

Distributed, Asynchronous,
Numerical and Adaptive Computing
From neurons to behavior

Nicolas P. Rougier

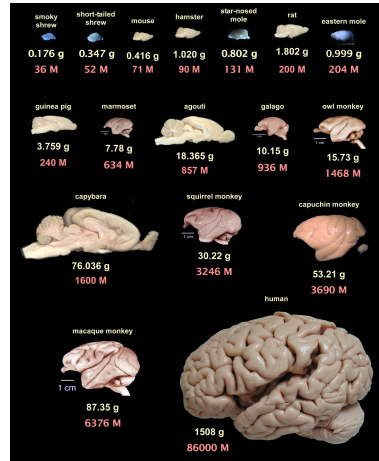
INRIA - University of Bordeaux
Institute of Neurodegenerative Diseases, France

GDR BioComp Workshop
Saint Paul de Vence, October 2015



Brains in numbers

- C.Elegans → 302 neurons
- Mouse → 71,000,000 neurons
- Hamster → 90,000,000 neurons
- Rat → 200,000,000 neurons
- Marmoset → 634,000,000 neurons
- Capucin → 3,690,000,000 neurons
- Macaque → 6,376,000,000 neurons
- Human → 86,000,000,000 neurons



The human brain in numbers [...], S. Herculano-Houzel, *Frontier in Human Neuroscience*, 2009

The case of *Caenorhabditis elegans*

A few neurons for a complex behavior

Sensory motor behavior

Q. Wen, M.D. Po, E. Hulme, S. Chen, X. Liu, S. Wai Kwok, M. Gershow, A. M. Leifer, V. Butler, C. Fang-Yen, T. Kawano, W.R. Schafer, G. Whitesides, M. Wyart, D.B. Chklovskii, M. Zhen, A.D.T. Samueln, **Proprioceptive Coupling within Motor Neurons Drives *C. elegans* Forward Locomotion**. *Neuron*, 2012.

Plasticity, learning and memory

H. Sasakura and I. Mori, **Behavioral plasticity, learning, and memory in *C. elegans***, *Current Opinion in Neurobiology*, 2013.

Decision making

T.A. Jarrell, Y. Wang, A.E. Bloniarz, C.A. Brittin, M. Xu, J.N. Thomson, D.G. Albertson, D.H. Hall, S.W. Emmons, **The Connectome of a Decision-Making Neural Network**, *Science*, 2012.

What really matters ?

Structure ?

- Neocortex
- Basal Ganglia
- Amygdala
- Frontal cortex

Other ?

- To recognize self/others
- To imitate
- To use tools
- To communicate

Architecture ?

- Connectivity
- Density
- Modularity
- Self-organisation



Experimental & Theoretical frameworks

Biological framework

- Anatomical facts
- Physiological recordings
- Experimental data

Computational framework

- Computational paradigm
- Plasticity & learning
- Evaluation of models

Cognitive framework

- Subsumption architecture
- Embodied cognition
- Affordances, emotions, etc.

Philosophical framework

- Strong AI / Weak AI
- Emergence
- Theories of mind

Where do we start ?

What is/are the right biological level(s) of description ?

- Molecule ? → neurotransmitters
- Organelle ? → axons, dendrites, synapses
- Cell ? → neurons, glial cells
- Tissue ? → brain lobes & structures
- Organ ? → brain

Trying to understand perception by studying only neurons is like trying to understand bird flight by studying only feathers: It just cannot be done. In order to understand bird flight, we have to understand aerodynamics; only then do the structure of feathers and the different shapes of birds' wings make sense.

Spatio-temporal framework

Continuous space

G.Schöner, **Dynamical Systems Approaches to Cognition**, *The Cambridge Handbook of Computational Psychology*, 2008.

... stable patterns of neuronal activation ultimately steer the periphery into dynamical states, from which behavior emerges, without any need to ever abstract from the space-time contiguous processes that embody cognition.

Continuous time

JP Spencer, S Perone and JS Johnson, **The Dynamic Field Theory and Embodied Cognitive Dynamics**, *Toward a Unified Theory of Development: Connectionism and Dynamic Systems Theory Re-Considered*, 2009.

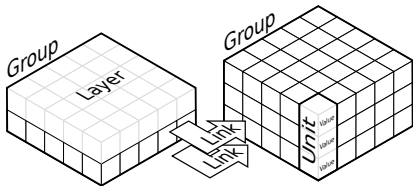
The first challenge is that sensori-motor systems evolve continuously in real time, but cognition can jump from one state to another, that is, from one thought to another

Computational Framework

Rougier & Fix (2011)

A unit is a set of arbitrary values that can vary along time under the influence of other units and learning.

- Distributed
→ No supervisor nor executive
- Asynchronous
→ No clock, no scheduler
- Numerical
→ No symbols
- Adaptive
→ No a priori knowledge



We want to make sure that emerging properties are those of the model and not those of the software running the model.

Neural Fields

Wilson & Cowan (1972), Amari (1977)

Equation

Let $u(\mathbf{x},t)$ be the membrane potential at position \mathbf{x} and time t , f a transfer function and w a kernel of lateral interaction. The temporal evolution of $u(\mathbf{x},t)$ is given by:

$$\tau \cdot \frac{\partial u(\mathbf{x}, t)}{\partial t} = -u(\mathbf{x}, t) + \int_{-\infty}^{+\infty} w(\mathbf{x}, y) \cdot f(u(\mathbf{y}, t)) dy + I(\mathbf{x}) + h$$

time constant leak term lateral interactions input resting potential

Velocity

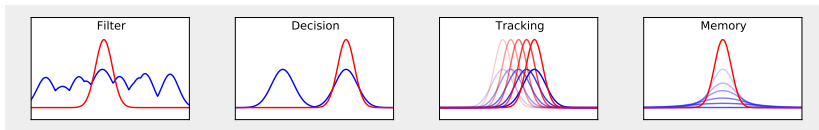
Unless specified otherwise, we'll generally consider infinite speed, i.e. instantaneous transmission of information.

Neural Fields

Wilson & Cowan (1972), Amari (1977)

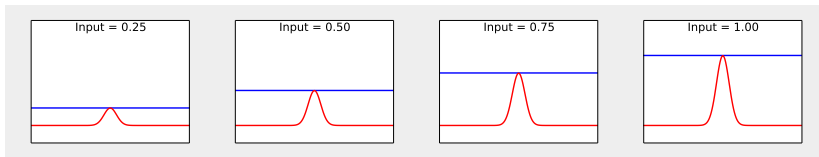
Function

The activity of a neural field can be interpreted from a functional point of view.



Measure

Using a specific set of parameters, the activity of a neural field can also be interpreted as a measure (of the input).



Part 1

The attentive brain

On ne voit que ce que l'on regarde

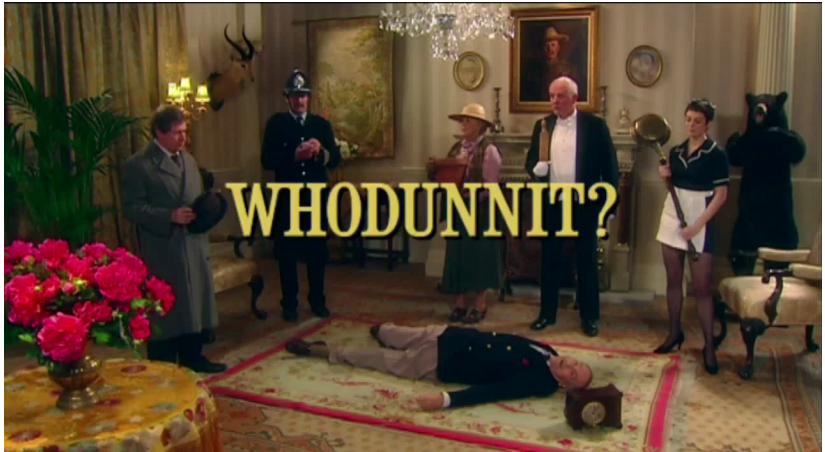
(We only see what we look at)

“L'Œil et l'Esprit”, Maurice Merleau Ponty, 1961

Everyone knows what attention is. It is the possession by the mind, in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought. Focalization, concentration, of consciousness are of its essence. It implies **withdrawal from some things in order to deal effectively with others**, and is a condition which has a real opposite in the confused, dazed, scatterbrained state which in French is called *distraktion*, and *Zerstreutheit* in German.

W. James, 1890

How much blind are you ?



Visual exploration

(Yarbus, 1967)



Free examination.

1



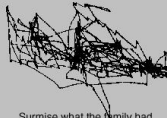
Estimate material circumstances
of the family

2



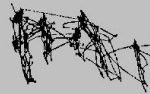
Give the ages of the people.

3



Surmise what the family had
been doing before the arrival
of the unexpected visitor.

4



Remember the clothes
worn by the people.

5



Remember positions of people and
objects in the room.

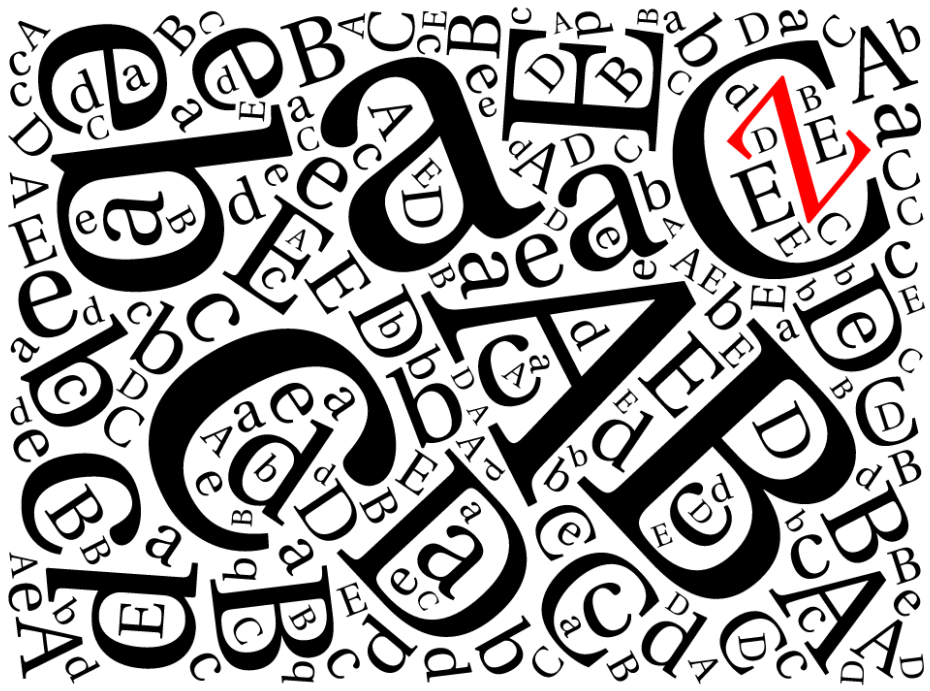
6



Estimate how long the visitor had
been away from the family.

7

3 min. recordings
of the same
subject

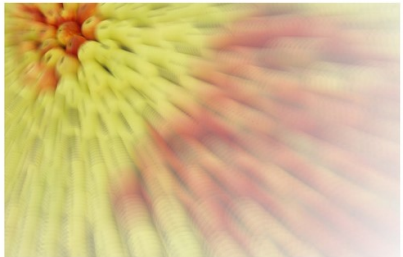


Visual Attention

Spotlight metaphor

Attention is the capacity to select a relevant region of the sensory space

- Topological region of the sensory space → **spatial attention**
- Featural region of the sensory space → **feature oriented attention**
- Object as such → **object oriented attention**



A computational approach

Theories of Visual Attention

→ Saliency Maps (Itti & Koch, 2001)

Saliency map is a topographically arranged map that represents visual saliency of a corresponding visual scene.

- Inhibition Of Return (IOR, Posner, 1980)

IOR operates to decrease the likelihood that a previously inspected item in the visual scene will be reinspected.

- Premotor Theory of Attention (Rizzolati, 1987)

Attention may derive from weaker activation of same fronto-parietal circuits.

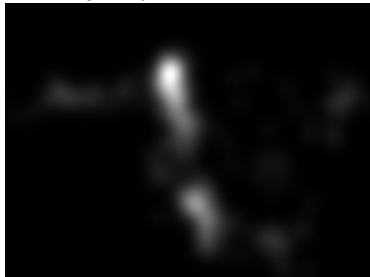
Saliency maps

(Itti & Koch, 2001)

Image



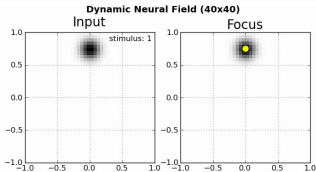
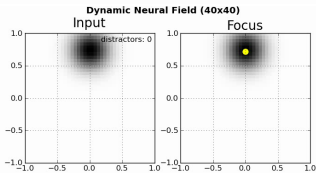
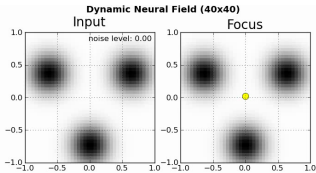
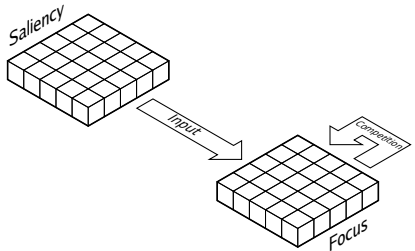
Saliency map



Saliency maps

(Rougier & Vitay, 2006)

- Simple model of visual tracking
- Robustness to noise, distractors and saliency
- Dynamic & reactive behavior



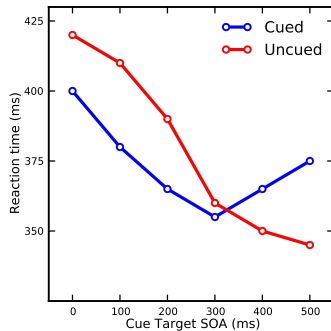
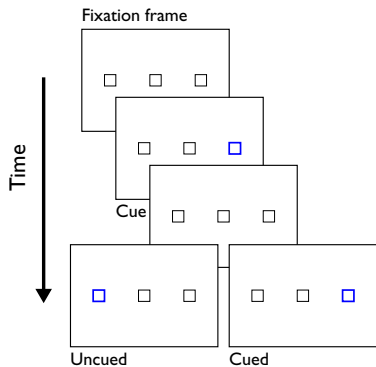
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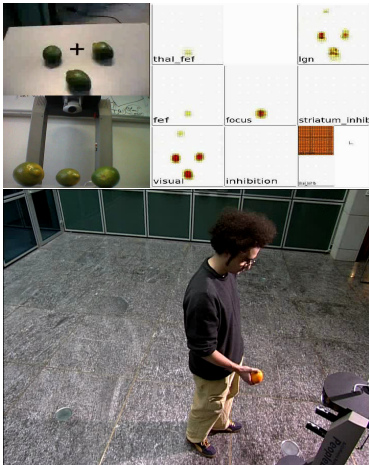
Inhibition of Return

(Posner, 1980)

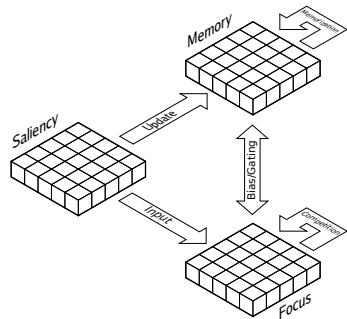


Inhibition of Return

(Vitay & Rougier, 2005)



- Dynamic Working memory
- Biased competition
- Sequential behavior

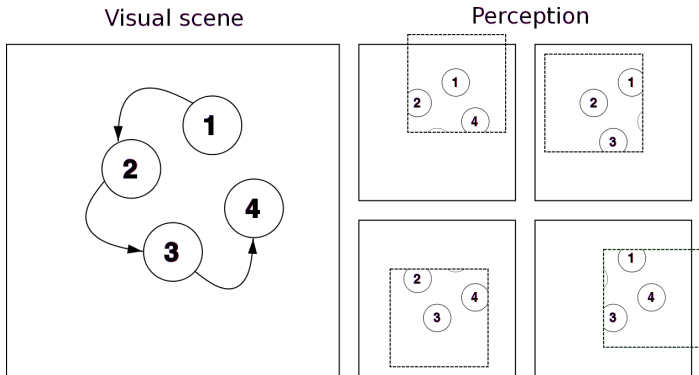


A computational approach

Theories of Visual Attention

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Making saccades



Ocular saccades lead to drastic changes in visual perception.

Visual anticipation

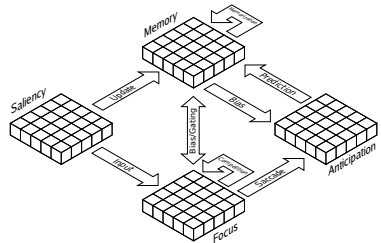
(Fix et al., 2007)

Spatial reference

- Independent of eye movements
- Eye-centered

Action in perception

- To anticipate the consequences of own actions
- To update working memory accordingly

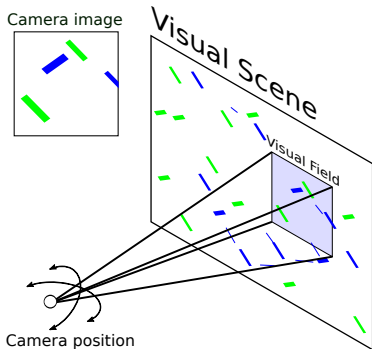


A model of covert and overt attention

(Fix et al., 2010)

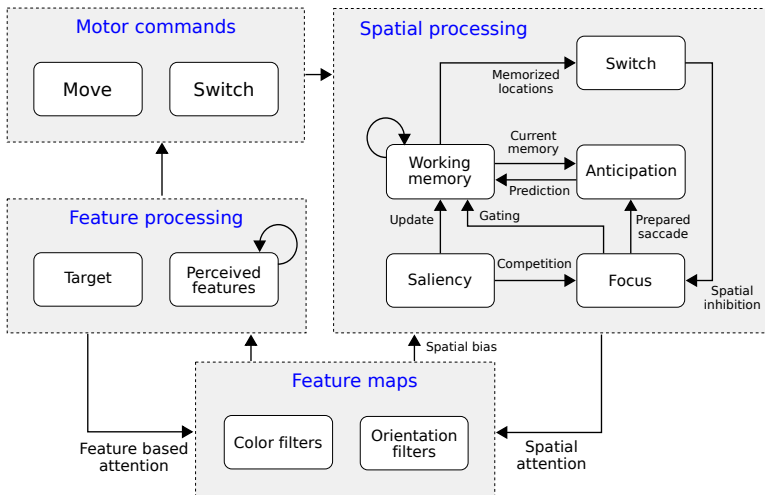
Search task

The camera is placed in front of a visual scene and is able to pan and tilt. The task can be either to look for a specific orientation or colour or to look for a conjunction of such features.



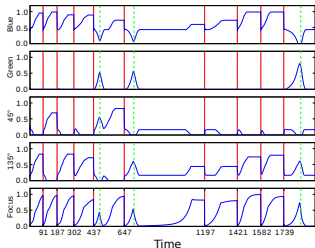
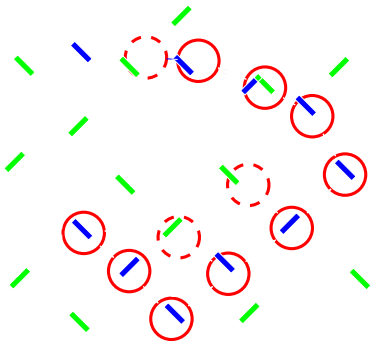
A model of covert and overt attention

(Fix et al., 2011)



A model of covert and overt attention

(Fix et al., 2010)



- Feature based attention facilitates processing of relevant features
- Spatial based attention facilitates processing of relevant region
- Working memory prevents to explore already seen location
- Model exhibits both overt and covert attention using same substrate

Towards the organization of visual behavior

From sequential to parallel to sequential

- A bottom-up sequential exploratory behavior has emerged from distributed & numeric computation.
- The sequential nature of the behavior is provided through the interaction with the external world.
- We ensured no shortcut is made between the simulation and the behavior.

Part 2

The resilient brain

The Somatosensory System

Donald O. Hebb

- Neurons that fire together wire together

Hubel and Wiesel

- Simple and complex cells (1959)
- Ocular dominance columns (1962)
- *Critical period*, no plasticity after that period (1963-1965)

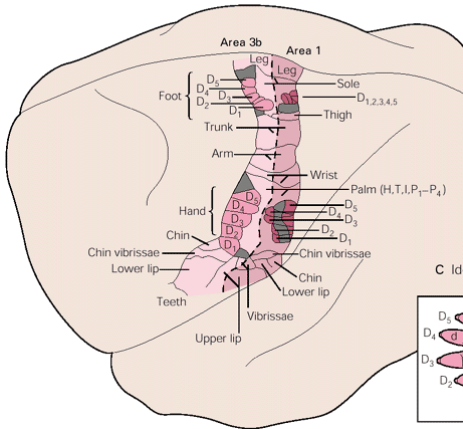
Merzenich, Kaas and Rasmusson

- Cortical organization of the primary somatosensory cortex (1981)
- Reorganization of the **adult** primary somatosensory cortex (1983)

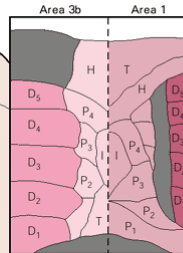
The Somatosensory System

(Kandel, 2013)

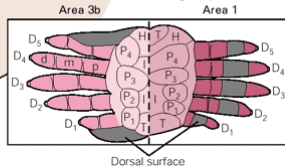
A Somatosensory maps in the cortex of the owl monkey



B Detail of representation of the palm



C Idealized somatosensory map of hands



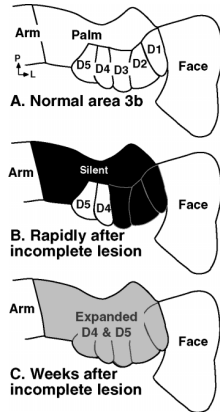
Plasticity in the Somatosensory System

(Florence, 2002)

Area 3b

Topographic organization of somatosensory cortical area 3b of owl monkeys after dorsal column transection.

- A. Normal somatotopy of the hand representation
- B. Complete dorsal column section at cervical levels deprives the hand representation of all activating inputs
- C. Over the course of weeks, the influence of the spared inputs expands



Plasticity in the Somatosensory System

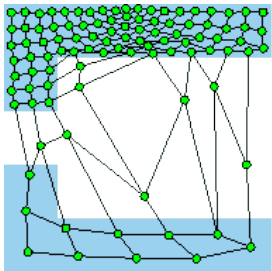
- When, where and how organization occurs in the first place ?
- How representations can be both stable and plastic ?
- How to cope with cortical and/or sensory lesions ?
- Do current computational models give a fair account on cortical plasticity ?
- Are there other mechanisms or structures involved ?
- What is actually represented through cortical activity ?
- What is the role of the motor-sensory loop ?

Self-Organizing maps

(Kohonen, 1982)

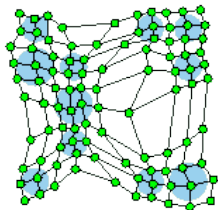
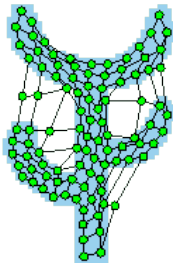
Self-organization...

- Simple 2D topology
- Unsupervised learning
- Density driven



but...

- Decreasing neighborhood & learning rate
- Frozen terminal state
- *Winner-takes-all* algorithm



Dynamic Self-Organizing maps

Rougier & Boniface (2010)

To what extent it is possible to have both stable and dynamic representations ?

Dynamic

The model must dynamically adapts itself to the data.

Stability

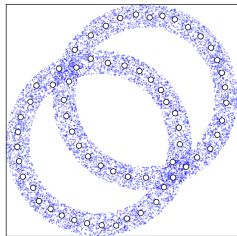
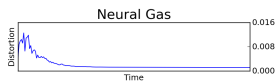
Model representations must be stable if the input is stable.

Topology

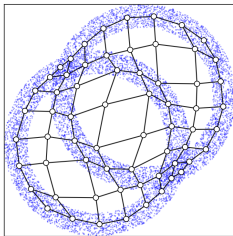
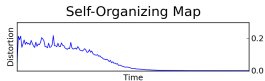
Two physically neighborhood cells must have similar representations.

Dynamic Self-Organizing maps

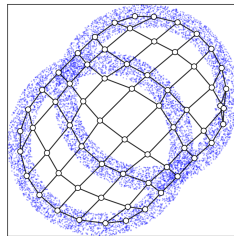
Rougier & Boniface (2010)



$$\lambda_i = 10.000, \lambda_j = 0.010, \varepsilon_i = 0.500, \varepsilon_j = 0.005$$



$$\sigma_i = 10.000, \sigma_j = 0.010, \varepsilon_i = 0.500, \varepsilon_j = 0.005$$



$$\text{elasticity} = 1.75, \varepsilon = 0.100$$

Dynamic Self-Organizing maps

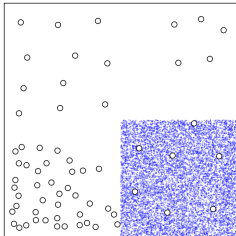
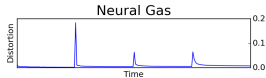
Rougier & Boniface (2010)

Dynamic...

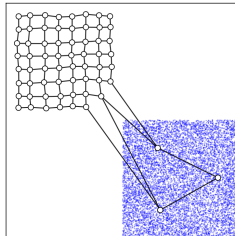
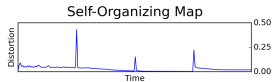
- Simple 2D topology
- Unsupervised learning
- No decreasing parameters

but...

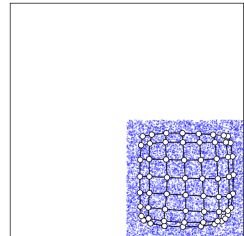
- *Winner-takes-all* algorithm
- Elasticity tuning



$\lambda_i = 10.000, \lambda_j = 0.010, \epsilon_i = 0.500, \epsilon_j = 0.005$



$\sigma_i = 10.000, \sigma_j = 0.010, \epsilon_i = 0.500, \epsilon_j = 0.005$

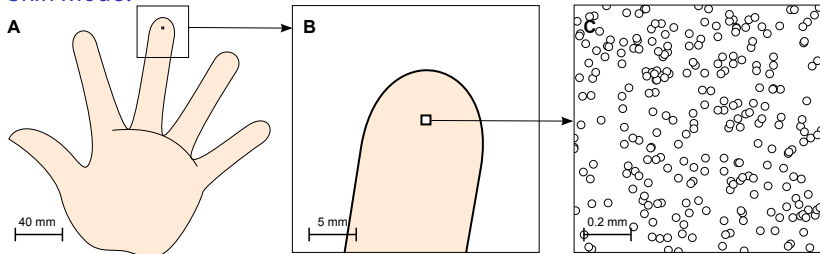


elasticity = 2.50, $\sigma = 0.100$

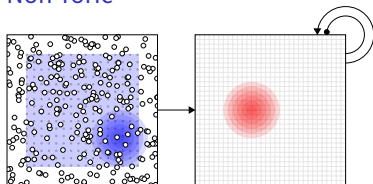
Computational model of area 3b

Detorakis & Rougier (2013)

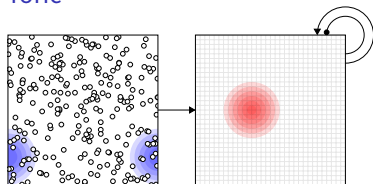
Skin model



Non Toric



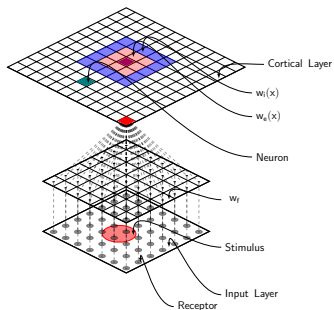
Toric



Computational model of area 3b

Detorakis & Rougier (2013)

- Neural field promotes competition
- Lateral connections are fixed and dynamic
- Feed-forwards connections are plastic
- Learning shapes receptive fields



Computational model of area 3b

Detorakis & Rougier (2013)

Competition

Let $u(\mathbf{x}, t)$ be the membrane potential at position \mathbf{x} and time t , f a transfer function and w a kernel of lateral interaction. The temporal evolution of $u(\mathbf{x}, t)$ is given by:

$$\tau \cdot \frac{\partial u(\mathbf{x}, t)}{\partial t} = -u(\mathbf{x}, t) + \int_{-\infty}^{+\infty} w_l(\mathbf{x}, y) \cdot f(u(\mathbf{y}, t)) dy + I(\mathbf{x}) + h$$

time constant leak term lateral interactions input resting potential

Learning

Learning occurs at every time step.

$$\tau \cdot \frac{\partial w_f(\mathbf{x}, t)}{\partial t} = \gamma (s(\mathbf{z}, t) - w_f(\mathbf{x}, t)) \int_{-\infty}^{+\infty} w_e(\mathbf{x}, y) f(u(\mathbf{y}, t)) dy$$

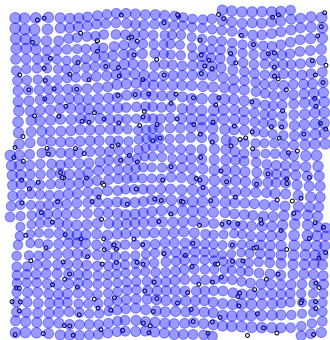
time constant learning rate thalamo-cortical excitatory lateral

Using $w_l(\mathbf{x}, y) = w_e(\mathbf{x}, y) - w_i(\mathbf{x}, y) = K_e \exp\left(\frac{-d^2}{2\sigma_e^2}\right) - K_i \exp\left(\frac{-d^2}{2\sigma_i^2}\right)$

Computational model of area 3b

Initial organization

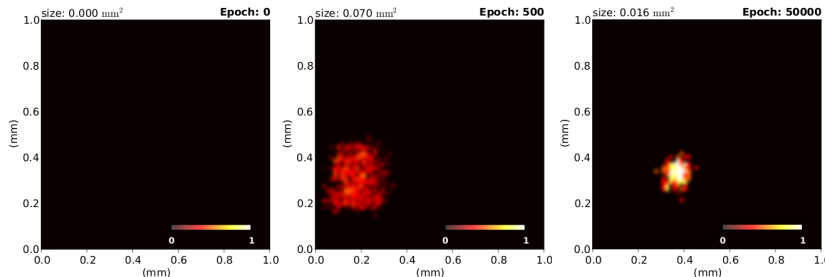
- Model has been trained on 50000 random samples
- Learning occurs at every time step
- Thalamo-cortical connections have been shaped
- Receptive fields covers uniformly the skin patch
- Topology is enforced everywhere



Computational model of area 3b

Shaping of (classical) receptive fields

Temporal evolution of a receptive field



The shaping of receptive fields occurs through an early expansion stage followed by a shrinking and a specialization stage.

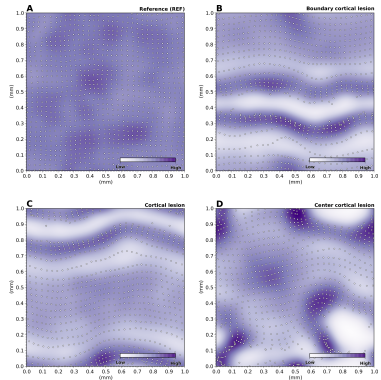
Cortical lesion

Reorganization and expansion of receptive fields

- 25% of neurons are killed
- 3 types of lesion



- Reorganization in three phases
 - Silence
 - Expansion
 - Shrinkage
- Expansion to non-represented skin areas.
- Partial recovery



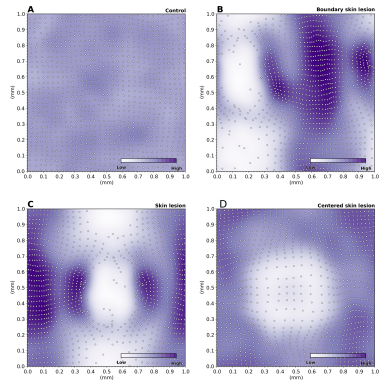
Sensory deprivation

Reorganization and shrinking of receptive fields

- 25% of receptors are silenced
- 3 types of lesion

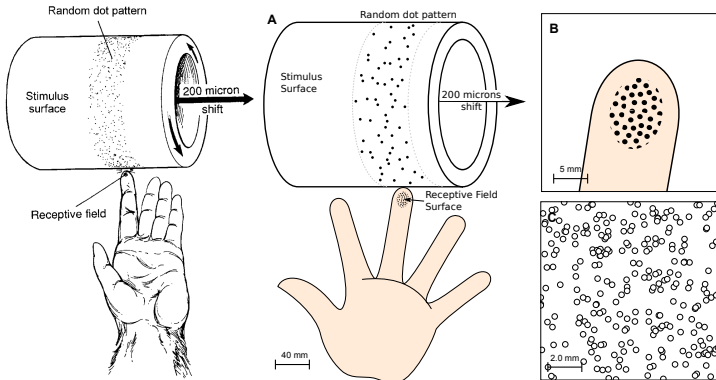


- Reorganization in three phases
 - Silence
 - Expansion
 - Shrinkage
- Migration of receptive fields
- Full recovery



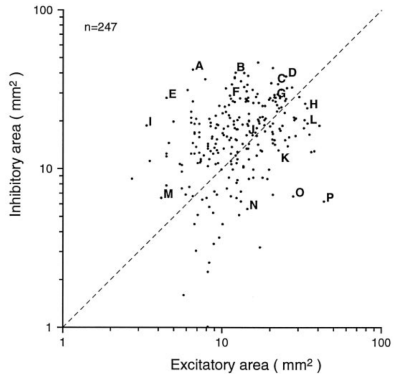
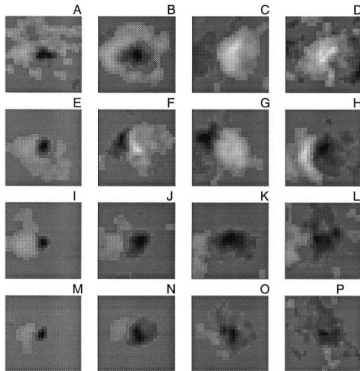
Structure of Receptive Fields...

...in Area 3b of Primary Somatosensory Cortex in the Alert Monkey (DiCarlo et al, 1998)



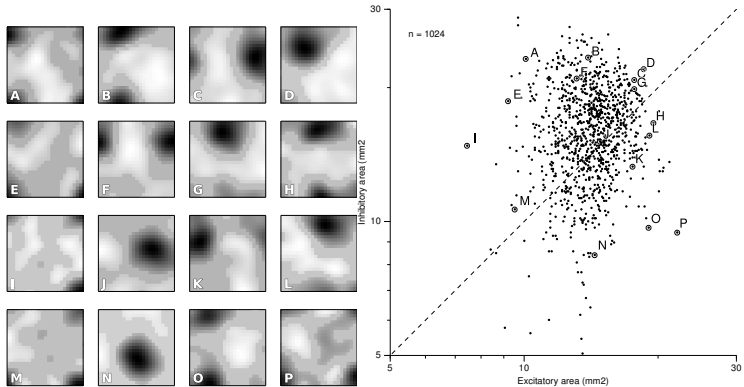
Structure of Receptive Fields...

...in Area 3b of Primary Somatosensory Cortex in the Alert Monkey (DiCarlo et al, 1998)



Structure of Receptive Fields...

... on the structure of receptive fields in area 3b (Detorakis & Rougier, 2014)

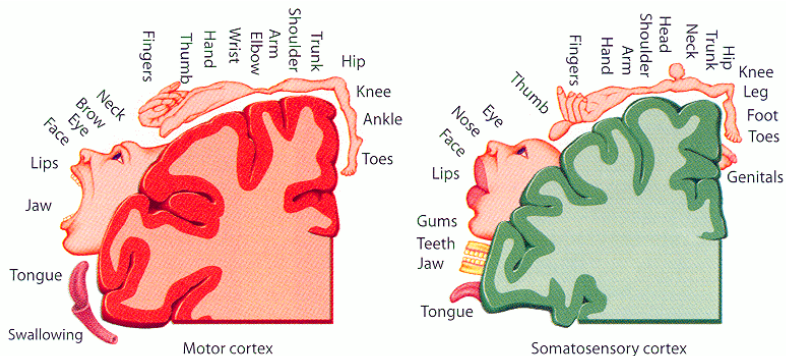


Some questions received (hypothetical) answers

- ✓ When, where and how organization occurs in the first place ?
- ✓ How representations can be both stable and plastic ?
- ✓ How to cope with cortical and/or sensory lesions ?
- ✓ Do current computational models give a fair account on cortical plasticity ?
- Are there other mechanisms or structures involved ?
- What is actually represented through cortical activity ?
- What is the role of the motor-sensory loop ?

Motor and Somatosensory homunculus

A missing link



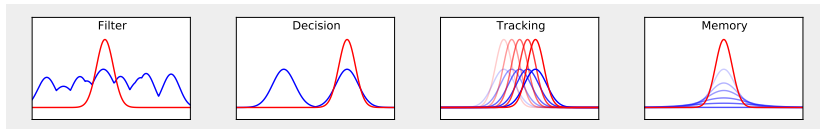
We (in our model) still miss the link between somatosensory and motor homunculus. You know you've been touched but you don't know where.

Conclusion

From neurons to behavior

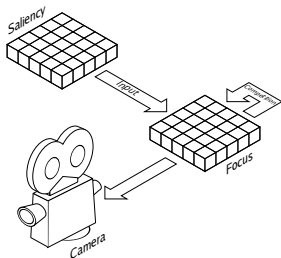
- Still many questions to be addressed
- Embodiment is a key concepts
- Mathematics are helpful but insufficient

Mathematical solutions do not characterize functional blocks



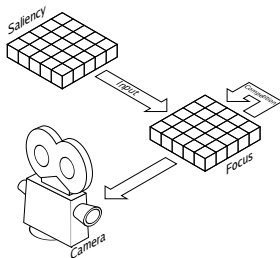
Is there something like an objective behavior ?

Curious (visual tracking) ?



We can connect the model to a pan-tilt camera such that it follows a given stimulus

Shy (visual avoidance) ?



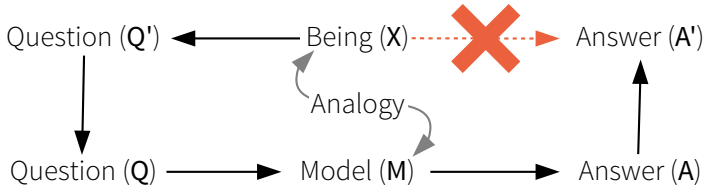
We can connect the model to a pan-tilt camera such that it looks away from a given stimulus

The actual behavior of the model depends on the links to its body. Ultimately, the modeler is the one who decide on the behavior.

What is a model ?

Supposons qu'un être (ou une situation) extérieur(e) X présente un comportement énigmatique, et que nous nous posions à son sujet une (ou plusieurs) question(s). Pour répondre à cette question, on va s'efforcer de **modéliser** X , c'est-à-dire, on va construire un objet (réel ou abstrait) M , considéré comme l'image, l'analogue de X : M sera dit le **modèle** de X .

R. Thom, *Modélisation et scientificité*, 1978



To an observer B, an object A^* is a model of an object A to the extent that B can use A^* to answer questions that interest him about A.

M. Minsky, *Matter, Mind and Models*, 1965

A hierarchy of models

The theoretical model

provides a direct access to the question

MODEL

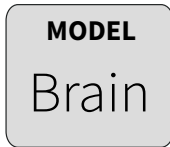
A hierarchy of models

The theoretical model

provides a direct access to the question

The computational model

objective mathematical properties
subjective functional interpretations



A hierarchy of models

The theoretical model

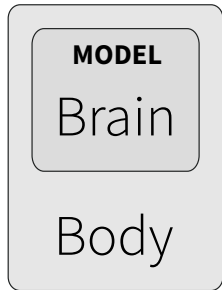
provides a direct access to the question

The computational model

objective mathematical properties
subjective functional interpretations

The embodied model

behavior through embodiment
quantifiable performances



A hierarchy of models

The theoretical model

provides a direct access to the question

The computational model

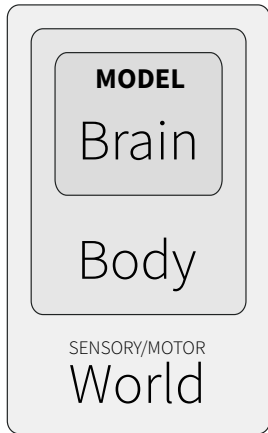
objective mathematical properties
subjective functional interpretations

The embodied model

behavior through embodiment
quantifiable performances

The cognitive model

observation through interaction
interpretation may depends on our own behavior



Where is my mind ?

Toward an embodied and social theory of mind

The Eye of the Beholder

Part of the cognition we lend to others may be rooted in our own cognition.

