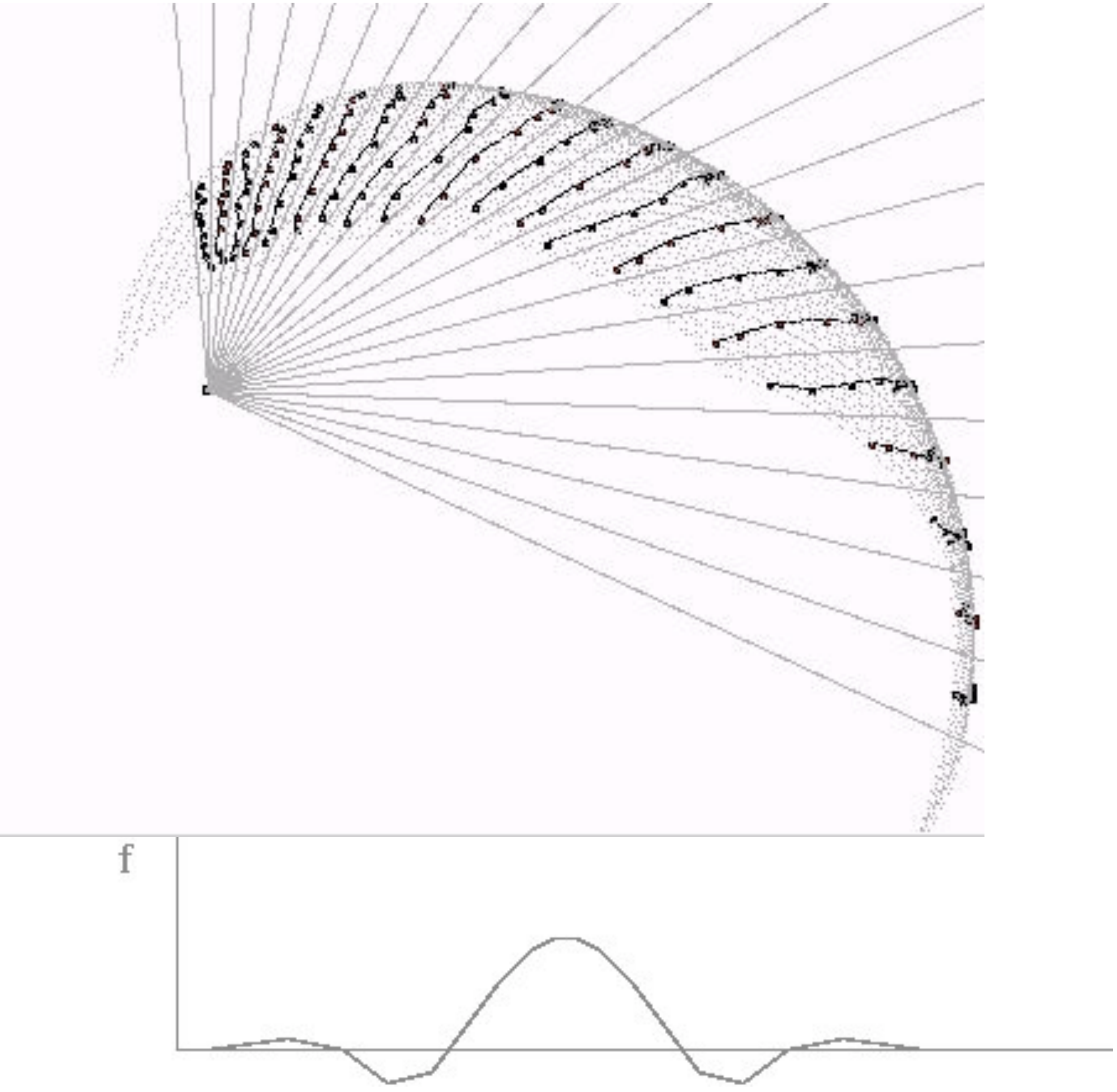
Learning: simulation results



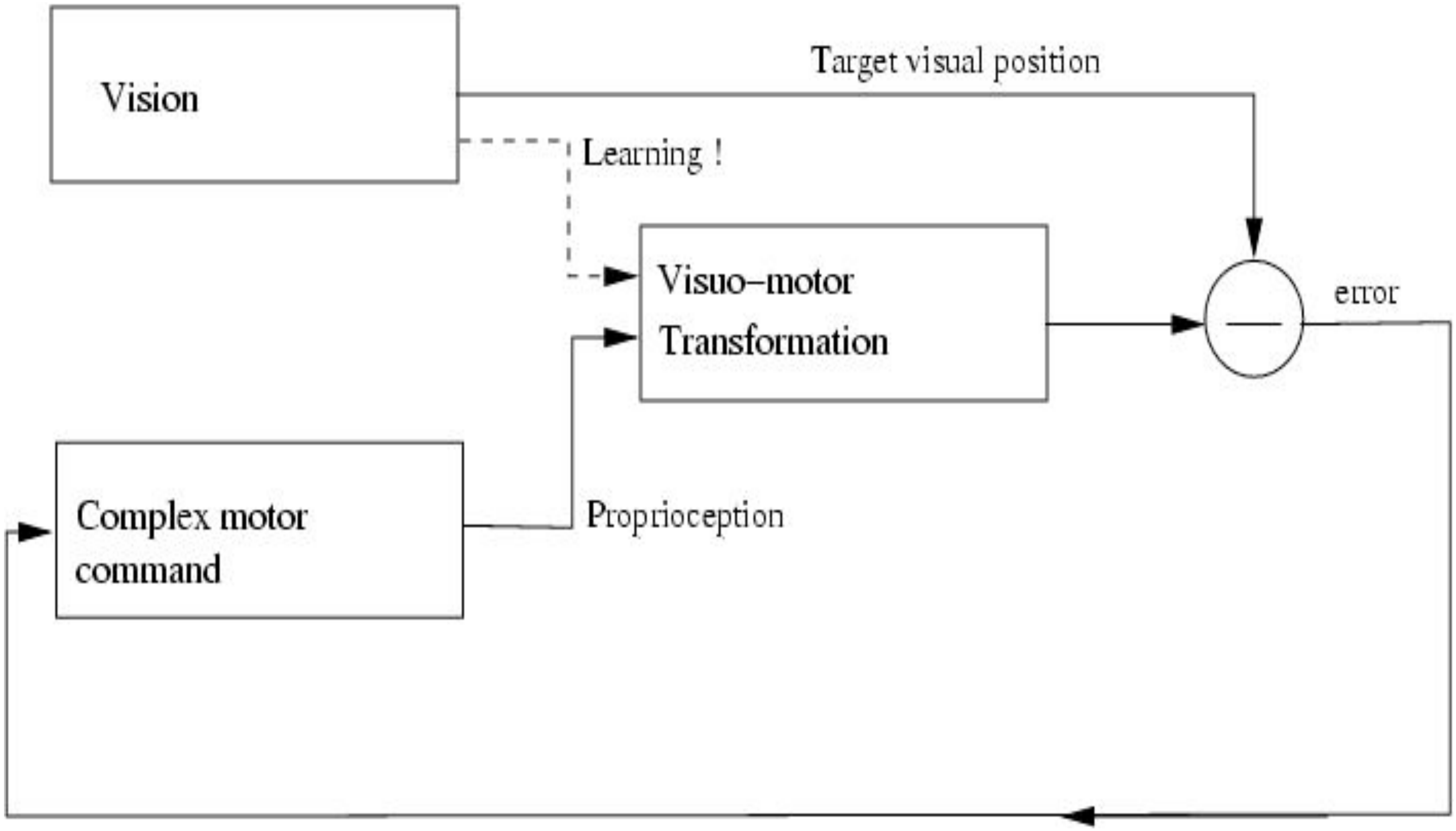
Learning: simulation results



Learning: simulation results



Learning visuo-motor associations

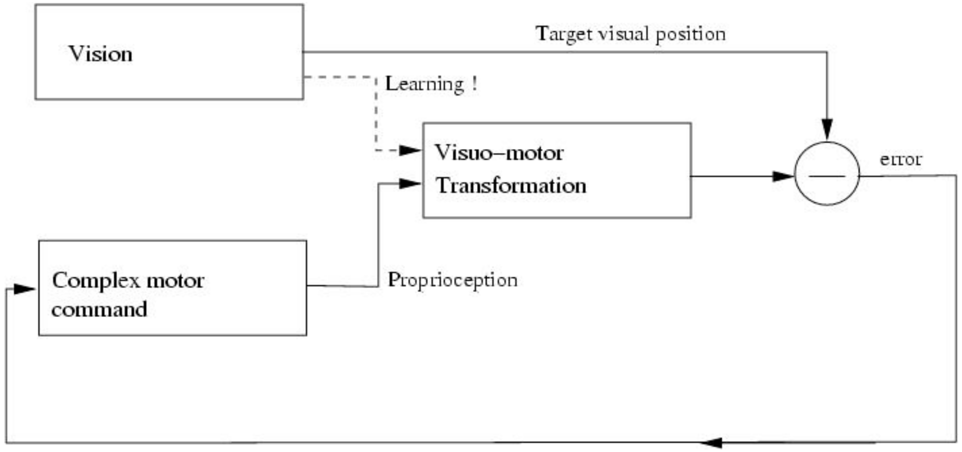


The visual space is used as a common representation

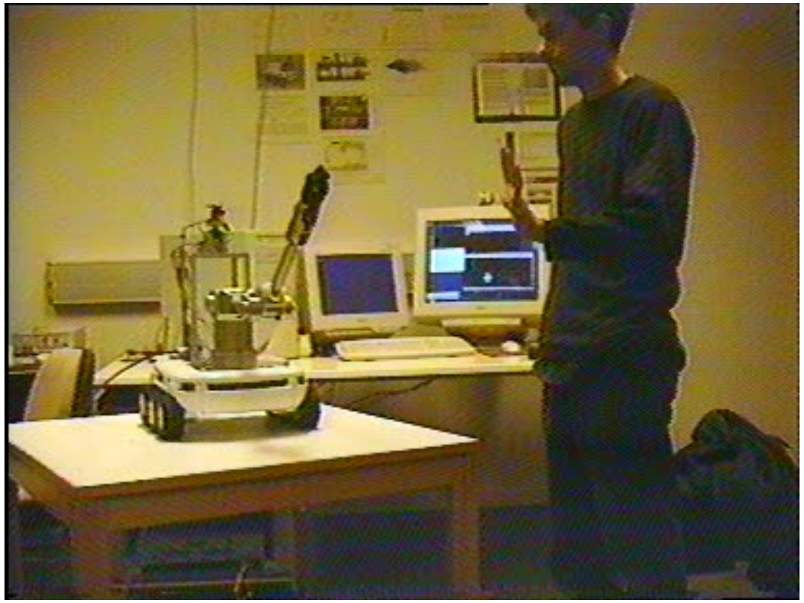
[Andry et al 2002]

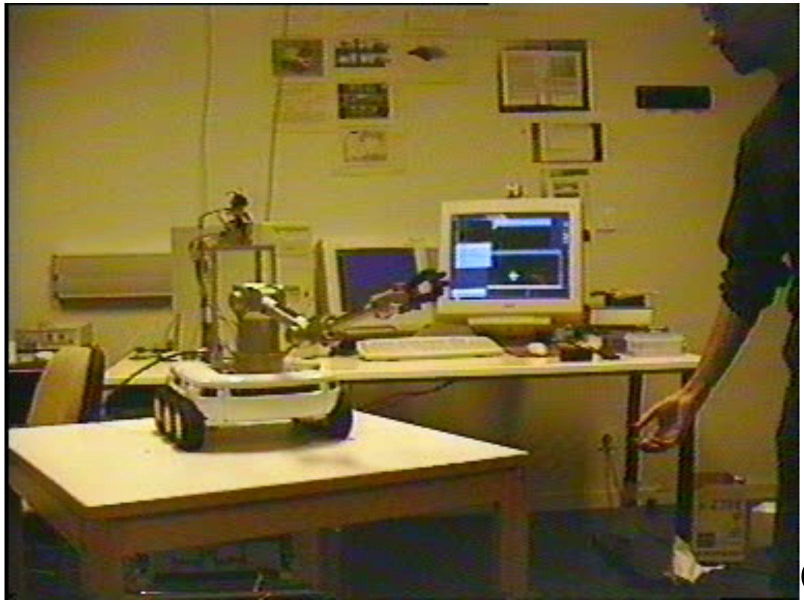
Experimental setup

Simple homeostatic system + perception ambiguity



[Andry et al 2002]





Imitation for learning

- Imitation can be used to reproduce a complex trajectory. Imitation can then be used for learning

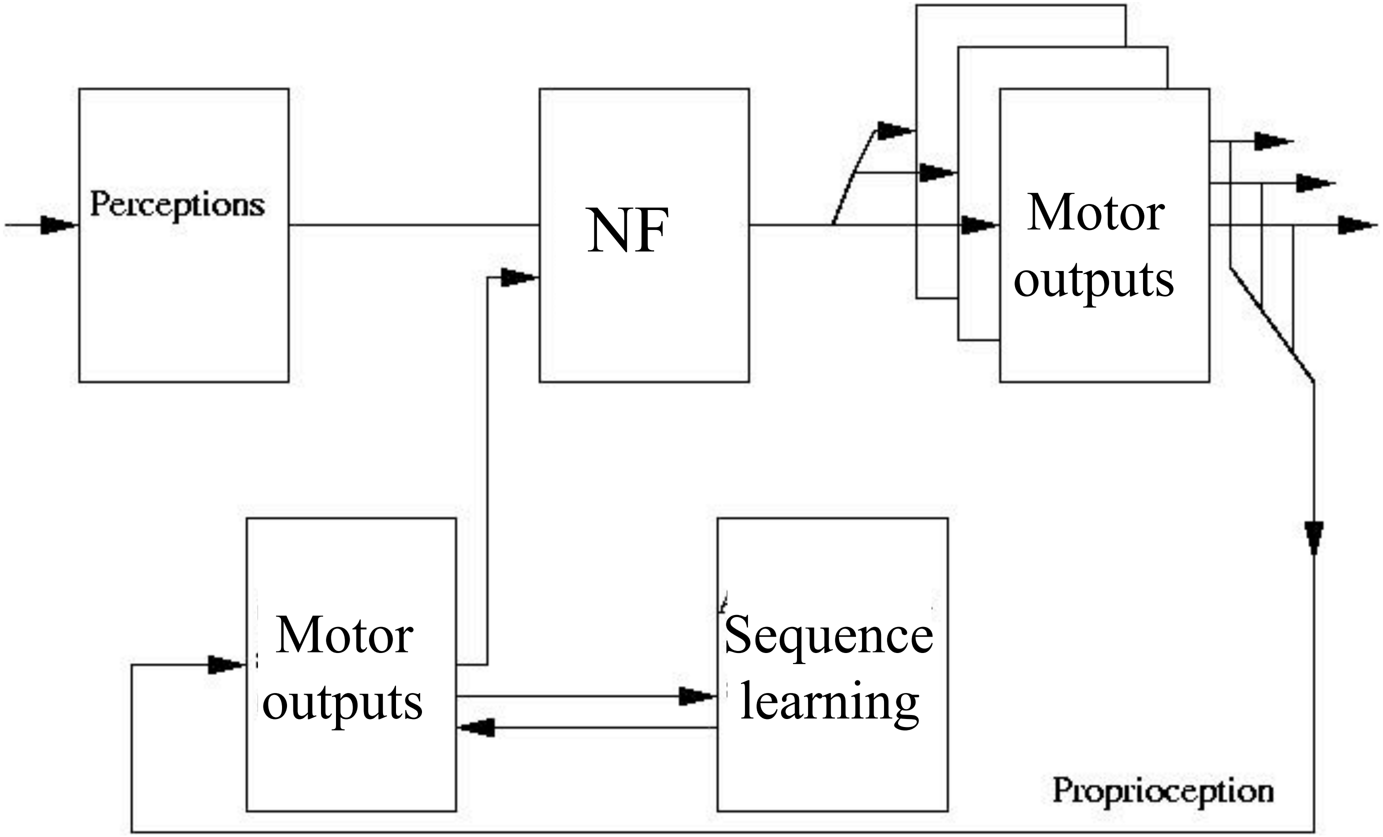
  - Extension of the sensori-motor repertoire

  - Solving more complex tasks

  - From gesture notion to action concept

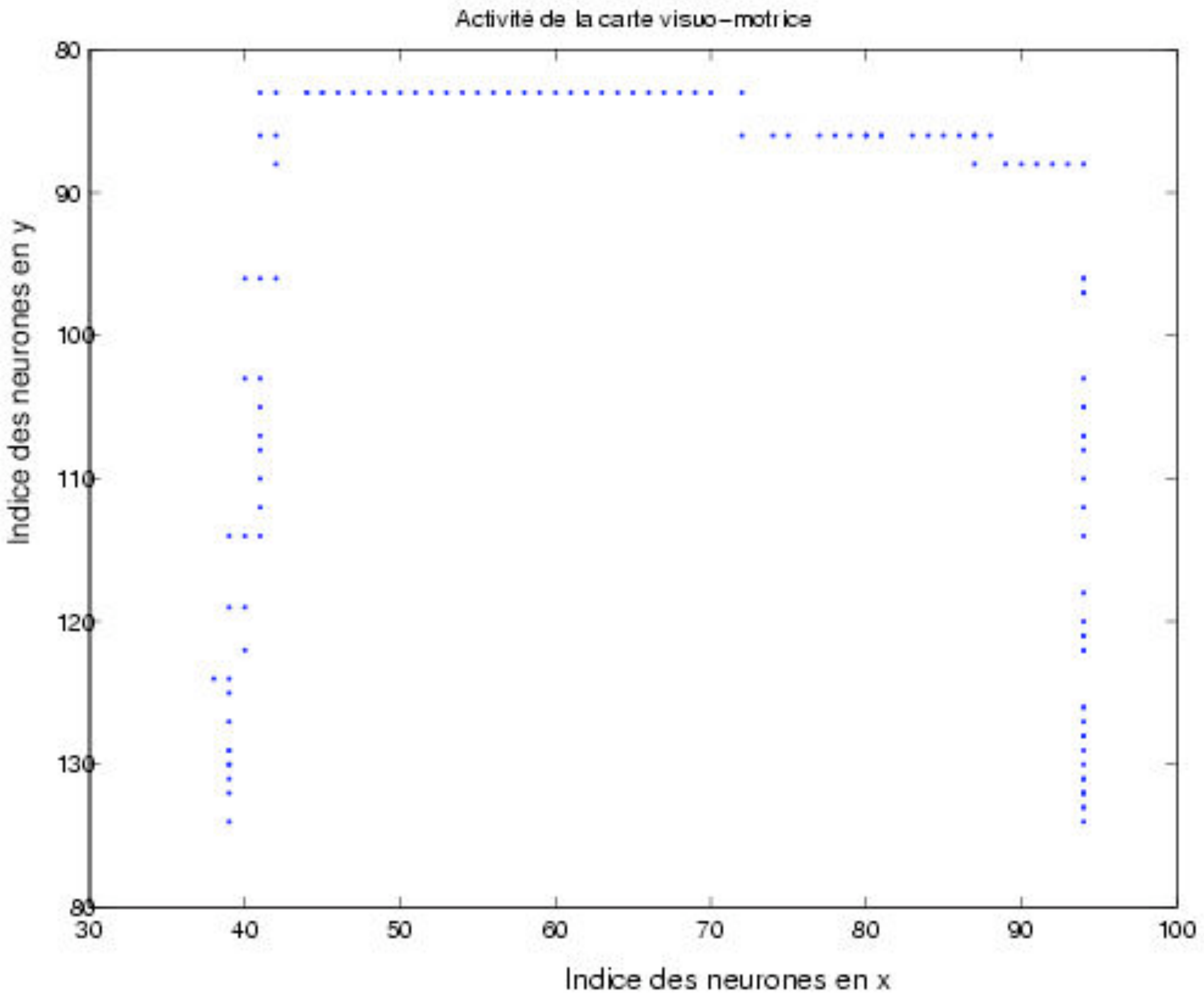
How to learn a trajectory?
What are the relevant informations?

Learning sequences of gestures



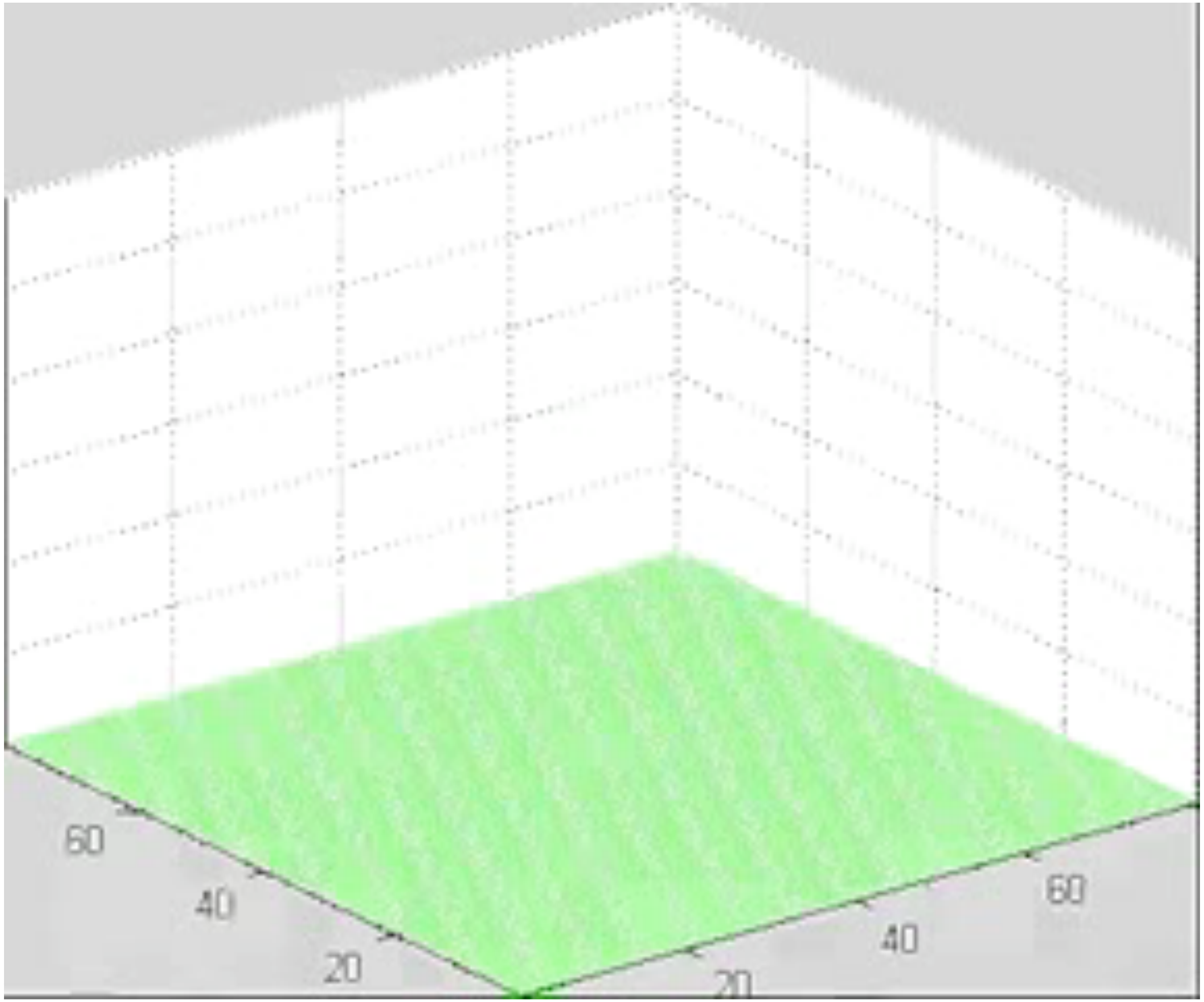
- No global coding of the sequence: each prediction induces the next one.
- Learning and performance/reproduction do not depend directly of the motor device (number of degree of freedom, arm, leg, head...).

Output of the visuo-motor map



- Extraction of feature points : remain a complex problem !

Result : sequence reproduction



- Sequence of attractors controlled by the visuo-motor map (moving from an attractor to the next one)

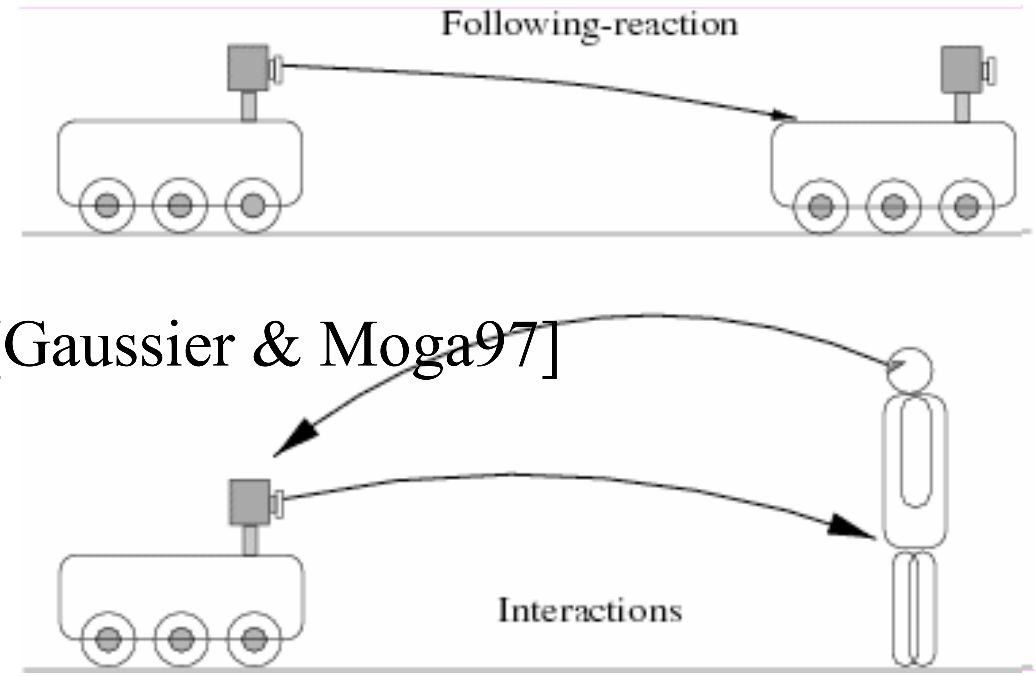
Learning motor sequences



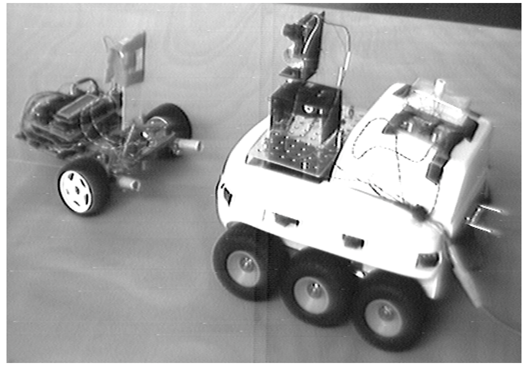
www.etis.ensea.fr/~neurocyber/Videos/

Limitations

- Need of an explicit reward or adhoc mechanism to decide if a given sequence must be learned
- Need of an explicit signal to specify the beginning and the end of the expriment

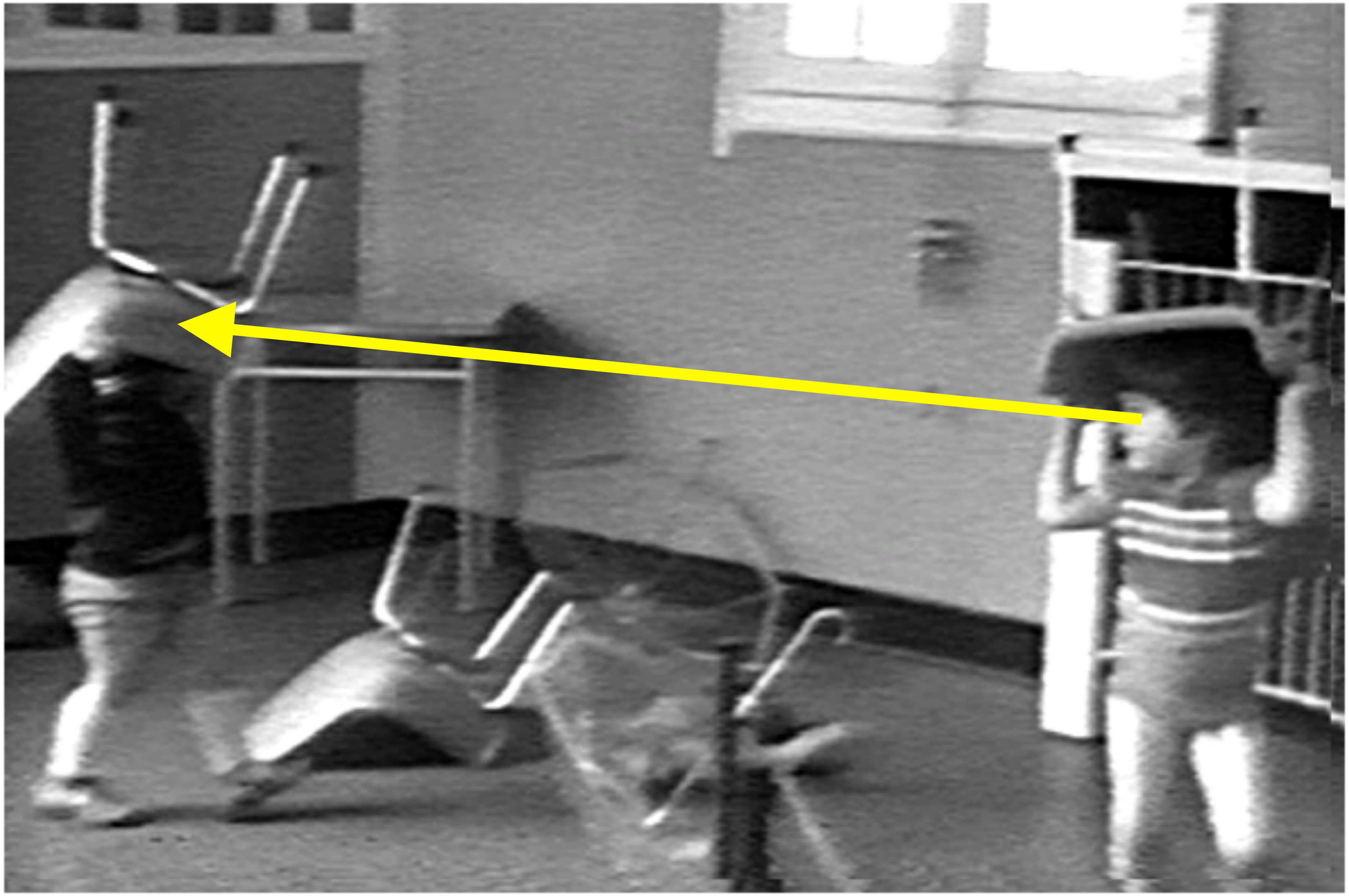


[Gaussier & Moga97]

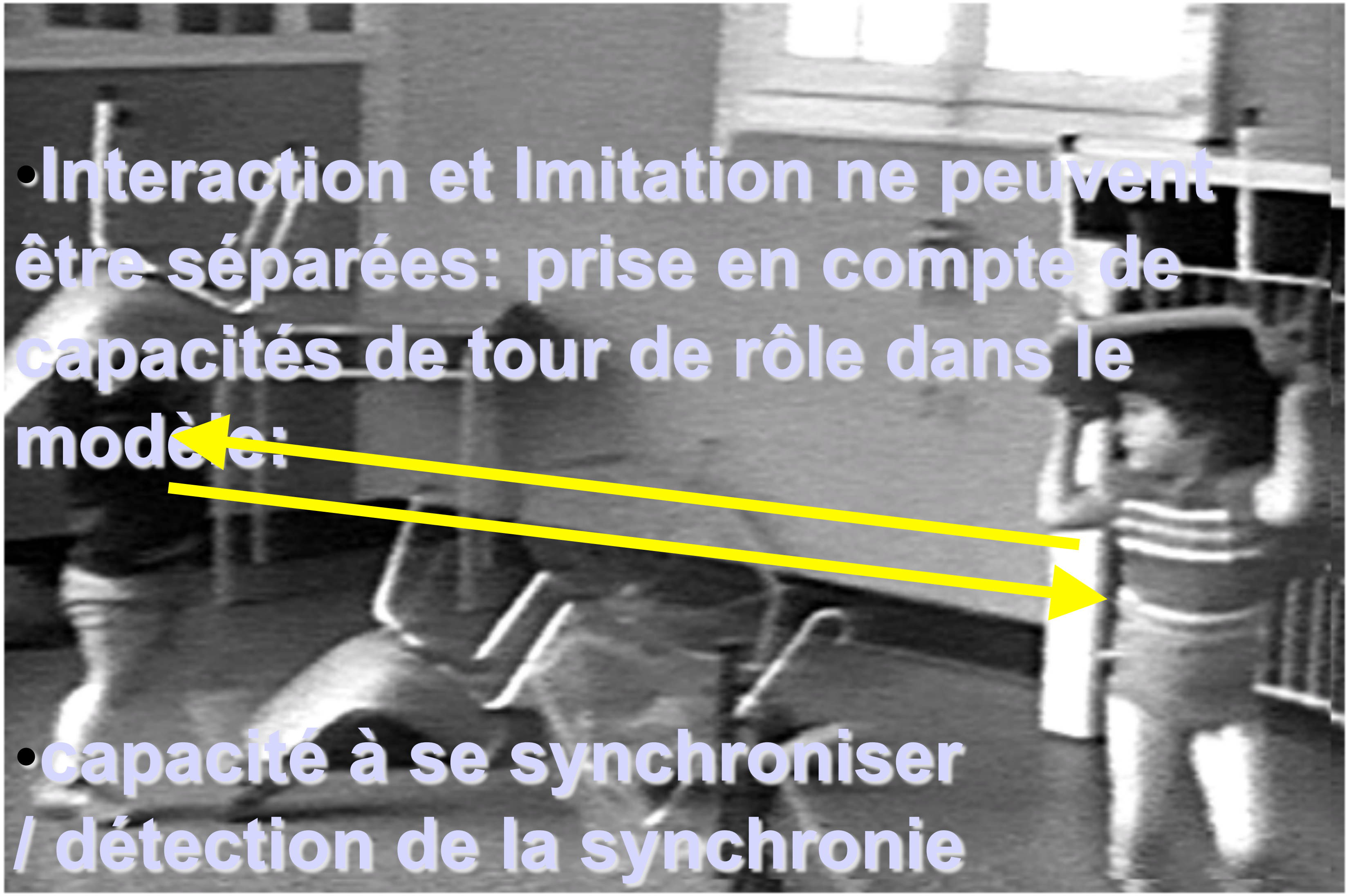


Imitation / interactions sociales

Imitation / interactions sociales



Imitation / interactions sociales



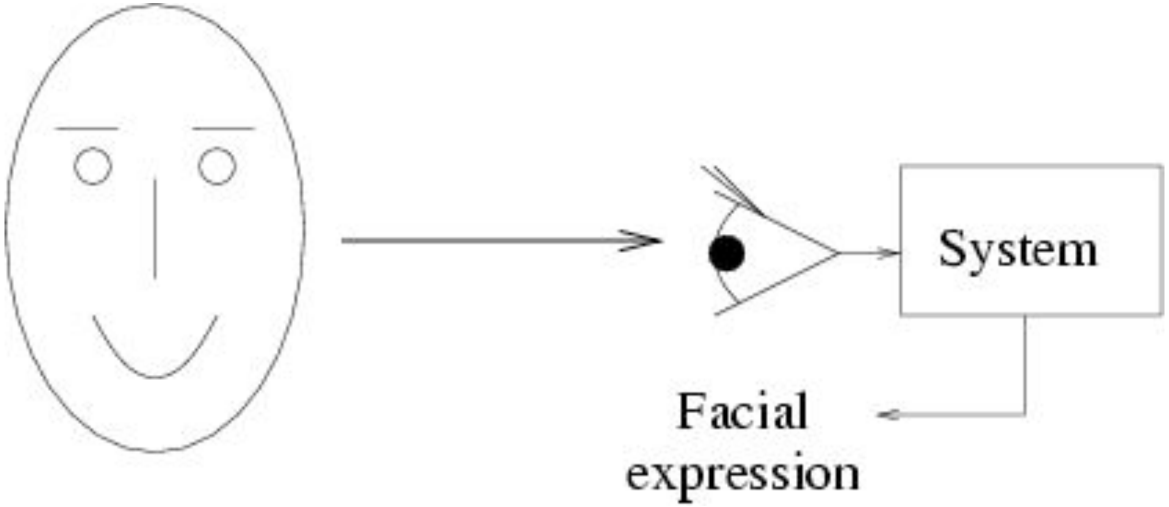
- Interaction et Imitation ne peuvent être séparées: prise en compte de capacités de tour de rôle dans le modèle:

- capacité à se synchroniser / détection de la synchronie

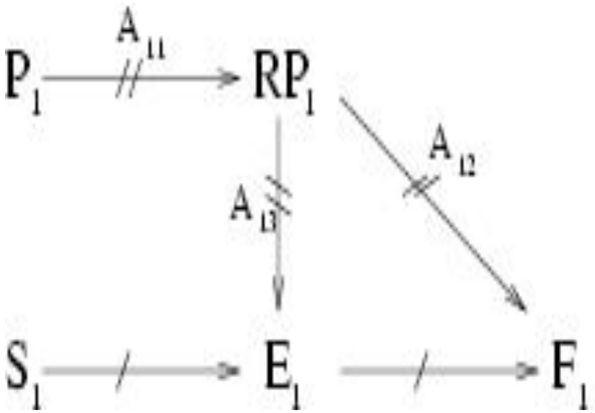
4^{eme} partie

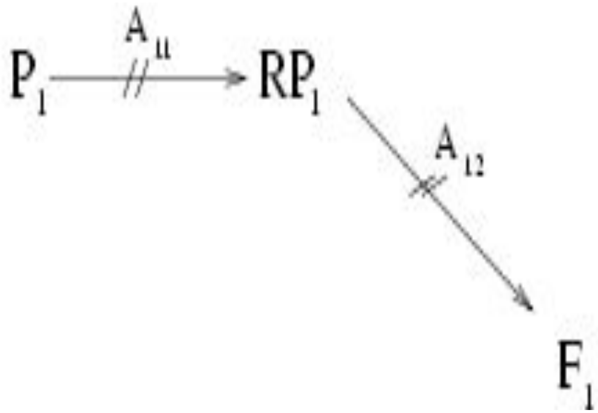
Et les émotions dans tout ça?

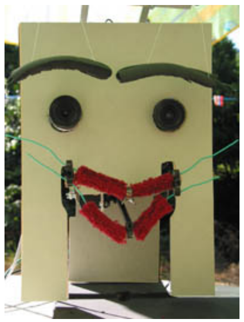
A toy problem: How to model baby learning?



One possible architecture

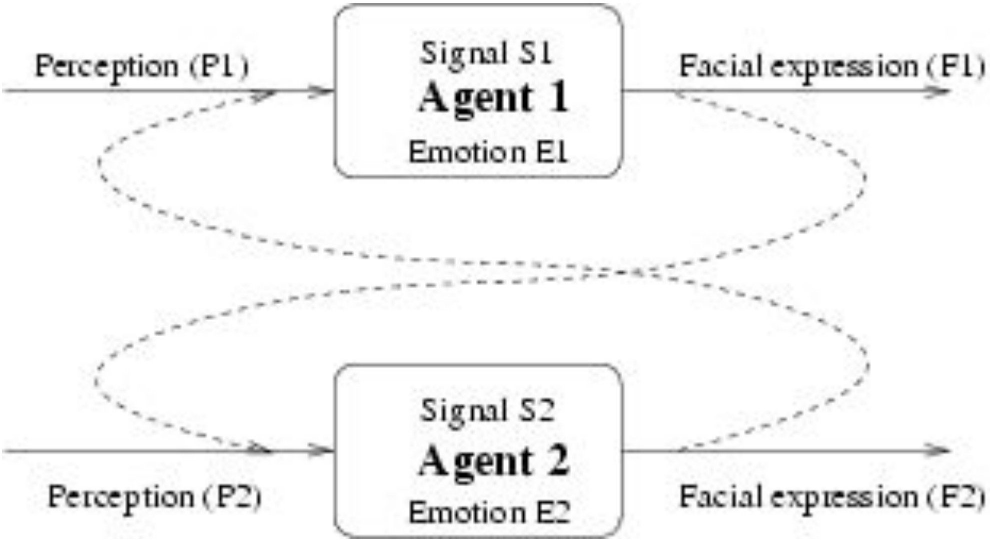


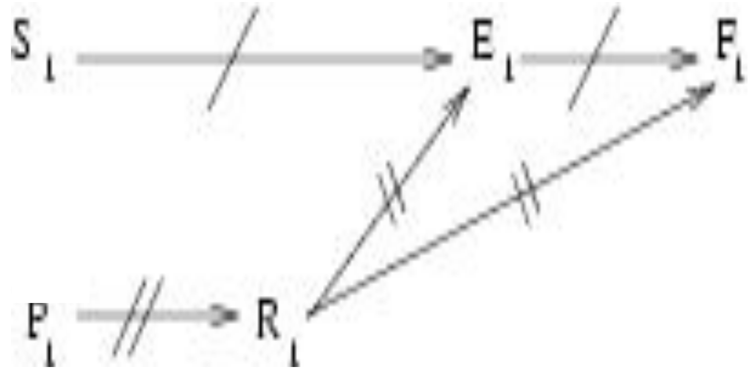


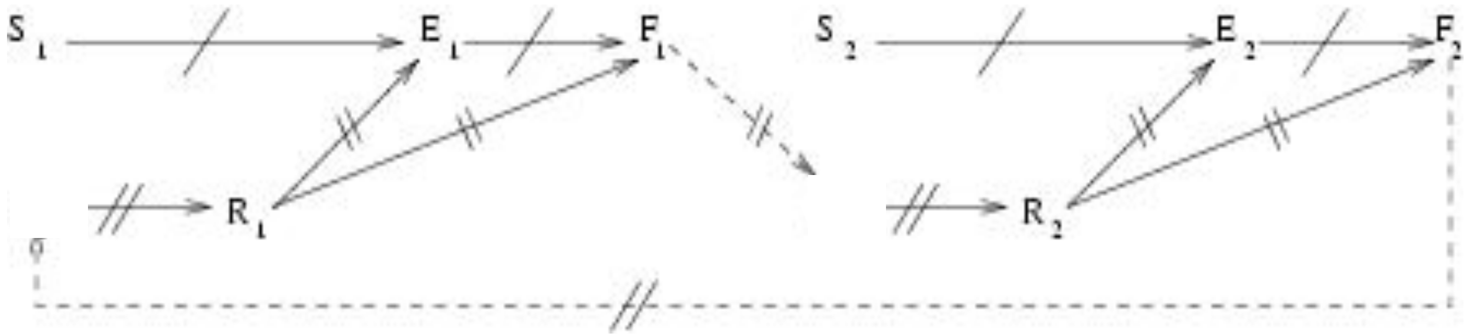


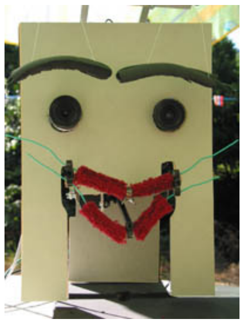
(based only on sensori-motor loops)

Study of a dynamical interaction

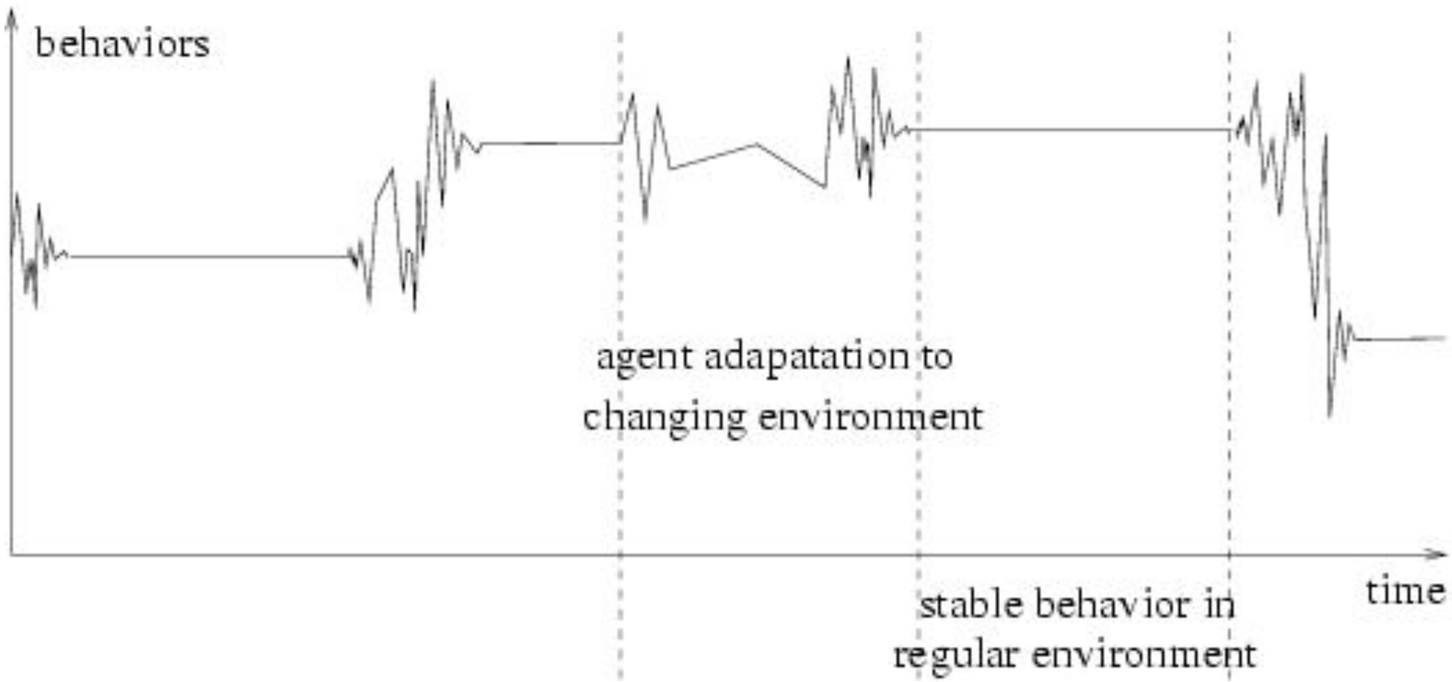


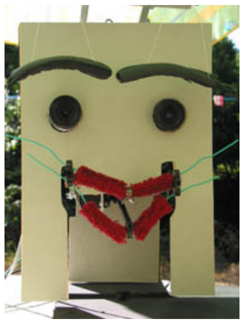


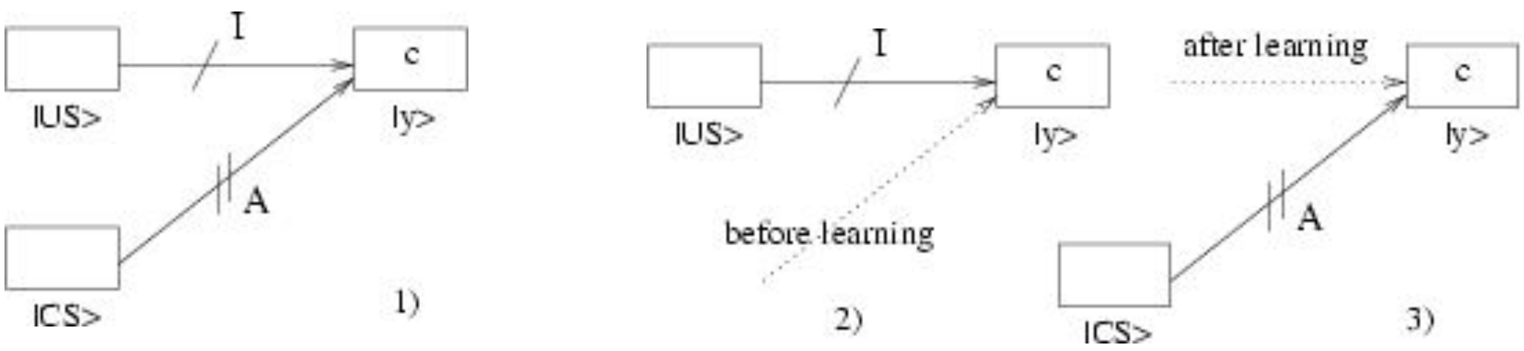




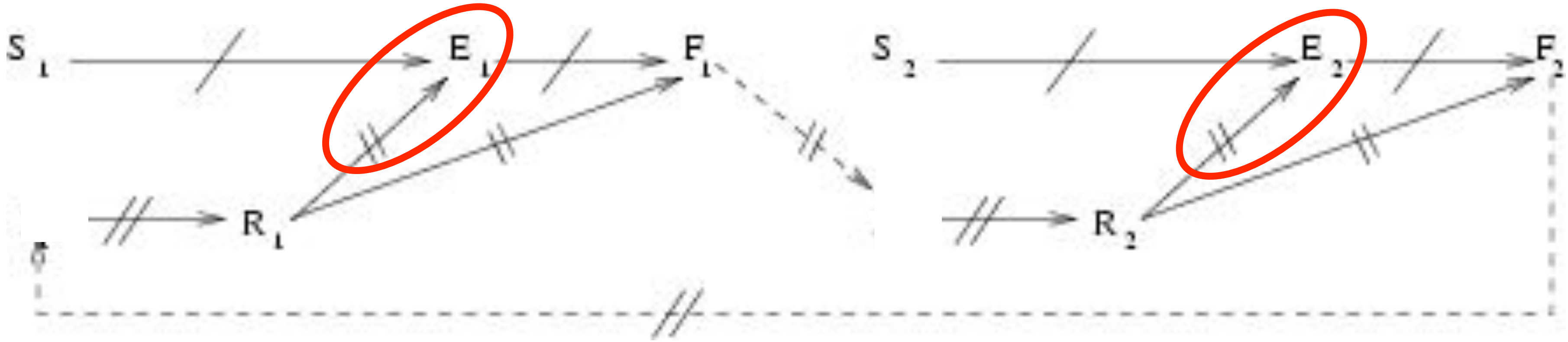
Stable state of “perception”



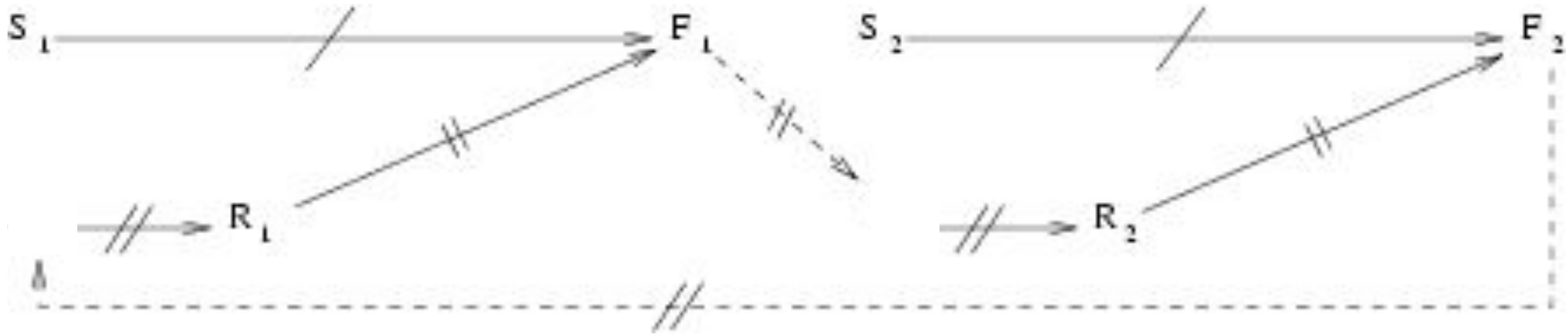




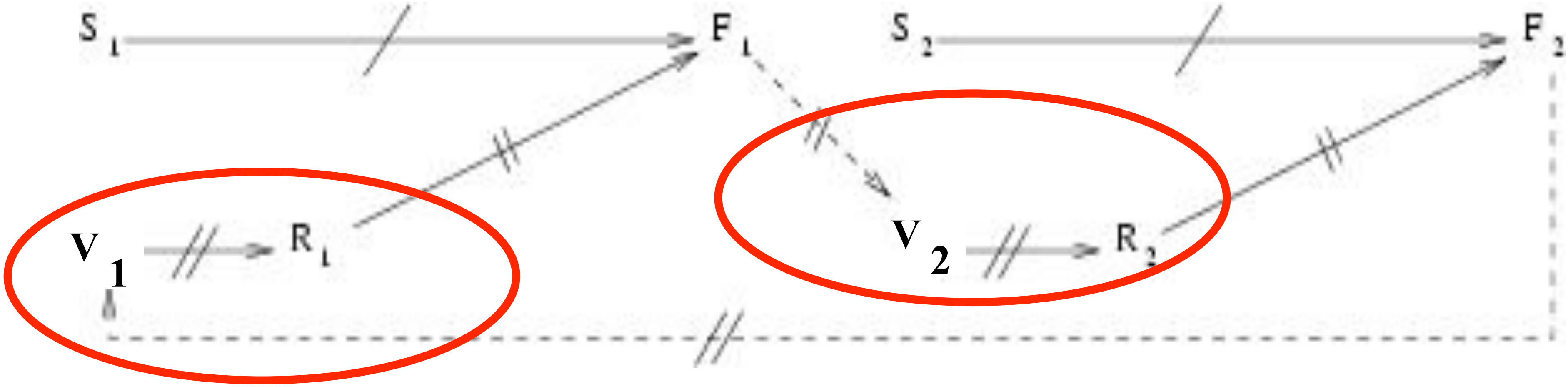
System simplification



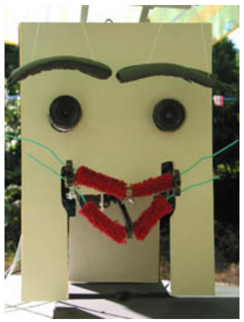
First simplification if learning is possible:

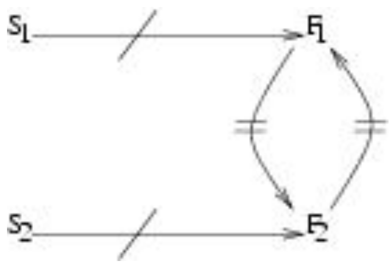


System simplification

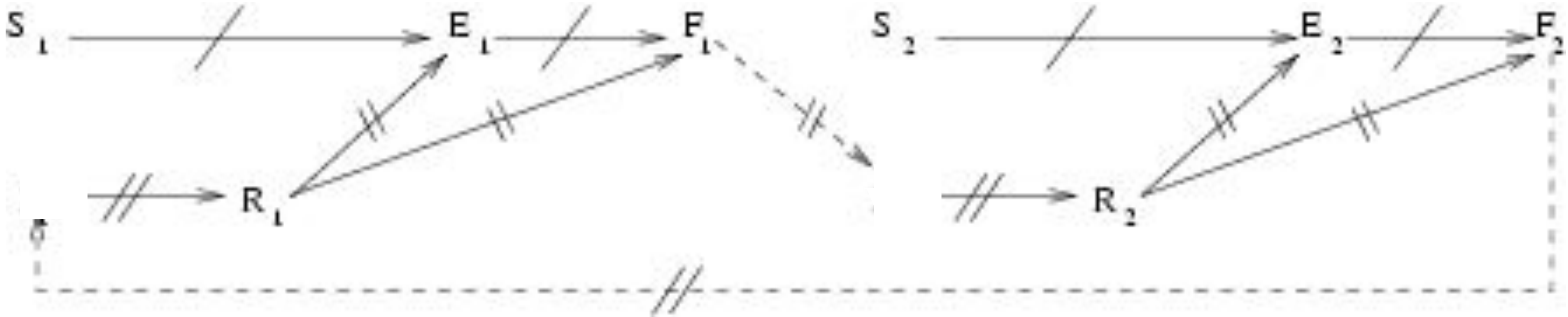


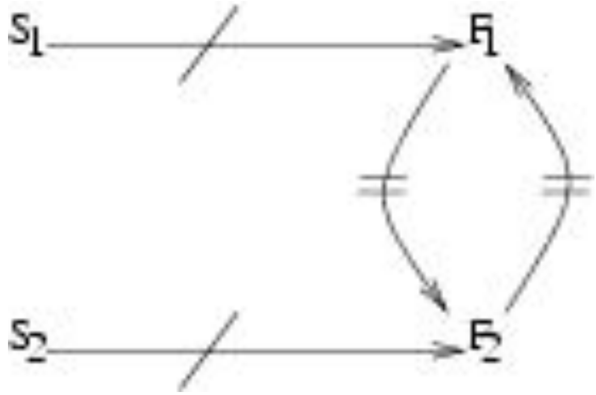
Second simplification:



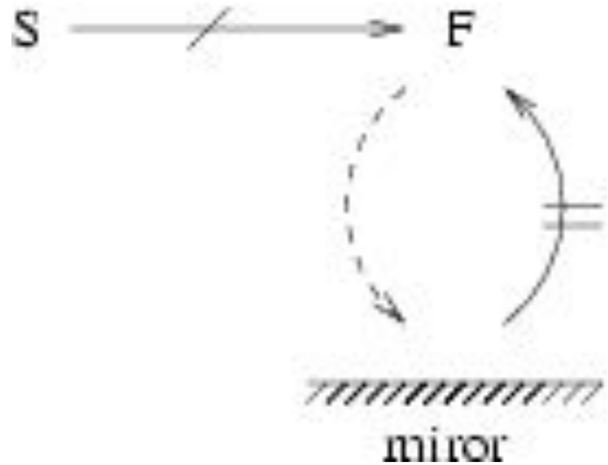


Stability condition





[Gaussier04]



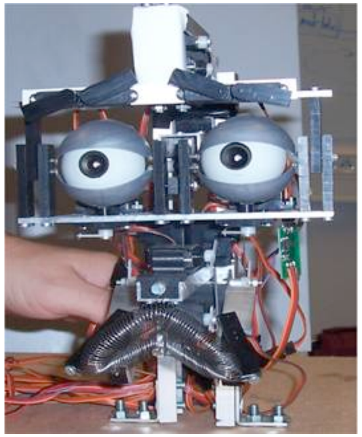
To allow learning:
→parents imitate / not the baby !

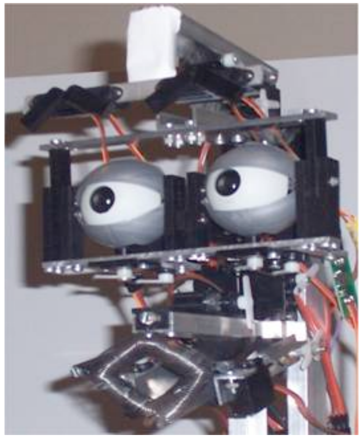
Human caretaker as a proprioceptive signal (social level)

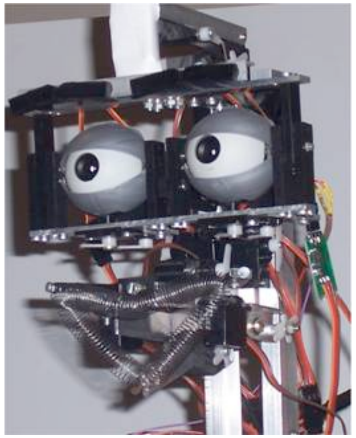
Development of facial expression recognition

[Boucenna08,09]

Videos on: www.etis.ensea.fr/~neurocyber/Videos/







Importance of the empathy

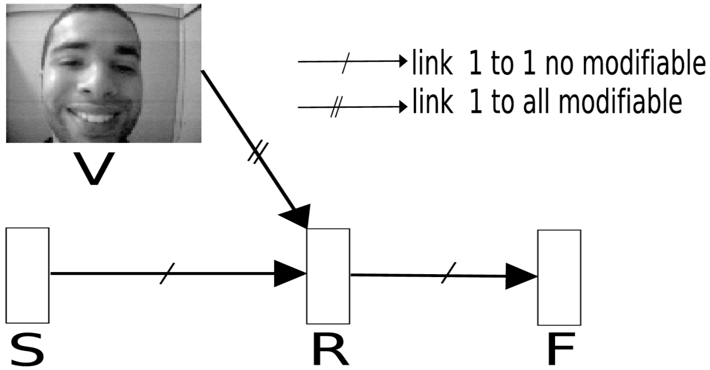
Humans do resonate to simple robot heads [Nadel06]

First computational models

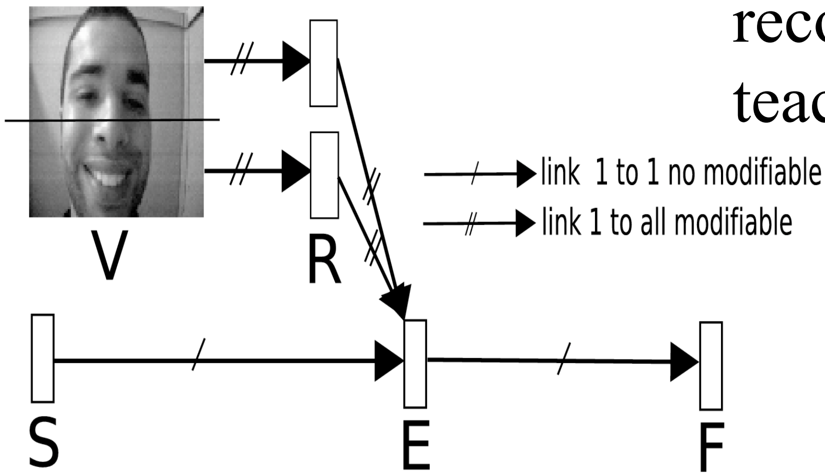
- Principle of the classical algorithms for facial expression recognition:

- Find the face in the image...
- Build a **frame** around the face
- Recognition of the normalized image (eigenvalues, supervised NN...)

“Classical” NN strategies



Limitation:
NO on-line and autonomous learning because the face / non-face recognition need an external teaching signal (supervision)!



Approche fonctionnelle “classique” vs approche developpementale holistique

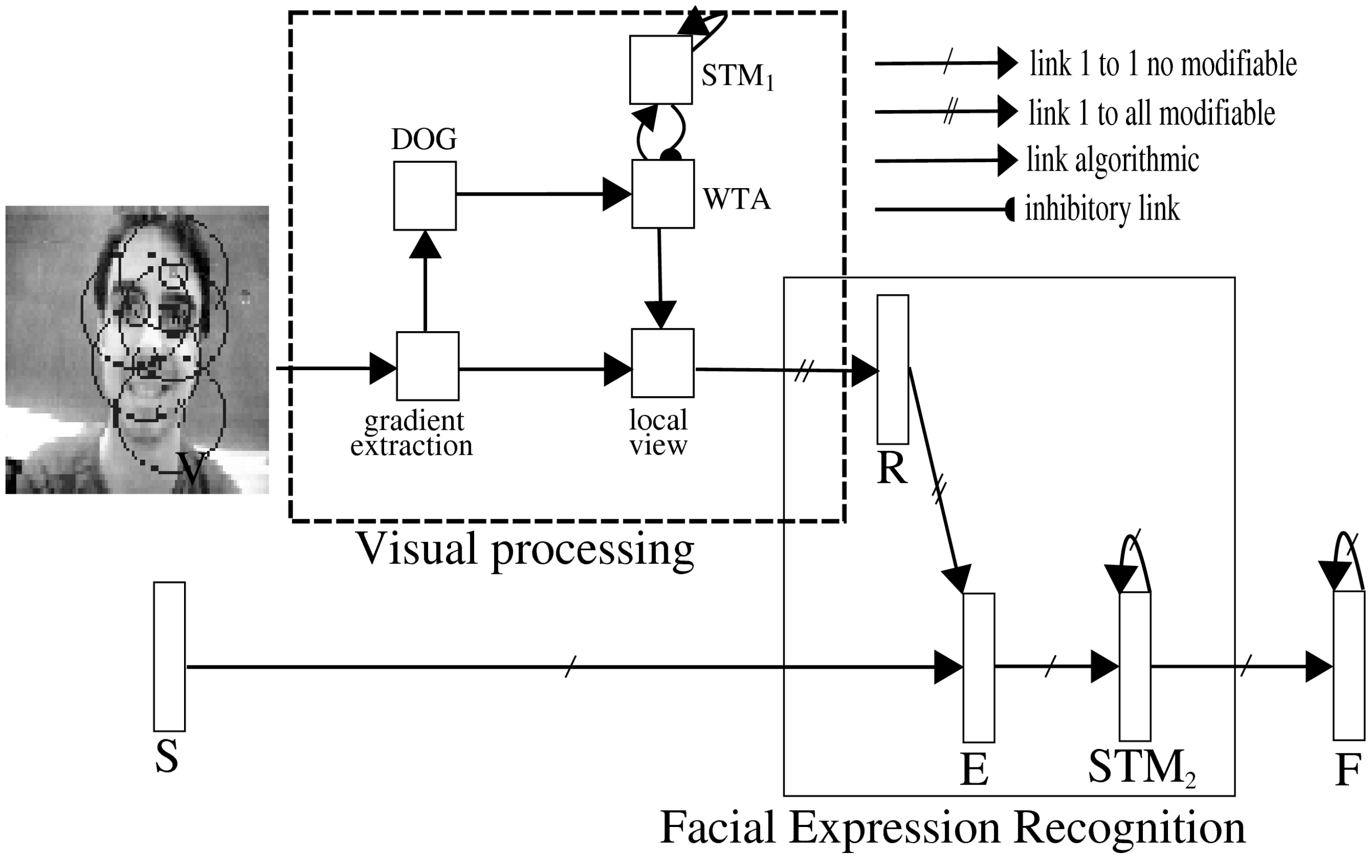
- Approche classique:
- Trouver le visage dans l’image…
- Construire un cadre autour du visage
- Reconnaissance de l’imagette cadrée (vecteurs propres, RN, SVM...)

Notre modèle développemental:

- Reconnaissance des expressions peut précèder la reconnaissance du visage !

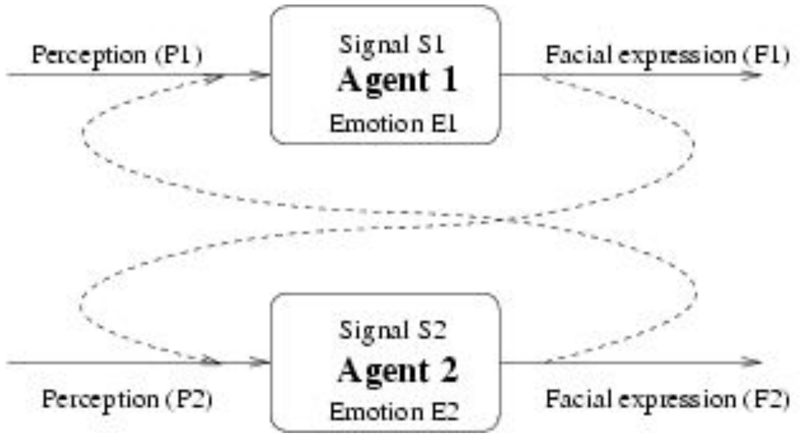
Facial expression recognition without face detection

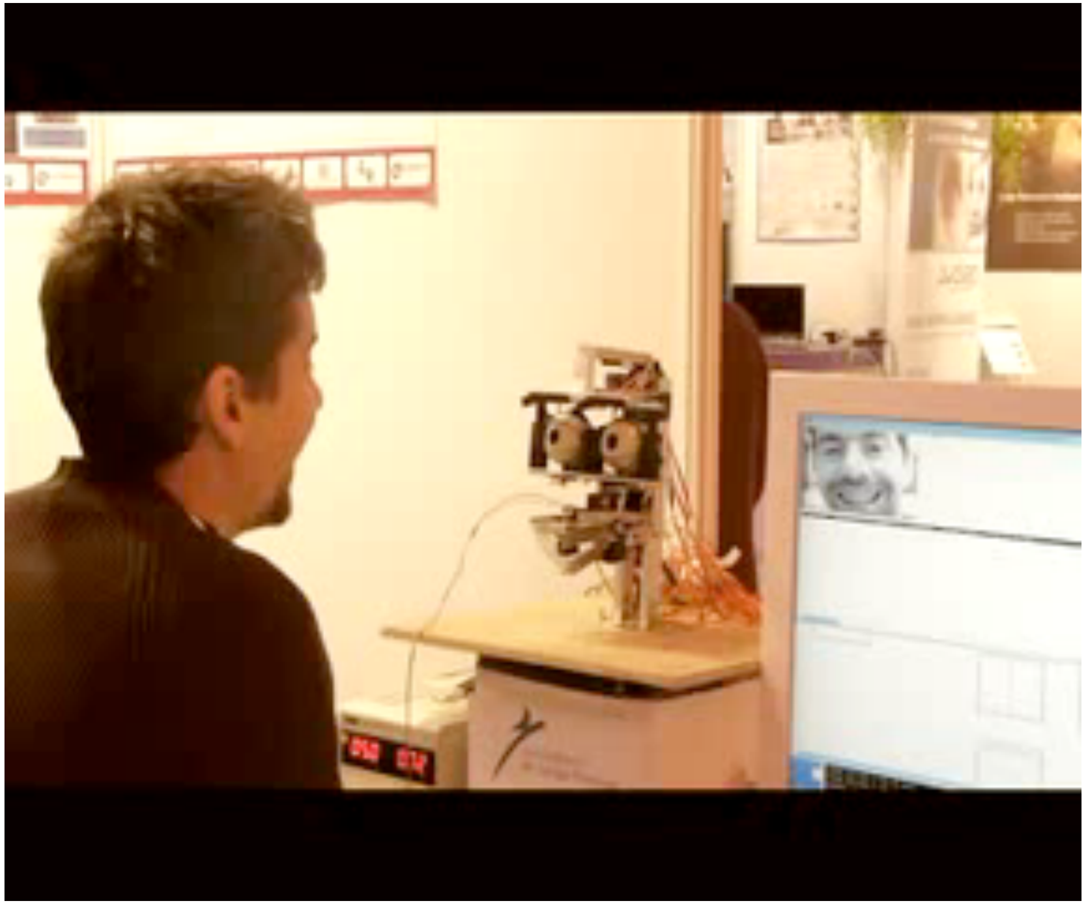
- Idea: math. model does not suppose a first step of face detection.

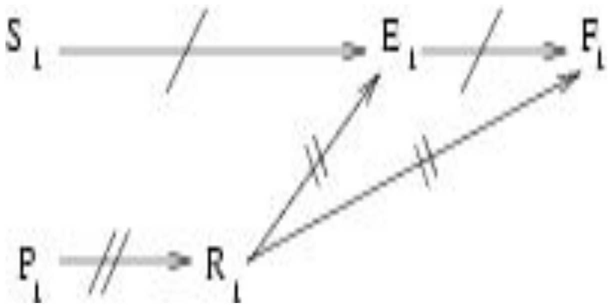


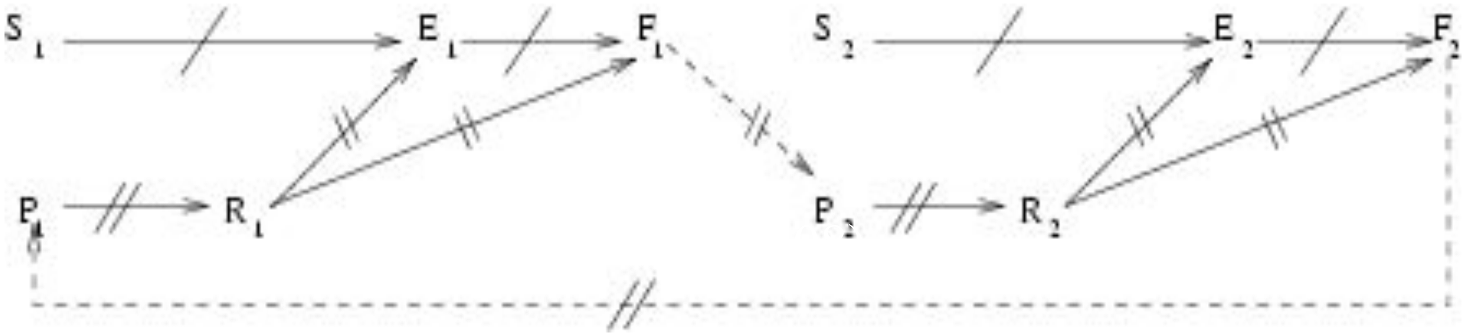
Success rate: happiness: 62 %, anger: 92 %, surprised: 89 %, sadness: 76 %, neutral: 50 %

Interactions faciales

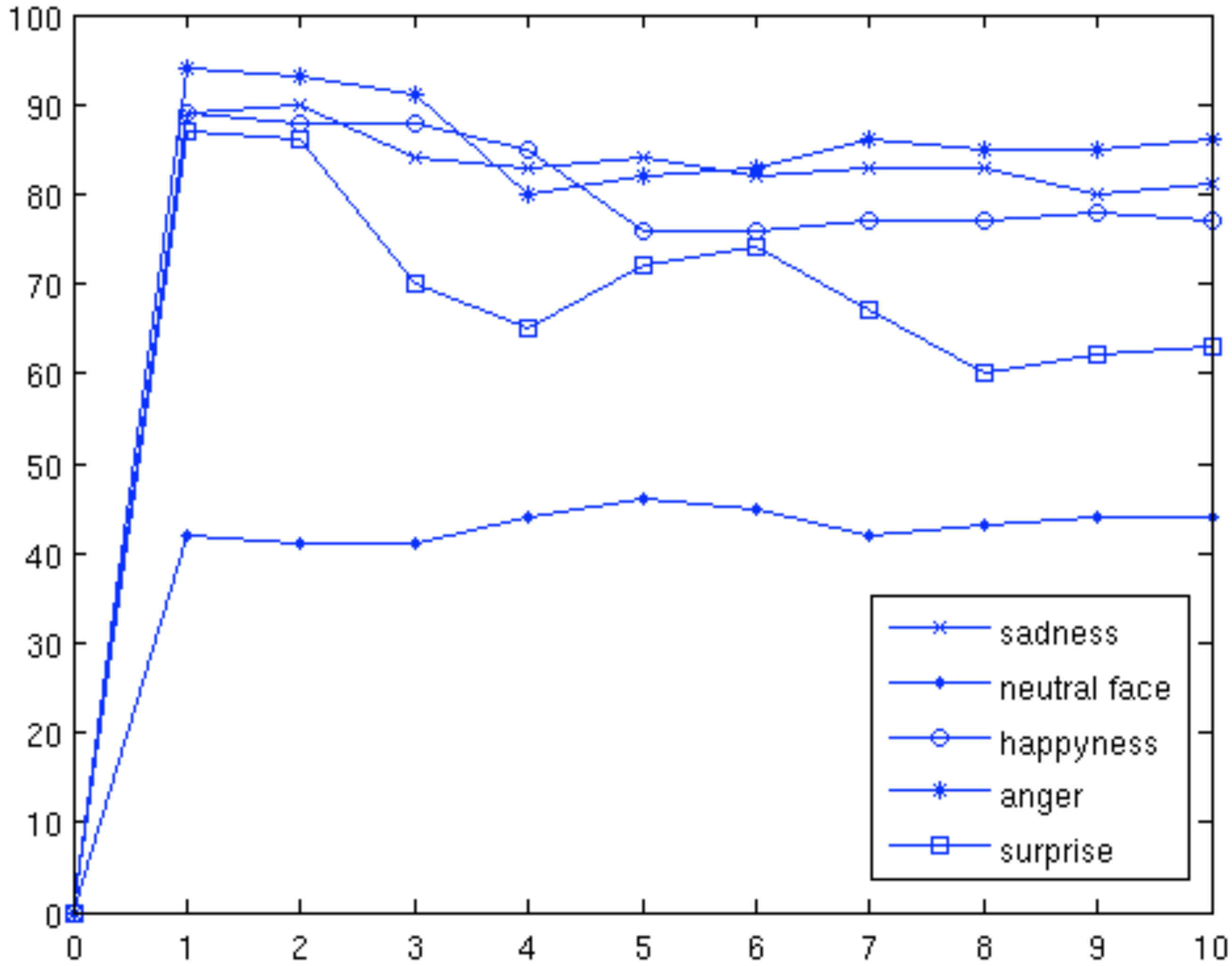






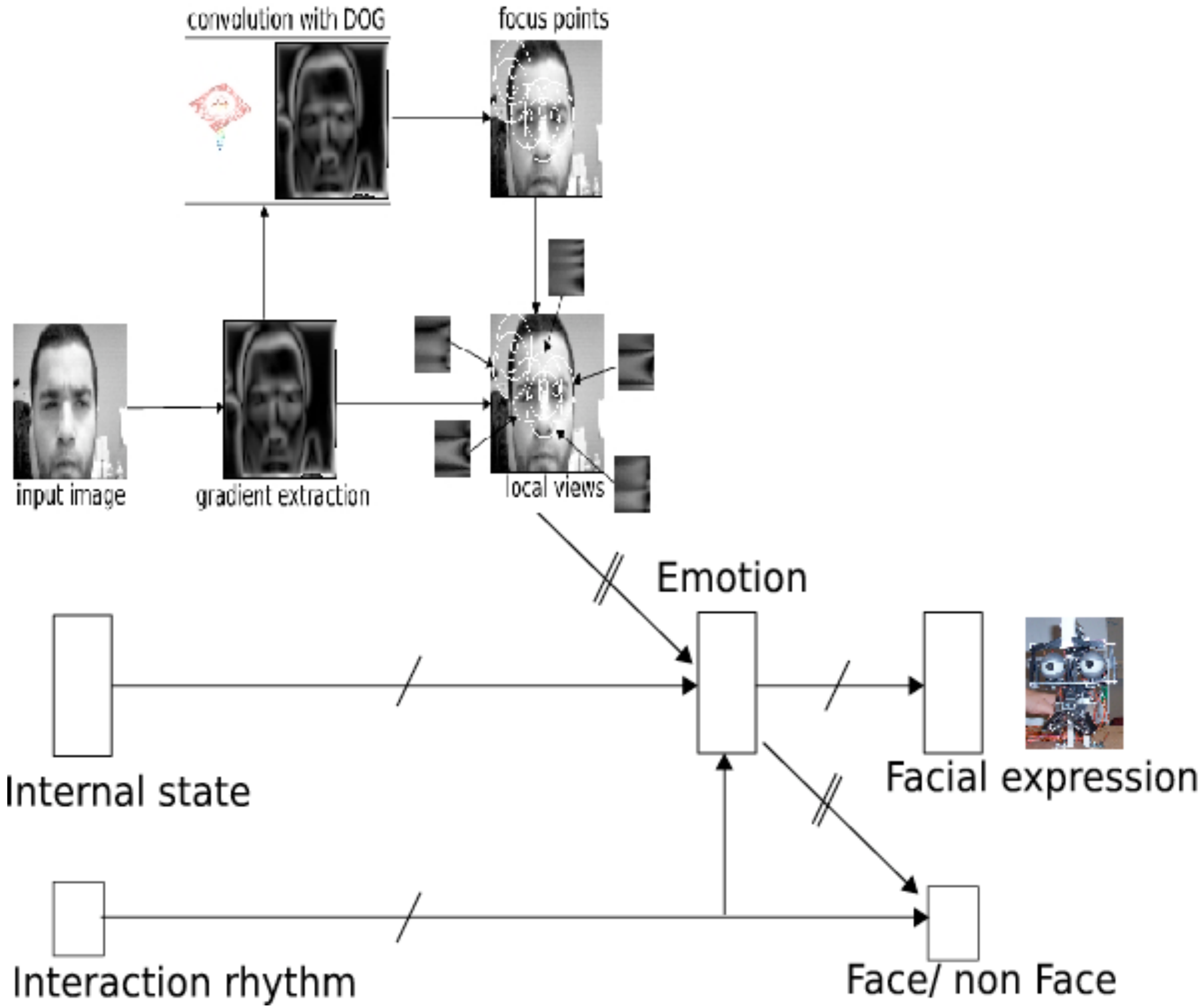


Performance measure

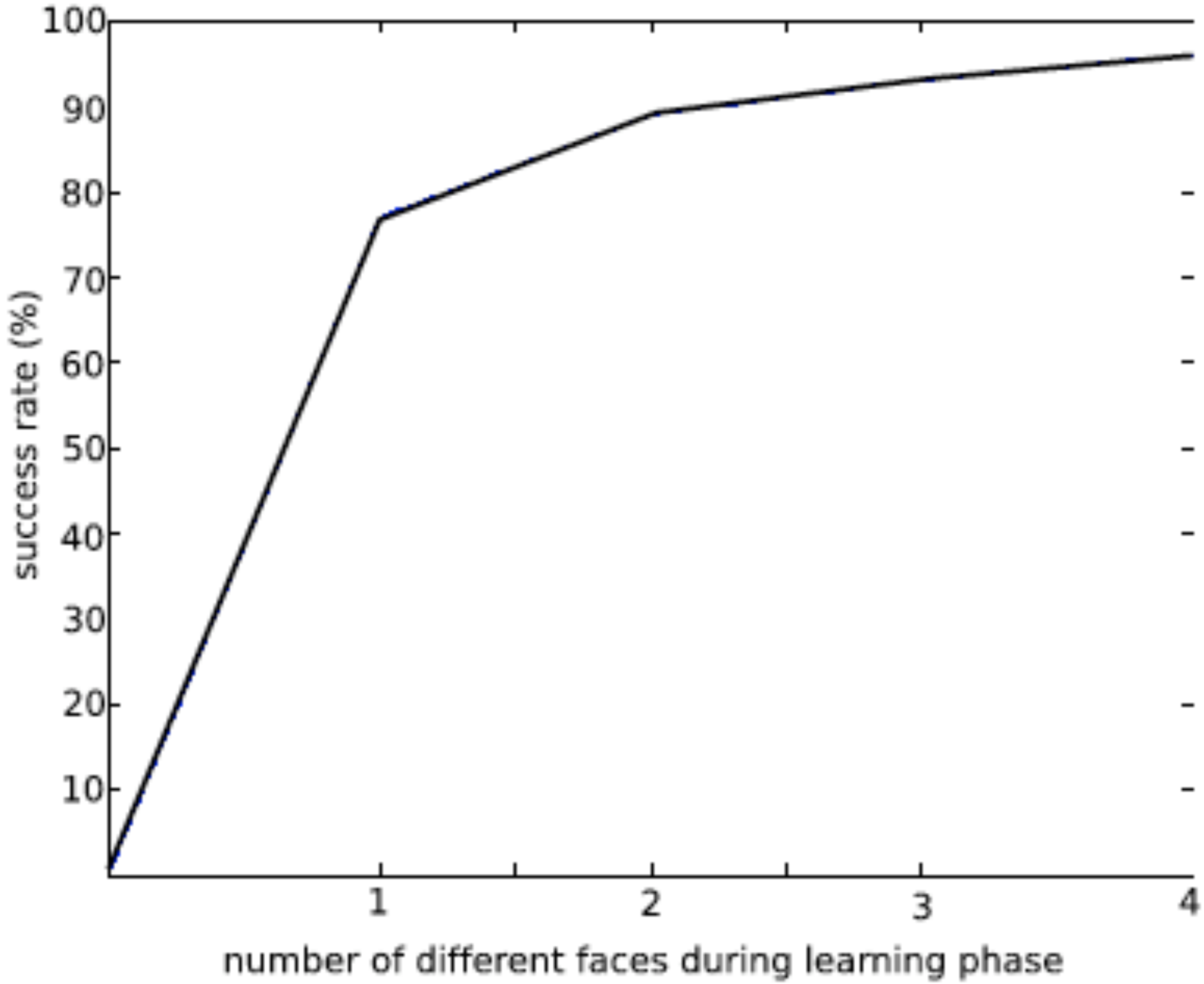


Online perf. 2 min learning. Test (32 images/expr) human annotation

Face/non face discrimination from emotional interaction



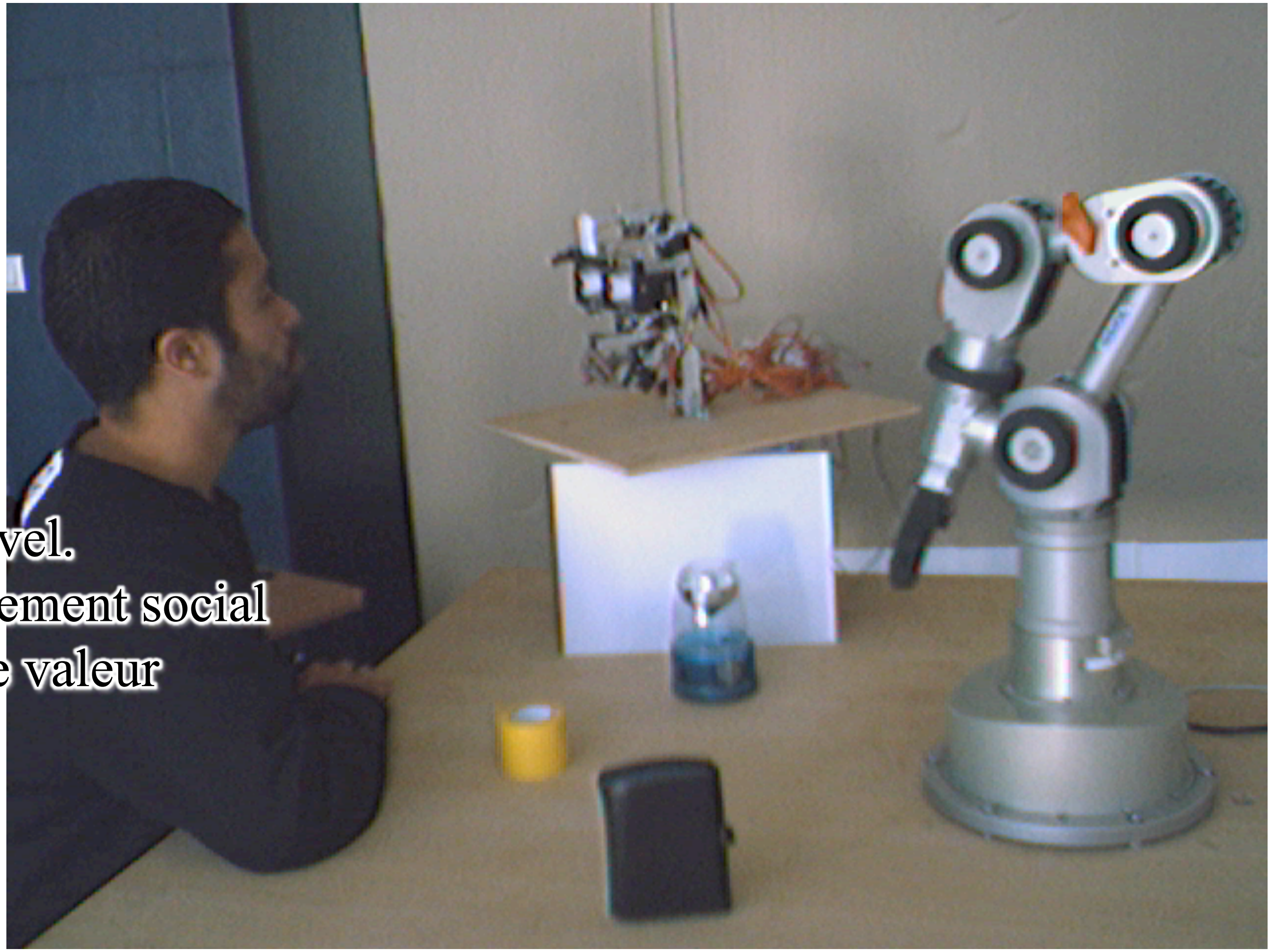
Performance measure



Generalization test on 21 persons (3360 images)

Social referencing

- Vers des **comportements complexes** (manipulation, interactions entre comportements de niveaux différents…)
- Modélisation des **émotions** (métacontrole /communication)



Exp. sur devel.
du référencement social
(donner une valeur
aux objets)

Emotions as a way to structure learning

- Facial expression recognition can precede face / non face recognition !

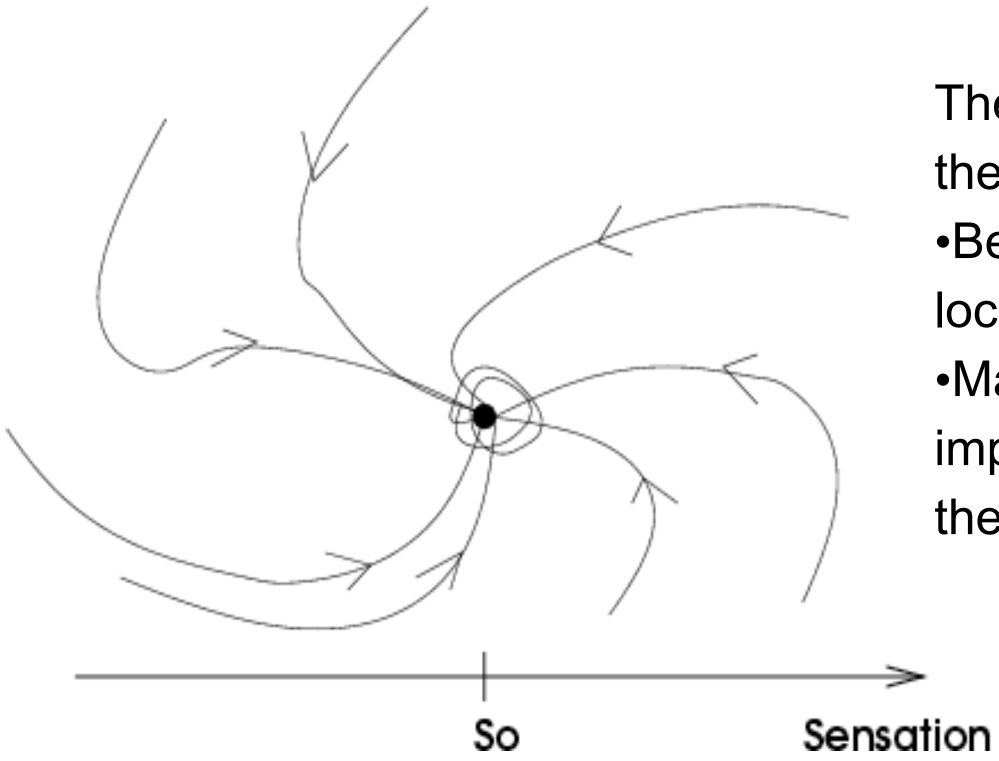
- The emotion **communication/interaction** may be used as a way to shape and trigger more and more complex learning when no explicit reinforcement signal can be used (➔**bootstrap**).

- Taking into account the emotional development opens new doors for autonomous learning

Conclusions

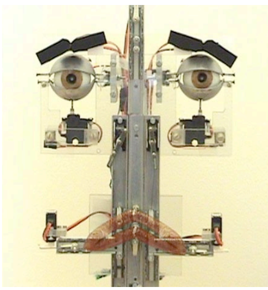
Limitations of simple conditioning

Dynamics of the interaction (and its perception) collapses to a fixed point attractor



The demonstrator controls the interaction :

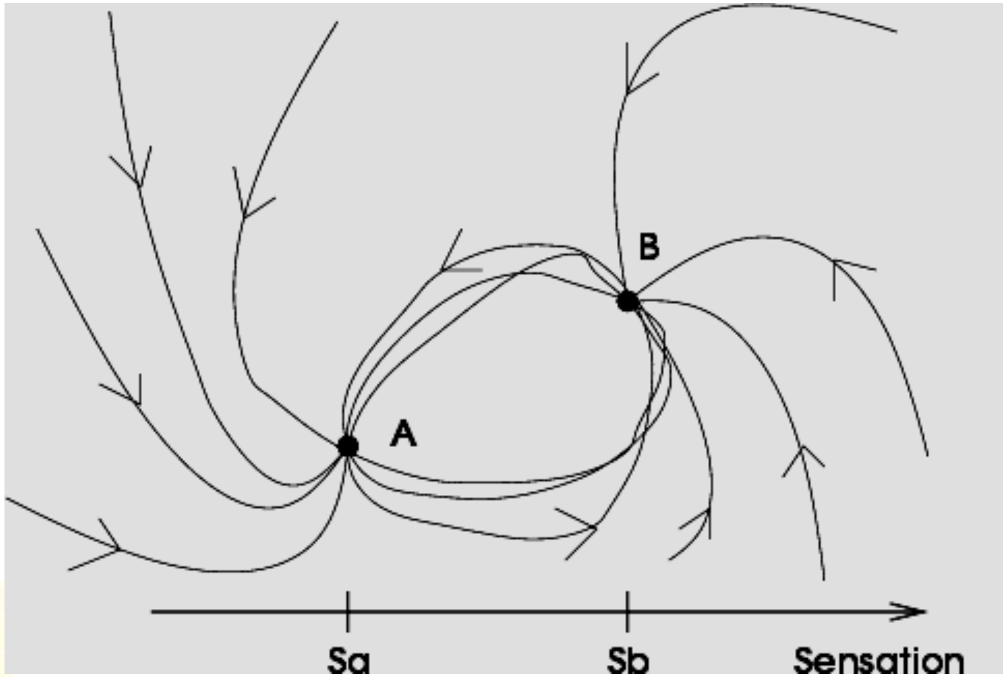
- Be sure of the visual locking ,
- Manage some explicit / implicit signals (begin/end of the exp.)



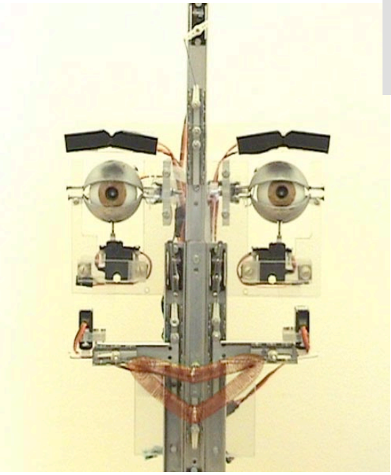
The innovation only comes from the other!

More complex Resonances

Need to introduce at least cyclic attractors:



Different levels:
- turn taking
- role switching



“Will” of interaction:
- a simple internal oscillator circuit?
- the emergent property of a NF?

Conclusion

- Perception ambiguity and proprioception

➔ Emergent homing behavior / robust route following

➔ Emergence of imitation capabilities in simple SM systems (mirror system is a consequence not the cause of learning!)

- Emotional state and social feedback

➔ Emergence of facial expression recognition and recognition of the other as similar to us

Conclusion

Hence we can imagine that baby considers

1. other agents/objects belong to his/her body
2. After learning, subtle differences between proprioceptive signal and external signal can be distinguished

➔ Differentiation between self and other

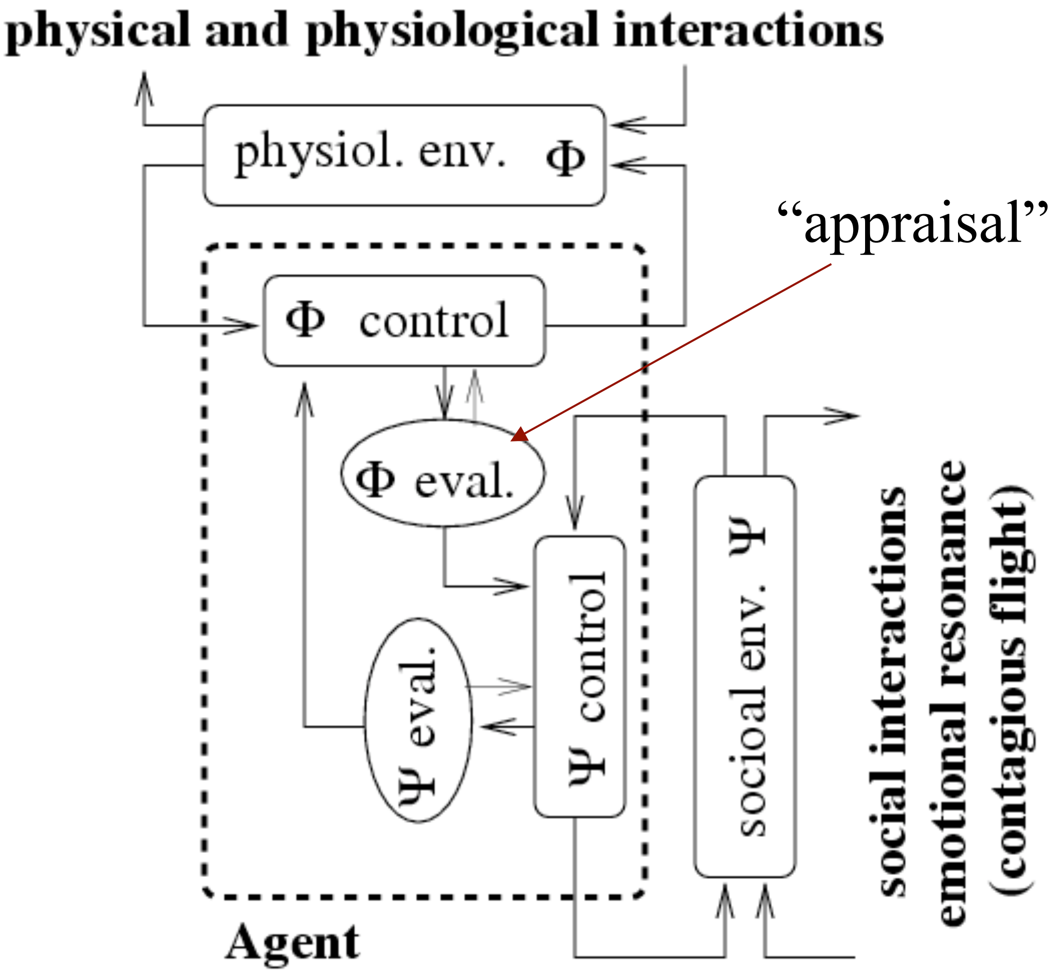
➔ Importance of the proprioceptive function and emotions in the development of more and more complex sensori-motor dynamics based on a simple homeostatic principle

Conclusion

- 1 structure → several emergent functions (self / social):
- Same visual system:
  - landmark / facial features learning
  - place / facial expression
- Imitation: learning and communication
- Emotions: 2d order controller and communication

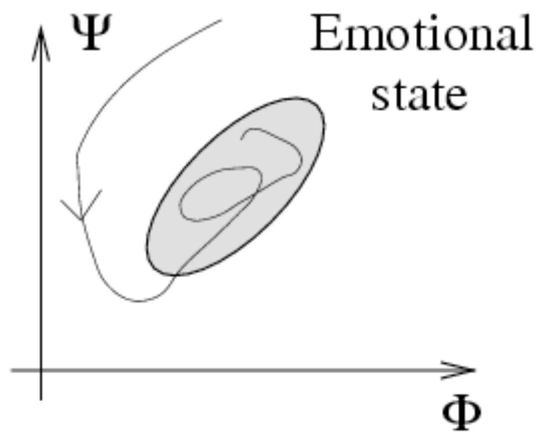
- Need of an holistic approach to cognition :
- Robot as model to understand cognitive mechanisms and their deficits
- Robot as tool for psychologists to test the validity of the model

Emotions as a dynamical system ?



No locus

for the "emotional states"?



shared sub-structures between both controllers --> Complex emotions built through the interaction and next useful for an isolated agent

Videos on: www.etis.ensea.fr/~neurocyber/Videos/

Thanks to: P. Andry, (J.-C. Baccon), D. Bailly, J.P. Banquet, A. Blanchard, S. Boucenna, N. Cuperlier, F. Demelo, L. Hafemeister, P. Henaff, (C. Giovannangeli), C. Hasson, J. Hirel, (C. Joulain), M. Lagarde, P. Laroque, (S. Leprêtre), (S. Moga), (M. Maillard), F. Pirard, (K. Prepin), M. Quoy, (A. Revel), A. Roland de Rengerver

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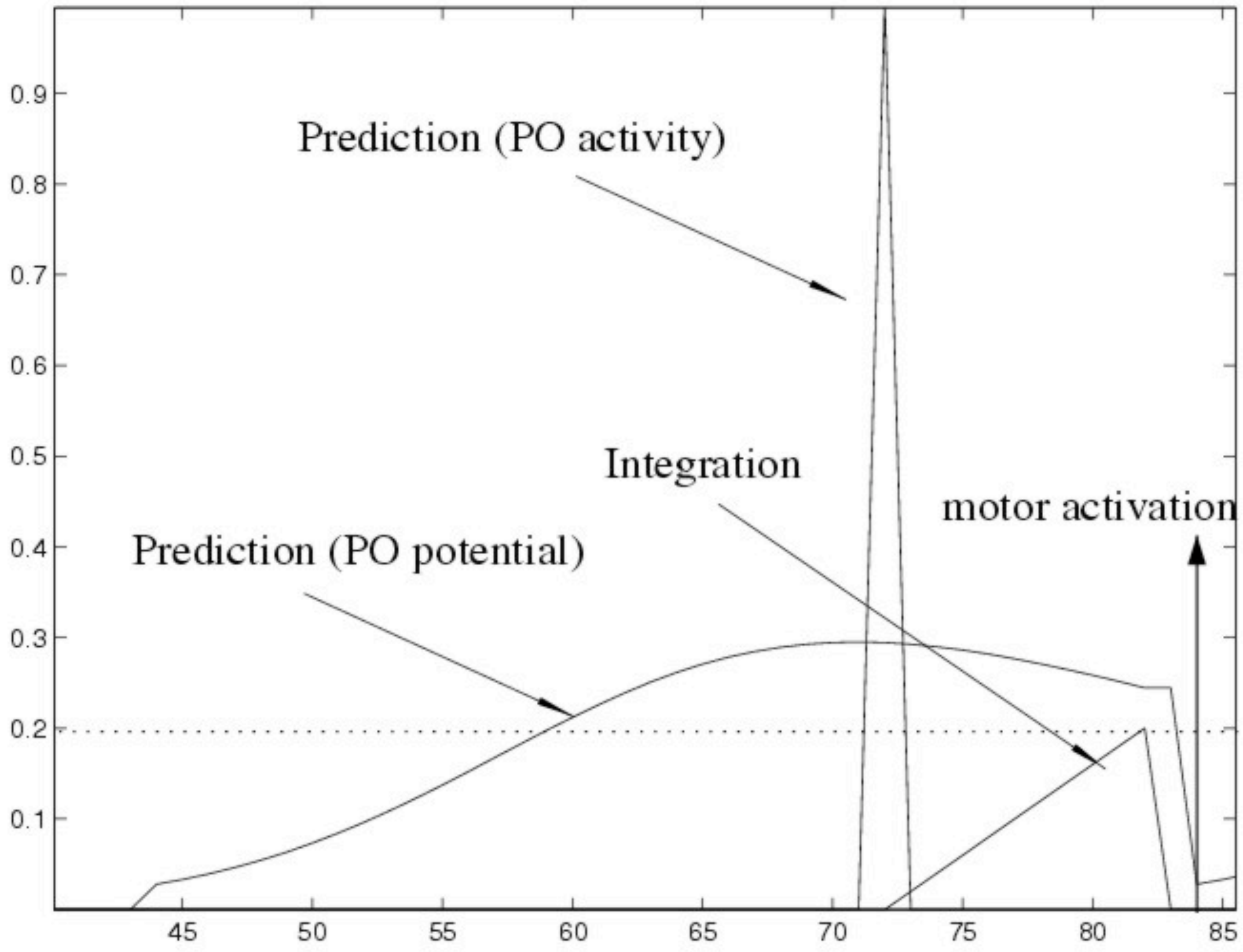
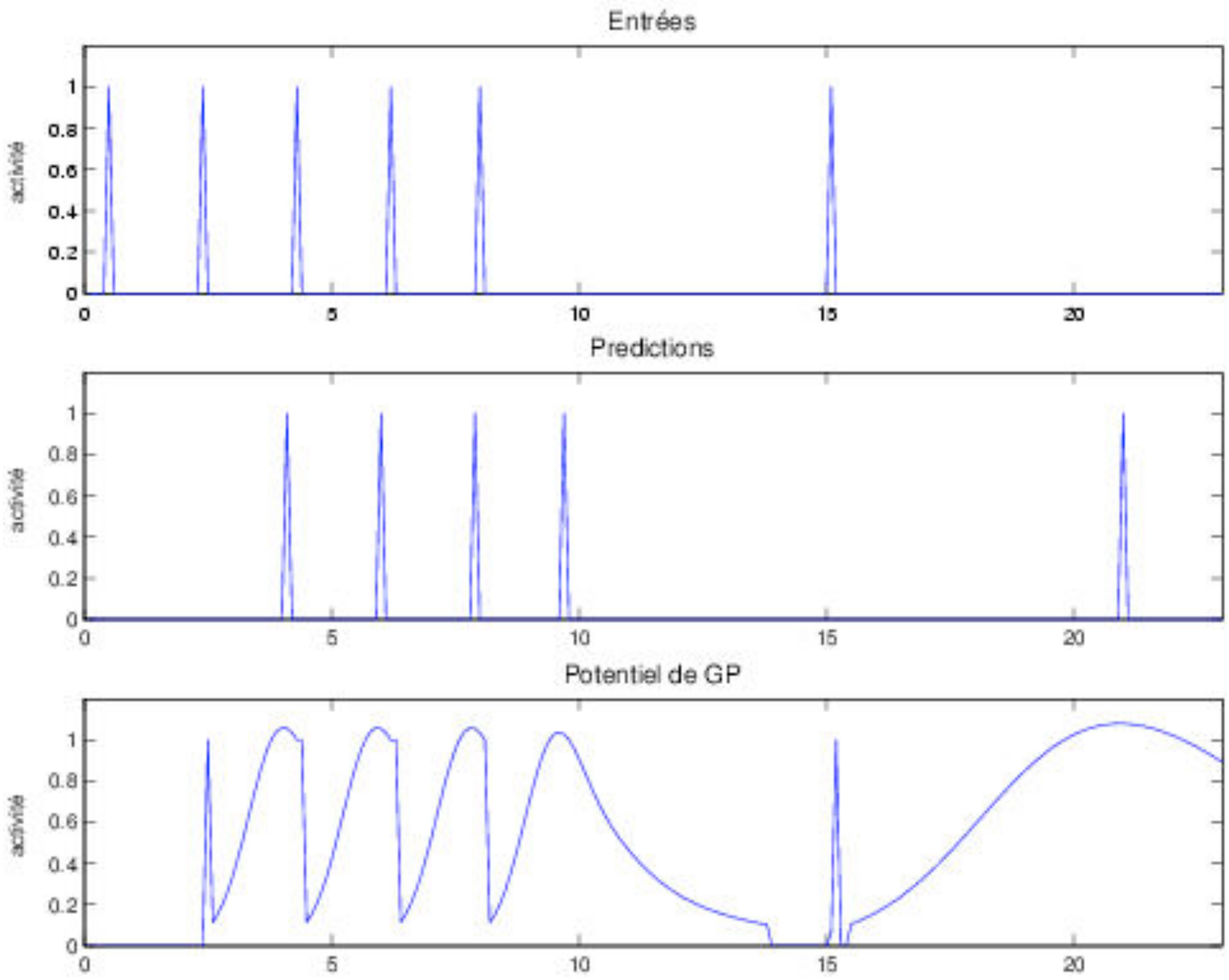
M. Dorigo et M. Colombetti, Robot shaping: An experiment in Behavior Engineering

Kelso, Dynamical patterns

Rythm prediction

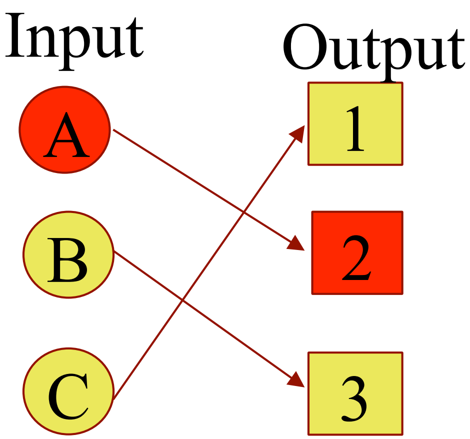


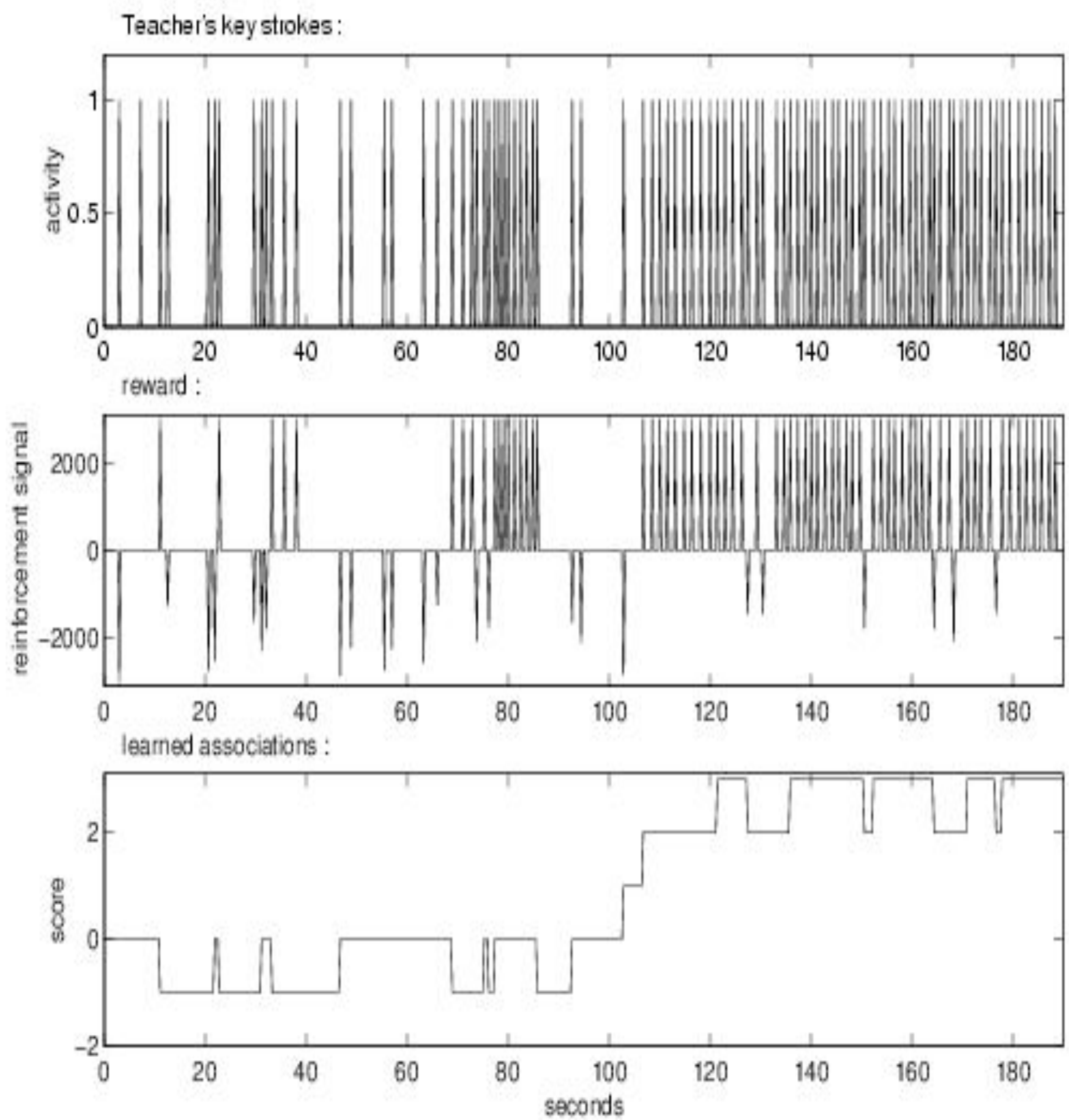
Building the reinforcement signal



- Simple application : using the reinforcement signal to learn an arbitrary set of associations

S/M learning without reward !



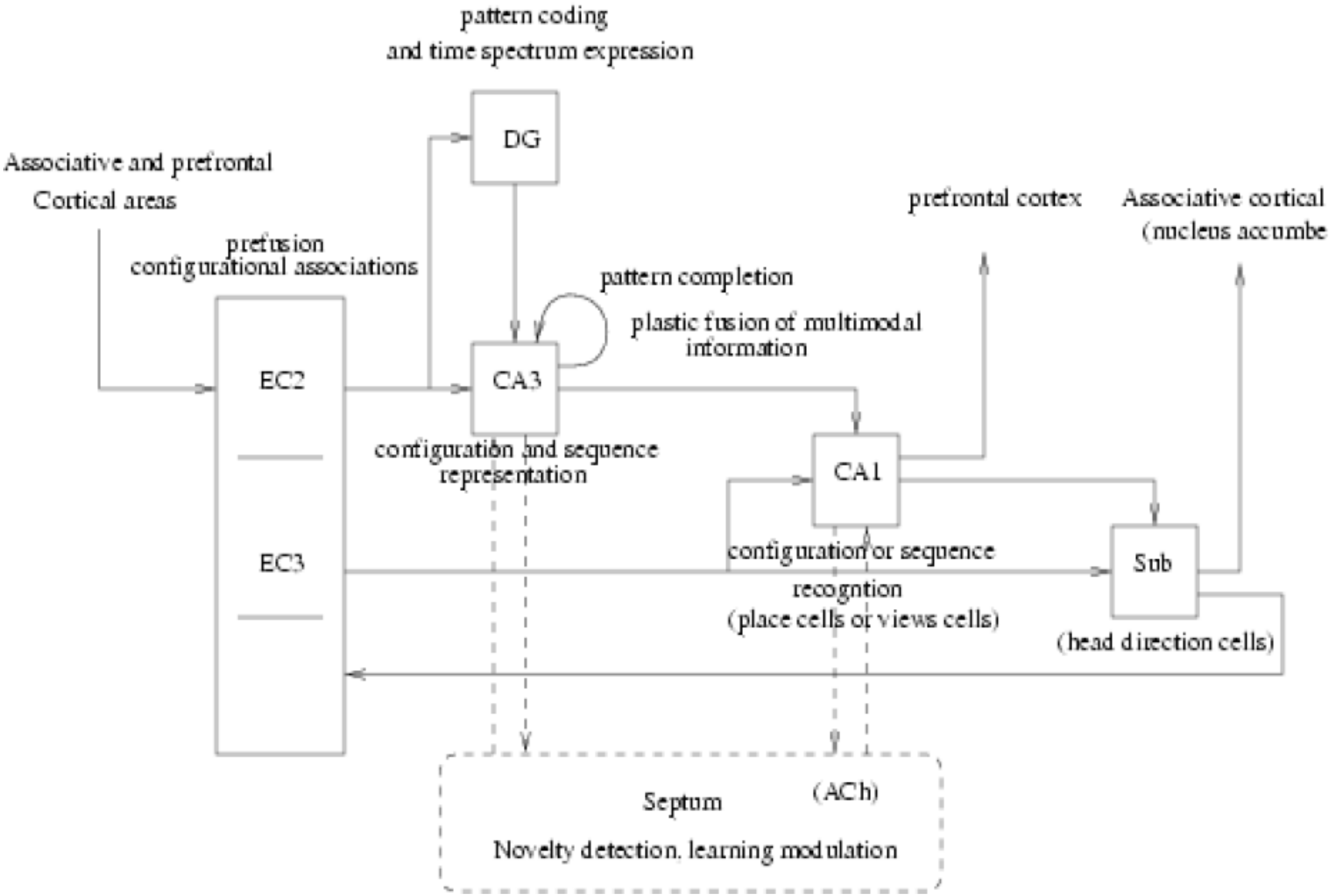


- Rythms variations drive learning (negative reward)

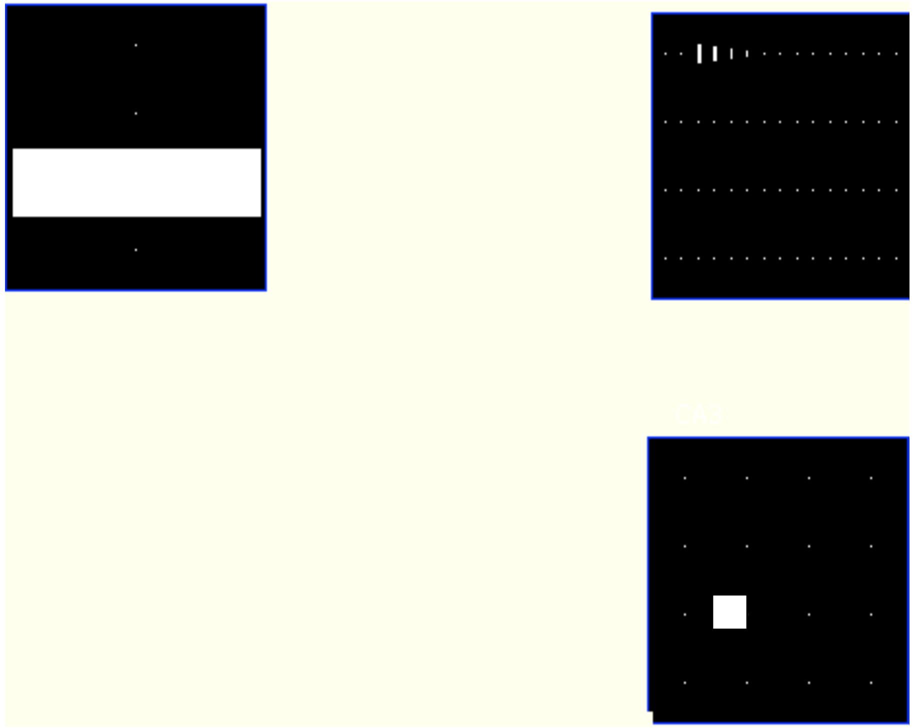
- Constant rythm stabilizes and reinforce learned associations

[Andry et al 2002]

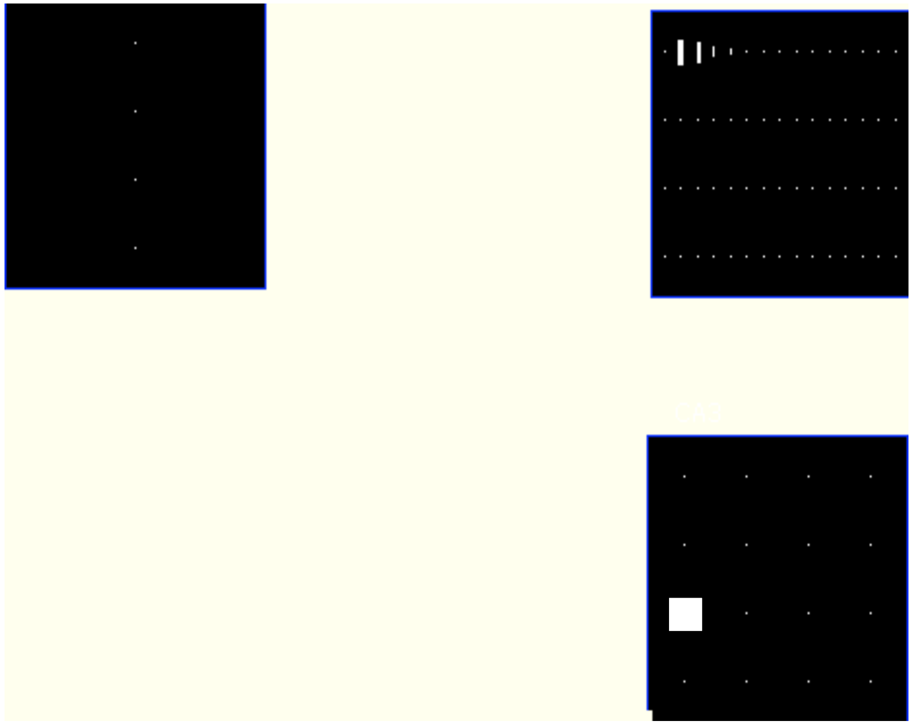
Sequence learning: hipp. model



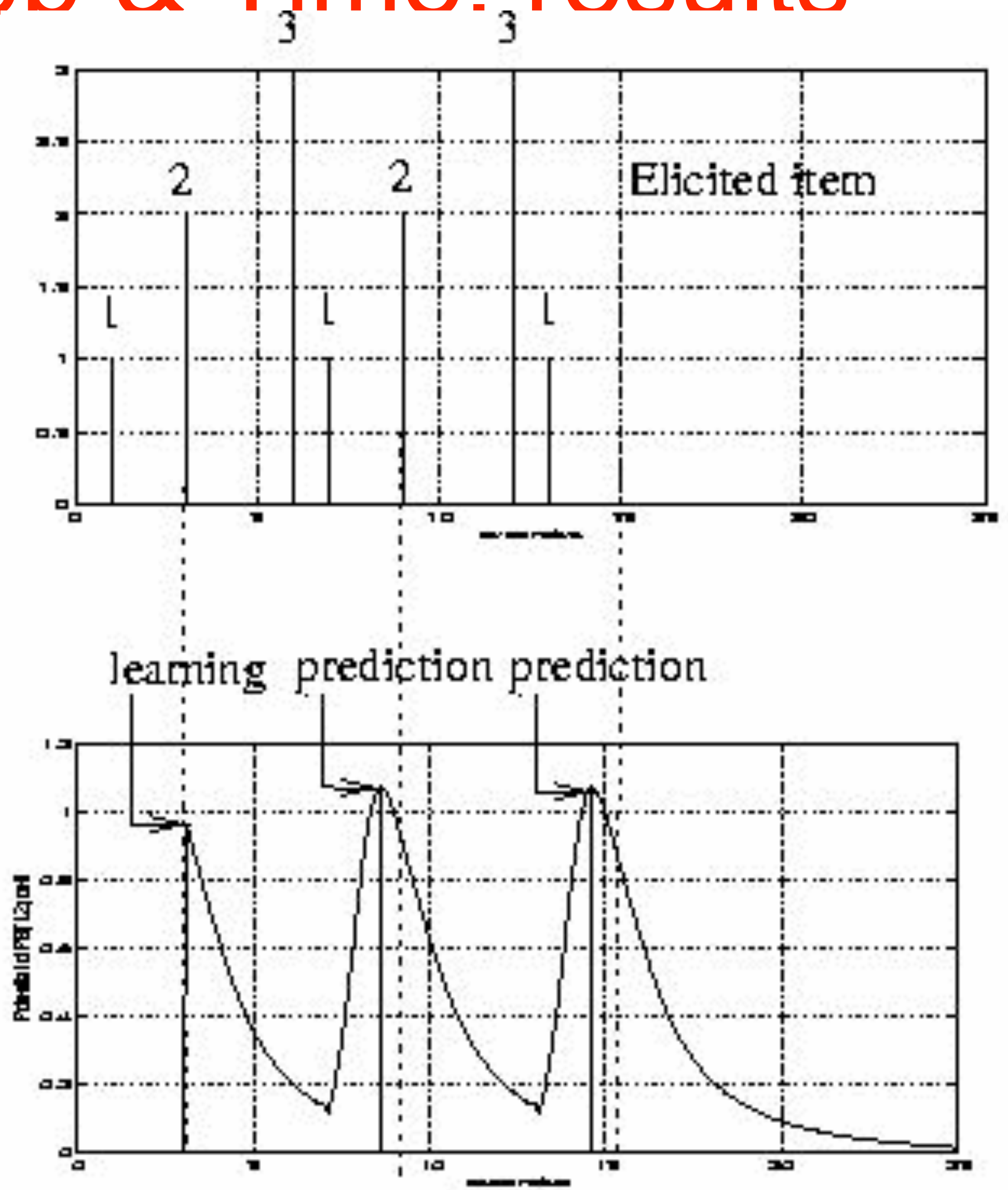
Sequence learning



Sequence learning



Hipp & Time: results



Système adaptatif

Système adapté:

Le comportement d'un système/agent est adapté à son environnement lorsque sa trajectoire respecte une contrainte C donnée (représentée par un volume dans l'espace des états)

Système adaptatif:

Un comportement est adaptif si les variables d'état restent dans ce volume.

Les contraintes

- Apprentissage en ligne et tout au long de la vie (online, life long)
- Est il si important d'apprendre juste les bons exemples?
- Qu'est ce que percevoir et reconnaître si le « symbol grounding problem » ne peut avoir de solution?
- Crée t'on des prototypes moyens ou doit on mémoriser des exemples précis?
- Une catégorie sémantique se limite t'elle a une collection d'exemples ou doit elle prendre en compte des aspects dynamiques?

Fabrication de tas

Etude des fourmilières (Denebourg 92)

Situation initiale

1. Mouvements aléatoires
2. Evitement d'obstacles
3. Prise objet
4. Dépos objet

Fabrication de tas

Le comportement n'est pas inscrit dans le réseau...

Situation après 30min

L'action modifie la perception

Ambiguité fondamentale de la perception