Neurorobotic models of spatial cognition

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I. **Background basic concepts**

- Computational neuroscience
- Neural coding
- Population vector coding
- Firing rate neuronal model
- Unsupervised associative learning

II. Spatial cognition and its neural bases

III. Neurorobotic models of spatial cognition
Computational neuroscience & neurorobotics

Experimental (empirical) approach

Set of rules:

- describing the experimental observations
- predicting/extrapolating unseen behaviour

Model of the system
Computational neuroscience & neurorobotics

**Computational neuroscience:** mathematical formalism to model the mechanisms underlying the S-R relation and provide experimentally testable predictions

Model = set of equations \( R(S, P_1, \ldots, P_n) \)

Analytical solutions

Numerical solutions

Robotic validation
Computational neuroscience & neurorobotics

Experimental neuroscience

Complex system

Experimental protocol

Experimental data

Computational neuroscience & neurorobotics

Mathematical formalism

Model

Simulations / robotics

Simulation data

Comparison

in vivo, in vitro, in situ

17/03/2015

CogMaster Course @ ENS-EHESS-Paris 5
Computational neuroscience & neurorobotics

- Experimental neuroscience
- Theoretical neuroscience

- Overall behavior
- System network
- Local network
- Single cell
- Synapse

17/03/2015
Neuronal activity & neural coding

Maps the input into neural responses

Encoding

Stimulus

Response

Decoding

Predicts the most likely stimulus that elicited an observed response
Neuronal activity & neural coding

Micro-electrode

Regular Spiking Pyramidal Cell: Visual Response
Neuronal activity & neural coding

Micro-electrode

Action potential or ‘spike’
Neuronal activity & neural coding

Firing rate

Spike count / $\Delta t$
(Hz or spikes/s)
Neuronal activity & neural coding

Spatiotemporal “signature”

\[
\begin{pmatrix}
t_1 & \ldots & t_M \\
\ldots & \ldots & \ldots \\
t_N & \ldots & t_M
\end{pmatrix}
\]
Neuronal activity & neural coding

Rate coding

Adrian (1926) – Mean discharge proportional to neural selectivity

Firing rate

Spike count \( / \Delta t \)

(Hz or spikes/s)
Neuronal activity & neural coding

Tuning curve of V1 simple cell

Hubel and Wiesel  J Physiol (Lond) 1968
Neuronal activity & neural coding

\[ f(s) = r_{\text{max}} \exp \left( -\frac{1}{2} \left( \frac{s - s_{\text{max}}}{\sigma_f} \right)^2 \right) \]

- \( s_{\text{max}} \): preferred orientation;
- \( r_{\text{max}} \): maximal response;
- \( \sigma_f \): tuning curve width (selectivity)

\[ a_i = f_i(\theta) + n_i(\theta) \]

\( n_i(\theta) : N(0, \sigma_i(\theta)) \)
Population vector decoding

One neuron

Many neurons

Tuning curve
Population vector decoding

1. “Winner take all” decoding (competitive decoding scheme)

2. “Population vector” decoding (cooperative decoding scheme)

Many neurons
The monkey is guided to move the lever from the center of apparatus to one of eight peripheral locations.

Neural activities in the motor area are recorded.
Population vector decoding


\[ \vec{v} = \sum_i \frac{r_i}{Z} \vec{c}_i \]

\( \vec{v} \): decoded direction
\( \vec{c}_i \): preferred direction
\( r_i \vec{c}_i \): contribution from \( i_{th} \) neuron
\( Z = \sum_i r_i \) normalization factor
Cortical control of motor neuroprostheses

Goal:
Decode arm movement direction from neural activity
Cortical control of motor neuroprostheses

COURTESY ANDREW SCHWARTZ, ET. AL
## Neuronal modelling

### Class of models

<table>
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<th><strong>Class of models</strong></th>
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Firing rate neuronal model

Mean firing rate

\[ r = \frac{N_{\text{spikes}}}{T} \]  

(spikes/sec) or (Hz)
Firing rate neuronal model

\[ I_i(t) = \sum_j w_{ij} \cdot r_j(t) \cdot \varepsilon = \sum_j w_{ij} \cdot r_j(t) \cdot \varepsilon \]  

Synaptic drive

\[ \tau_i \frac{dV_i(t)}{dt} = -V_i(t) + \gamma + I_i(t) \]  
System dynamics

\[ \tau_i = 10 \text{ ms} \]  
Membrane time constant

\[ w_i \]  
Synaptic input

\[ \rho \]  
Density of synaptic inputs

\[ V_i \]  
Membrane potential (mV)

\[ V^R_i \]  
Resting membrane potential (-60 mV)

\[ V^T_i \]  
Threshold membrane potential (-40 mV)

\[ \gamma = V^R_i - V^T_i \]  
Activation threshold
**Firing rate neuronal model**

**Transfer function:** relation between input intensity and mean firing activity

\[ r_i(t) = f(V_i(t) \pm \varepsilon) \]
Firing rate neuronal model

Example of activity of a population of firing rate neurons

(Pouget & Snyder 2000)

(Arleo et al. 2001)
Learning: modelling synaptic plasticity
Learning: modelling synaptic plasticity

- SUPERVISED Learning
- UNSUPERVISED Learning
- REINFORCEMENT Learning
Unsupervised learning

Data → Learner

Discover statistical regularities in the input space and build compressed representations of the data
Associative Hebbian learning

“Neurons that fire together wire together”

\[ \Delta w_{ij}(t) = \alpha \cdot r_i(t) \cdot r_j(t) \]
Spike timing dependent plasticity (STDP)

Hebb’s postulate:
If A then B, then potentiate
Long-term potentiation
LTP

Stent’s postulate:
If B then A, then depress
Long-term depression
LTD

HL provides a simple formalization of the synaptic long-term potentiation (LTP) and depression (LTD) mechanisms.
Spike timing dependent plasticity (STDP)

Pre

Post

tpre

tpost

tpre

tpost

LTP

LTD

Bi & Poo (1998)
Associative memory

Naïve network

Item memorized

Recall based on partial information
I. Background basic concepts

II. Spatial cognition and its neural bases
   - The spatial learning problem
   - Hippocampal place cells
   - Head direction cells
   - Entorhinal grid cells
   - Multisensory integration

III. Neurorobotic models of spatial cognition
Spatial cognition

“Navigation is the process of determining and maintaining a course of trajectory from one place to another”

C. R. Gallistel (1990)
Spatial cognition

“Navigation is the process of determining and maintaining a course of trajectory from one place to another”

C. R. Gallistel (1990)

It looks simple but ... 

1. Where am I?

2. Where are other places relative to me?

3. How do I get there from here? Optimally?

4. Shall I reshape my plan?
Spatial cognition

PARALLEL INFORMATION PROCESSING ACROSS A NETWORK OF BRAIN REGIONS

- Multisensory integration
- Episodic & procedural learning
- Decision making

Structures involved:
- Prefrontal cortex
- Hippocampal formation
- Striatum
- Cerebellum
Spatial cognition
Spatial cognition
Neural basis of spatial cognition
In 1971, O'Keefe & Dostovsky discovered the “place cells”
Neural basis of spatial cognition

In 1971, O'Keefe & Dostovsky discovered the “place cells”
Neural basis of spatial cognition

Jung et al. J Neurosci 1994
Neural basis of spatial cognition

Population coding

80 simultaneously recorded place cells
Wilson & McNaughton, 1993
Neural basis of spatial cognition

Population coding
Neural basis of spatial cognition

Hippocampal place cells...in space

Knierim et al. (2004)
Neural basis of spatial cognition

In 1984, Rank discovered the “head direction cells”
Neural basis of spatial cognition

Arleo et al. (2004)

Peyrache et al. (2015)
Neural basis of spatial cognition

POSS

Population coding

Peyrache et al. (2015)

Zugaro et al. (2003)

Ado

Peyrache et al. (2015)
Neural basis of spatial cognition

Maintenance of HD signal during locomotion in the vertical plane

Cylinder Floor

B

Mesh 0°

Animal climbing up

C

Mesh 180°

Animal climbing down
Neural basis of spatial cognition

In 2005, Edvard & May-Britt Moser discovered the “grid cells”
Neural basis of spatial cognition

In 2005, Edvard & May-Britt Moser discovered the “grid cells”

Multiscale periodic hexagonal (triangular) structure

Hafting et al. (2005)
Neural basis of spatial cognition

Grid cells reported in mice, bats, monkeys and humans, suggesting they originated early in mammalian evolution.

Taken from May-Britt Moser’ presentation
Neural basis of spatial cognition

Grid cells have at least three dimensions of variations

1. Phase

2. Scale

3. Orientation

Taken from May-Britt Moser’ presentation
Neural basis of spatial cognition

The scale of the grid follows a dorso-ventral organization

Taken from May-Britt Moser’s presentation
Neural basis of spatial cognition

Hippocampal place cells
O'Keefe & Dostovsky (1971)

Head direction cells
Rank (1984)

Grid cells
Hafting et al. (2005)

Border cells
Solstad et al. (2008)
Neural basis of spatial cognition

Understanding neural spatial coding by focusing on the multisensory integration of environmental & internal cues

Hippocampal place cells
O’Keefe & Dostovsky (1971)

Head direction cells
Rank (1984)

Grid cells
Hafting et al. (2005)

Border cells
Solstad et al. (2008)
Multisensory integration

- Allothetic sensory inputs
  - Vision
  - Smell
  - Muscle receptors
  - Joint receptors

- Idiothetic sensory inputs
  - Hearing
  - Vestibular receptors
    - Semicircular canals
    - Otoliths
    - Cochlea

Motor commands
Multisensory integration

Idiothetic cues
(self-motion signals)

Allothetic cues
(landmarks)

Idiothetic cues
(self-motion signals)
Using allothetic cues for self-localization

Photo: A. Alvernhe
Using idiothetic cues for path integration

McNaughton et al. 2006

Arleo & Rondi-Reig 2007; Etienne et al. (1998)

Muller & Wehner 1988
Multisensory integration

Environmental landmarks

Path integration
Neural basis of spatial cognition

Allothetic cues (landmarks)

Idiothetic cues (self-motion signals)

Hippocampal place cells
O'Keefe & Dostovsky (1971)

Head direction cells
Rank (1984)

Grid cells
Hafting et al. (2005)

Border cells
Solstad et al. (2008)
Neural basis of spatial cognition

Persistence of place coding in the dark

Quirk et al. 1990

Knierim et al. 1998
Neural basis of spatial cognition

Persistence of place coding in the dark

Hafting et al. 2005
Neural basis of spatial cognition

Anchorage on visual landmarks and geometrical cues

Cell 1

Session 1
East

Session 2
West

Session 3
East

Session 4
North

Cell 2
Neural basis of spatial cognition

Anchorage on visual landmarks and geometrical cues

(O’Keefe & Burgess, 1996)
Neural basis of spatial cognition

Anchorage on visual landmarks and geometrical cues

Zugaro et al., (2000)
Neural basis of spatial cognition

Anchorage on visual landmarks and geometrical cues

The preferred directions of all HD cells rotate simultaneously

Neural basis of spatial cognition

Anchorage on visual landmarks and geometrical cues

CA3 place cell

90° cue rotation

-90° cue rotation

ADN HD cell

Knierim et al., (1996)
Neural basis of spatial cognition

Anchorage on optic flow cues

rotating planetarium: 4-5 °/s

Arleo et al. (2013)
Outline

I. Background basic concepts

II. Spatial cognition and its neural bases

III. Neurorobotic models of spatial cognition
Spatial learning model

Stressing the importance of multisensory integration

place code
Place cells

direction code
HD cells

Associative Hebbian learning

Allothetic cues
(visual landmarks)

Idiothetic cues
(path integration)

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Neurorobotic methods

Khepera miniature mobile robot

- CCD camera
- light detector
- 8 IR sensors
- odometer

Allothetic inputs
Idiothetic input

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Neurorobotic methods

Khepera miniature mobile robot

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Neurorobotic methods

Psikharpax: the artificial rat

Meyer et al., 2005
Processing visual information

Khepera miniature mobile robot

Visual input

422 x 316 pixels

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Processing visual information

Modeling the orientation selectivity of V1 Simple Cells

Gabor filters

Tuning curve of V1 simple cell

8 different orientations
3 different scales

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
**Processing visual information**

Modeling the orientation selectivity of V1 Simple Cells

Gabor filters

Retinotopic sampling

8 different orientations

3 different scales

*Arleo et al. (2000, 2001, 2004); Boucheney et al. (2005); Sheynikhovich et al. (2009)*
Processing visual information

Modeling the orientation selectivity of V1 Simple Cells

Gabor filters

8 different orientations
3 different scales

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Odometry-based path integration

Modeling a grid-cell like network

\[ r_i(t) = \exp \left( -\frac{(\vec{s}_d(t) - \vec{s}_i)^2}{2\sigma^2} \right) \]

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Odometry-based path integration

Modeling a grid-cell like network

\[
    r_i(t) = \exp \left( -\frac{(\vec{s}_d(t) - \vec{s}_i)^2}{2\sigma^2} \right)
\]

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Hippocampal place cells

Visual cues

Self-motion cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

View cells

Feature extraction

Visual cues

Processing

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Unsupervised growing Network

- if $\sum_i H(r_i - \varepsilon) < A$
- then growing
  $w_{new,j} = H(r_j - \varepsilon) \cdot \text{rnd}_{0,1}$
- else Hebbian learning
  $\Delta w_{ij} = \alpha \cdot r_i \cdot r_j \cdot (1 - w_{ij})$

vision-based PCs LEC

View cells

Feature extraction

Visual cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Vision-based place cells

Feature extraction

View cells

Visual cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Vision-based place cells

- Feature extraction
- View cells
- Visual cues

Position-reconstruction error based on population vector coding

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Vision-based place cells

Correlation between the dispersion around the center of mass and the reconstruction error

Vision-based place cells

Feature extraction

Visual cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Places are identified by path integration

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Hippocampal place cells

Hebbian learning

View cells

Feature extraction

Path integration

Self-motion cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

- View cells
- Feature extraction
- Path integration
- Self-motion cues

Hebbian learning

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Population vector coding

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Population vector coding

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Population vector coding

Population activity in the dark

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Hippocampal place cells

Hippocampal place cells

Hebbian learning

Calibration

vision-based PCs LEC

View cells

Feature extraction

Visual cues

PI-based PCs MEC

Path integration

Self-motion cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

View cells

Feature extraction

Hebbian learning

Path integration

Self-motion cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

**Multisensory integration shapes exploratory behavior**

- Loop-based exploration centred on the home base
- Length of excursions increases over time
- Maintaining allothetic & idiothetic representations consistent over time

**Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)**
Spatial learning model

Multisensory integration shapes exploratory behavior

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Multisensory integration shapes exploratory behavior

Model data

Experimental data

Data by Brandner & Arleo

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Anchorage on external (visual) stable landmarks

Importance of landmark stability

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Anchorage on external (visual) stable landmarks

Consistent with Knierim et al. (1998)

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
Spatial learning model

Hebbian learning

View cells

Feature extraction

Path integration

Self-motion cues

Arleo et al. (2000, 2001, 2004); Boucheny et al. (2005); Sheynikhovich et al. (2009)
I. Background basic concepts

II. Spatial cognition and its neural bases

III. Neurorobotic models of spatial cognition
Spatial cognition

- Combination of experimental and theoretical approaches
- Interrelation between multimodal sensory information
- Focus on spatial learning

Next part: SPATIAL NAVIGATION STRATEGIES
Inspiration sources...
Appendices
Purkinje cell movie: complex spike

Reproduces Fig. 5 of De Schutter E., and Bower J.M.: An active membrane model of the cerebellar Purkinje cell. Simulation of synaptic responses. *Journal of Neurophysiology* 71: 401-419 (1994).

Visit www.cerebellum.org/models for more info and movies.

Climbing fiber activation, 0.1 msec/frame.
Left: Membrane potential: - 80 mV (blue) to 20 mV (red).
Right: Ca$^{2+}$ concentration: 0 µM (blue) to 10 µM (red).

Produced by E. De Schutter, H. Cornelis, P. Franck and M. Wijnants
Copyright © Erik De Schutter BBF-UlA, 2000.
CONTROL ANIMAL
Supervised learning

![Diagram showing the process of supervised learning with a teacher and a learner, and the back-propagation algorithm equations]

**Back-propagation Algorithm**

**Update rule**

\[ \Delta \tilde{w}(t) = -\alpha \cdot \frac{dE(t)}{d\tilde{w}} \]

**Error**

\[ E(\tilde{w}) = \frac{1}{2} \sum_{\mu} [\tilde{t}(\mu) - \tilde{y}(\mu)]^2 \]
Reinforcement learning

\[ Q(s_t, a_t) \]

\[ R_{t+1} \]

**Update rule**

\[ \Delta w_{ij}(t) \approx \alpha \cdot \delta(t) \]

**Teaching signal**

\[ \delta(t) = R_{t+1} + \gamma \cdot \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \]

is a measure of the difference between the expected reward and the actual reward
Interplay between parallel learning systems

Multisensory integration → Episodic & procedural learning → Decision making

PARALLEL INFORMATION PROCESSING ACROSS A NETWORK OF BRAIN REGIONS

- Prefrontal cortex
- Hippocampal formation
- Striatum
- Cerebellum
Interplay between parallel learning systems

Multisensory integration

Episodic & procedural learning

Decision making

Multisensory integration framework to study spatial learning

Hippocampal spatial maps

Cerebellum

Self-motion cues

Allothetic cues
Interplay between parallel learning systems

Led by Rondi-Reig's team

Transgenic mouse model L7-PKCI
(De Zeeuw et al., 1999)

L7-PCKI mice have a spatial learning deficit
(Burguière et al. 2005)
Cerebellar role in spatial memory
Passot et al. (2012)
Interplay between parallel learning systems

Transgenic mouse model L7-PKCI
(De Zeeuw et al., 1999)

Cerebellar model
(Passot et al. 2012)
Interplay between parallel learning systems

Hippocampal spatial maps

Self-motion cues

Allothetic cues

Cerebellum

visual landmarks

Environment

Corrected motor command

Contextual information

Motor command correction

Spatial representation

Hippocampus

Cerebellum

Movement generator

Inverse dynamics

Prefrontal cortex

Motor cortex

goal

start

Interplay between parallel learning systems
Interplay between parallel learning systems

- Hippocampal spatial maps
- Self-motion cues
- Allothetic cues

Cerebellum

- Visual landmarks

Environment

- Corrected motor command
- Contextual information
- Motor command correction

Spatial representation

- Forward predictor
- Inverse corrector

Trajectory generator

- Inverse dynamics

Prefrontal cortex

Motor cortex

- Goal
- Start
- Goal

CONTROL ANIMAL
Interplay between parallel learning systems

Cerebellar contribution to spatial cognition

Spatial learning model
(Passot et al. 2012)

L7-PCKI mice have a spatial learning deficit
(Burguière et al. 2005)

![Graphs and diagrams related to spatial learning and cerebellar contribution.]

*Note: The text and figures are presented as they appear in the image, without any additional annotations or modifications.*
Interplay between parallel learning systems

Cerebellum influences the accuracy of hippocampal place maps

Spatial learning model
(Passot et al. 2009, 2012)

Prediction of the model

Rochefort et al. (2011)
Interplay between parallel learning systems

Cerebellum influences the accuracy of hippocampal place maps

Spatial learning model
(Passot et al. 2012)

Inaccurate spatial maps in mutants

consequences on exploratory behaviour

Prediction of the model

Rochefort et al. (2011)