Decision Making in (multi) Robot Systems

Olivier Simonin

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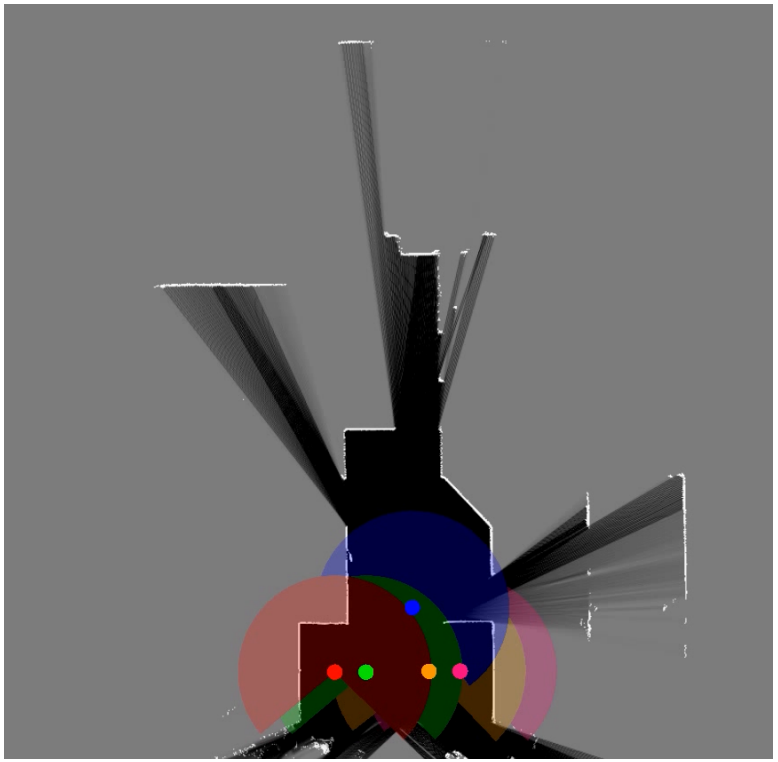
INSA Lyon – CITI Lab. - Inria Chroma team

Illustration ..



ANR Carotte Challenge - Final 2012
Cartomatic team

Outline

I. Decision making ?

II. Classical architectures

III. Learning based architectures

IV. Decision in multi-robot systems

V. Strategies for multi-robot exploration

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I. Decision making ?

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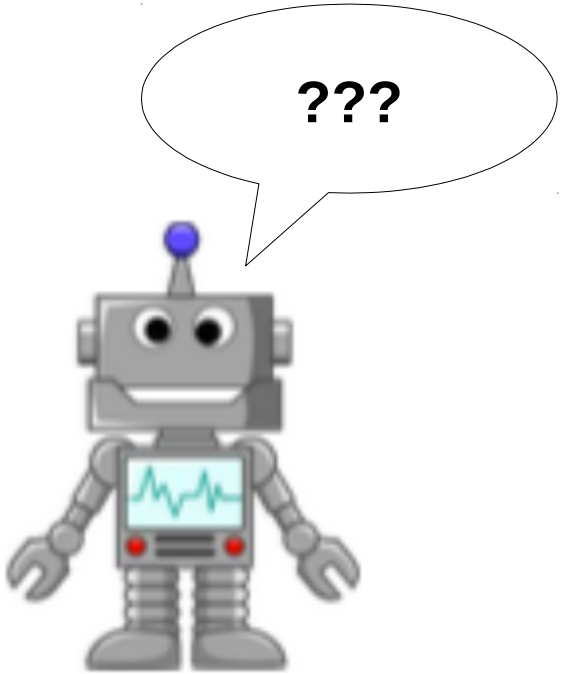
Decide what ?

Actions to fulfill my task

To avoid collisions / risks / breakdown

To cooperate with other robots

…



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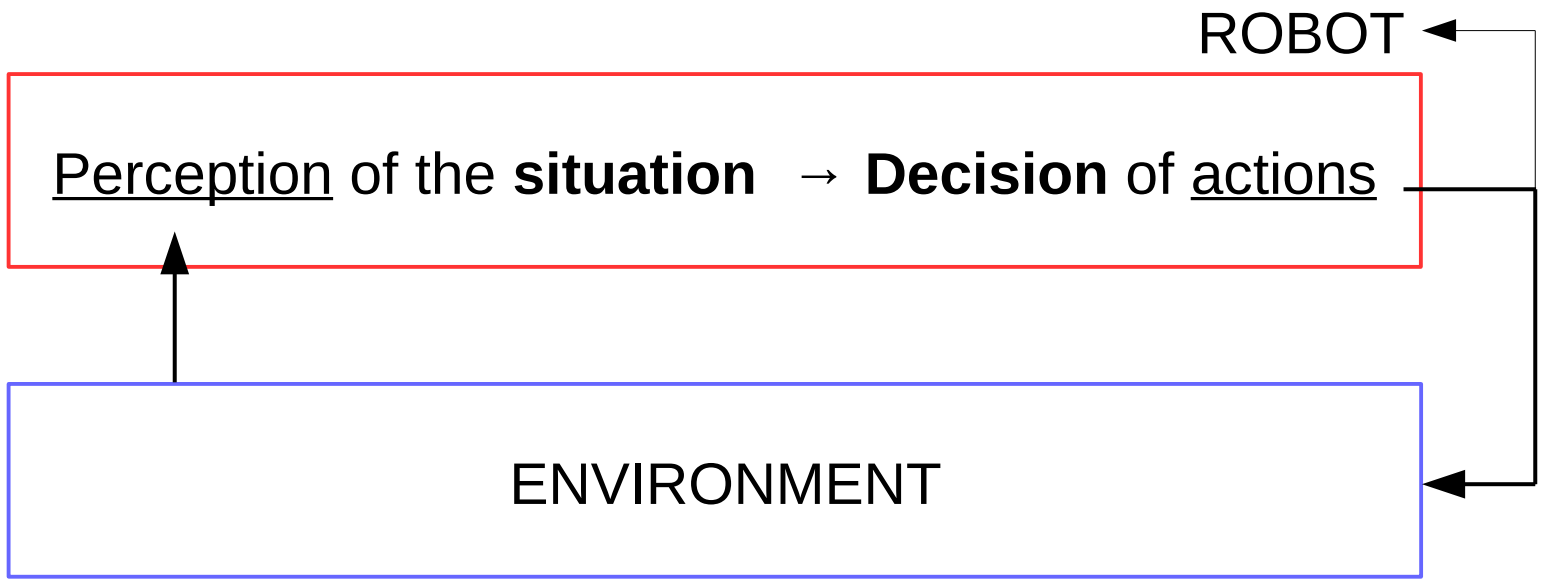
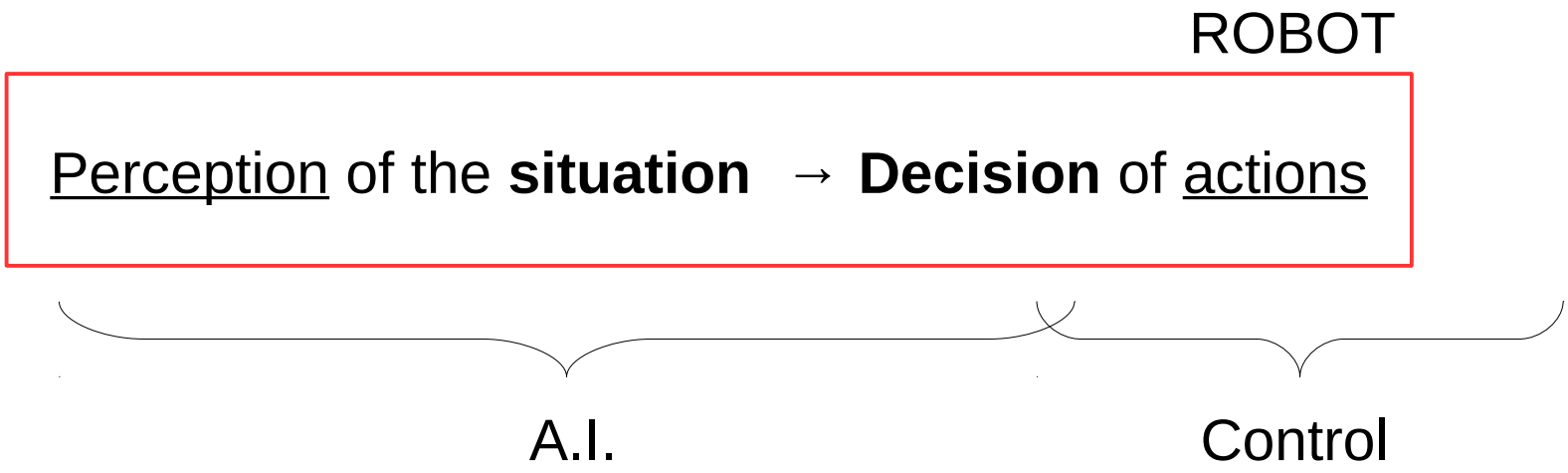
Perception of the **situation** → **Decision** of actions

Loop Perception-Decision-Action



Loop Perception-Decision-Action



Loop Perception-Decision-Action

ROBOT

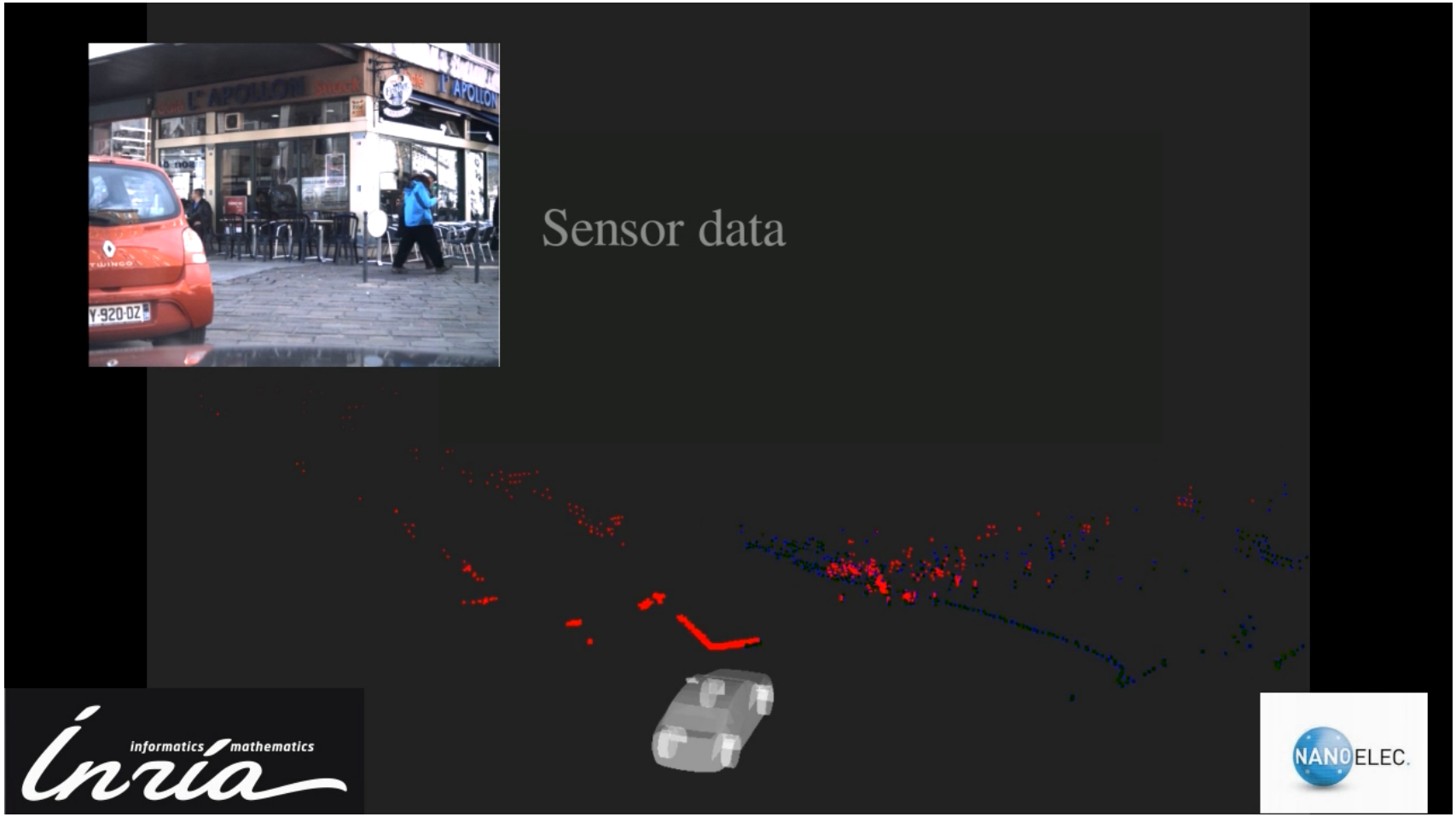
Perception of the **situation** → **Decision** of actions

Modeling the environment

Situation awareness

Predict

Ex.1 Situation awareness with probabilistic grid



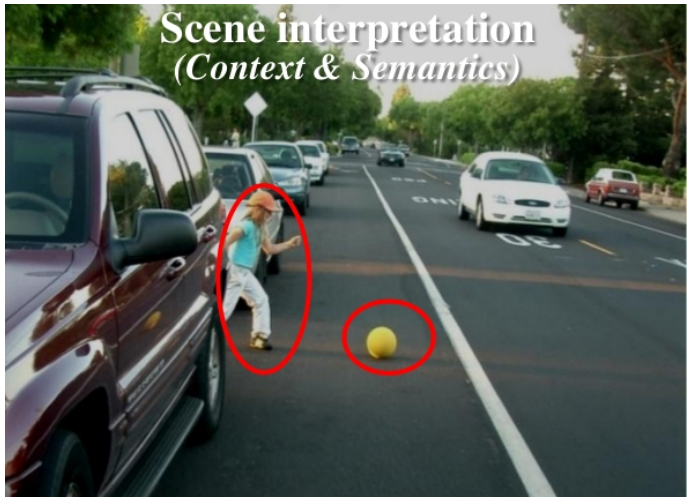
Occupancy grid + veloc. + Bayesian F.

[Laugier et al. 2012-2018]

Ex.1 Situation awareness with probabilistic grid

Bayesian Occupancy Filtering (BOF[1], CMCDOT[2])

- **Occupancy grid**
- **Velocity** distribution / cell
- **Object** identification (cell clustering)
- **Prediction** of motion (bayes. filtering)

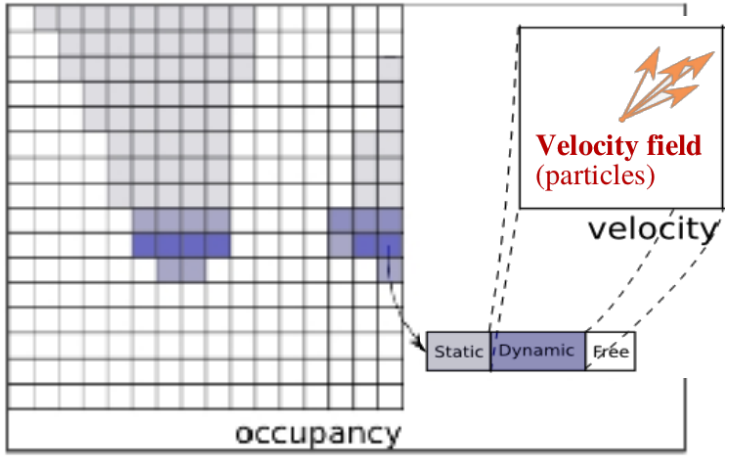


Occupancy grid :

Probability of occupancy in each cell, $P_{occ}(x,y)$

1 : occupied cell (black)
0.5 : unknown (gray)
0 : free cell (white)

e.g. Frequency approach (counting) :
$P_{occ}(x,y) = occ(x,y) / (empty(x,y) + occ(x,y))$



[1] C. Laugier et al., IJRR 2005, [2] Rummelhardt et al. ITS 2015

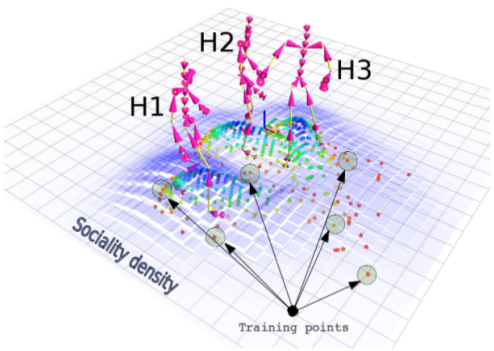
Ex.2 Social navigation : Proxemics approach

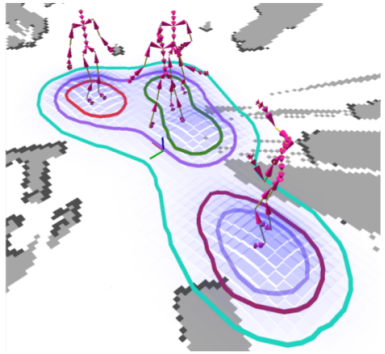
Identify humans and **predict** their motion

Comply with **social rules**

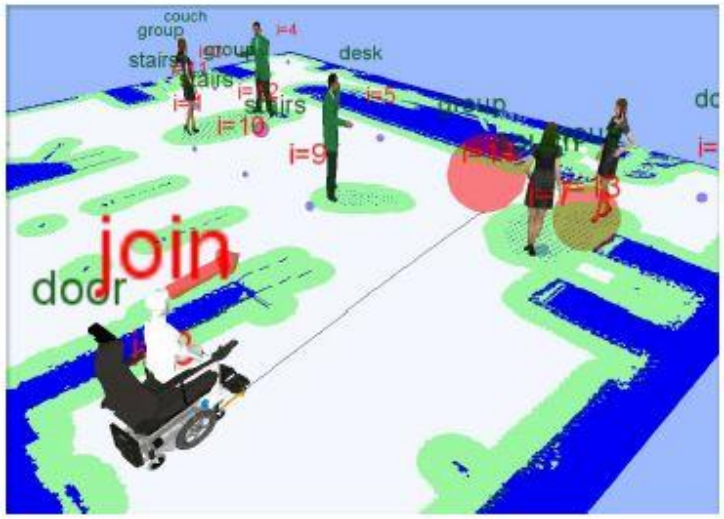
Map human activities

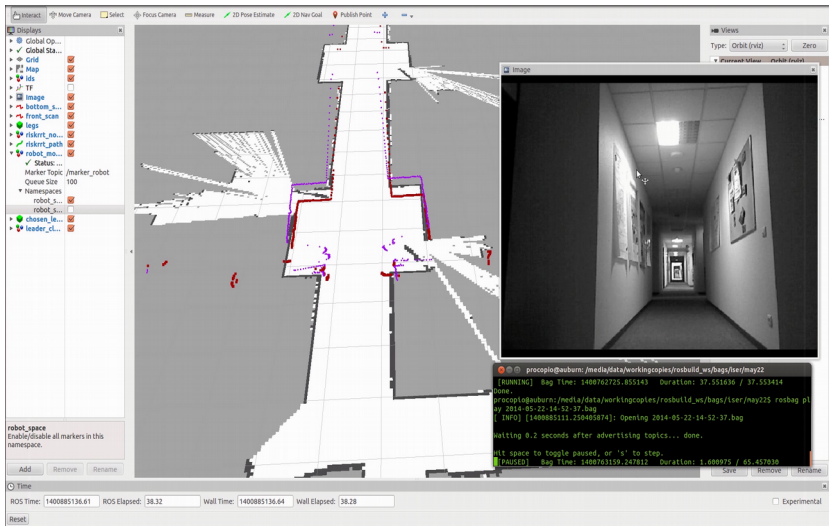
Compute **secure** paths and decisions





Gaussian model of personal area + geometric formation





[Spalanzani et al. 2015-18]

Loop Perception-Decision-Action

ROBOT

Perception of the **situation** → **Decision** of actions

Reacting

Planning / Learning

Reacting vs. Planning vs. Learning

Reacting : compute **one** action (real time)

Planning : compute a **sequence** of actions (eg. motion planning)

Learning : compute a **policy** (state→action)

+

Cooperate/compete : add other agents in the decision

Reacting vs. Planning vs. Learning

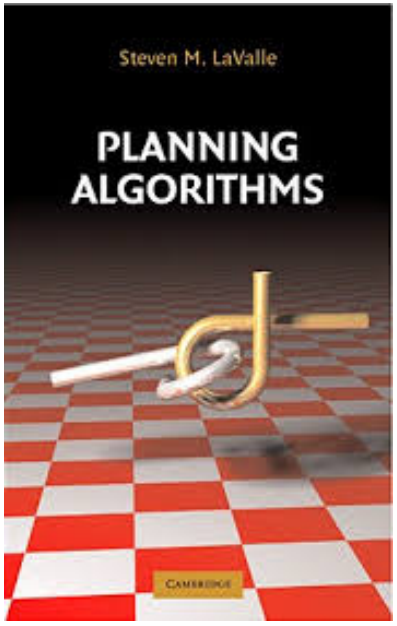
Reacting : Bio-inspired behaviors, Connexionism

Planning : STRIPS, PDDL, SAT, CSP, PRM ..

Learning : Reinforcement L., (PO)MDP, RNN, DeepLearning

+

Cooperate/compete : add other agents in the decision



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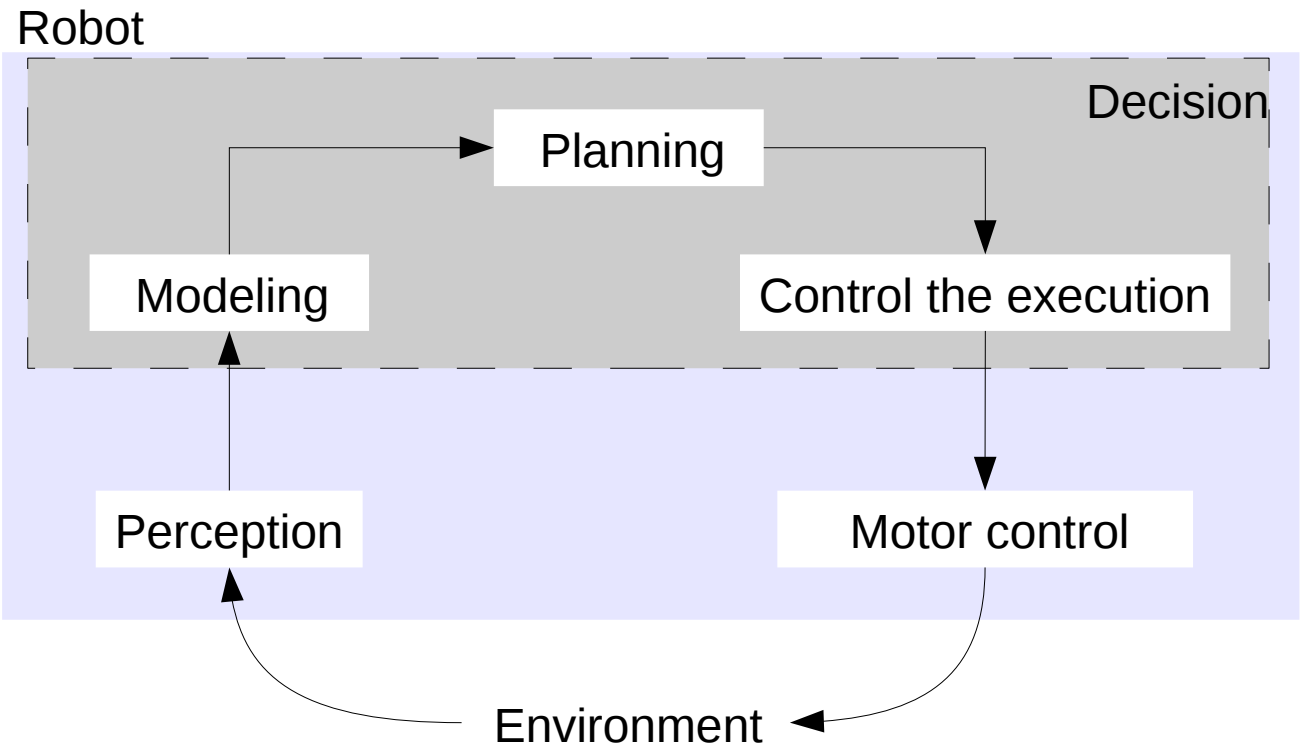
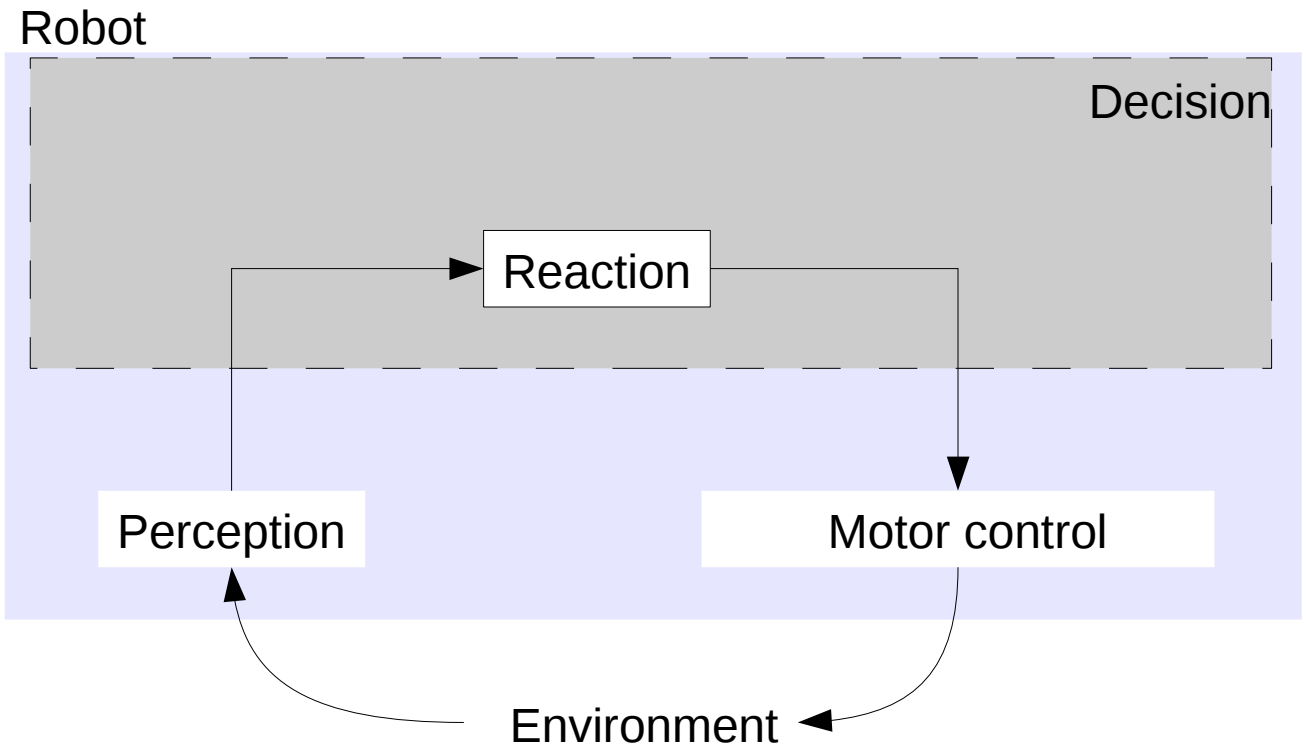
Sense-Plan-Act

[Nilsson80]



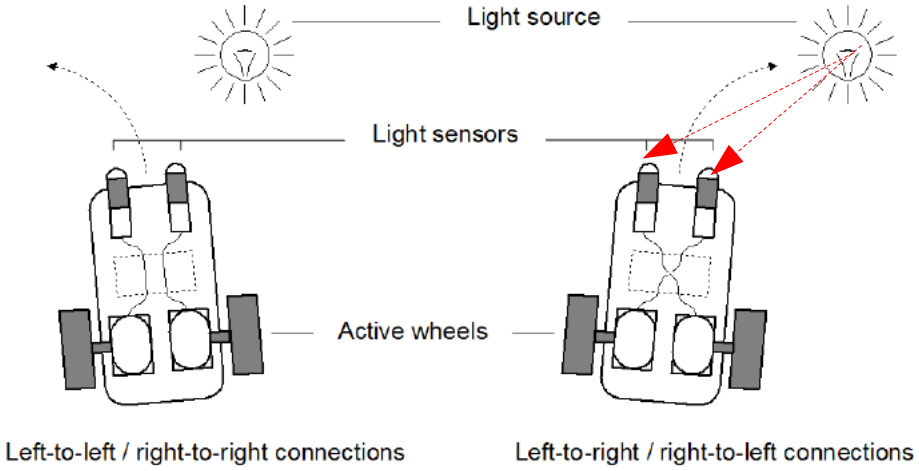
Slow planning → bottleneck !

Reactive architecture

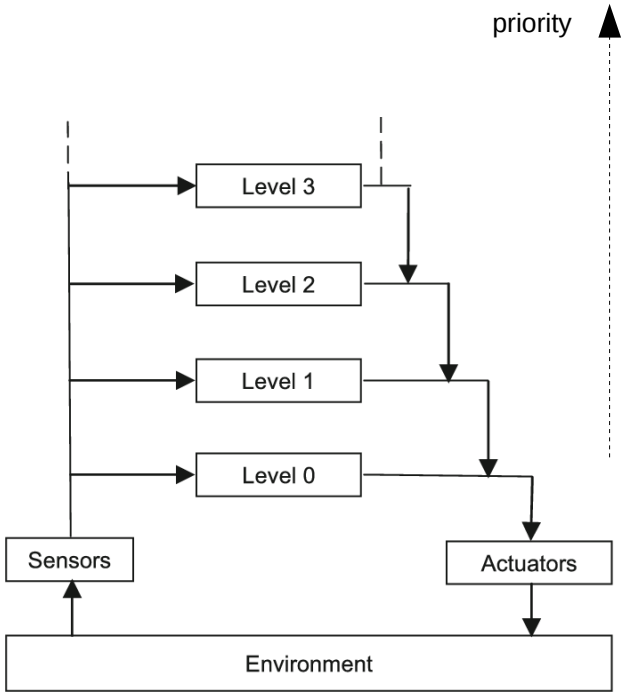


[Brooks 86] [Arkin 98]. Connecting sensors-motors, but **deadlocks** are possible !

Reactive architecture : Braitenberg, Brooks



[Braitenberg 84] Vehicle (phototaxis)



[Brooks 86] Subsumption architecture

Reactive architecture : Braitenberg, Brooks

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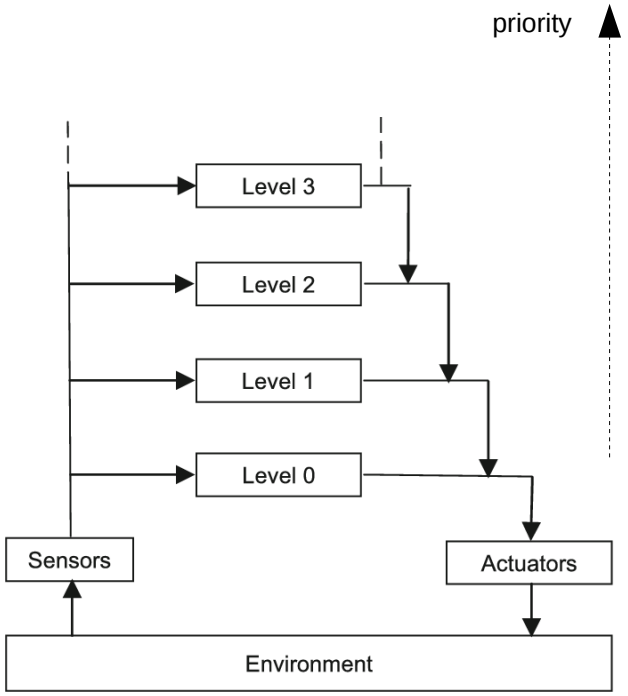
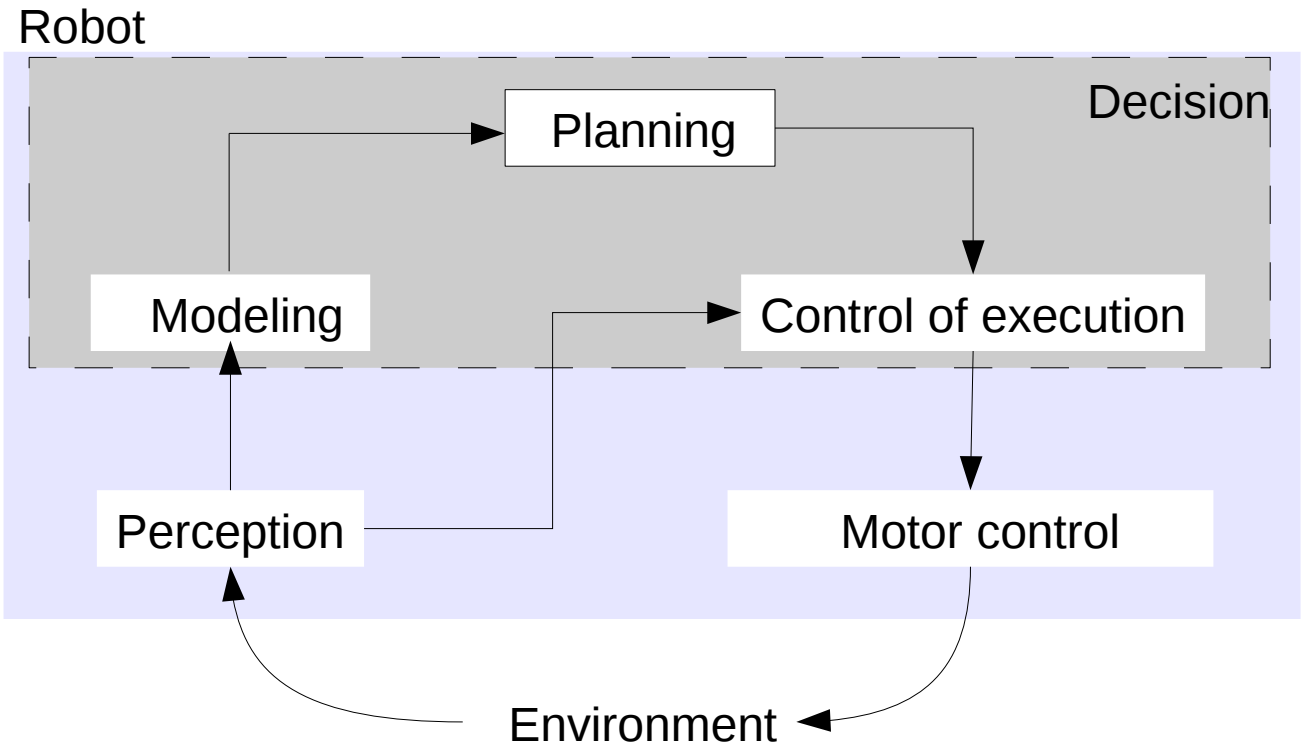


[Brooks 86] Subsumption architecture

Multi-level architecture



Allow to combine fast reaction and planning

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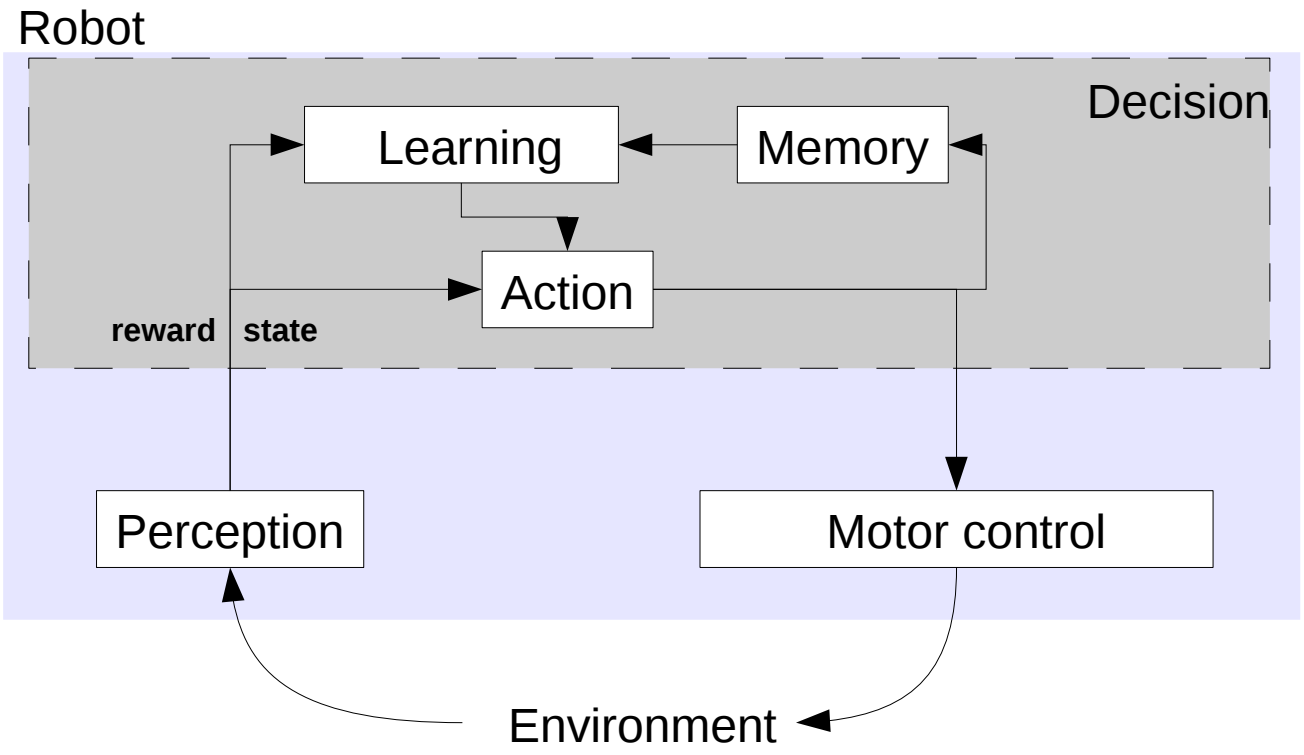
Learning architecture : non explicit knowledge repr.



Neuronal networks, Reinforcement Learning, Markov Decision Process (MDP) ..

Q-Learning [Watkins 89] (Reinforcement Learning)

Compute the quality of an action ***a*** in state ***s*** ($s \in S$, $a \in A$)

$$Q : S \times A \rightarrow \mathbb{R}$$

Each time step ***t*** the agent selects an action $\boldsymbol{a_t}$, observes a reward $\boldsymbol{r_t}$, enters in new state $\boldsymbol{s_{t+1}}$.
Then *Q(s,a) is updated :*

$$Q^{new}(s_t, a_t) \leftarrow (1-\alpha) \cdot \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\left(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}} \right)}^{\text{learned value}}$$

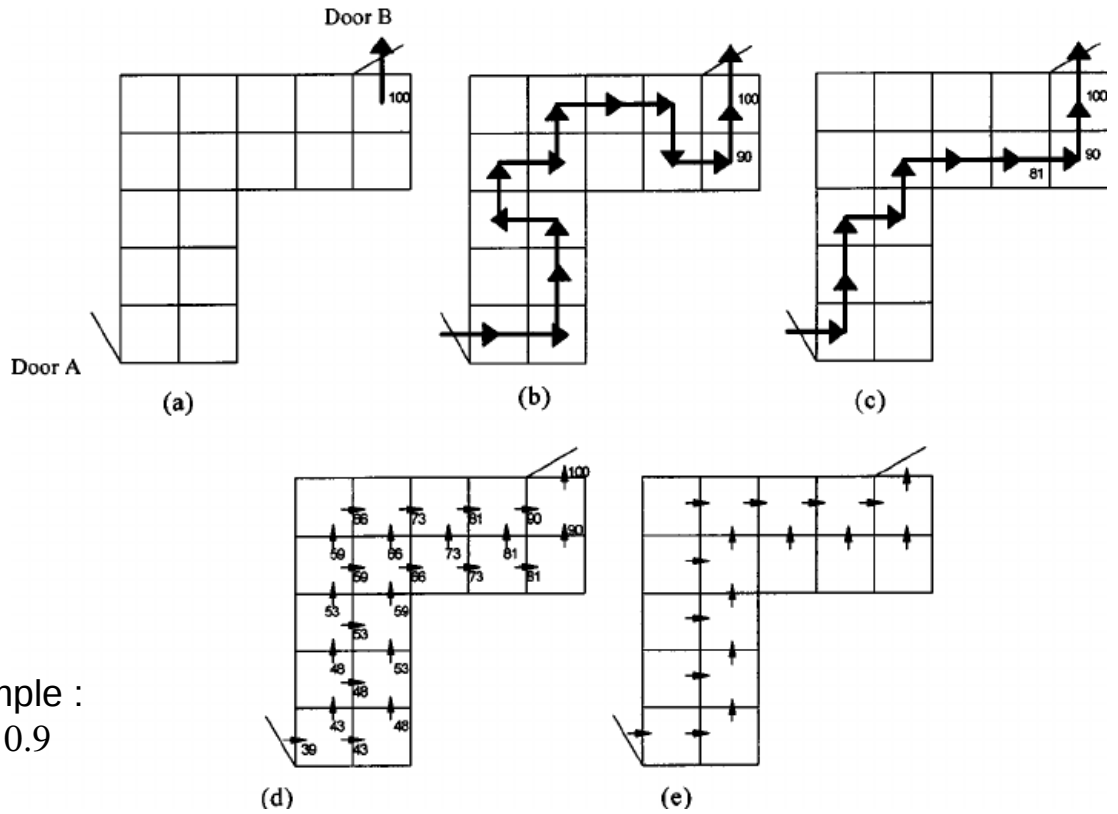
Converge to optimal policy that **maximizes the expected cumulative reward** $\sum_{t=0}^{\infty} \gamma^t r_t$
(proof [Watkins, Dayan 92])

Q-Learning [Watkins 89] (Reinforcement Learning)

$$Q^{new}(s_t, a_t) \leftarrow (1-\alpha) \cdot \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\left(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}} \right)}^{\text{learned value}}$$

The agent must explore/experiment the environment

→ exploration/exploitation dilemma



Grid example :
$\alpha = 1 \quad \gamma = 0.9$

Modeling uncertainty : Markov Decision Process

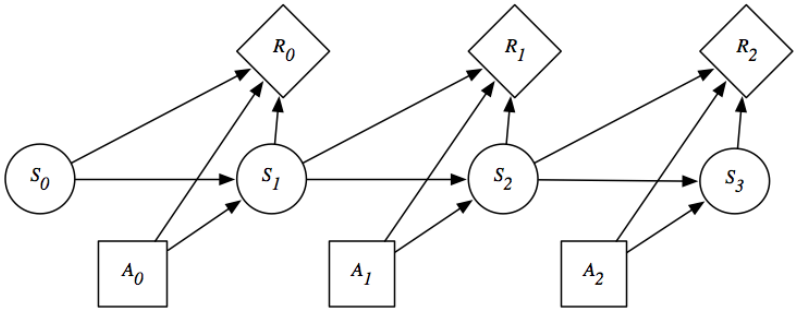
MDP : 4-tuple (S, A, P_a, R_a)

Actions' result is uncertain : that is true in robotics !

Exploit a model of the environment/system dynamics :

The probability that action ***a*** , in state ***s*** at time ***t*** will lead to state **s'** at time **t+1** is
$\boldsymbol{P_a}(s,s') = \Pr(s_{t+1} = s' \mid s_t = s, a_t = a)$

Each action ***a*** , from state ***s*** to state **s'** gives an immediate reward $\boldsymbol{R_a}(s,s') \in \Re$



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Problem : finding a **policy π** that maximizes a cumulative function of the random rewards

$$\sum_{t=0}^{\infty} \gamma^t R_{a_t}(s_t, s_{t+1})$$

$a_t = \pi(s_t)$

→ **Reinforcement Learning**

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Several solutions :
- Value iteration [Bellman 57]
- Policy iteration [Howard 60]
- ..

$$\pi(s) := \arg\max_a \left\{ \sum_{s'} P(s'|s,a) \left(R(s'|s,a) + \gamma V(s')\right) \right\}$$

$$V(s) := \sum_{s'} P_{\pi(s)}(s,s') \left(R_{\pi(s)}(s,s') + \gamma V(s')\right)$$

Computation can be very expensive..

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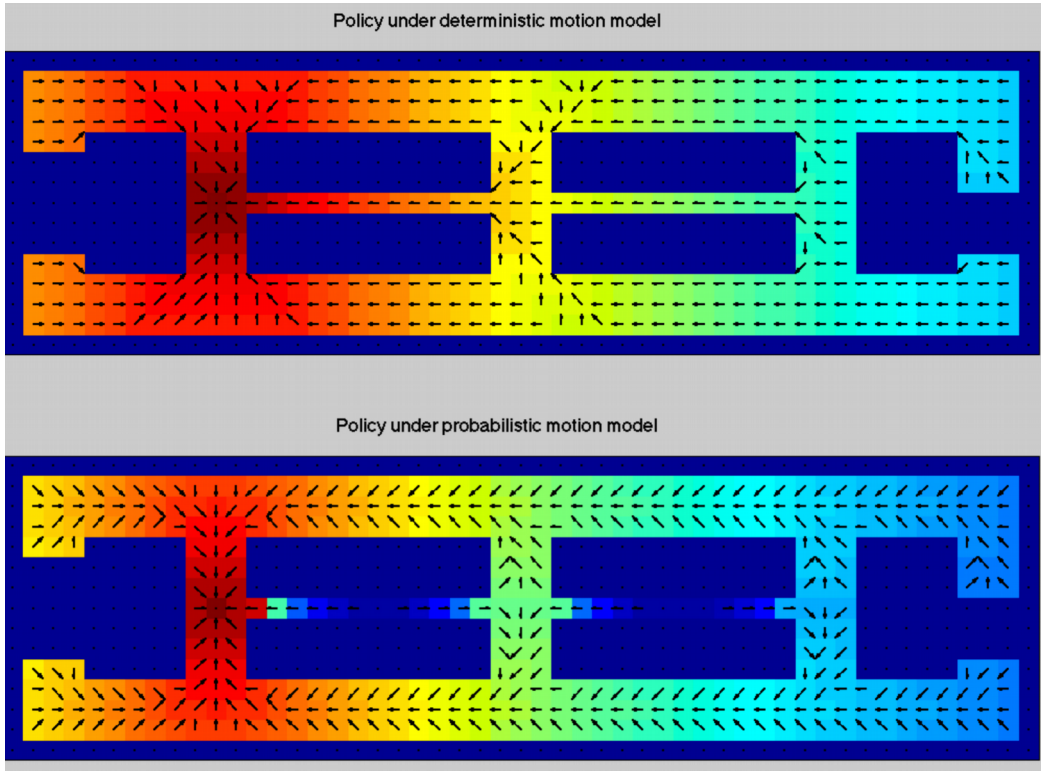

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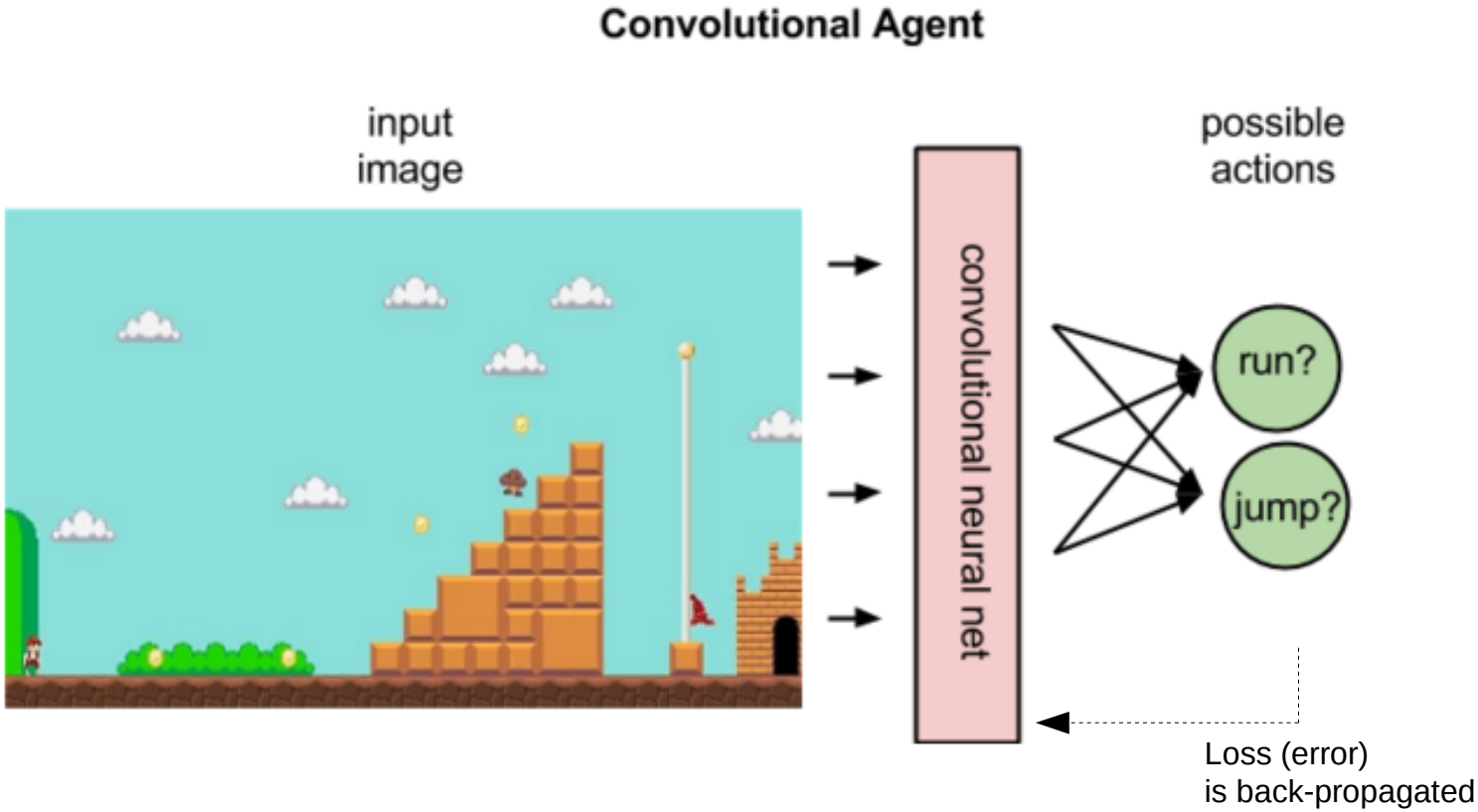
Milind Tambe team USC, CAIS

Good introduction :
Reinforcement Learning: a Survey
L. P. Kaelbling, M. L. Littman, W. Moore
1996.

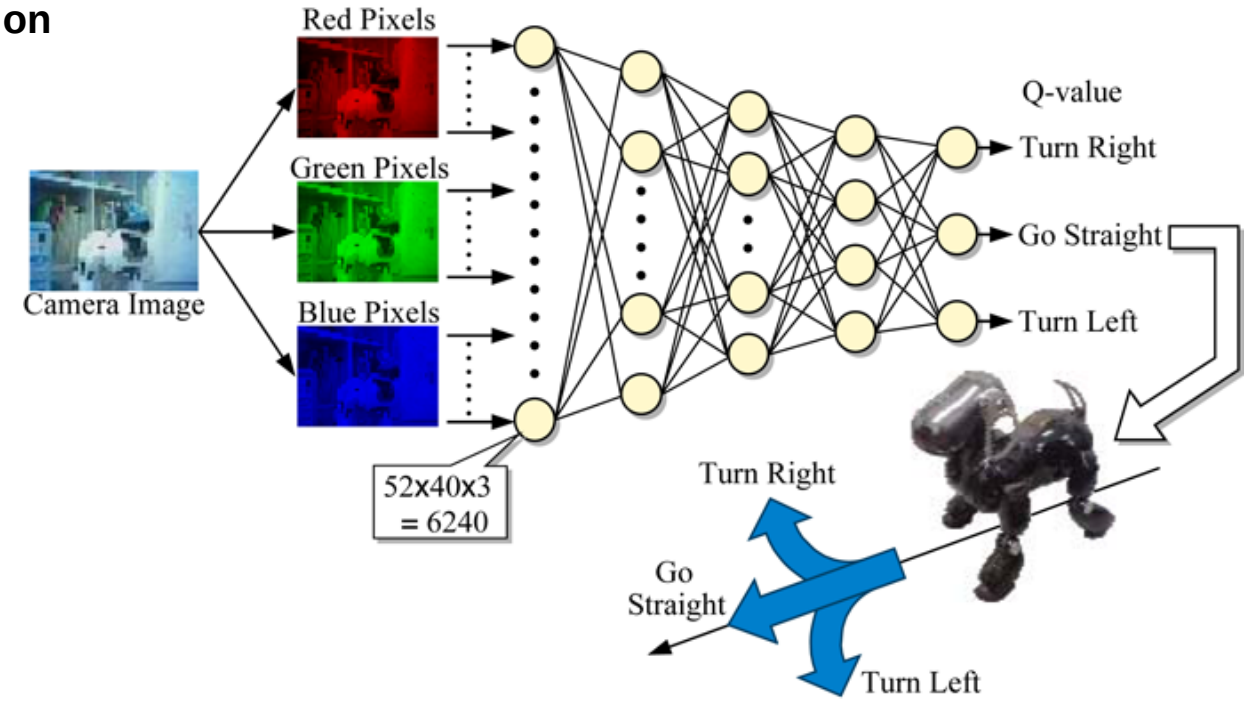
End to End Deep Learning

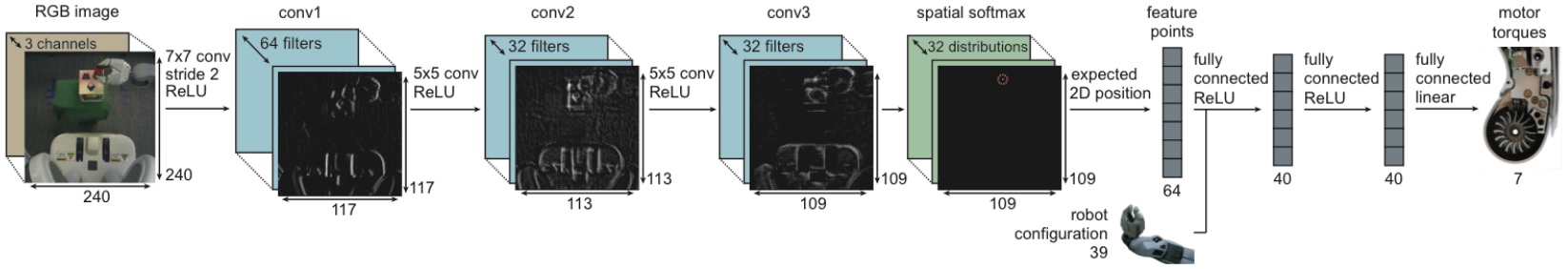
n processes → 1 single Neural Network



End to End Deep Learning

CNN allows generalization





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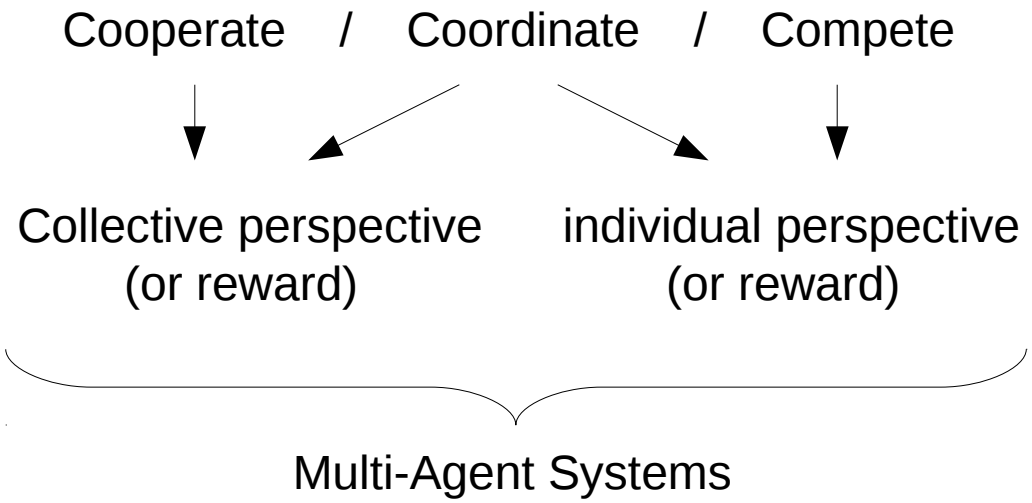
Multi-Agent Systems (MAS)



Autonomous agents that interact in a common environment in order to fulfill collective and/or individual objectives

J. Ferber, Multi-Agent Systems, Addison Wesley, London, 1999

Multi-robot missions

EXPLORATION

Mapping (eg. SLAM)

Search, Coverage, Patrolling

Tracking, Active perc.

OBSERVATION

TRANSPORT

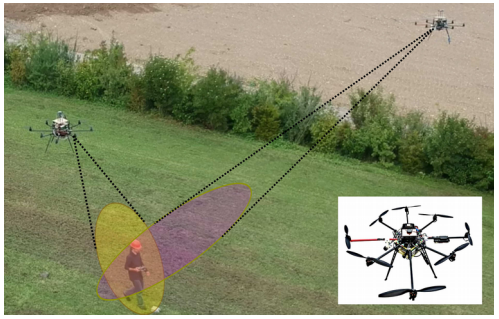
Collective Trans.
(eg. box pushing)

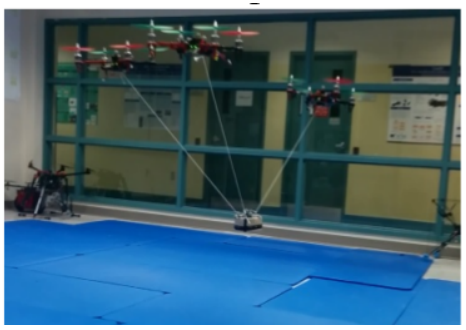
Traffic regulation

Autonomous fleet navig.

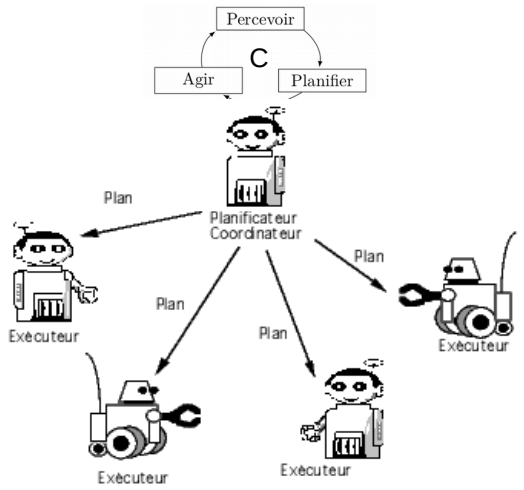
Connectivity

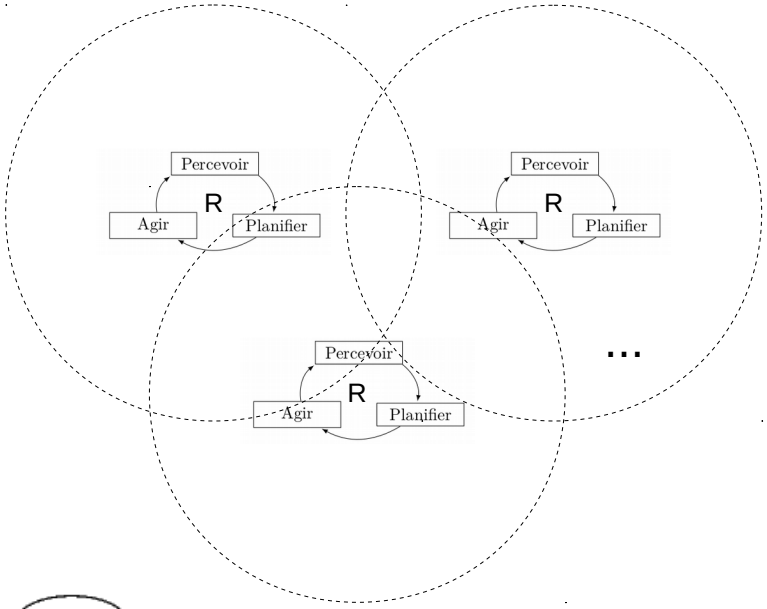
FORMATION MAINT.

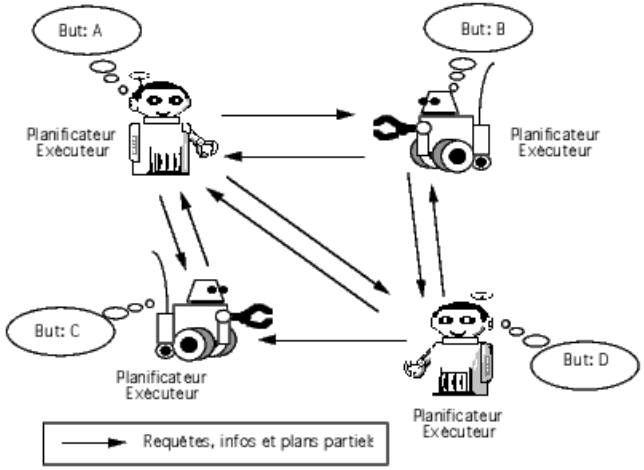




Centralized, Decentralized and Distributed systems

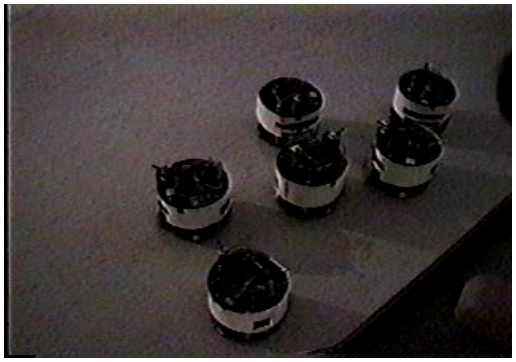




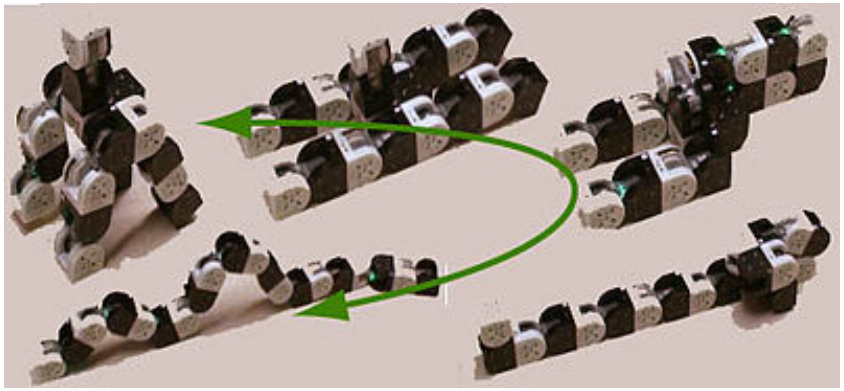


J. Ferber, Multi-Agent Systems, Addison Wesley, London, 1999

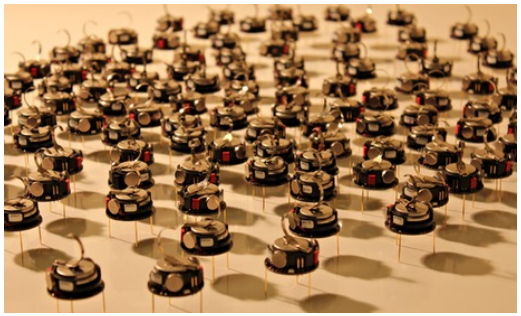
Decentralized : collective navigation and self-config.



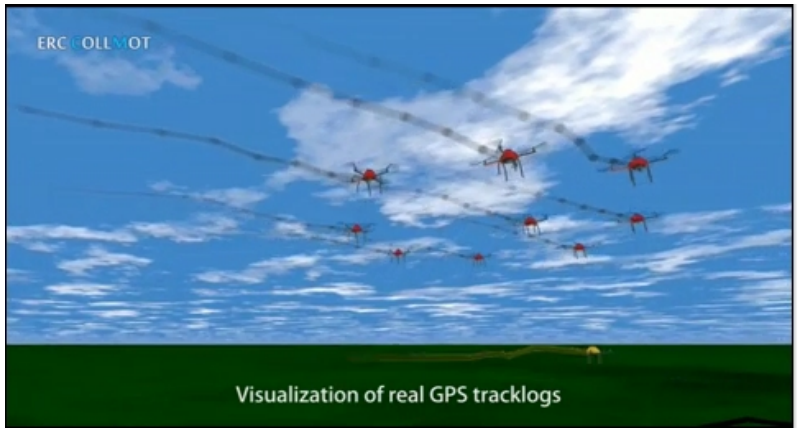
Box-pushing 1988



Self-configurable robots (M-TRAN III) 2005



Kilobots (2011)

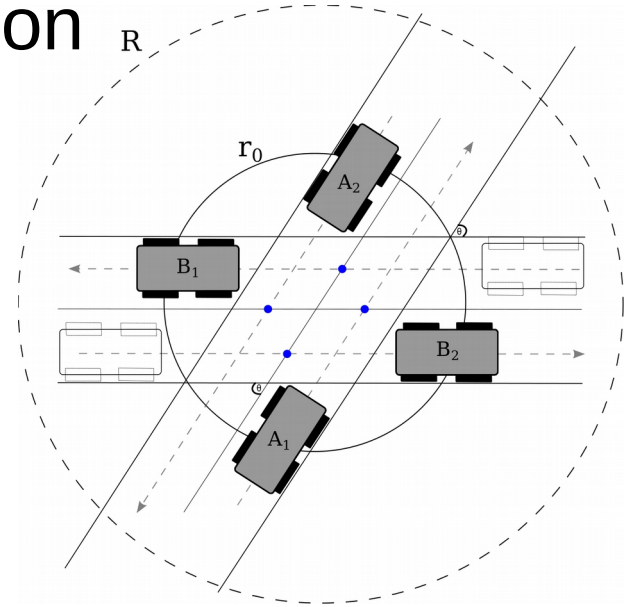


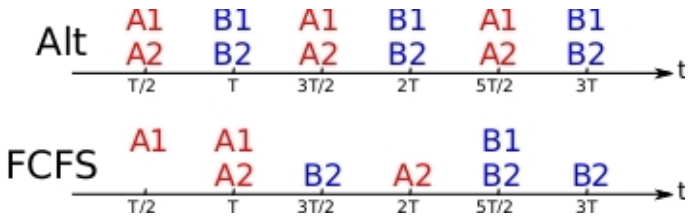
CollMot project (UAV **flocking**) Pennsylvania 2012

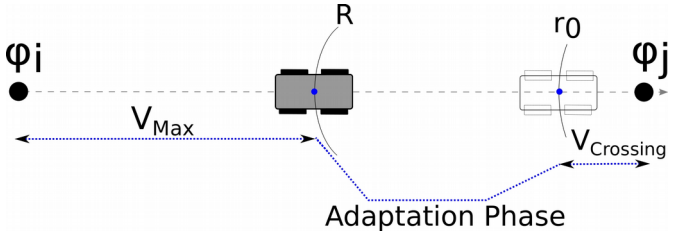
Local coordination at intersection

Non stop strategies

- First Come First Serve (**FCFS**)
  [Dresner Stone, 2005]
- **Alt**ernate [Tlig PhD, 2015]







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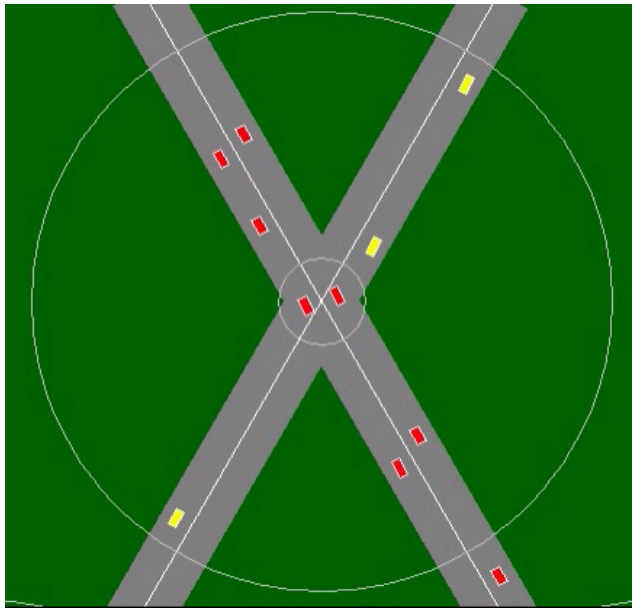
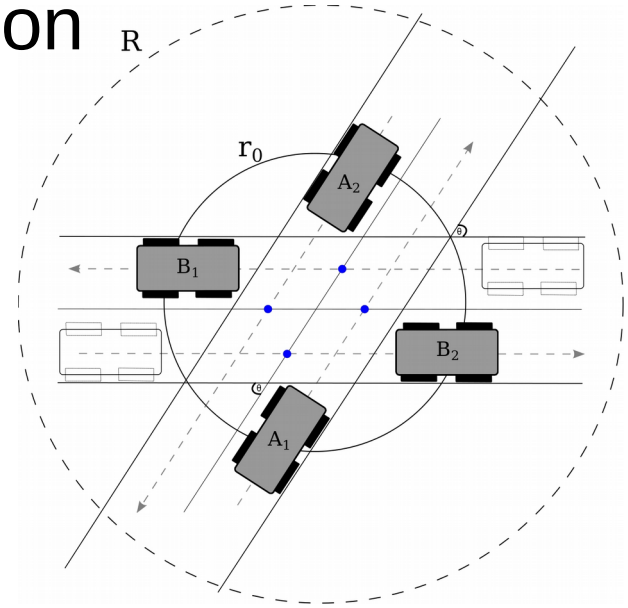
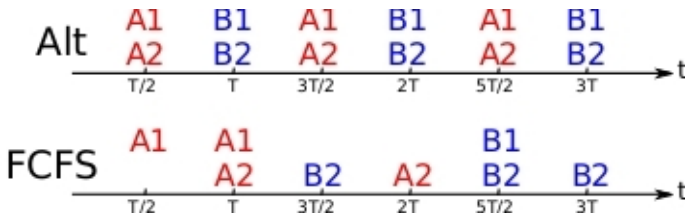
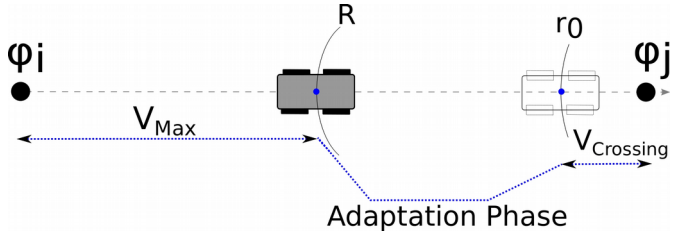


Tlig, Buffet, Simonin, ECAI 2014







Local coordination at intersection

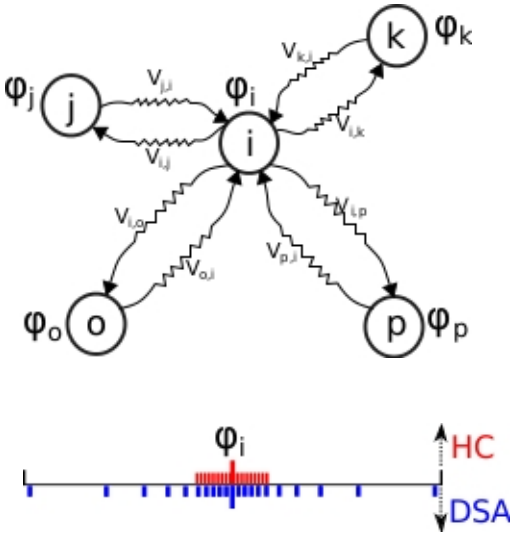
Cooperation between intersections

Decentralized (global) optimization → emergence of **green waves**

parameters : temporal phases φ_i

Optimizing time / energy → **online adaptation** to traffic changes

Hill Climbing, ρ-DSA



INRIA INVENTEURS DU MONDE NUMÉRIQUE — INSA INSTITUT NATIONAL DES SCIENCES APPLIQUÉES LYON

Outline

I. Decision making ?

II. Classical architectures

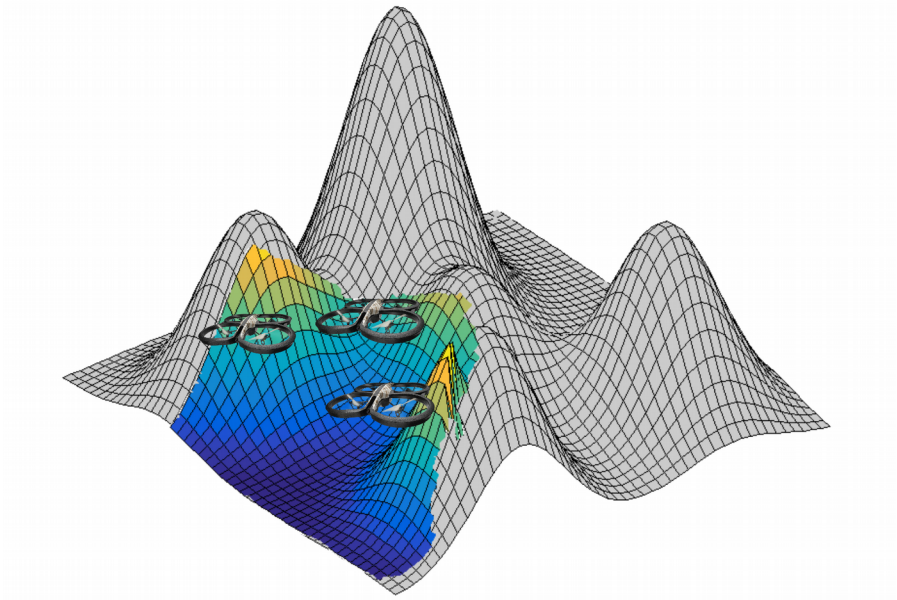
III. Learning based architectures

IV. Decision in multi-robot systems

V. Strategies for multi-robot exploration

3D Mapping with a fleet of drones

A. Renzaglia, J. Dibangoye, O. Simonin

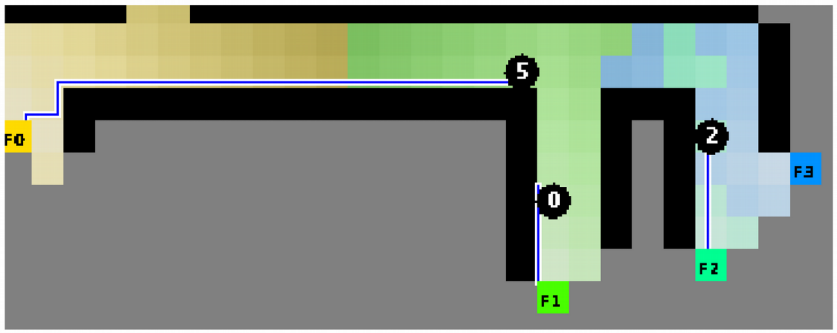


Strategy of exploration: approaches and limits

Mapping relies on visiting frontiers (known-unknown areas)

→ Repeat assignation robot-frontier : **min $\Sigma_{(i,j)}$ cost-Dist(r_i,f_j)**

[Yamauchi98] (mindist), [Burgard05] (greedy), [Bautin12] (minpos) ..



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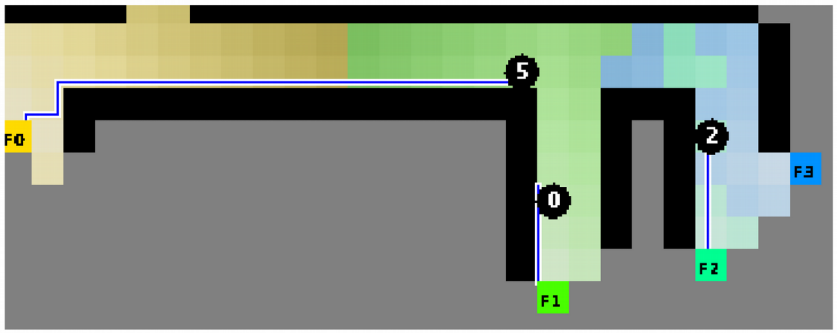
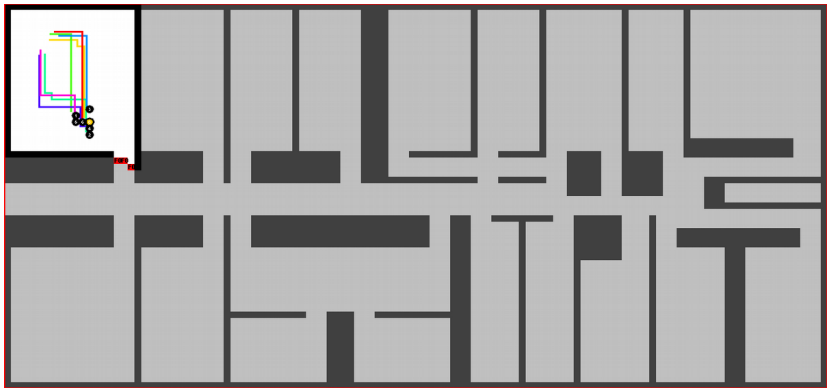
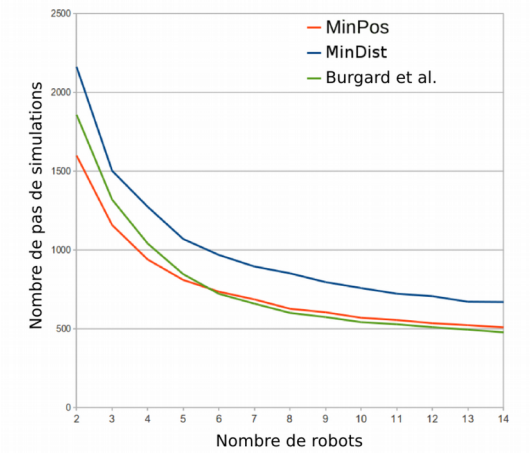
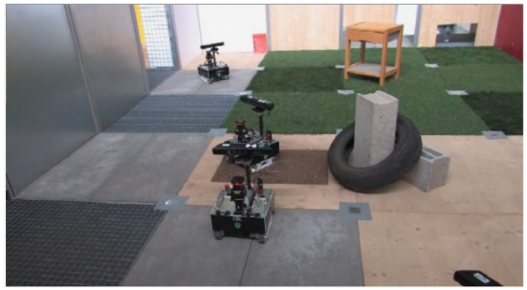




Multi-robot exploration : MinPos
[Bautin, Simonin, Charpillet, 2012], ANR Cartomatic





3D mapping : exploit optimal coverage

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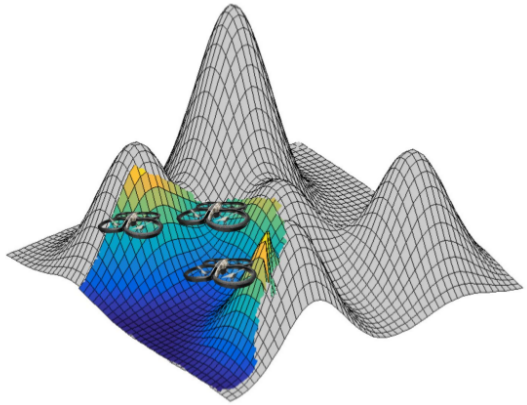
Sub-problem: **optimal coverage**

→ deploying robots such as **maximizing the observed area**



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Sub-problem: **optimal coverage**

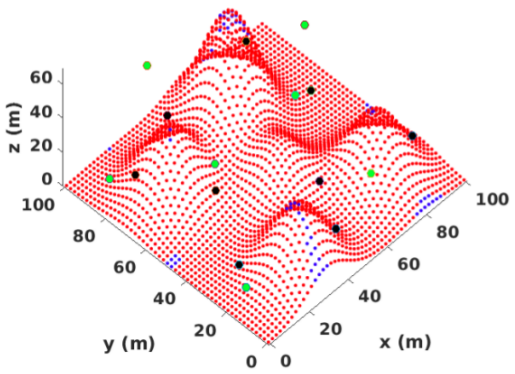
→ deploying robots such as **maximizing the observed area**

CAO (Cognitive-based Adaptive Optimization) [Renzaglia et al. 12]

Local approx. of the **objective** function : $\hat{J}(x_1(t), .. x_N(t))$ ← **measures** (short T)

Move : **Stochastic search** on $\hat{J}$

→ converge to a local optimum



Combining local search and frontier-based app.

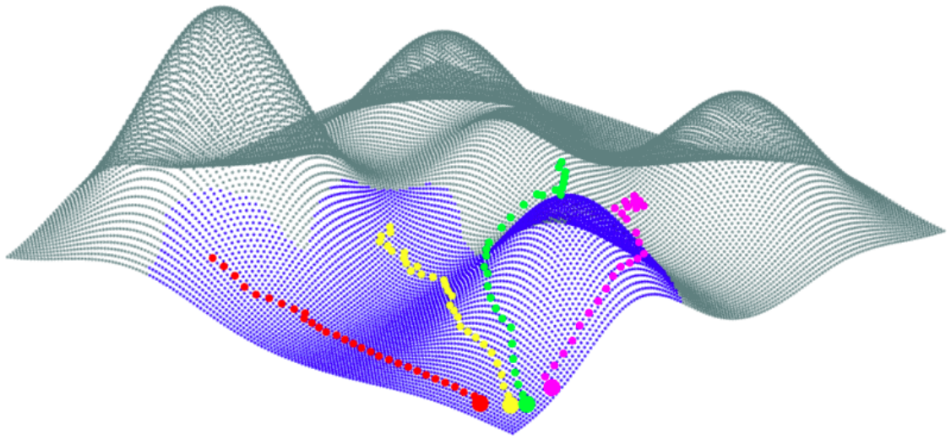
For each robot

Repeat

Follow local search

When a local minima is reached **Move** to the closest frontier

Until no more frontier



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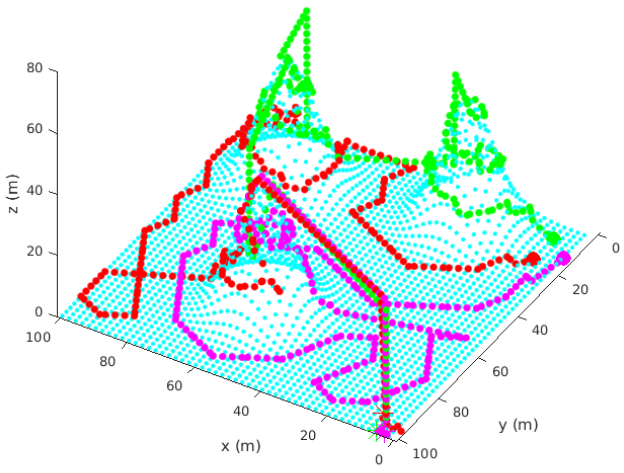
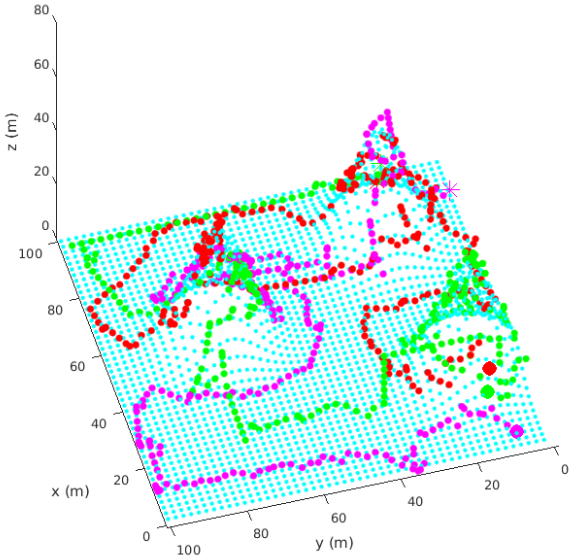


Only frontiers



Local search + frontiers

Combining local search and frontier-based app.

For each robot

Repeat

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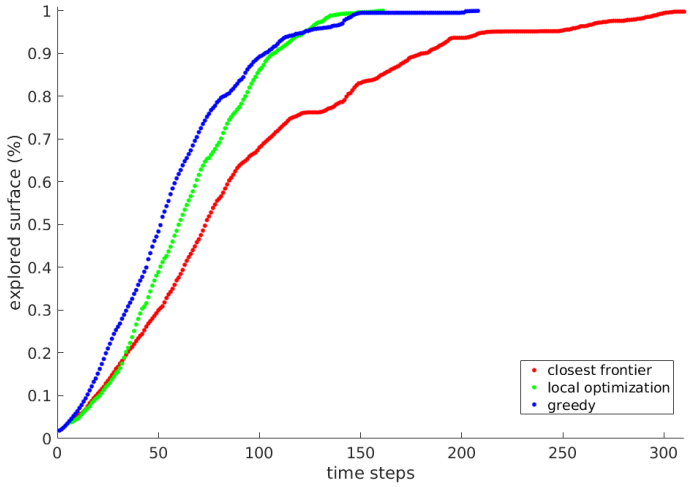

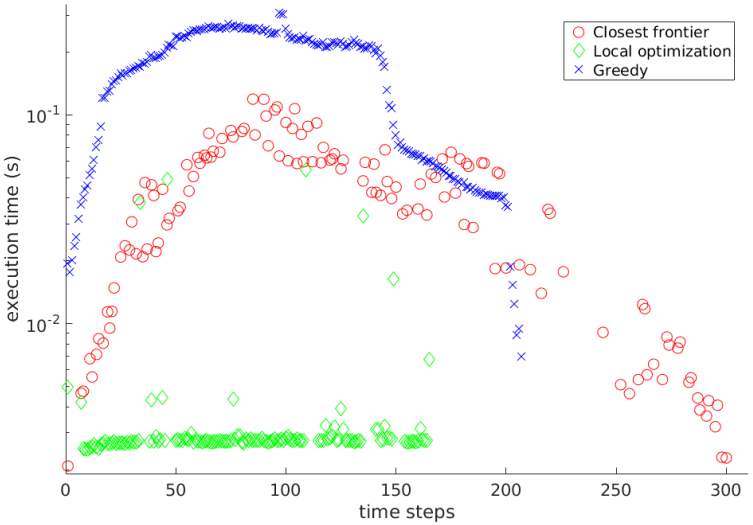

Thank you !

https://team.inria.fr/chroma/