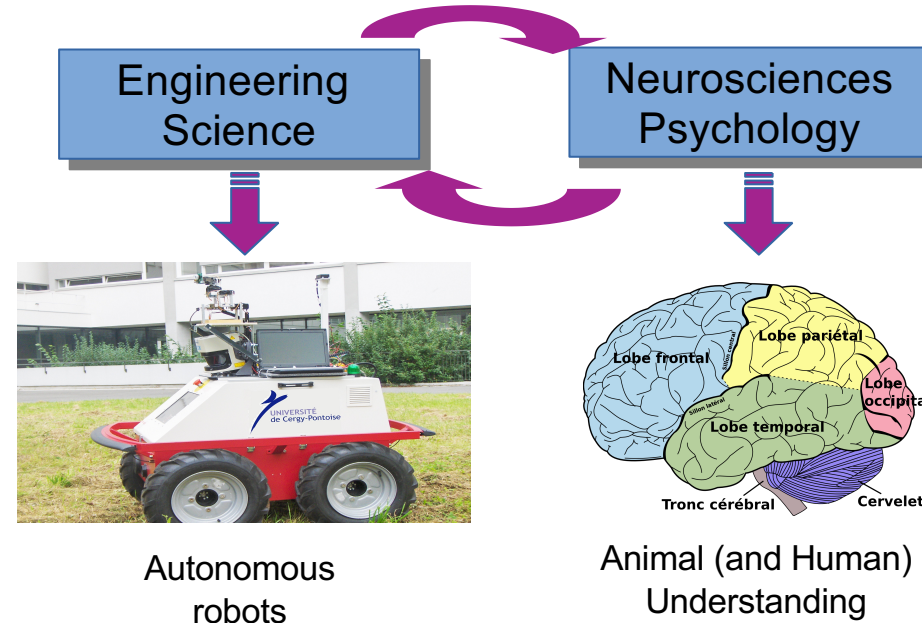


# From spatial navigation in rodents to the autonomous vehicle: a neurorobotics perspective

Nicolas Cuperlier<sup>1</sup>, Sylvain Colomer<sup>1,2</sup>, Philippe Gaussier<sup>1</sup>  
Olivier Romain<sup>1</sup> and Guillaume Bresson<sup>2</sup>

1:ETIS Lab.

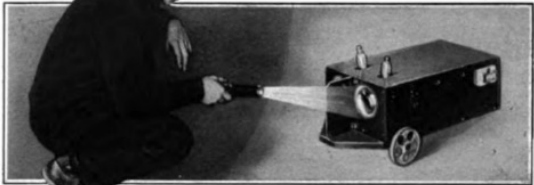
2: VEDECOM Institute



# Robot navigation

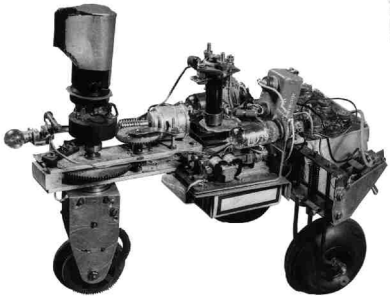
## The Electric Dog and How He Obeys His Flashlamp Master

By B. F. Meissner

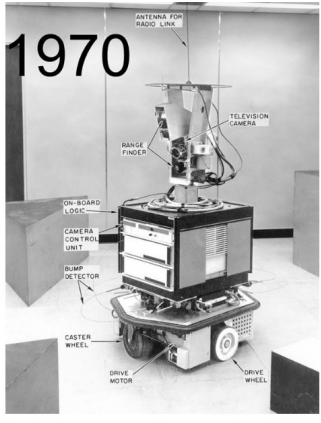


The electric dog and its master. A pocket flashlight is the magic wand which it obeys

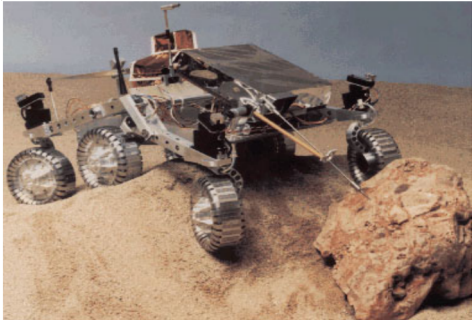
Electric Dog 1912



« Tortue »  
W. Grey Walter  
1949-53



« Shakey »  
Stanford 1970

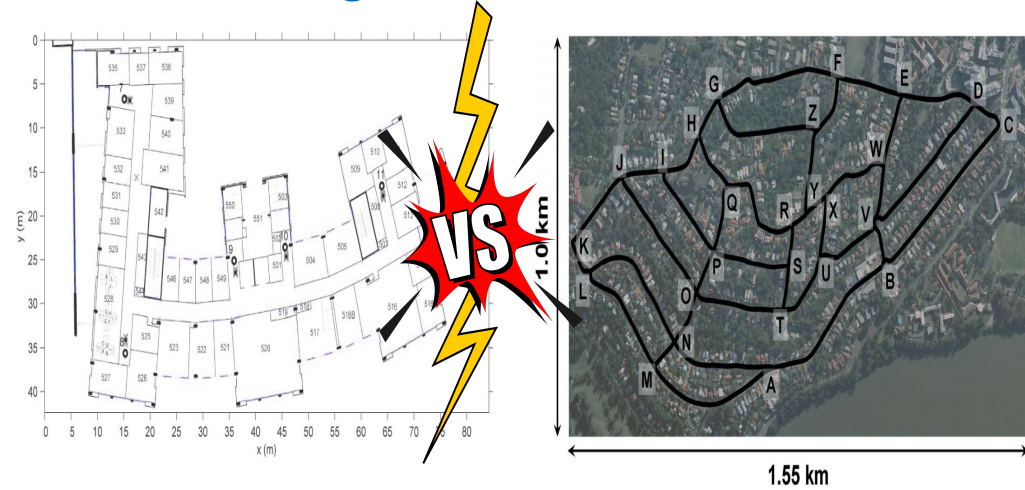


# Challenge: Outdoor vision-based navigation

Autonomous vehicles (AV) face **large** and **dynamic** environments  
Still **unsolved** !

Changing conditions

Large volume of data



Reference



Illumination



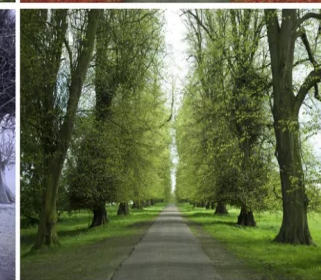
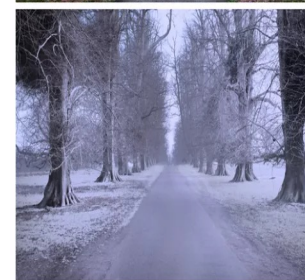
Activity



Weather



Season



# Spatial cognition and navigation

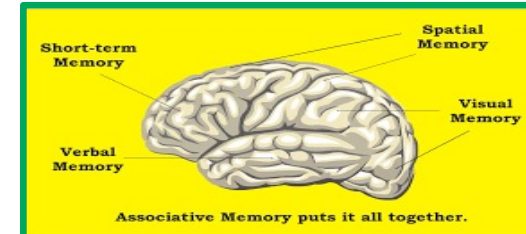
“how to **extract** (*perception*), to **code** (*memory*) and to **process** (*strategy and action selection*) useful **spatial information** from the environment?”

- Require **several cognitive processes**:

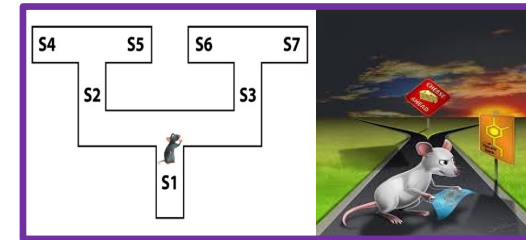
- **Perception**



- **Memory**



- **Planning / action selection**

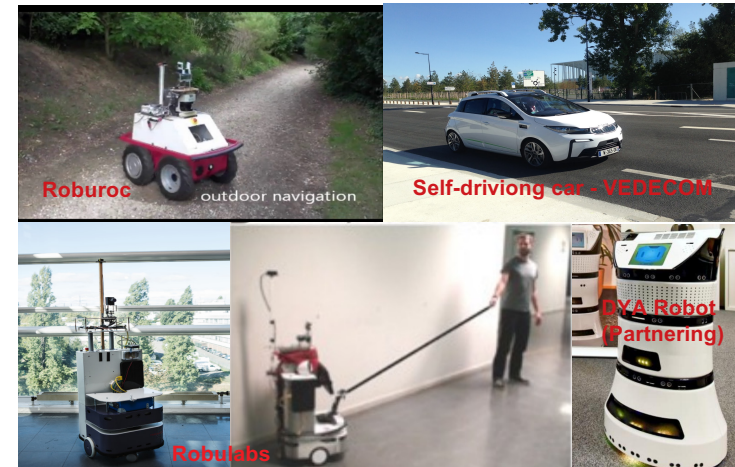
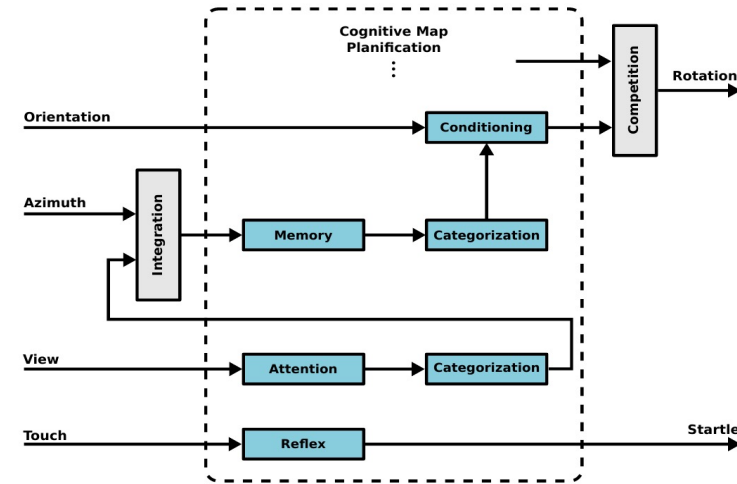


# Toward autonomous mobile robots...

A **neurorobotics** approach to study **navigation**

→ To improve our understanding of the **mechanisms** underlying **spatial cognition**

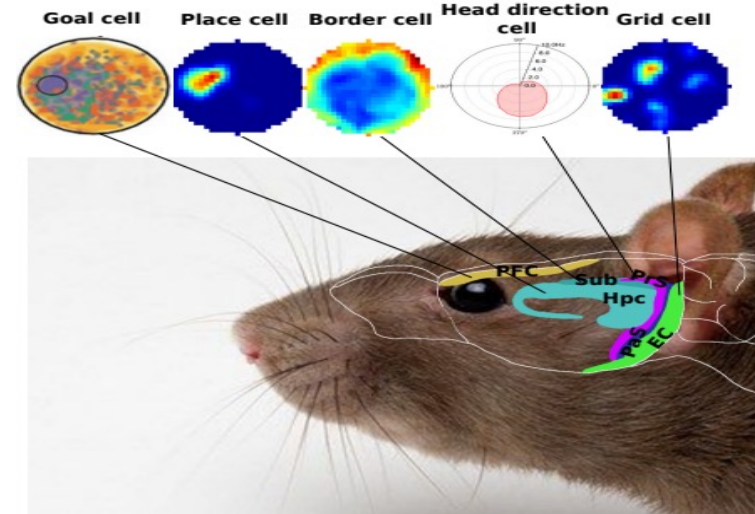
→ To propose alternative **solutions** for **autonomous robotics**



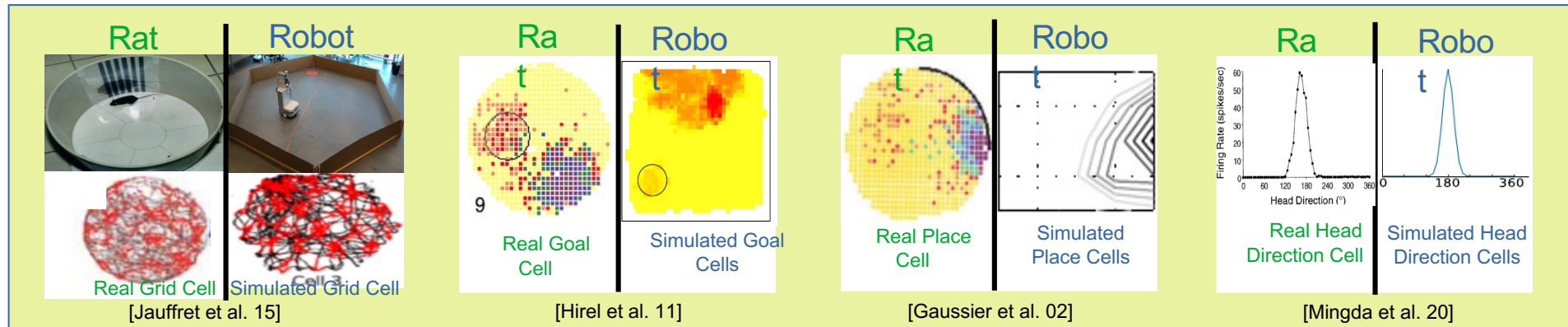
# A neurorobotics approach

- Find a minimalist neural model (rate coding):

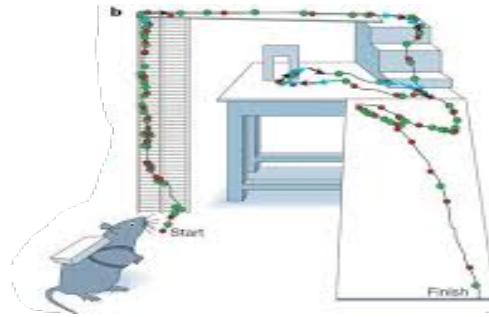
- Accounting for the **spatial behavior** of mammals
- Taking into account a **minimum number of biological structures**



- **Explainable** (not a black box), providing **testable predictions**

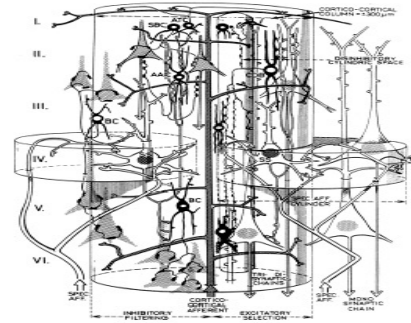


# A neurorobotics approach



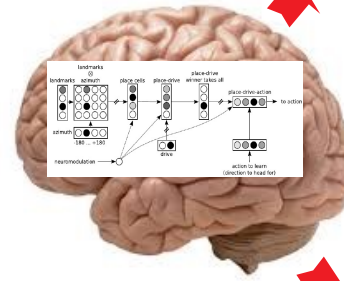
Behavioral data

+

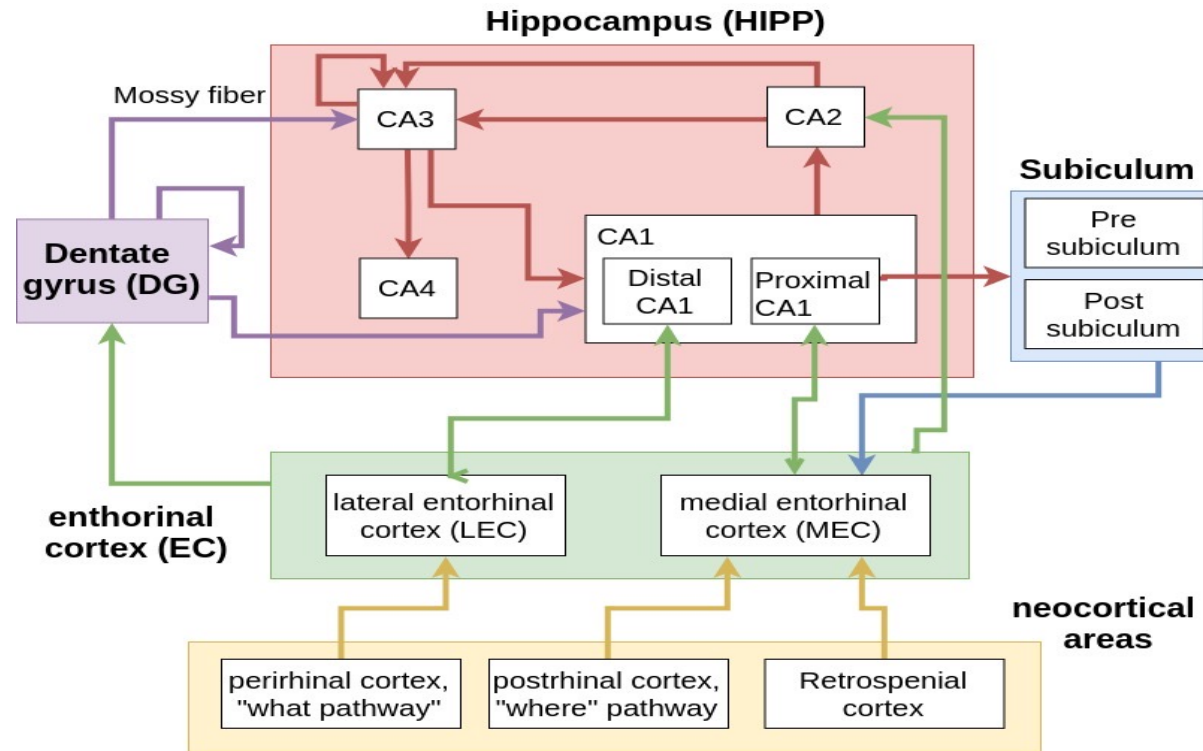


Neurobiological data

=



# Hippocampal Area



Beyond spatial cognition :

- Episodic memory (anterograde amnesia, Alzheimer...)

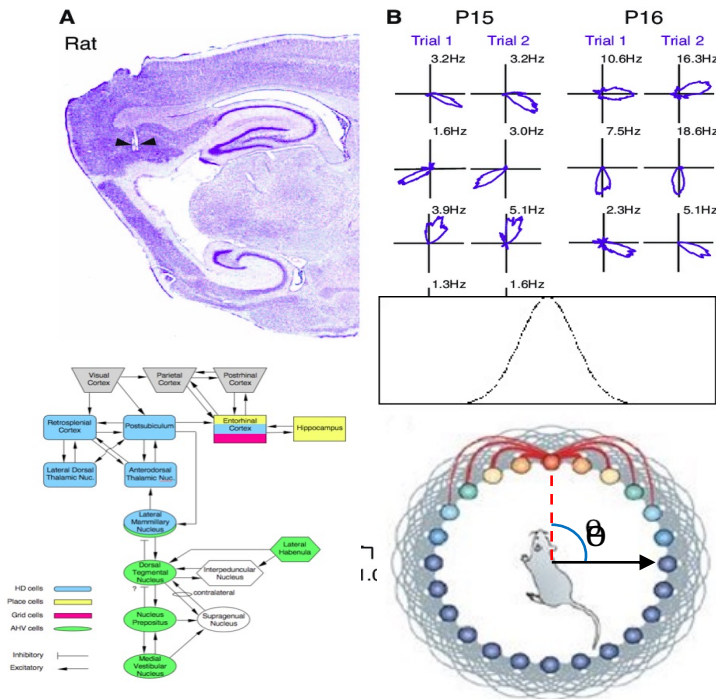


# Spatial cells in mammals

## Head direction cells (HD)

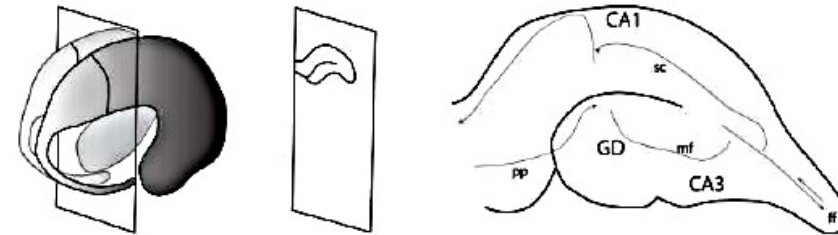
Discovered by Taube J. S., Muller R. U., Ranck J. B. [1990]

- Fire only when the animal's head points in a specific direction

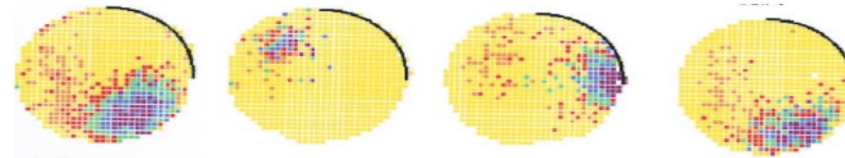


## Place cells (PC)

- Discovered by O'Keefe J, Dostrovsky J. [1971] in the hippocampus and the Dentate Gyrus

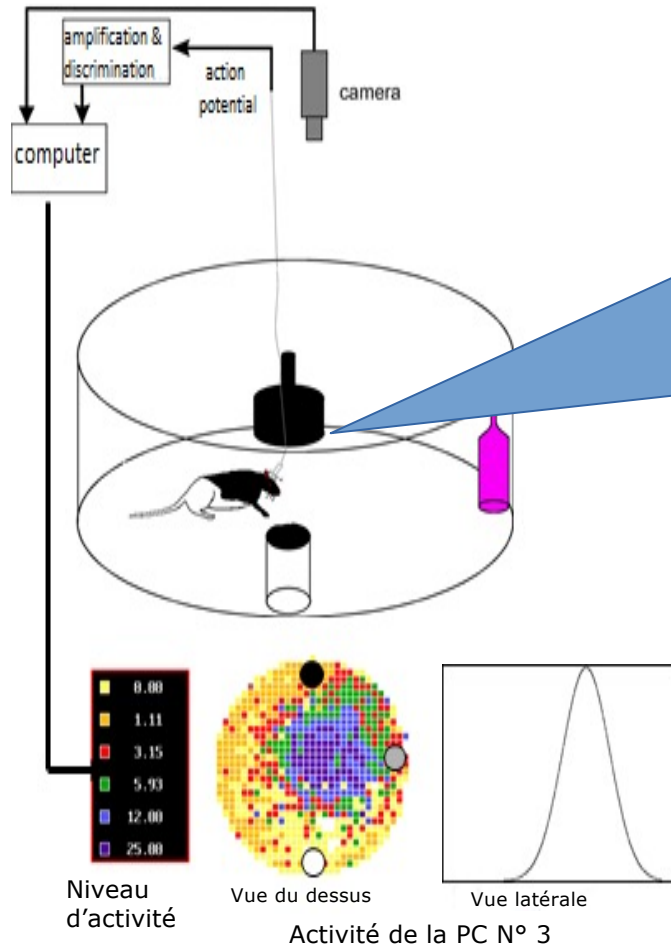


- Respond only at a given location in the environment (place field).

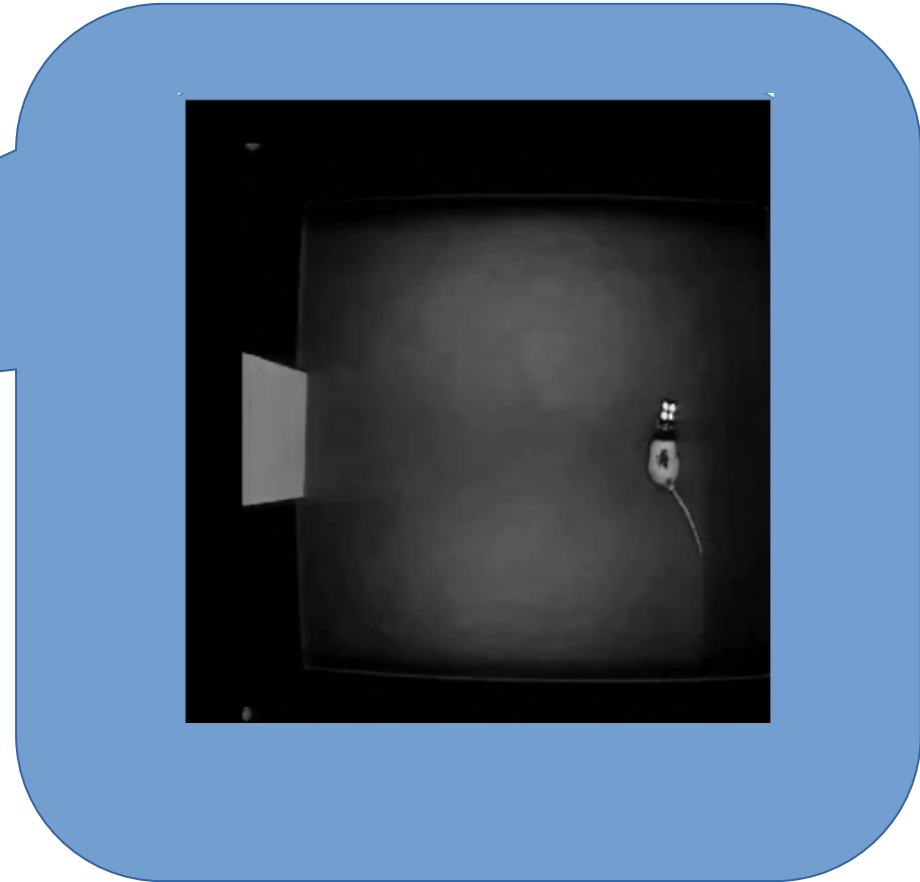


But other cells: Grid Cells, Border cells, Time cells, Speed cells, + **Conjunctive cells** ...

# Zoom on Place Cells (PC)

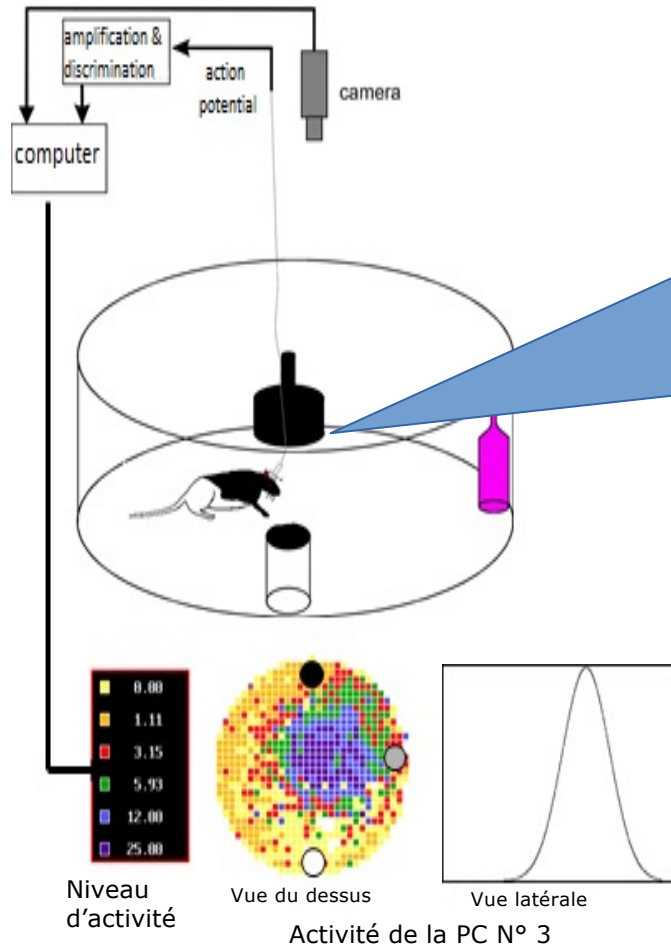


**Une cellule de lieu dans l'hippocampe du rat  
(Lab. B. Poucet – Marseille)**



**10 place cells (rat hippocampus CA1)  
recorded simultaneously over 50  
minutes of foraging (Roddy Grieves)**

# Zoom on Place Cells (PC)



Niveau  
d'activité

Vue du dessus

Activité de la PC N° 3

Vue latérale

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



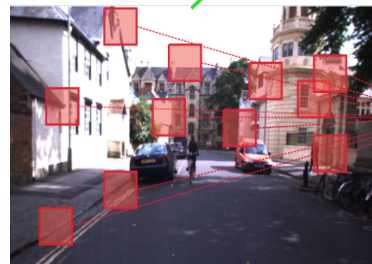
**10 place cells (rat hippocampus CA1)  
recorded simultaneously over 50  
minutes of foraging (Roddy Grieves)**

# Visual Place Recognition (VPR)

## Working of VPR System



- Legend**
- Trajectory
  - Learned position
  - Current position



Detector

For each landmark

Encoder

Request

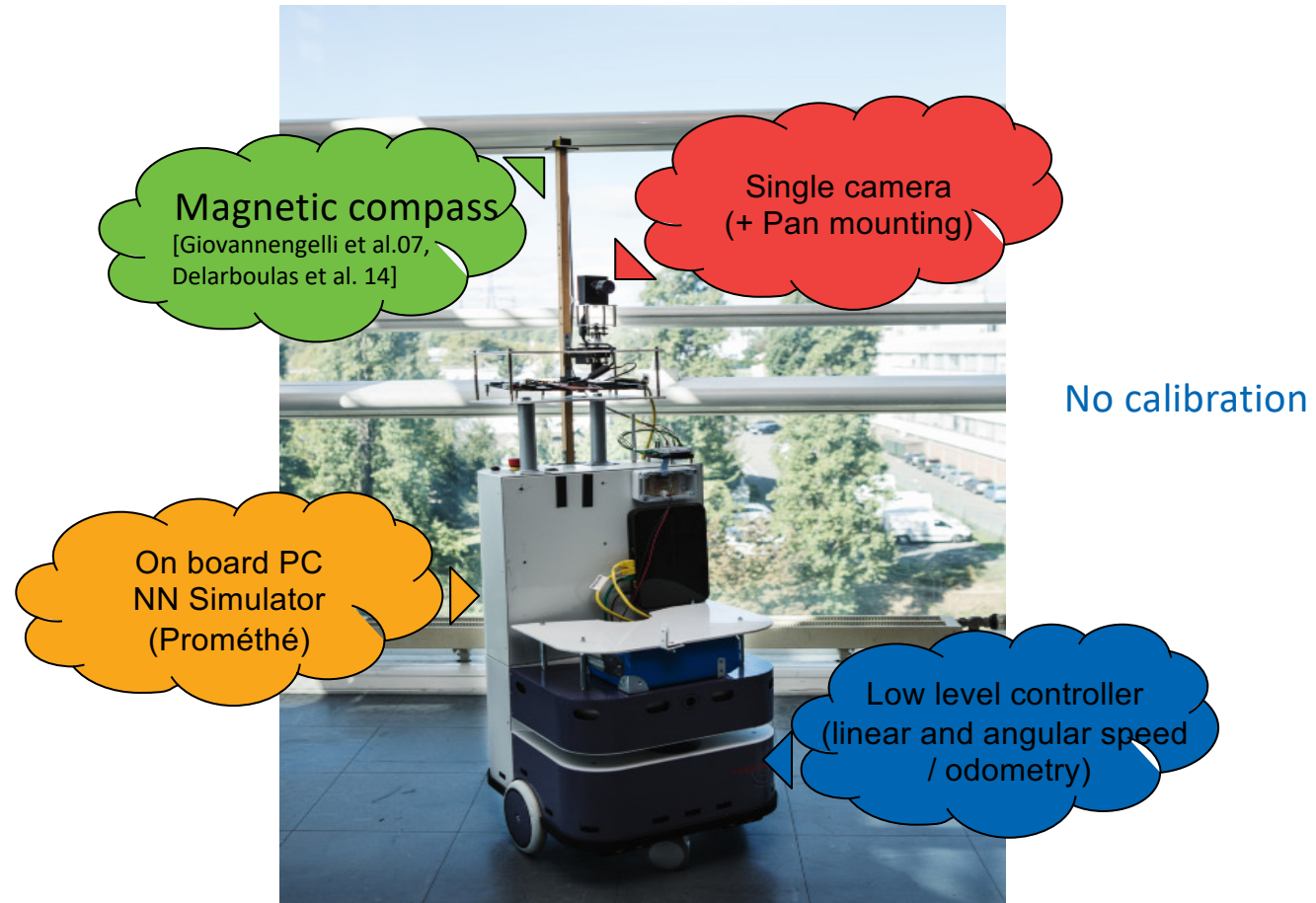
Memory



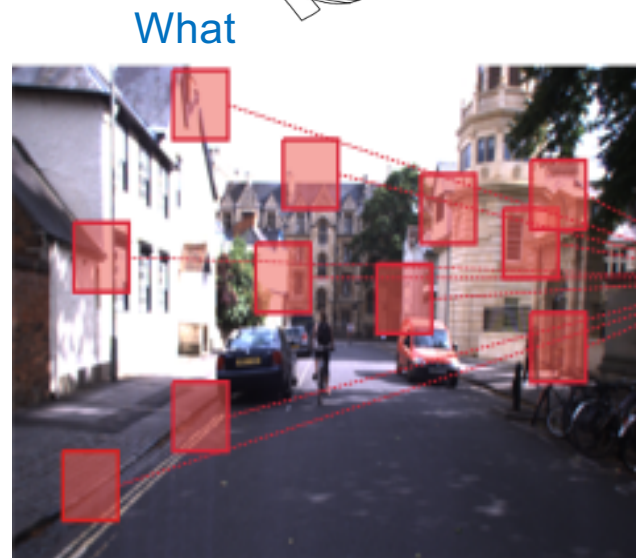
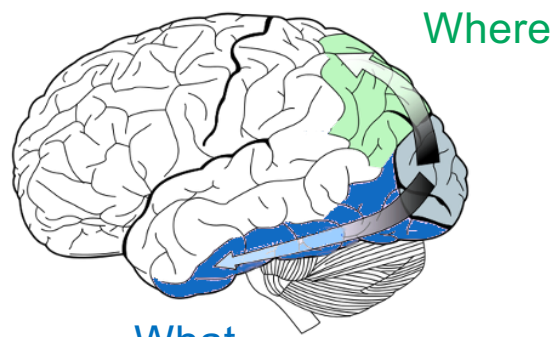
- 1 <5m
- 2 <5m
- 3 >5m

Return n best hypothesis

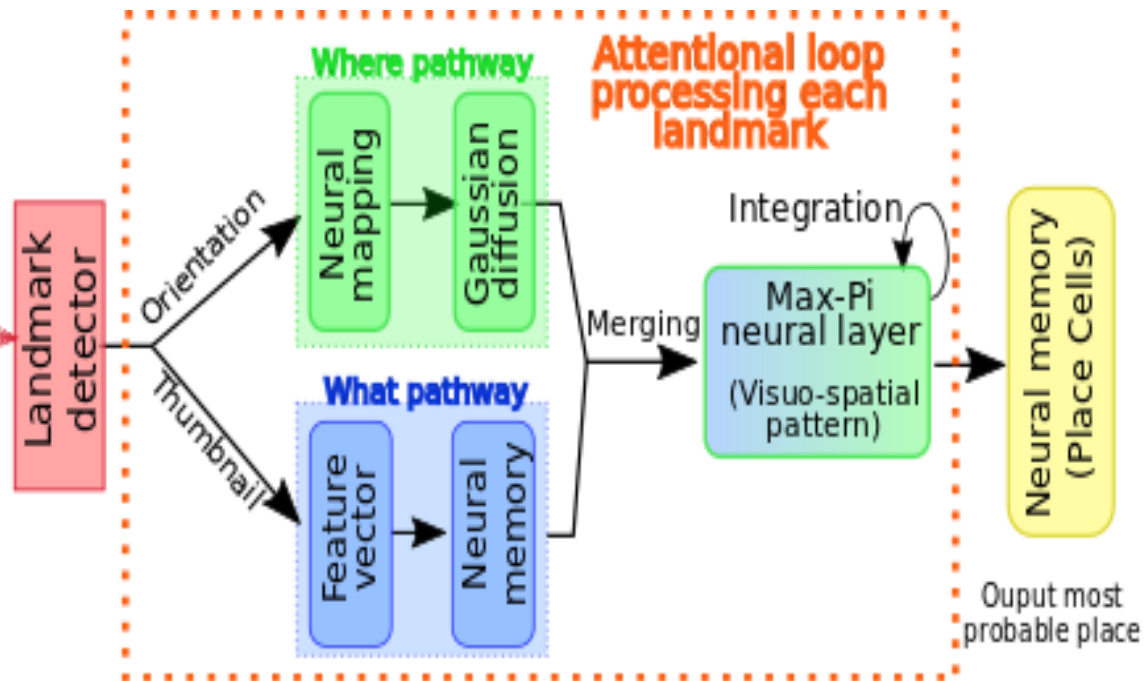
# Robotic platform



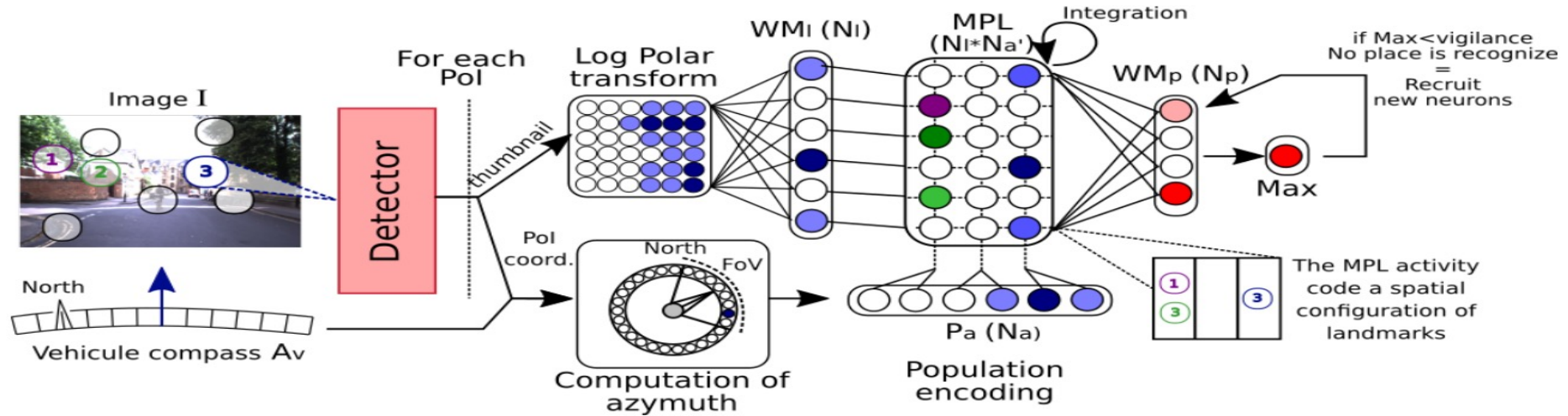
# Vision based model of hippocampal Place Cells



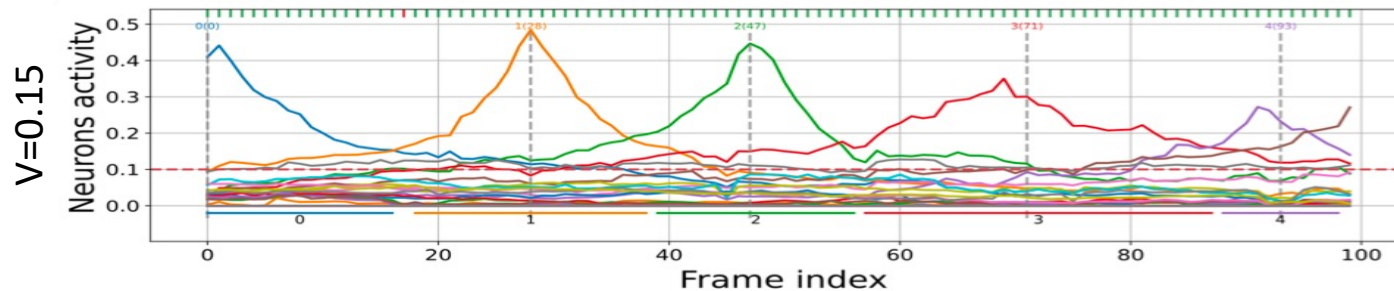
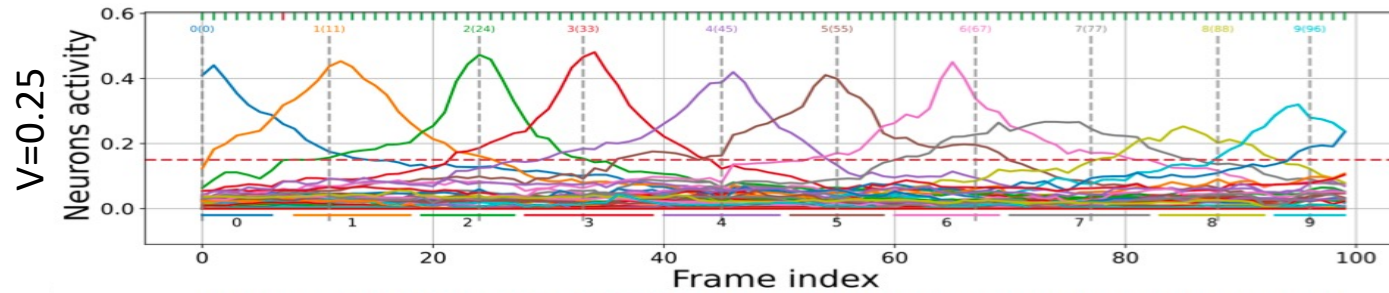
One-shot learning  
No a priori information



# LPMP (log-polar Max-Pi) model

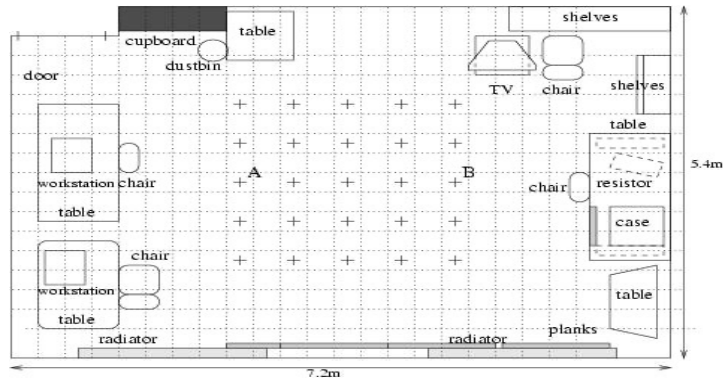


One-shot learning

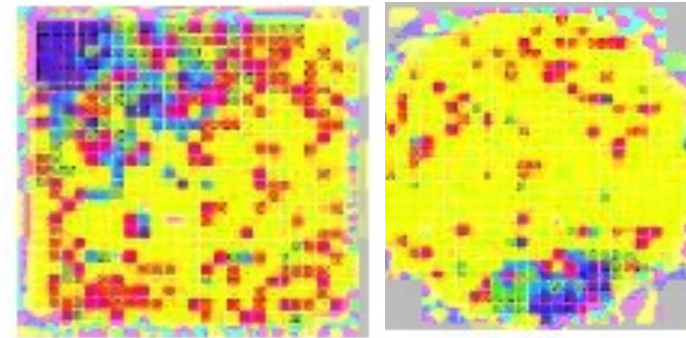


# Key results (1) : simulated PC

Experiment setup

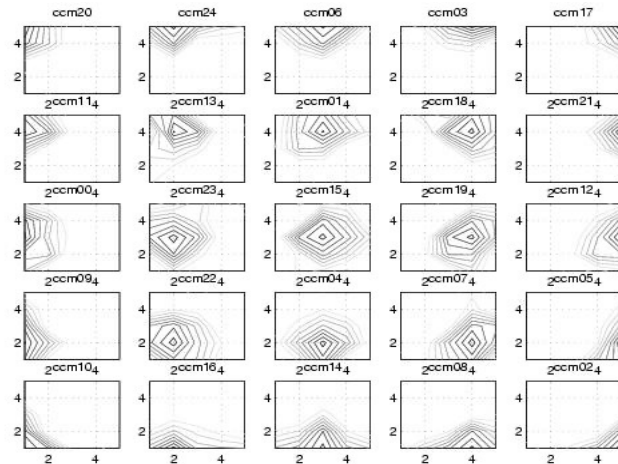


Rats place cells

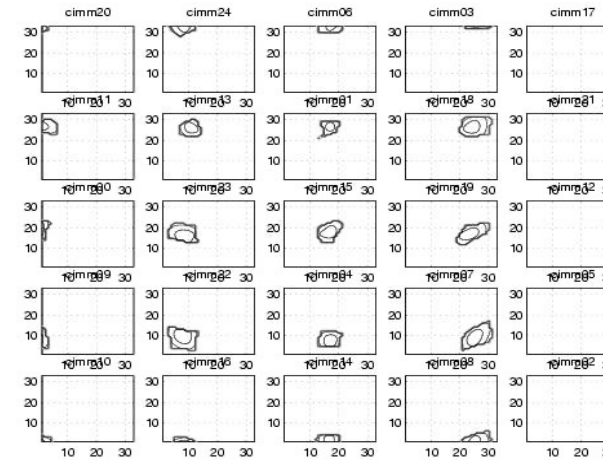


Simulated PC in robot:

Before competition



After competition :



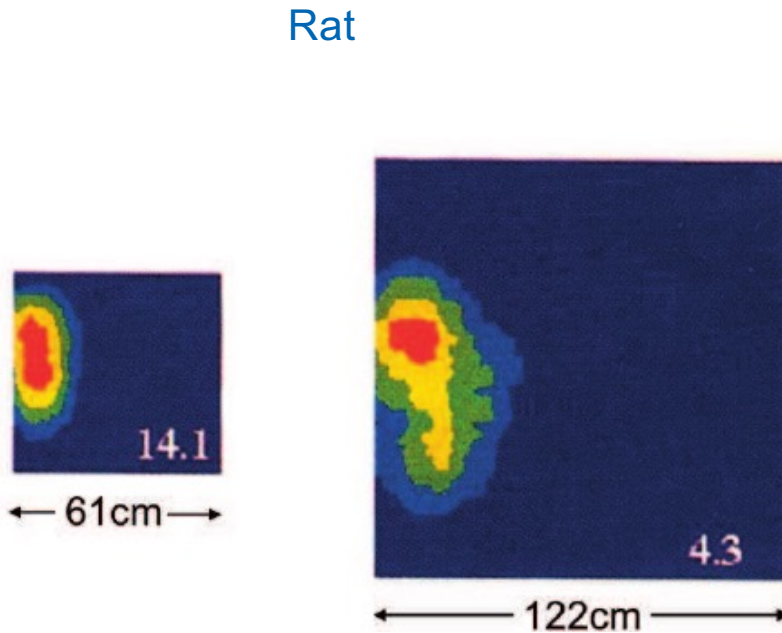
[Gaussier&Zrehen94, Gaussier&Joulain96]



**Simulated visual place cells can exhibit similar activities than biological ones (in DG, in HS if followed by a WTA)**



# Key results (2) : adaptation of place field size

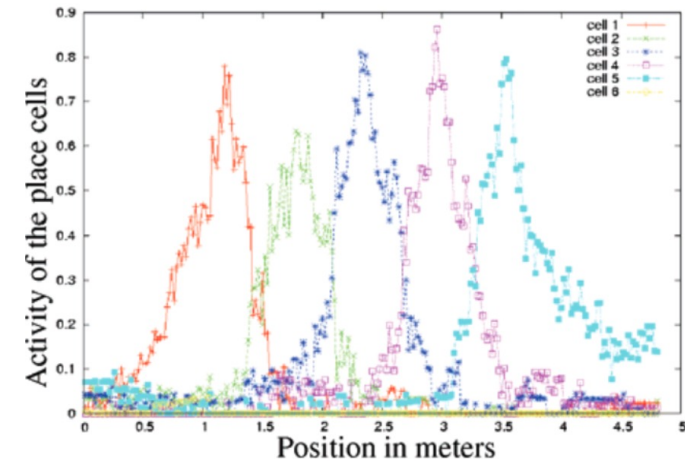


Individual place field increases in size when the environment dimensions are enlarged

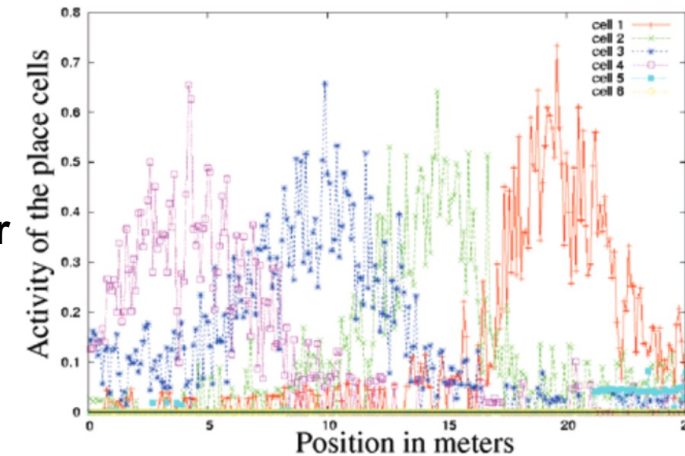
[Okeefe et al. 1996]

Robot

Indoor



Outdoor



[Giovannangeli et al. 2006]

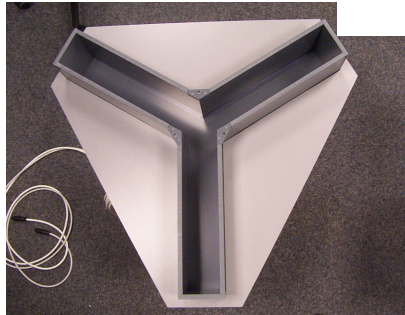


**Place field size is controlled by the distance of visual landmarks**

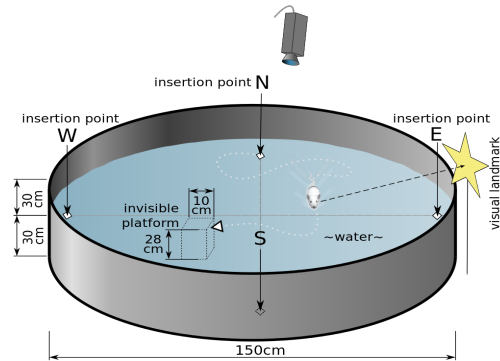
# Study of spatial cognition in mammals

- **Laboratory:** 80 cm – 2/3 m diameter (small environments)

- Rodents (rats/mice)

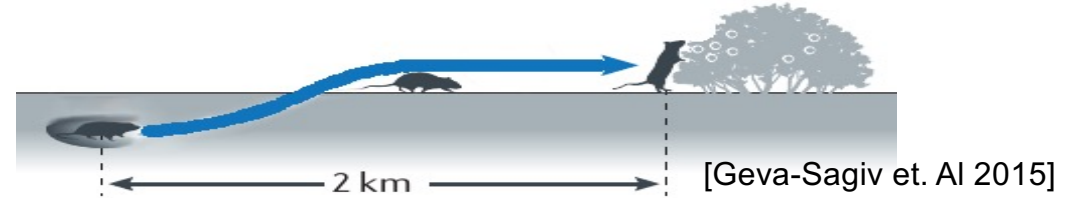


Y- Maze

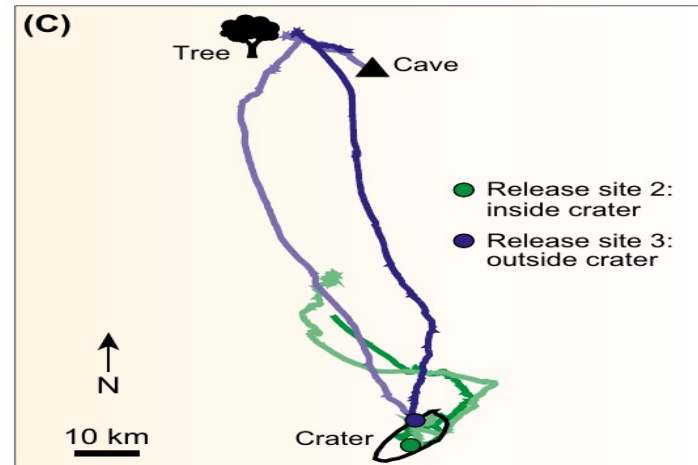
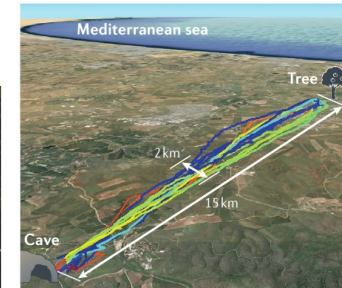


Morris water pool

- **Natural environments:** trajectories from 600m to 2km



- Fruit bats



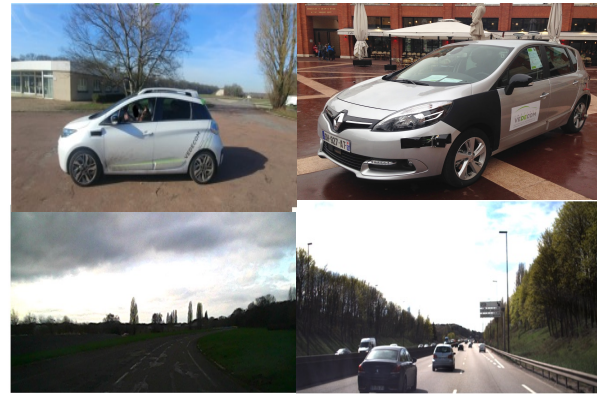
# Vehicle localization in large, complex and dynamic environments

## KITTI odometry datasets



KITTI dataset	00	01	05	06	07	09
Nb of images	4541	1101	2761	1101	1101	1501
Type	urban	highway	sub-urban	sub-urban	urban	sub-urban
Length (m)	3721	2450	2203	1232	695	1701
Framerate (Hz)	10	10	10	10	10	10
Average speed (m/s)	7.90	21,54	7.61	10.80	6.09	10.33

## Vedecom datasets



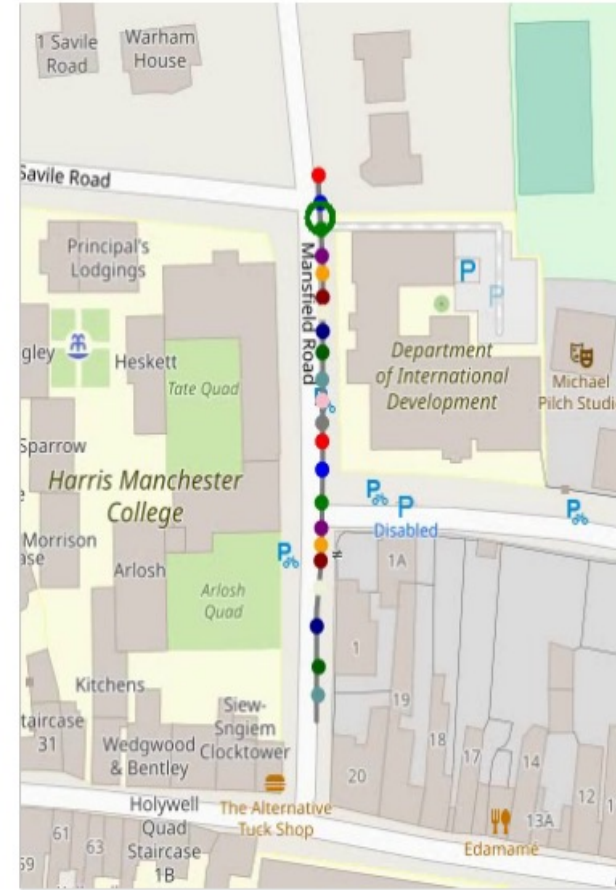
Dataset	Satory tracks	Scenic highway
Nb of images	1366	2000
Type	rural	highway
Length (m)	4064	4082
Frame rate (Hz)	4	12
Average speed (m/s)	12.74	25.53

## Oxford robucar datasets

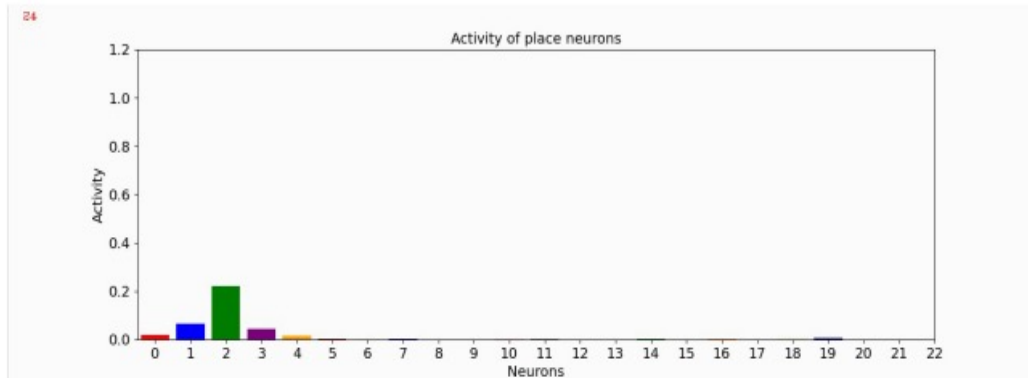


Id	Env.	Images	Distance(m)	duration(s)	activity rate
S-1	Suburb	1930	632	125	4.5
S-2	Suburb	1401	625	89	6.8
S-3	Suburb	1159	624	74	7.0
S-4	Suburb	1572	626	101	7.1
C-1	City	1521	532	104	10.6
C-2	City	1904	569	124	10.9
C-3	City	2227	527	143	12.0
C-4	City	2134	585	140	13.5
R-1	Road	927	292	61	5.9
R-2	Road	828	289	54	6.2
R-3	Road	566	286	38	6.6
R-4	Road	595	287	37	8.6

Front view

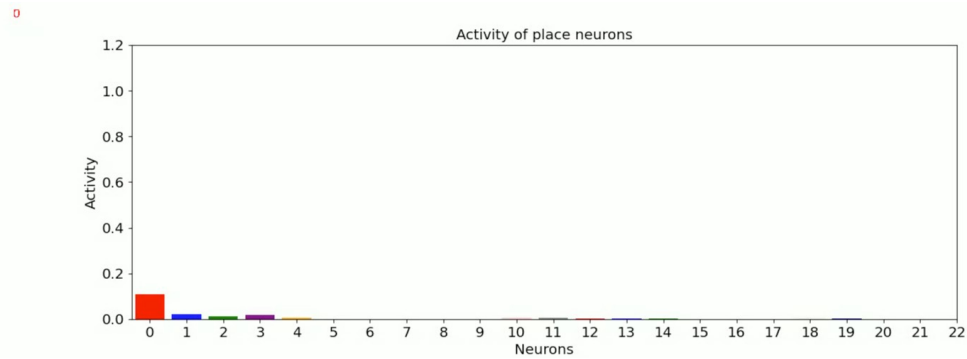
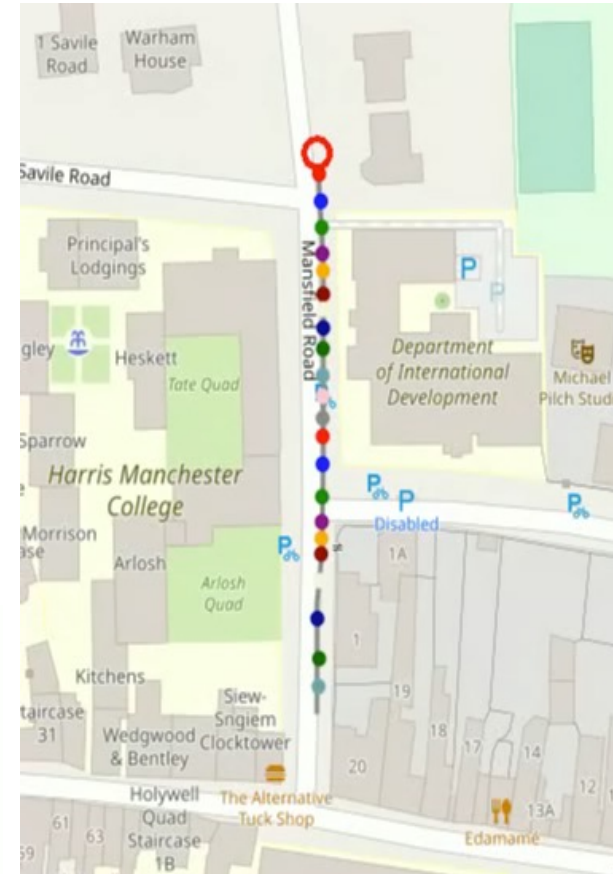
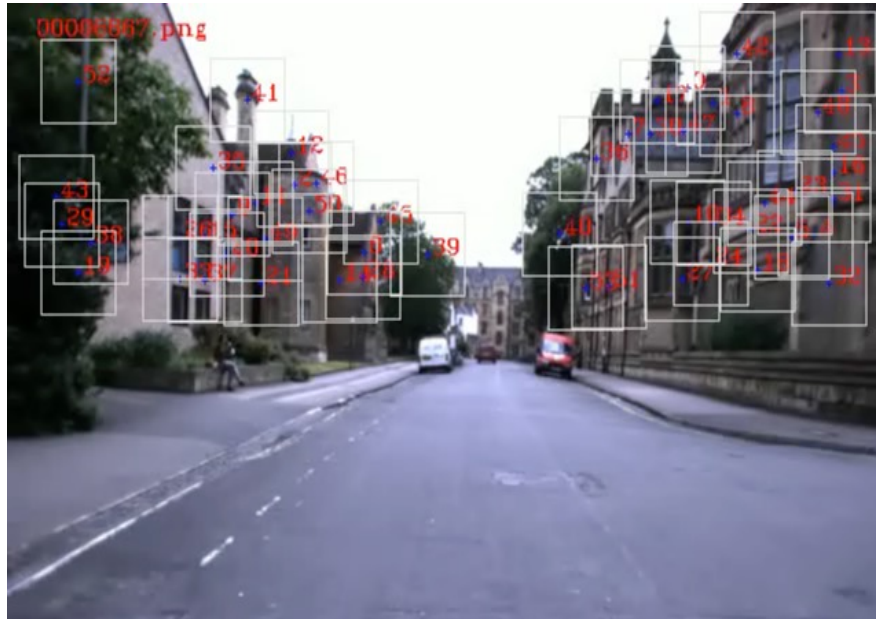


Place cells maps



Place cells activity

Front view

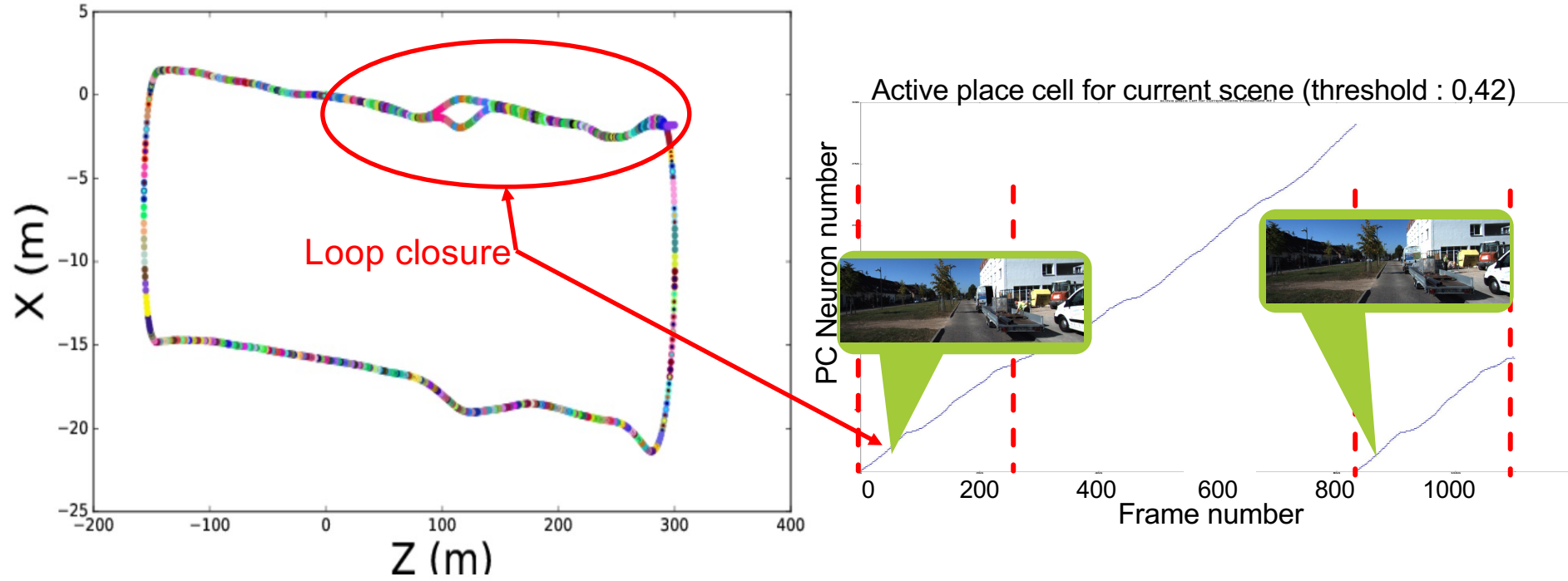


Place cells activity

Place cells maps

# Key results (3): outdoor loop closure

Kitti 06 dataset

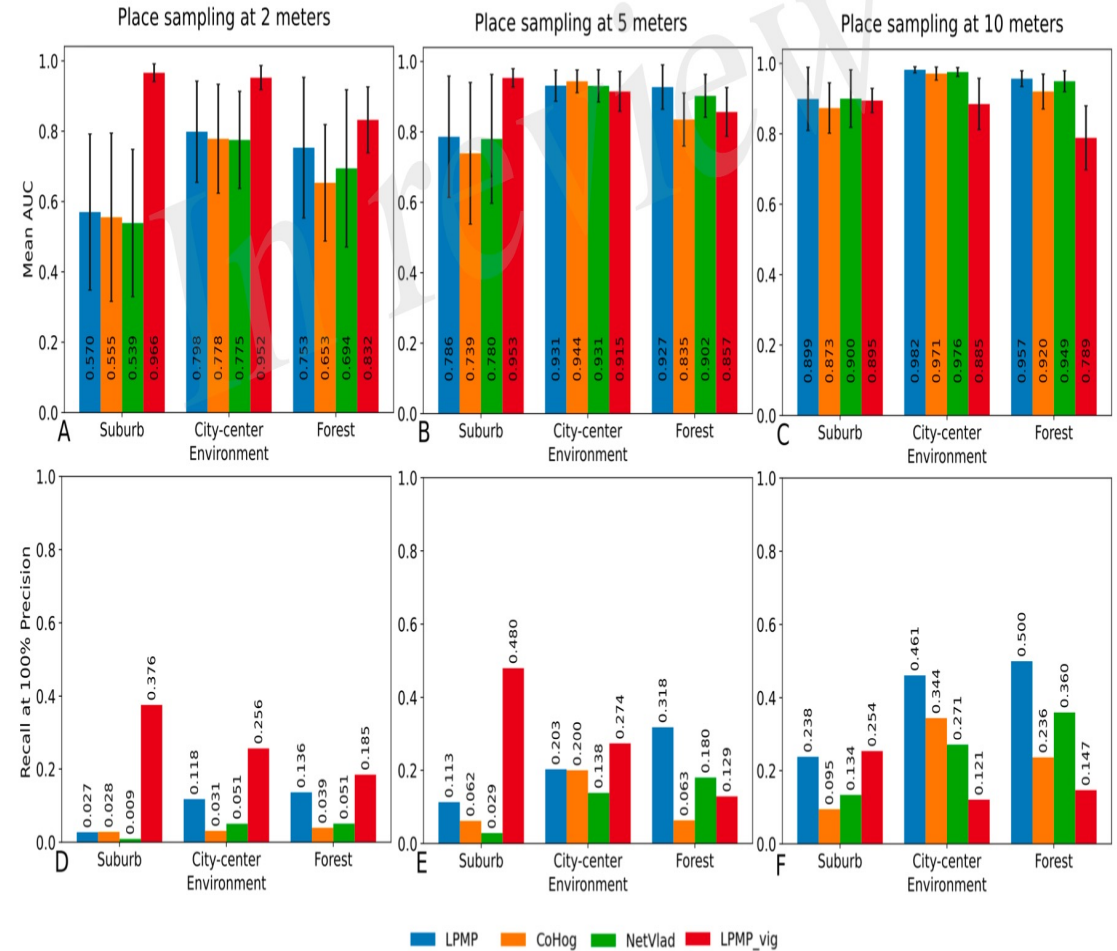


➔ Correctly performs loop closure

# Key results (3): outdoor loop closure

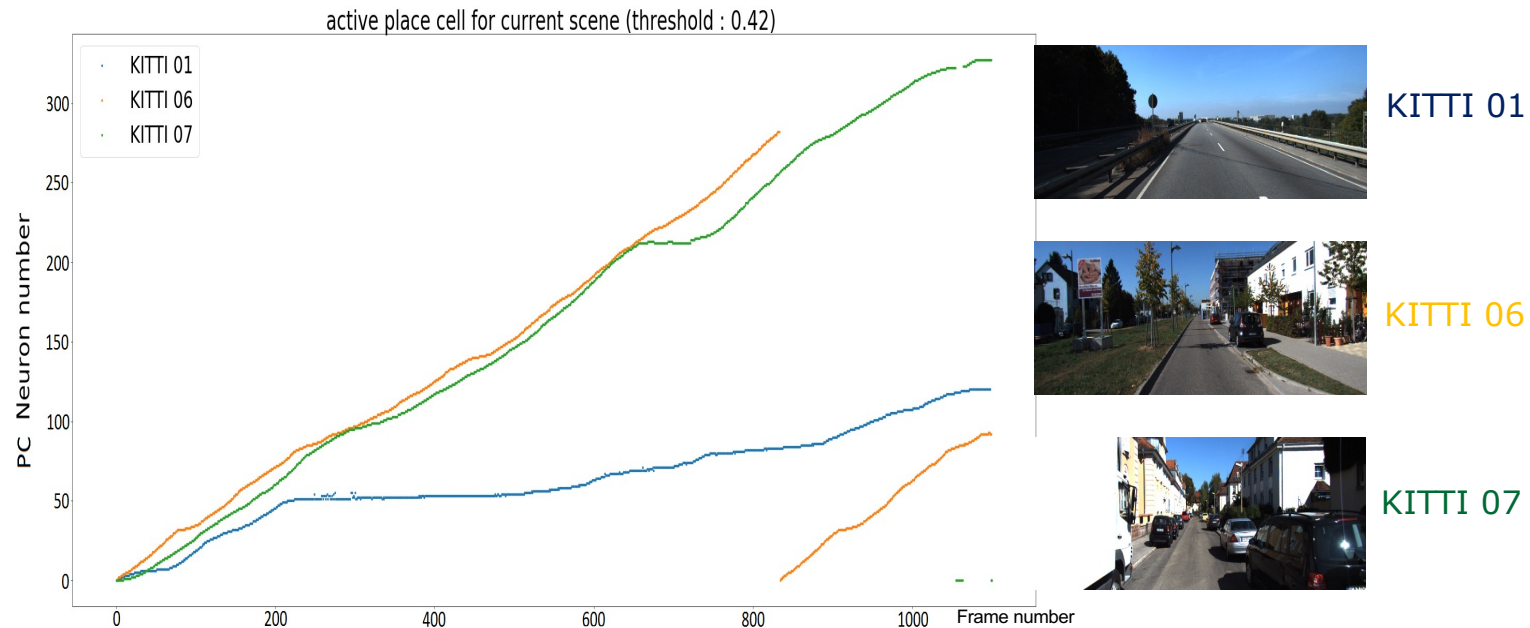
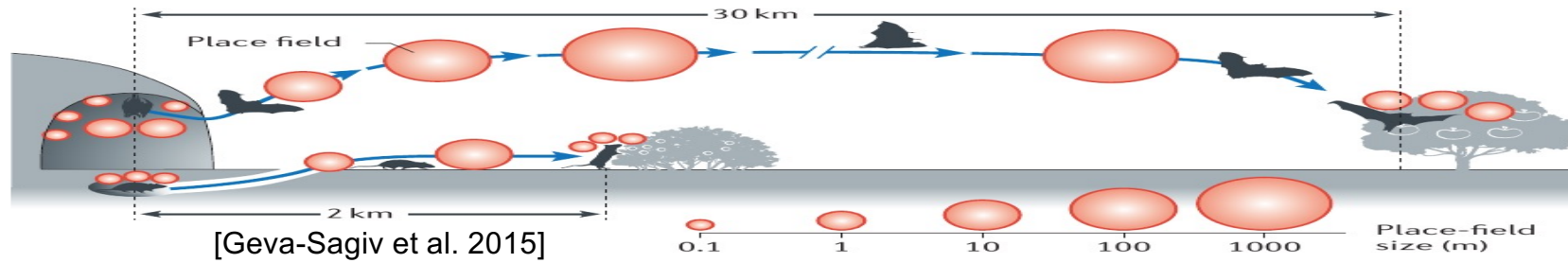


Test dataset illustrations: recorded trajectories; images from the dataset



AUC (Area Under Curve) and recall obtained on the suburb sequence between LPMP, NetVlad (2018) and CoHog (2020)

# Key results (4): adaptative place field

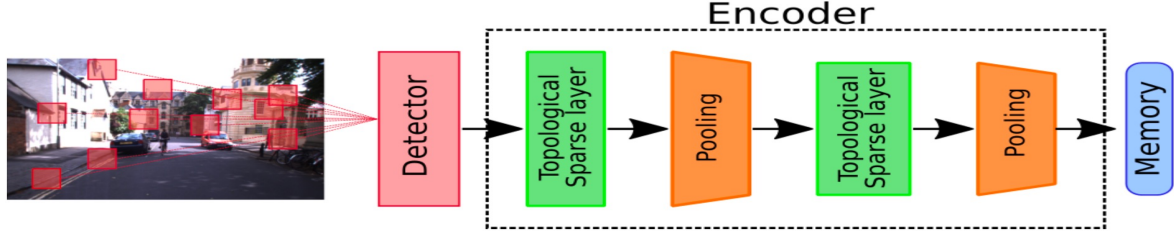


➔ Place field size adapts to the environment.

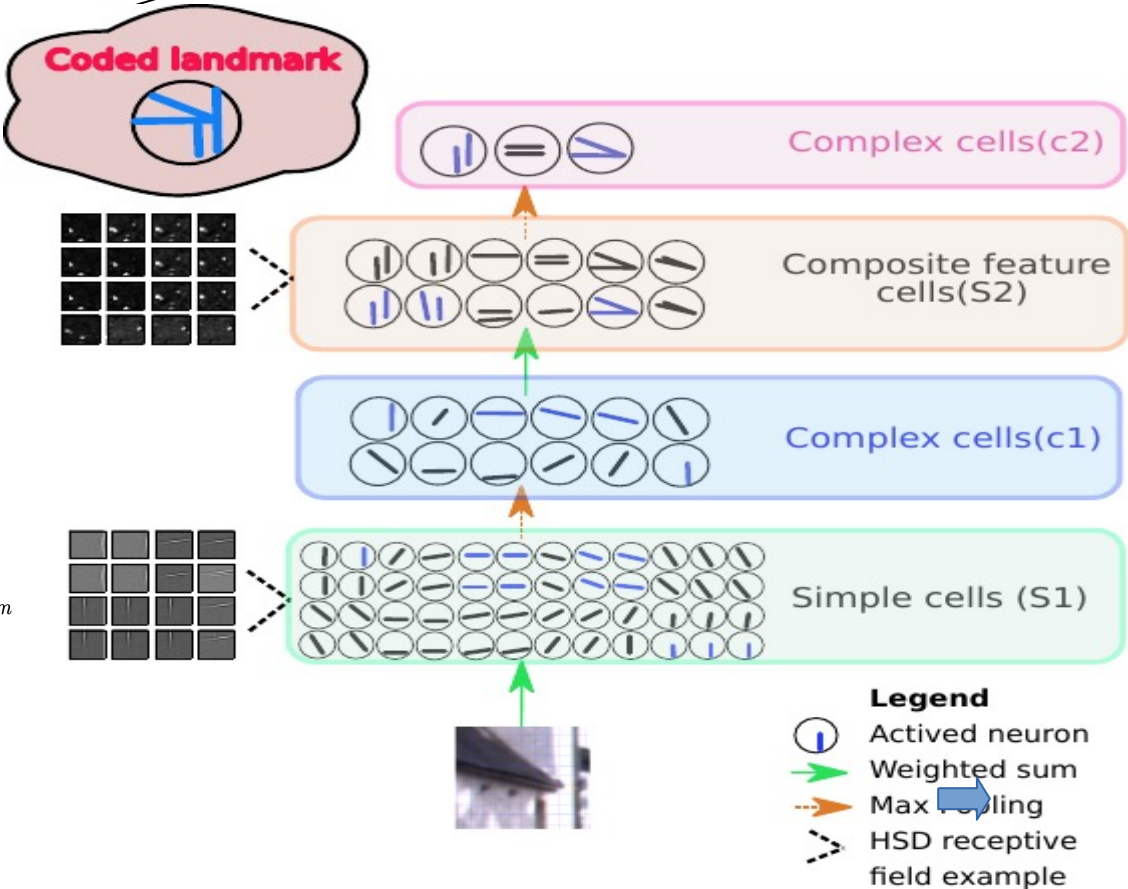
[Espada et al. 2018, 2019]



# Visual landmarks sparse coding



Sparse encoding of visual landmarks:  
**Hierarchical Sparse Dictionary (HSD)**

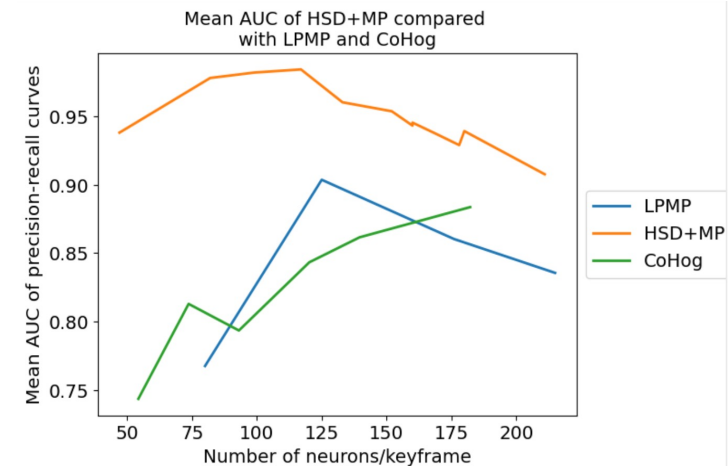
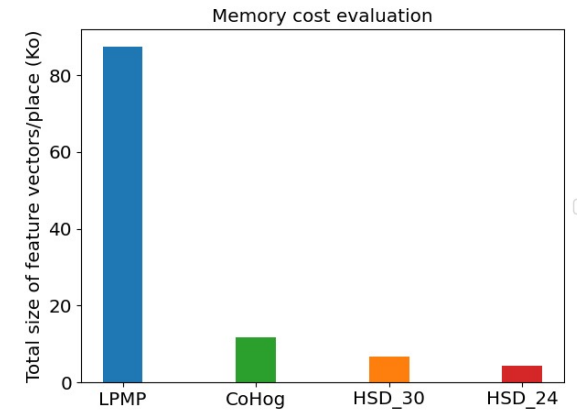


$$\min_{\mathbf{a}} \|\mathbf{a}\|_0 \quad \text{subject to} \quad \mathbf{s} = \sum_{m=1}^M a_m \phi_m$$

[Colomer et al. 21b]

# Key results (5): toward scaling up LPMP

Name	K0-1	K2-1	K3-1
Dataset	KITTI 00	KITTI 05	KITTI 05
Size (learn;test)	(540;440)	(106;91)	(230;265)
Index learn	392-932	10-116	550-780
Index test	3399-3839	2420-2511	1289-1554
Distance	378m	96m	199m
Type	Street	City	Suburb

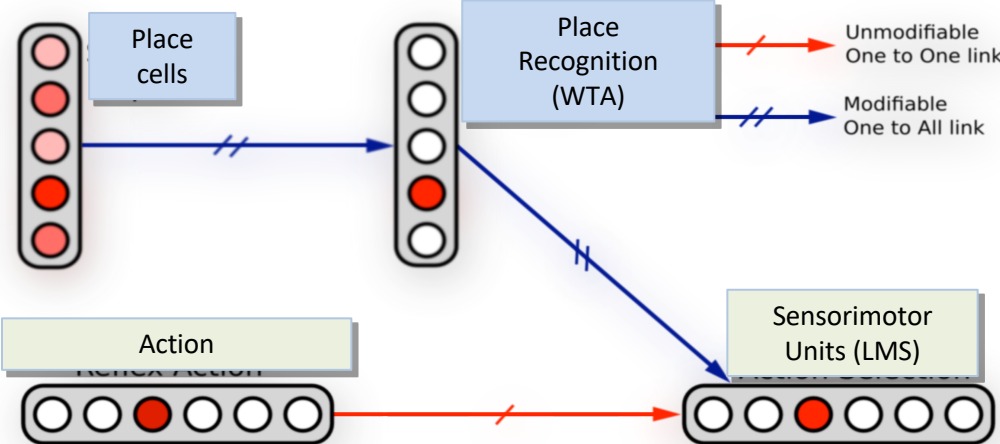


➔ Increased accuracy and lower memory footprint

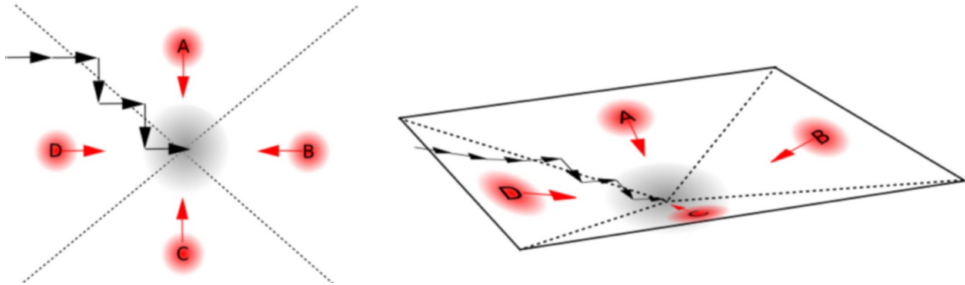
# Sensorimotor learning : place/action

## PerAc

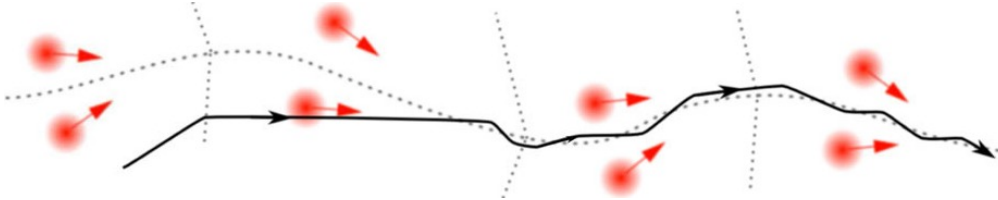
[Gaussier et al. 95,  
Giovannangeli et al. 06,  
Cuperlier et al. 07, Jauffret  
et al. 15]



Return to a goal place  
(homing):



Path following  
(proscriptive learning):





## **A real robot performing robust path following by the learning of multimodal sensorimotor associations**

**Adrien Jauffret**

Nicolas Cuperlier

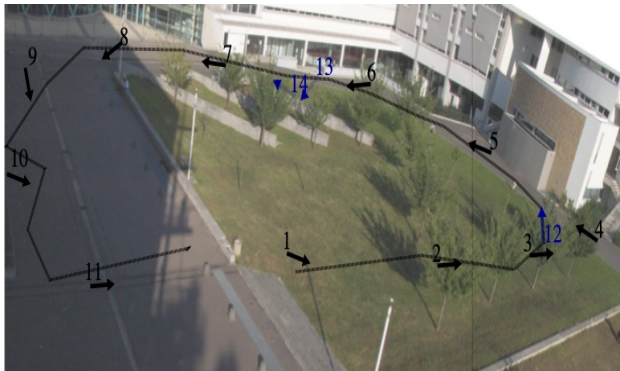
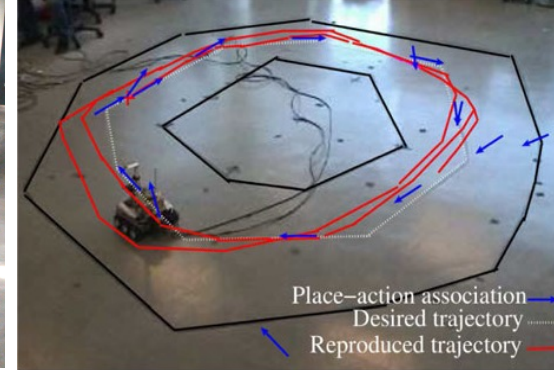
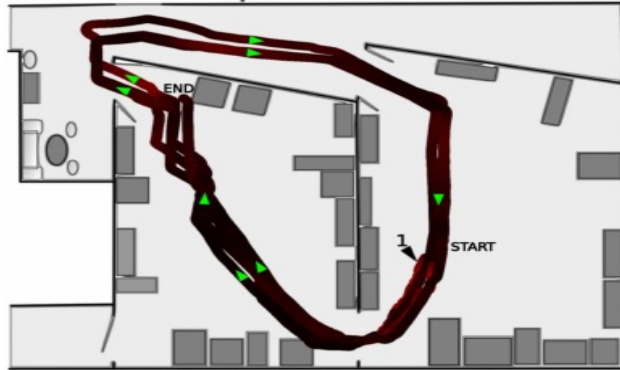
Philippe Gaussier

**Nuit des chercheurs**

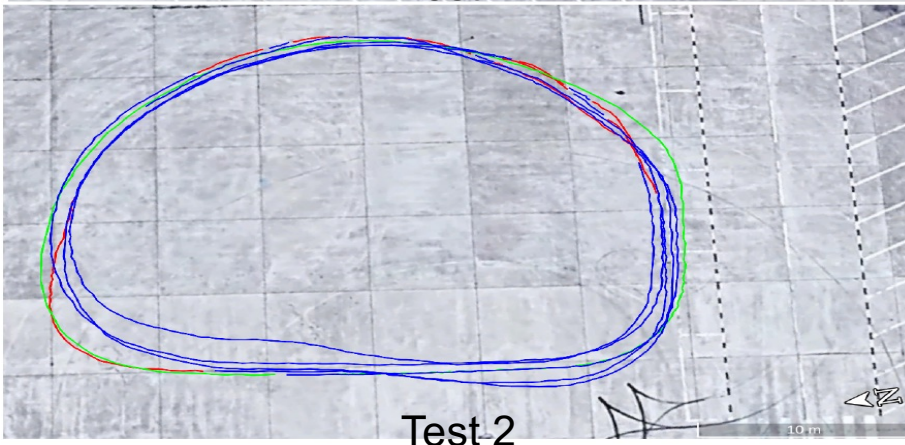
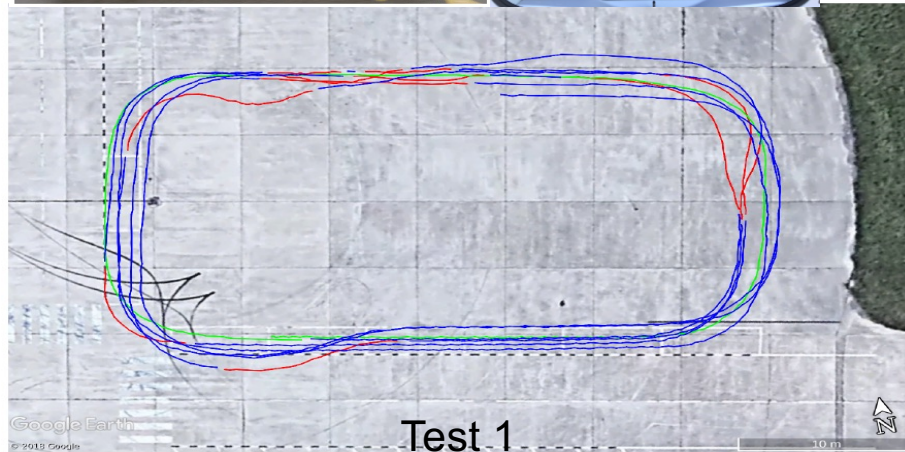
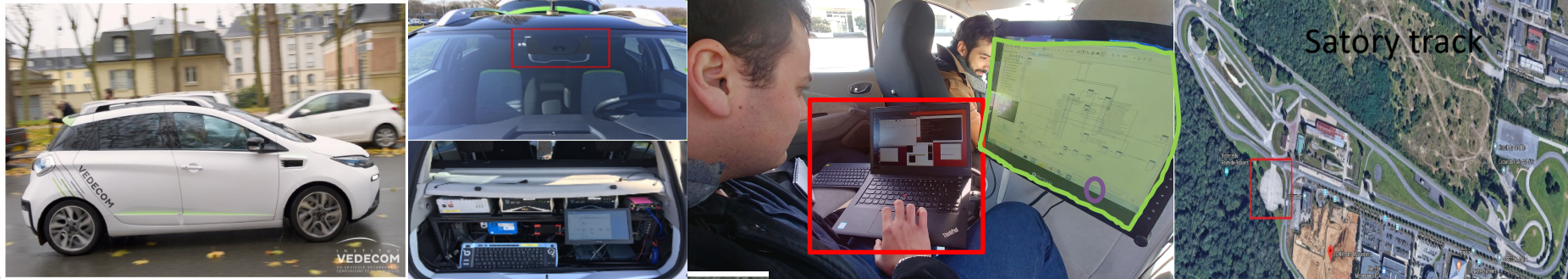
Ecole polytechnique de Palaiseau

ETIS Laboratory, CNRS UMR 8051  
Cergy-Pontoise University

# Key results (6): Path learning: indoor / outdoor (off-road)



# Key results (6): Sensorimotor navigation with a self-driving car



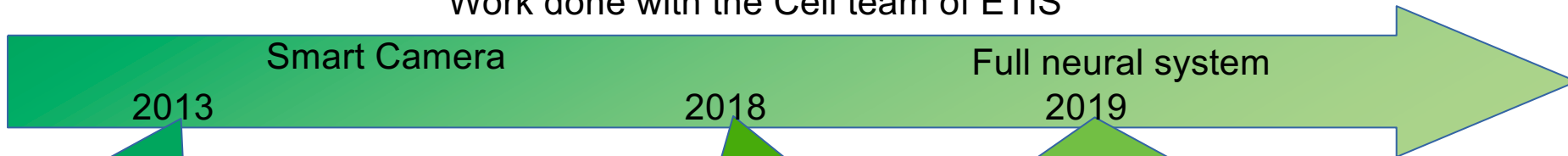
	Test 1	Test 2
Path length	105.35 m	86.06 m
Mean positioning error (Std)	0.71 (0.53)	0.63 (0.51)
Number of trajectory corrections	11	9



**3 interactive teaching laps** are enough to learn to reproduce a loop-shaped trajectory

# Embedded system solutions

Work done with the Cell team of ETIS



**2013**

**RobotSoC**  
FPGA Zynq 7020  
B. Miramond et al. (Fiack et al. 2013)

**2018**

**Jetson TX2 (GPU)**  
S. Zuckerman

**2019**

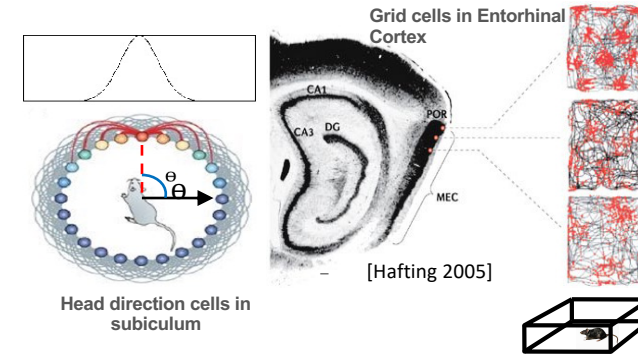
**Full neural system**

**WIZARDE : Heterogeneous Multi-FPGA Systems** (T. Elouaret et al. 2019)

# Current and future challenges

- **Computational neurosciences:**

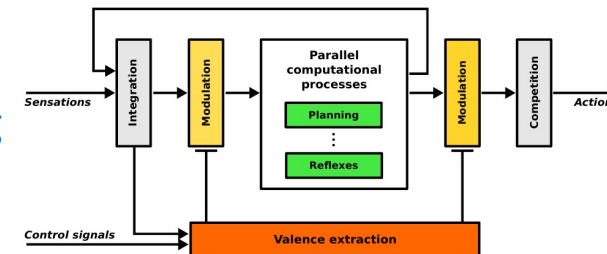
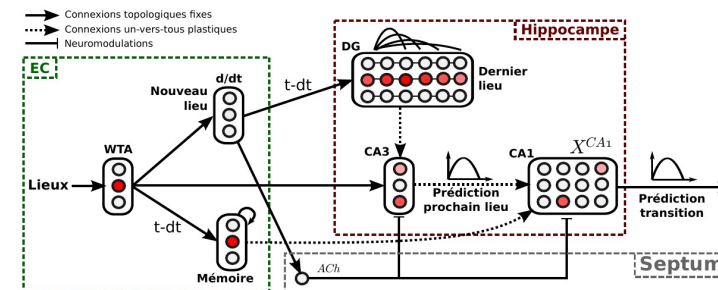
- Taking into account more **brain structures** (Entorhinal Cortex, Subiculum, Retrosplenial Cortex, ...)
- with other **cell types** (grid cells, head direction cells, border cells, ...)
- and their **interactions ...**



- **Neural control architecture for robot navigation :**

- toward **long term** and **large distance**
  - deal with **highly dynamic environments** (day/night, weather, seasons)
  - Improve sensorimotor **prediction** and **learning**

→ Sparse coding, contextual neuro-modulation, population decoding of PC, transition cells, ...





# People involved

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