Dynamic Neural Fields

International Lecture Serie

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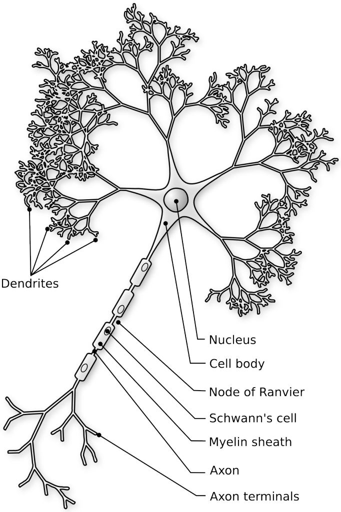
Outlook

1. From spikes to population
2. The link to cognition
3. Dynamic neural fields
4. A Computational Framework for the Study of Cognition

From spikes to population

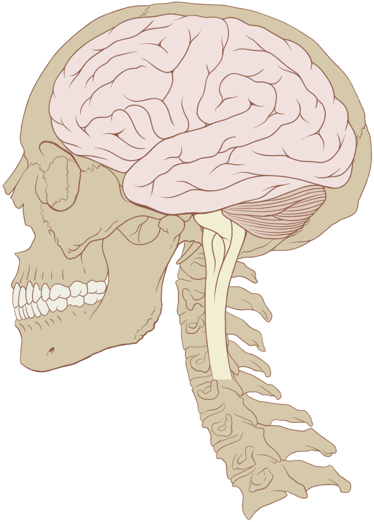
The biological neuron

- A neuron is an excitable cell that can transmit information through connections (synapses) with other neurons.
- There exists several types of neurons (pyramidal, basket, Purkinje, etc.) with different functions (sensory, motor, inter,etc.)
- Neurons are connected together and form networks.



The human brain

- The human brain is made of 50 to 100 billions neurons (rough estimate)
- The average number of connections for a single neuron is estimated to 10 000.
- 1mm^3 of cortex $\approx$ 1 billion connections



Different classes of neural models

Biophysical models

Greatly detailed models that aimt at modeling biological processes.

- Integrate and Fire
- Leaky integrate-and-fire
- Hodgkin-Huxley
- FitzHugh-Nagumo

Connectionist models

Simplified models of neuron that aim at solving problems (machine learning).

- Multi-layer Perceptron
- Kohonen maps
- Hopfield networks

Cognitive models

Computational models that aim at understanding cognition.

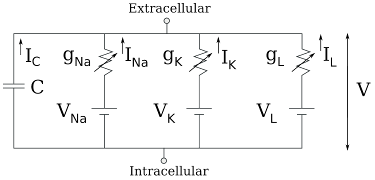
- PDP++/Emergent (Parallel Distributed Processing)
- NEST initiative

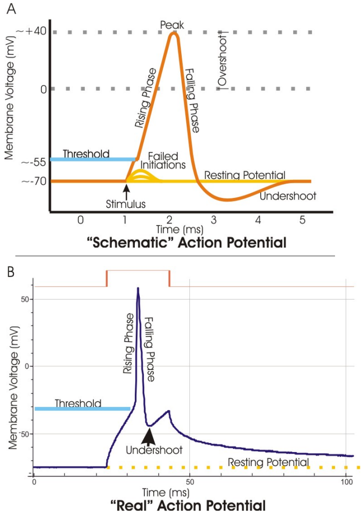
Biophysical model: Hodgkin Huxley

(Hodgkin Huxley, 1952)

The Hodgkin-Huxley model is a conductance based model where the membrane potential $I_m(t)$ is described using the following set of equations:

$$
\begin{aligned}
I_m(t) &= I_C + I_{ionic} \\
I_C &= C_m dV(t)/dt \\
I_{ionic} &= I_{Na} + I_K + I_L \\
&= g_{Na}(V)[V(t) - V_{Na}] \\
&\quad + g_K(V)[V(t) - V_K] \\
&\quad + g_L(V)[V(t) - V_L]
\end{aligned}
$$



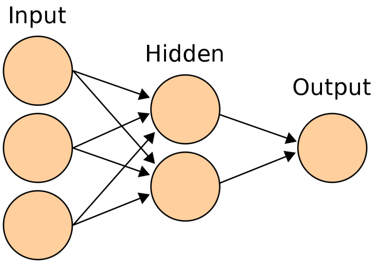


Connectionist model: multi-layer perceptron

(Le Cun, 1985), (Rumelhart et al., 1986)

Scalar output y of a neuron is a function of the weighted (w_i) sum of the inputs (x_i): $y = \varphi\left(\sum_{i=0}^{n} w_i x_i\right)$

- Feedforward netwok
- Learning through error back-propagation algorithm
- Universal approximators

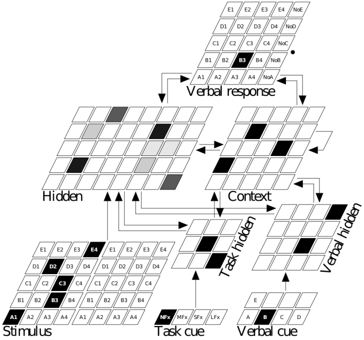


Speech/image recognition, classification, approximation of industrial processes, prediction, etc.

Computational model: PDP++
(McClelland & Rumelhart, 1986), (O'Reilly, 2001)

PDP++ promotes the parallel distributed processing approach and considers several aspects such as propagation rule, activation rule, learning rule, etc.

- A model of the prefrontal cortex that (may) explain cognitive control.
- Error-driven learning
- Reward-based learning



(Rougier et al., 2005)

From spikes to population

What approach to use for the study of cognition ?

- Biophysical are quite hard to handle when using large populations
  $\rightarrow$ blue gene project `http://bluebrain.epfl.ch/`
- Connectionist are slanted toward machine learning
  $\rightarrow$ Biological plausibilty is not a requirement
- Cognitive models may revealed themselves too static
  $\rightarrow$ Embodiment in real world certaintly requires higlhy dynamic networks

How to make the link with cognition then ?

The link to cognition

The link to cognition
(Schöner, 2008)

The same principles that govern low-level processings continue to work as the distance from the sensory-motor surfaces increases.

Thus, understanding cognition cannot be separated from understanding

- the link of cognition to the sensory and motor surfaces,
- the immersion of embodied cognitive systems in real-time environments
- the context of a behavioral history on which cognition builds

The continuity principle
(Schöner, 2008)

Continuous space

There is no evidence of the graininess of the neural sampling in human behavior and cognition.

- Cognitive processes are based on continuous dimensions (sensory & motor)
- Discrete categorization emerges from such continuum

Continuous time

The microscopic discreteness (spikes) does not scale up to behavior.

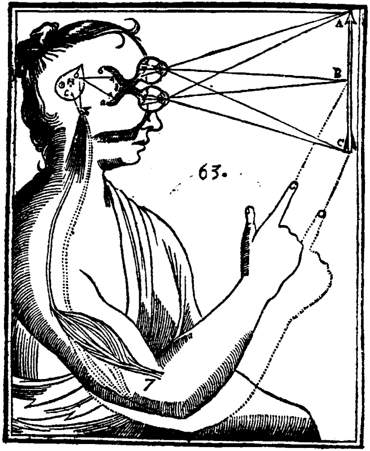
- Cognitive processes are temporally continuous processes
- Stabilized states exist in such continuum

The curse of the homunculus

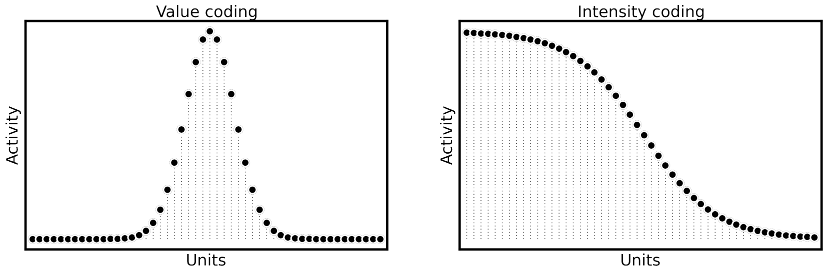
The homunculus
For Descartes, the non physical mind controls the physical body

The central executive
Baddeley & Hirsh, 1974 proposed a model of working memory with a central executive on top

The central supervisor
Both multi-layer perceptron and Kohonen maps benefit at some point from a central supervisor coordinating activities.



Neural encoding



- Value coding is defined as a selective response of the neuron to a compact range of a parameter.
  $\rightarrow$ (Georgopoulos et al., 1982)
- Intensity coding relates to the monotonic variation of the discharge frequency.
  $\rightarrow$ (Ballard, 1986; Guigon, 2003)

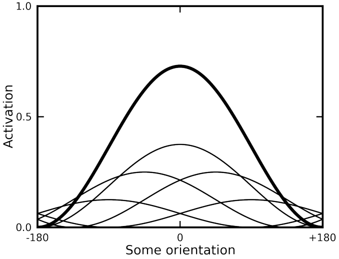
Neural population

Coarse coding

- Cortical neurons appeared to be broadly tuned white is has been rpoved not necessary.
- Information seems to be sampled quite extensively

Additive models

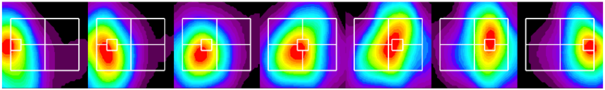
Distribution of population activation = sum of individual activities modulated by their respective tuning curves



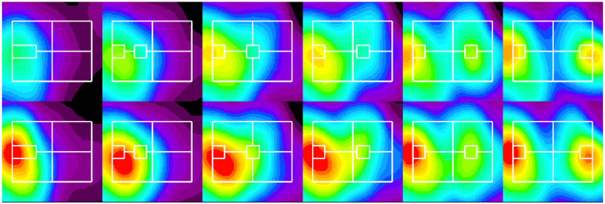
Some evidences from neurobiology

Recording in the cat visual cortex A17 (From Jacker et al. 1999).

Temporal evolution of retinal location



Interaction between two stimuli locations



Dynamic Neural Fields

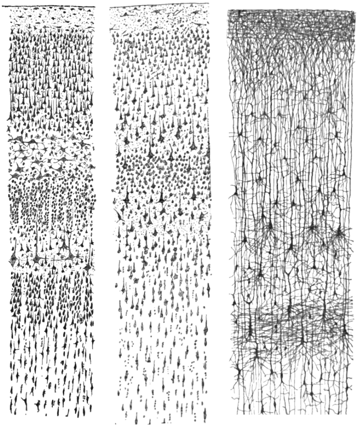
The cerebral cortex

Laminar structure

- Molecular layer I
- External granular layer II
- External pyramidal layer III
- Internal granular layer IV
- Internal pyramidal layer V
- Multiform layer VI

Regular structure

- Minicolumns
- Hypercolumns
- Cortical modules



Drawings by Santiago Ramon y Cajal (1852-1934)

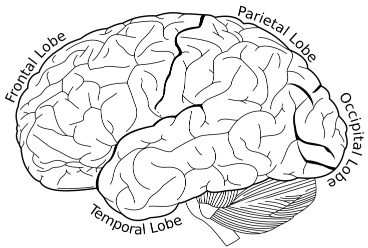
The cerebral cortex

Topographic structure

- Frontal
- Occipital
- Partietal
- Temporal

Modular structure

- Sensory areas (V1, A1, etc.)
- Motor areas (M1, SM1, etc.)
- Associative areas



The gas analogy

Temperature is a intensive property of an object determined by the average of a property of many particles and is defined at thermal equilibrium.

Modeling the hard way

- To model a whole system of particles
- To measure individual movements
- To average all movements and extract a temperature

Modeling the easy way

Let's pretend you have an equation for temperature...

A short history of neural fields (DNF)

1956 R.L. Beurle, "Properties of a mass of cells capable of regenerating pulse", *Philosophical Transactions of the Royal Society London B*, 240:55–94.

1972 H.R. Wilson and J.D. Cowan, "Excitatory and inhibitory interactions in localized populations of model neurons", *Biophysical Journal* 12:1–24.

1973 H.R. Wilson and J.D. Cowan, "A mathematical theory of the functional dynamics of nervous tissue", *Kybernetik* 13:55—80.

1977 S.I. Amari, "Dynamics of pattern formation in lateral-inhibition type neural fields", *Biological Cybernetics*, 27:77–87.

1999 J.G. Taylor "Neural 'bubble' dynamics in two dimensions: foundations", *Biological Cybernetics*, 80:393–409.

Dynamic neural fields

Definition

Neural fields are tissue level models that describe the spatio-temporal evolution of coarse grained variables such as synaptic or firing rate activity in populations of neurons.

(S. Coombes, Scholarpedia)

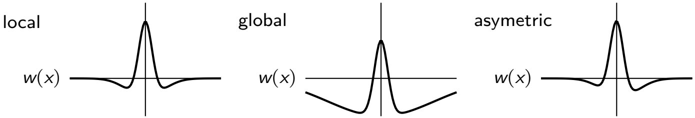
Equation

Let $u(x,t)$ be the membrane potential of neuron at position x and time t, f a transfer function and w a lateral kernel function. The evolution of $u(x,t)$ is given by equation:

$$\underbrace{\tau}_{\text{time constant}} \frac{\partial u(x,t)}{\partial t} = \underbrace{-u(x,t)}_{\text{decay}} + \int_{-\infty}^{+\infty} \underbrace{w(y)\ f\left(u\left(x-y, t-\frac{|y|}{v}\right)\right)}_{\text{lateral interaction}} dy + \underbrace{I(x)}_{\text{input}} + \underbrace{h}_{\text{threshold}}$$

Dynamic neural fields

Kernel examples



Dynamic behavior

In the general case, DNF are very difficult to analyze mathematically. In 1977, S.I. Amari published an article building the mathematical foundations in the one-dimensional case and in 1999, J.G. Taylor extended these results to the multi-dimensional case.

- Spatially and temporally periodic patterns
- Localised regions of activity such as bumps or multi-bumps
- Travelling waves

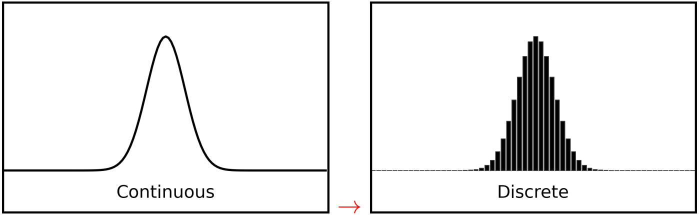
Dynamic neural fields

From the continuous theory

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

... to the discrete world

$$\tau \frac{\Delta u(x,t)}{\Delta t} = -u(x,t) + \sum_{i=1}^{i=n} w(y)\ f(u(x-y,t))\Delta y + I(x) + h$$



A Computational Framework for the Study of Cognition

Computational approach
(Marr, 1982)

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.

David Marr, 1982

Computational approach

(Marr, 1982)

Computational level

- What is the goal of the computation ?
- Why is it appropriate, and what is the logic of the strategy by which it can be carried out?

Algorithmic level

- How can this computational theory be implemented ?
- In particular, what is the representation for input and output ?
- What is the algorithm for the transformation?

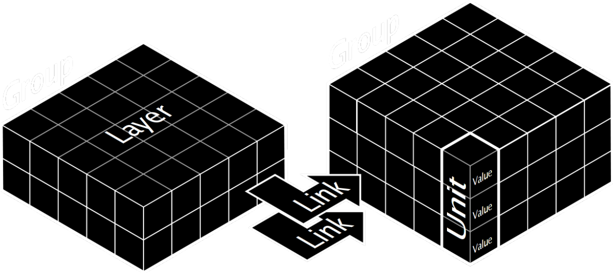
Mechanism level

- What mechanism is needed to implement the algorithm ?
- How can the representation and algorithm be realized physically?

Distributed Asynchronous Numerical Adaptive computing

http://dana.loria.fr

The idea is to consider neurons at the level of population and to consider the unit of decision to be a group of neuron with correlated activities (a.k.a bumps) instead of a small subset of neurons.



The computational paradigm supporting the DANA framework is thus grounded on the notion of a unit that is a essentially a set of arbitrary values that can vary along time under the influence of other units and learning. Each unit can be connected to any other unit (including itself) using a weighted link and a group is a structured set of such homogeneous units.

Distributed Asynchronous Numerical Adaptive computing

http://dana.loria.fr

4 properties to be enforced anywhere, anytime

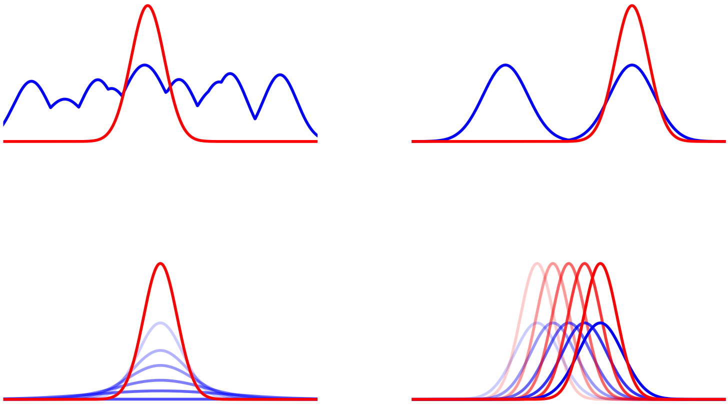
- Distributed → No central supervisor
- Asynchronous → No central clock
- Numerical → No central symbol
- Adaptive → To learn something

Embodiment

A model has to be embodied to interact with the real world such that new properties can emerge from this interaction.

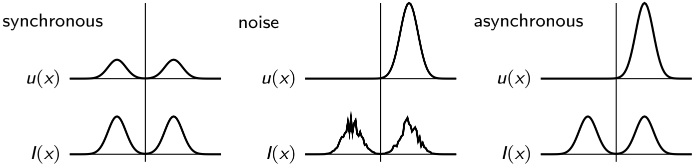
Reconsidering dynamic neural fields

Some cognitive properties



Conclusion

How does the system make a decision ?



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An extensive introduction on dynamic neural field theory (Schöner & Spencer):
→ http://www.uiowa.edu/delta-center/research/dft/index.html