Developmental learning in non-markovian processes:
Premises of a new biologically plausible cognitive architecture

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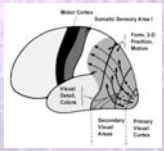
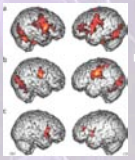
Cognitive architecture

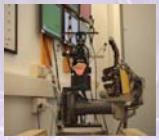
Physiological pathway hypothesis

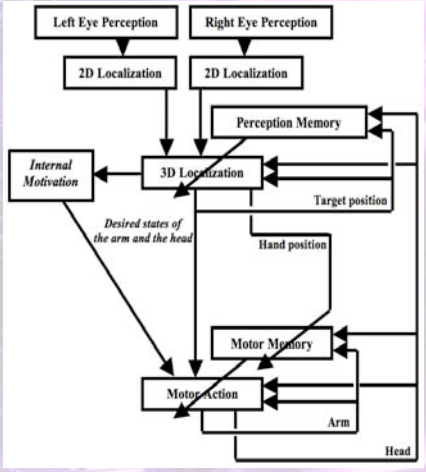


Mirror Neurons



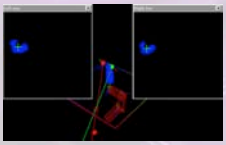
Embodiment



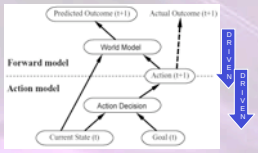


Interactive Activation Model

Triangulation



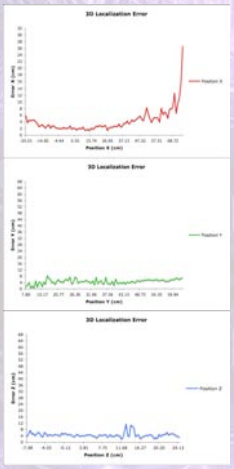
Forward Model



Experiments & Results

Exp 1: Localization

- Low levels performs color detection in each eye,
- Intermediate levels operates blob localization in each eye,
- Higher level achieves triangulation and retrieves the hand position in the Cartesian space

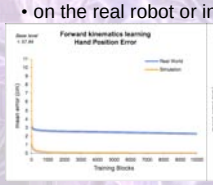


EXPERIMENT 1	3D Localization	
	// Error	
	X (cm)	3.49
	Y (cm)	5.22
	Z (cm)	4.21
	Mean (cm)	4.30
	Standard deviation	3.37

Experiments & Results

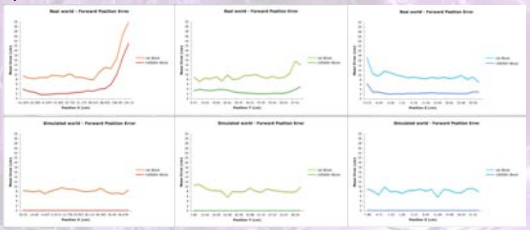
Exp 2: Learning of forward kinematics

- on the real robot or in simulation

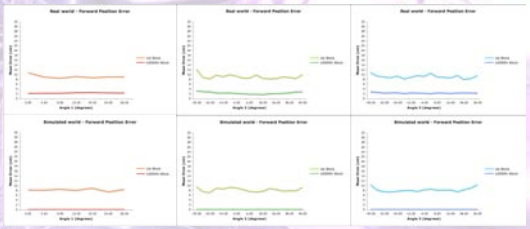


EXPERIMENT 2a	Forward Real World	
	// Error	10000th loop
	X (cm)	2.29
	Y (cm)	2.68
	Z (cm)	2.04
	Mean (cm)	2.33
	Standard deviation	2.15
	Forward Simulation	
	// Error	10000th loop
	X (cm)	0.07
	Y (cm)	0.02
	Z (cm)	0.06
	Mean (cm)	0.05
	Standard deviation	0.05

- Hand position's prediction error along the Cartesian/Visual space either on the real robot or in simulation



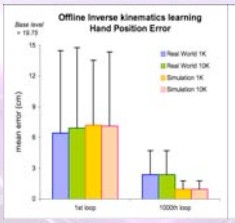
- Hand position's prediction error along the Geometrical/Motor space either on the real robot or in simulation

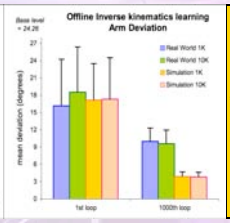


=> Preference for the motor space, which is more reliable

Exp 2b: Offline Learning of Inverse kinematics

- on the real robot or in simulation
- with a *good* (1K) or a *perfect* (10K) model of forward kinematics



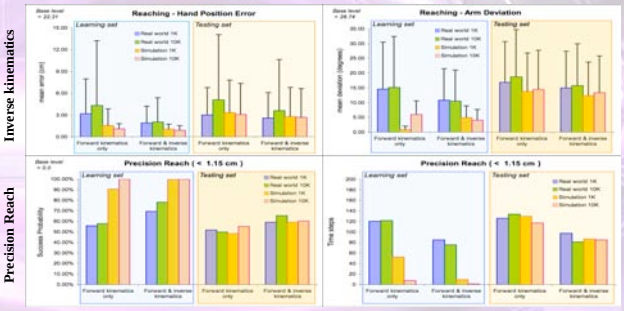


EXPERIMENT 2b	Offline Inverse Real World 1K	
	// Error	1000th loop
	X (cm)	2.48
	Y (cm)	2.31
	Z (cm)	2.36
	Mean (cm)	2.38
	Standard deviation	2.32
	Offline Inverse Real World 10K	
	// Error	1000th loop
	X (cm)	2.27
	Y (cm)	2.43
	Z (cm)	2.43
	Mean (cm)	2.37
	Standard deviation	2.34
	Offline Inverse Simulation 1K	
	// Error	1000th loop
	X (cm)	1.18
	Y (cm)	0.74
	Z (cm)	0.91
	Mean (cm)	0.94
	Standard deviation	0.89
	Offline Inverse Simulation 10K	
	// Error	1000th loop
	X (cm)	1.13
	Y (cm)	0.80
	Z (cm)	0.94
	Mean (cm)	0.96
	Standard deviation	0.79

=> Approximate knowledge of forward kinematics is sufficient

Exp 3 and 4: Online Learning of Inverse kinematics

- on the real robot or in simulation
- with a *good* (1K) or a *perfect* (10K) model of forward kinematics
- with the learning set and a new testing set
- with naive or already learned inverse kinematics



=> Better performances when inverse kinematics are previously learned

=> Loss of the simulation's advantage in real world testing

Discussion

- No effect of world's type (simulated or real) is retrieved in the overall performances in real world
- An approximate knowledge of forward kinematics allows the same level of performance as if knowledge was perfect
- Best performances are achieved thanks to a combination of offline and online learning phases of forward and inverse kinematics, independently of other conditions.

	Perception	Action	Reaching (cm)	Success probability	Time steps
Real 1K	4.39	1.00	5.45	59.09%	97.86
Real 10K	4.39	1.03	5.43	65.30%	81.20
Simu 1K	4.39	0.97	5.36	59.09%	86.22
Simu 10K	4.39	0.95	5.34	60.29%	84.62

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