

PROBABILISTIC MODELS OF SENSORY-MOTOR SYSTEMS


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BAYESIAN-PROGRAMMING.ORG

PLAYING CHESS

WHO IS THE CLEVEREST?



Garry Kasparov
The best player in the world shows no signs of slowing down



Deep Blue
This 1.4 ton 8-year-old sure plays a mean game of chess

PLAYING WITH CHESS

WHO IS THE CLEVEREST?



BARON WOLFGANG VON KEMPELEN (1769)

AMOEBEBA

HOW TO USE AN **INCOMPLETE** AND **UNCERTAIN**
MODEL OF THE ENVIRONMENT
TO PERCEIVE, INFER, DECIDE AND ACT
EFFICIENTLY ENOUGH TO SURVIVE ?



OVERVIEW

- HOW TO SURVIVE (PERCEIVE, REASON, LEARN, DECIDE AND ACT) WITH INCOMPLETE INFORMATION ?
- PROBABILITY AS AN ALTERNATIVE TO LOGIC
 - HOW TO DEVELOP BETTER ARTIFACTS USING BAYESIAN REASONING?
 - BIOLOGICAL PLAUSIBILITY OF BAYESIAN REASONING AT A MACROSCOPIC LEVEL?
 - BIOLOGICAL PLAUSIBILITY OF BAYESIAN REASONING AT A MICROSCOPIC LEVEL?

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PROBABILITY AS ALTERNATIVE TO LOGIC

INCOMPLETENESS

PRELIMINARY KNOWLEDGE
+
EXPERIMENTAL DATA
=
PROBABILISTIC REPRESENTATION

LEARNING
ENTROPY PRINCIPLES

↓

UNCERTAINTY

$$P(a) + P(\neg a) = 1$$

BAYESIAN INFERENCE

$$P(a \wedge b) = P(a) \times P(b|a) \\ = P(b) \times P(a|b)$$

↓

DECISION

BAYESIAN PROGRAMMING & PROBT®

BAYESIAN PROGRAM

DESCRIPTION

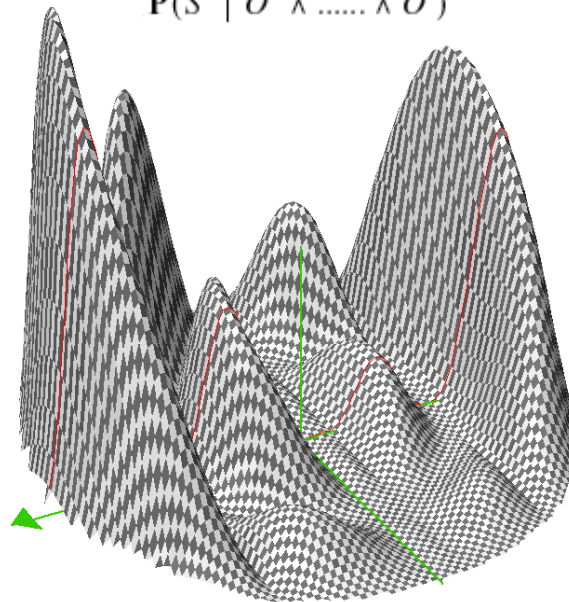
QUESTION

```

main ()
{
//SPECIFICATION
plFloat read_time;
plIntec
plFloat
//Par
• DECOM
plProbv
P(S^0
//Const
plProbv
• PARAM
//Const
plKerne
plValue
t_and_i
Pt_id.p
t_and_i
IDENTIFIC
Pt_id.p
• LEARN
//Par
// P(ti
plJoint
P(S^t | O^0 ^ ..... ^ O^t), time);
pridkernel Pid_t;
jd.ask(Pid_t,id,time);
//Read a time from the key board
cout<<"P(id,time)= " << Pid << "\n";
cout<<"Time? : ";
cin>>read_time;
//Castig P(id,time) a read time
plkernel Pid_readTime,

```

$$P(S^t | O^0 \wedge \dots \wedge O^t)$$



$$S^i | S^{i-1} \times P(O^i | S^i)$$

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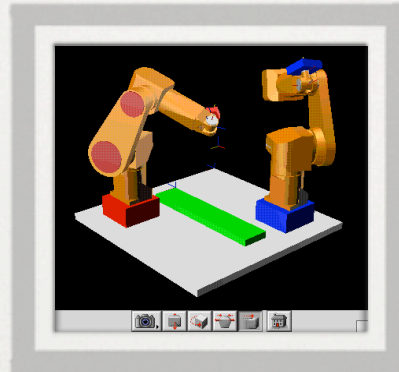
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ROBOTICS



PhD Olivier Lebeltel



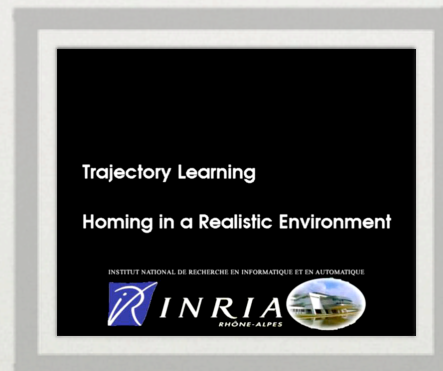
PhD Kamel Mekhnacha



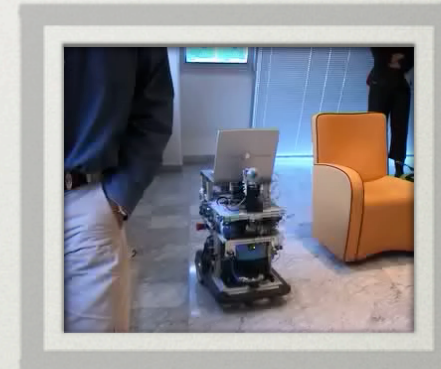
PhD Ruben Garcia



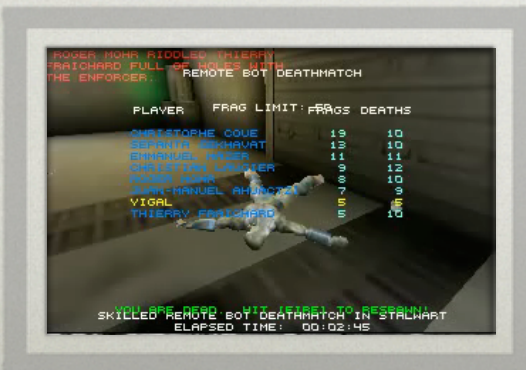
PhD Christophe Coué



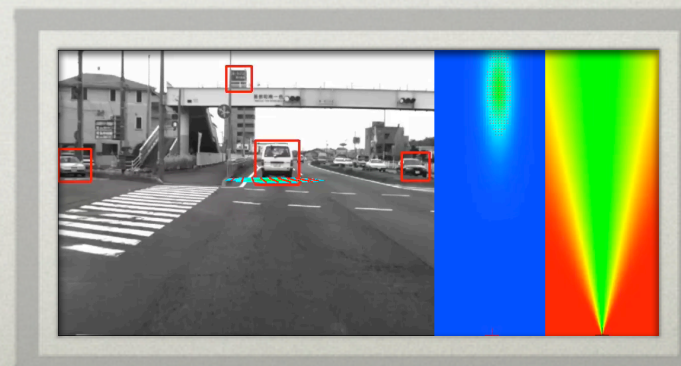
PhD Cédric Pradalier



PhD Carla Koike



PhD Ronan Le Hy



ProBAYES

OVERVIEW

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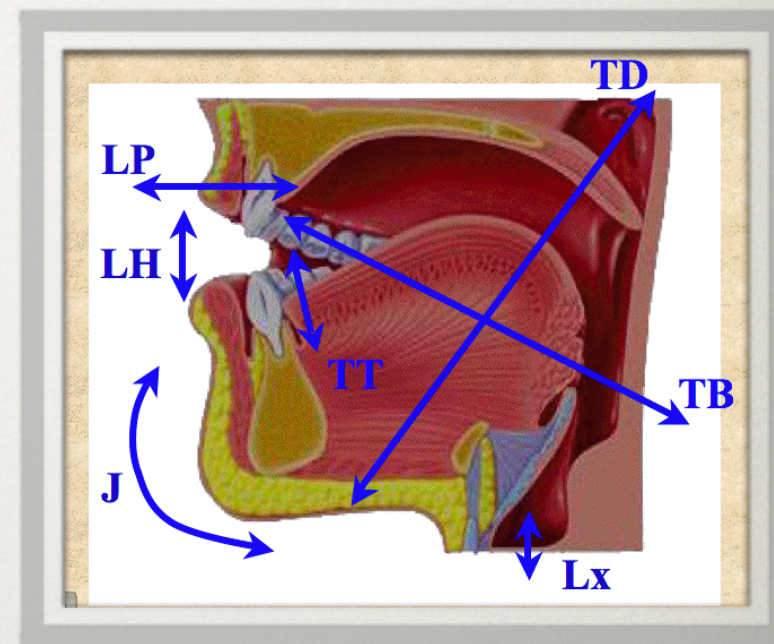
MODELING BEHAVIORS



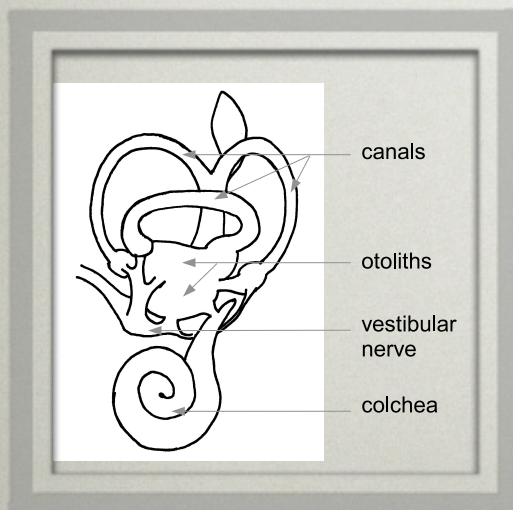
PhD Jihene Serkhane



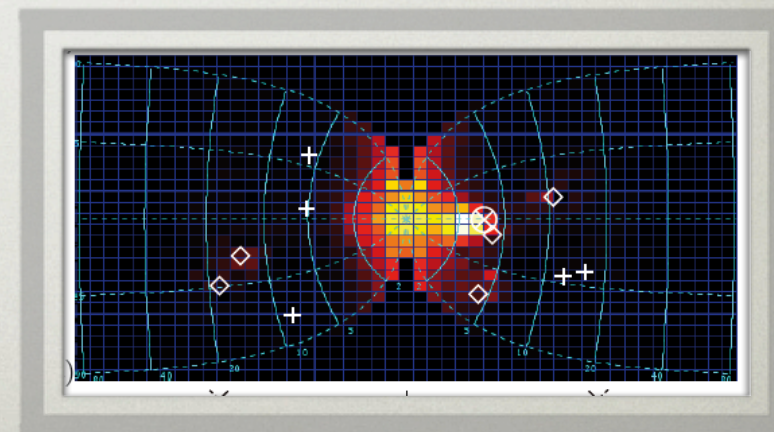
PhD Francis Colas



PhD C. Moulin-Frier



PhD Jean Laurens



PostDoc Francis Colas

BAYESIAN ACTION PERCEPTION:

HANDWRITING EXPERIMENTS

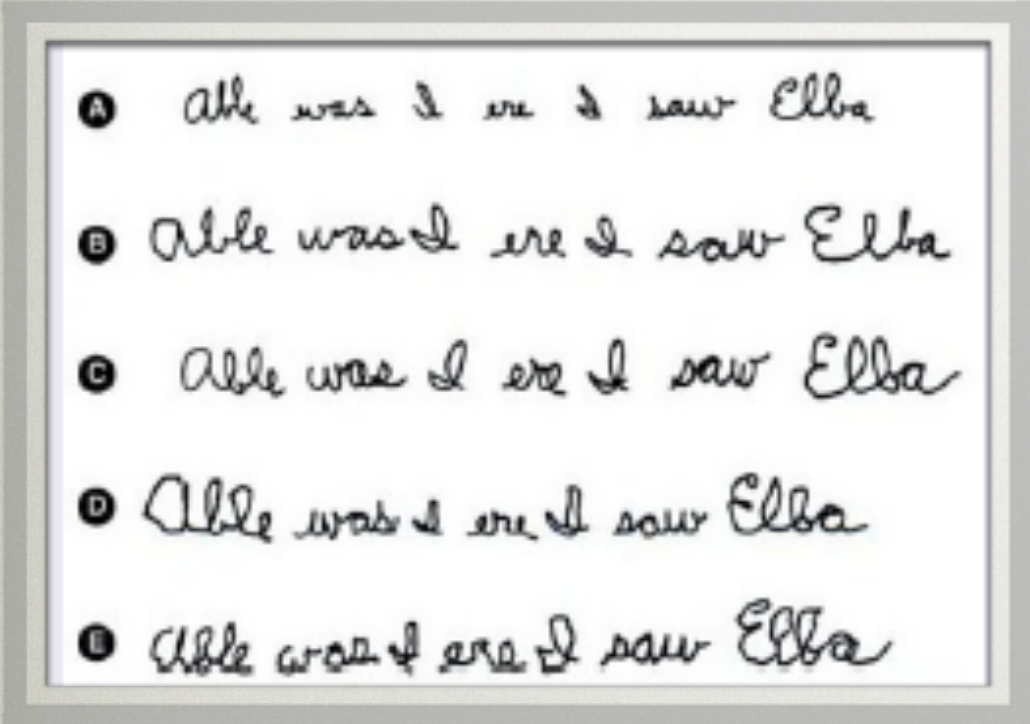
PHD ESTELLE GILET



MOTOR EQUIVALENCE?



MOTOR EQUIVALENCE?

- 
- A Able was I ere I saw Elba
 - B Able was I ere I saw Elba
 - C Able was I ere I saw Elba
 - D Able was I ere I saw Elba
 - E Able was I ere I saw Elba

[Serratrice93]

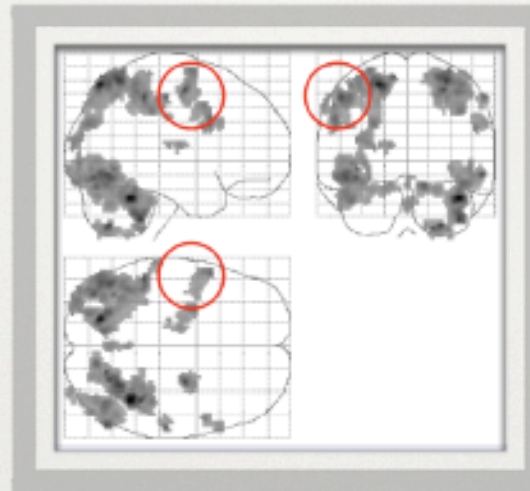
- Writer “style”
 - [Wright90]
- Common activated motor areas
 - [Wing00]

SIMULATION OF ACTION DURING PERCEPTION?



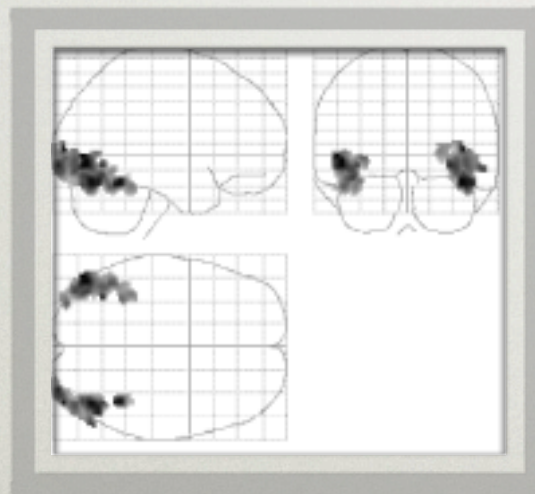
[Calvo-Merino04]

SIMULATION OF ACTION DURING PERCEPTION?

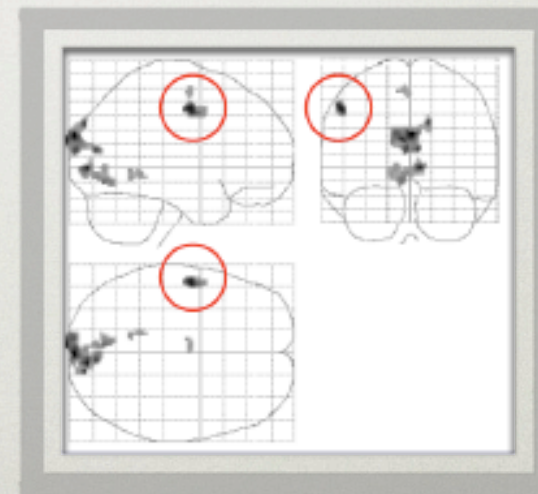


[Longcamp03]

Writing

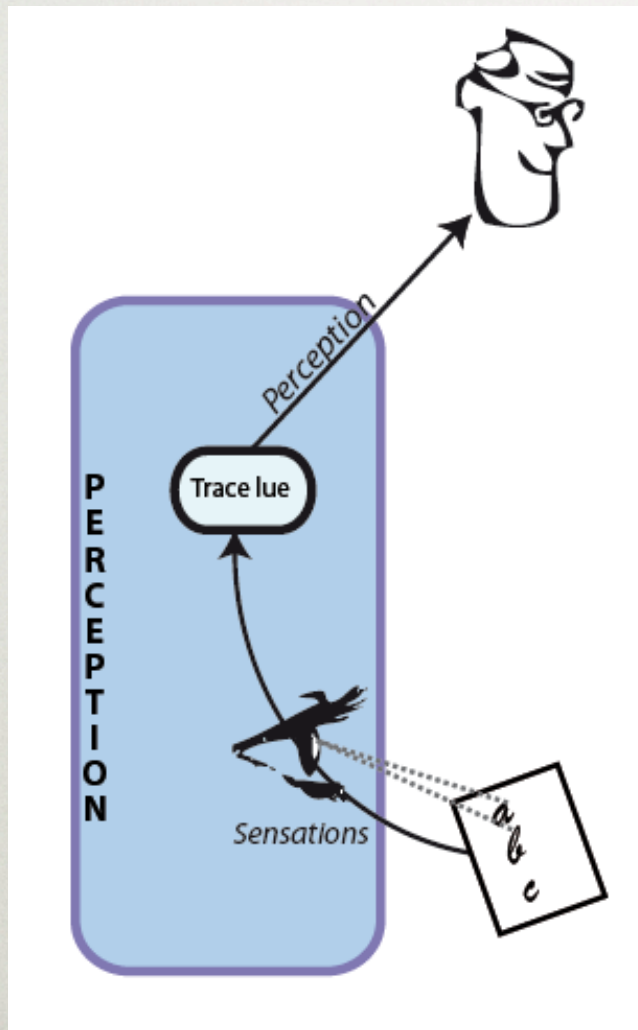


Pseudo letter reading



Letter reading

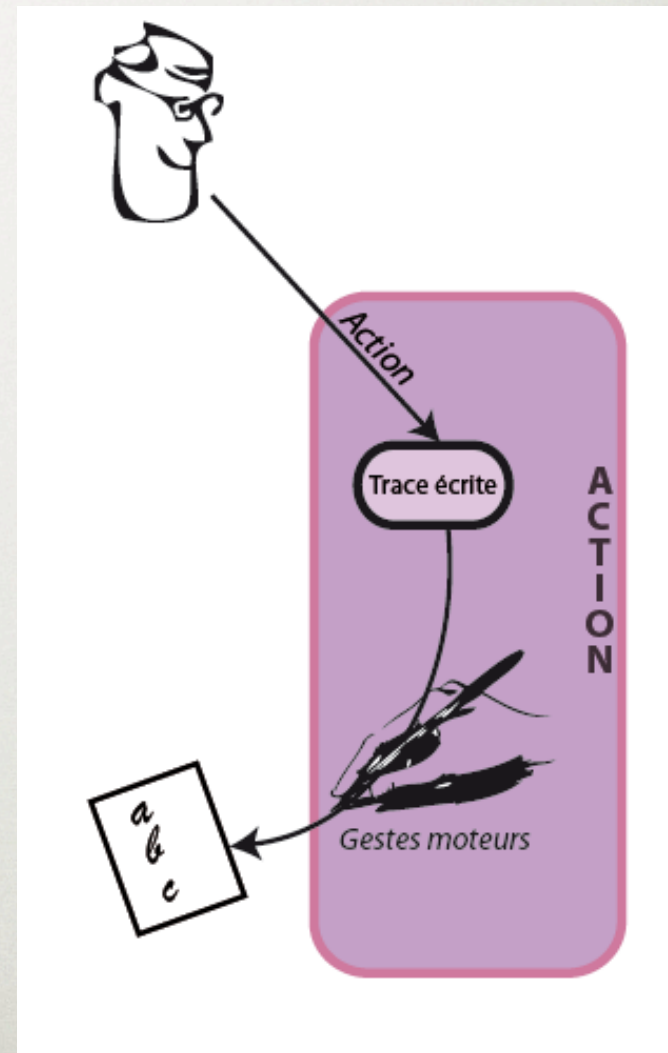
READING



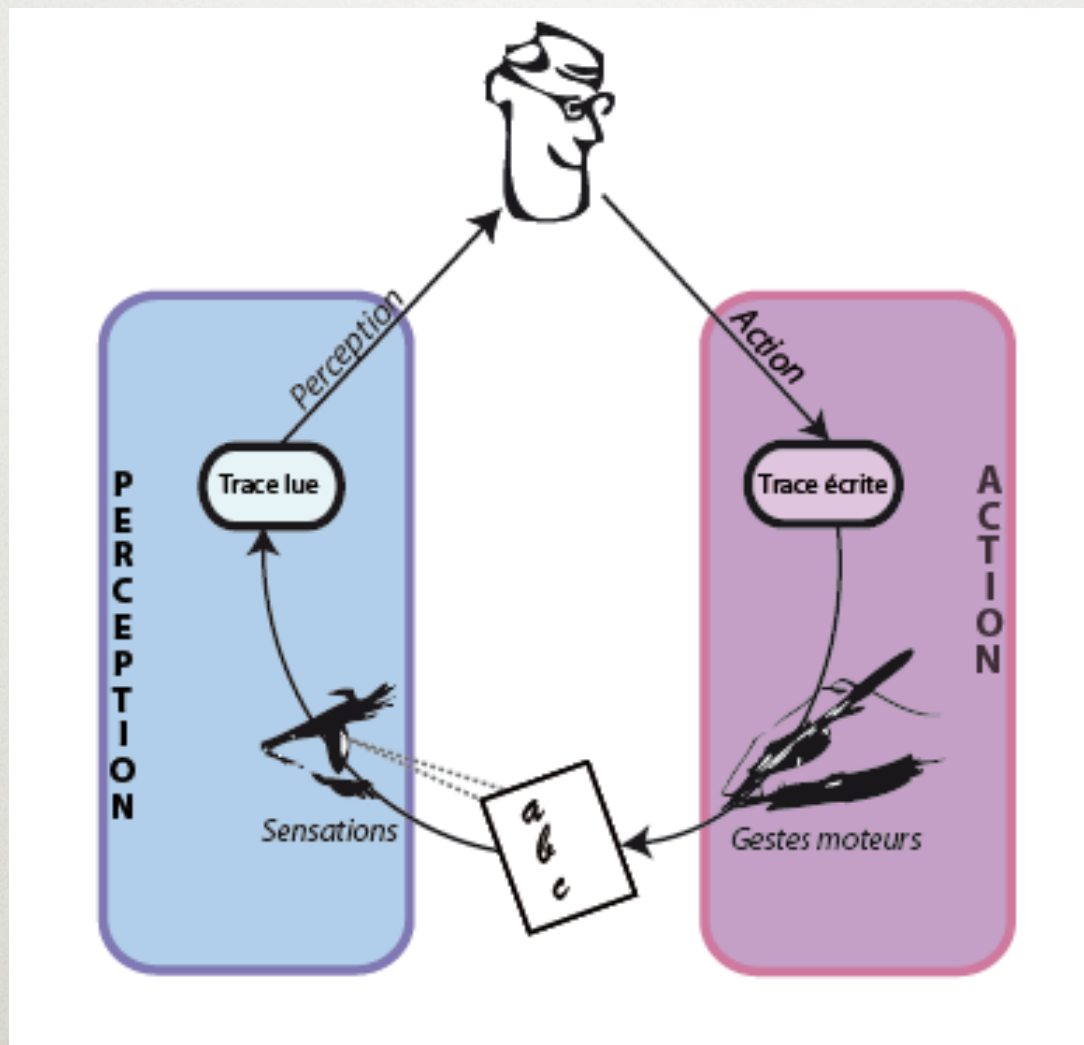
- OCR
 - [Meulenbroek96]
 - [Flash95]
- Human models
 - [Crettez98]
 - [Vuori02]
 - [Dehaene07]

WRITING

- [Hinton05]
- [Meulenbroek96]
- [Flash95]

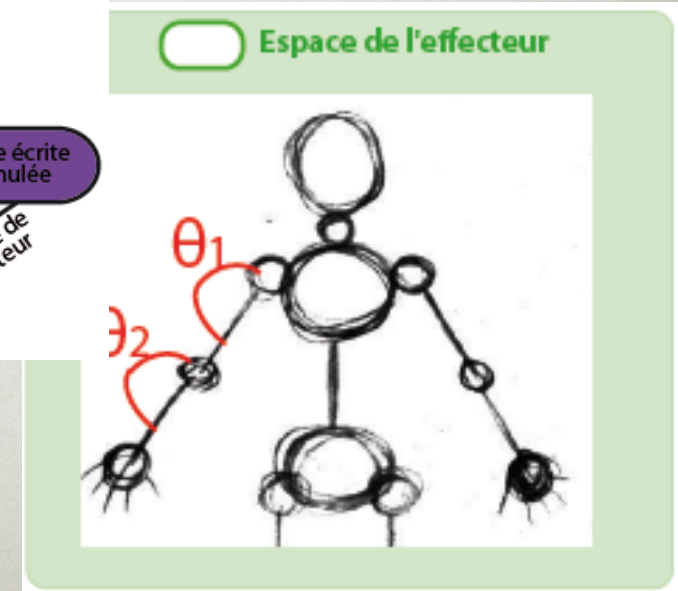
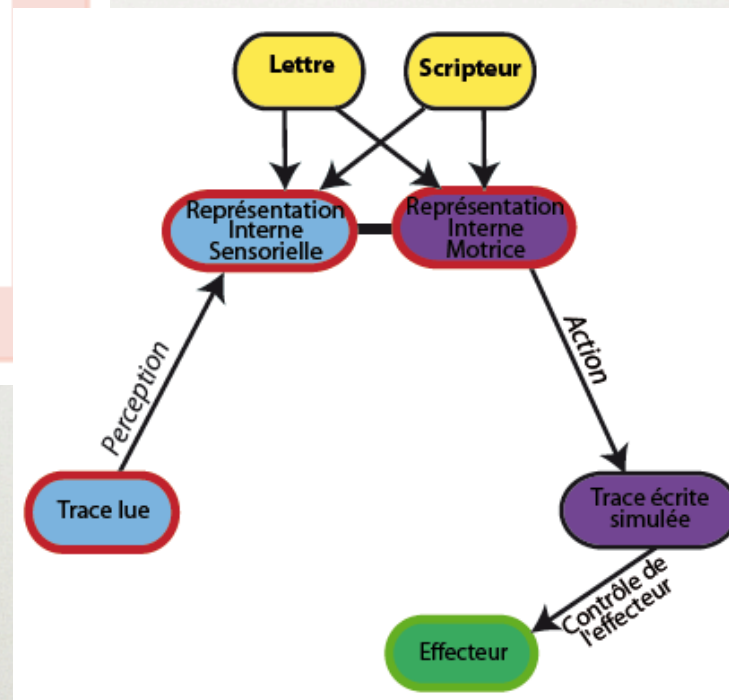


BAP MODEL



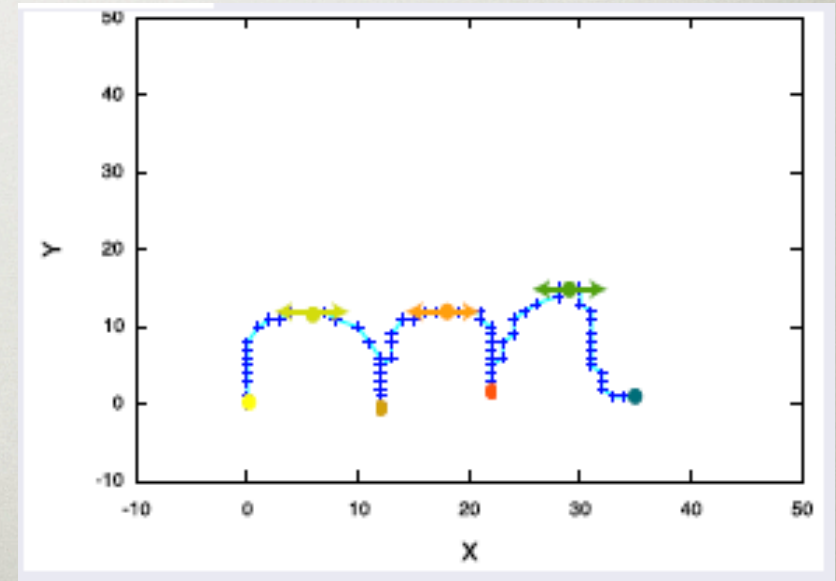
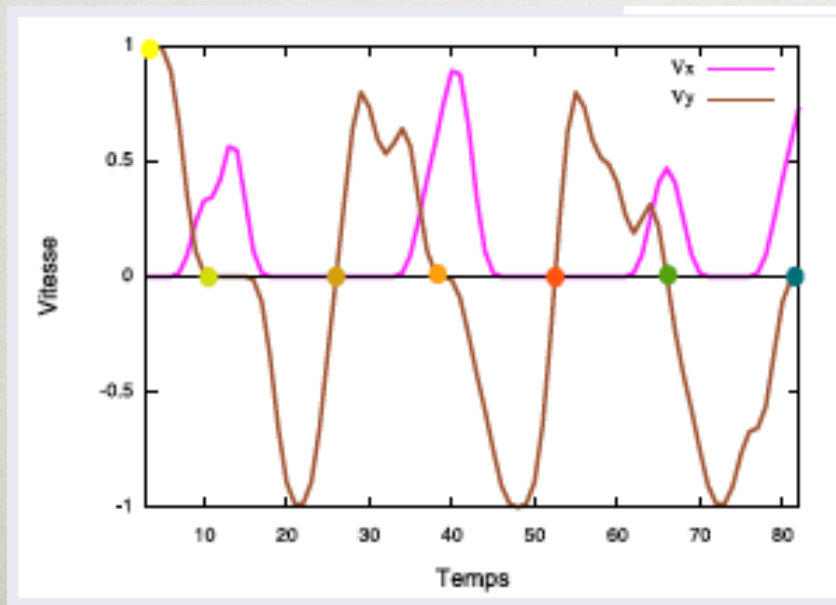
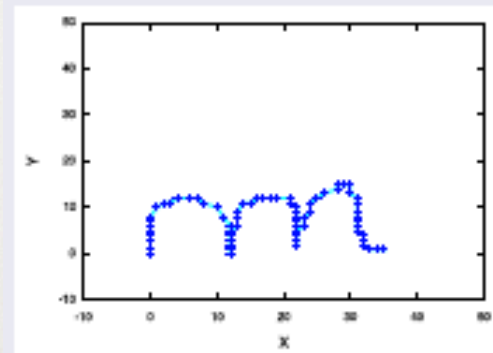
A COMMON SPACE FOR MOTOR AND PERCEPTION

INTERNAL REPRESENTATION

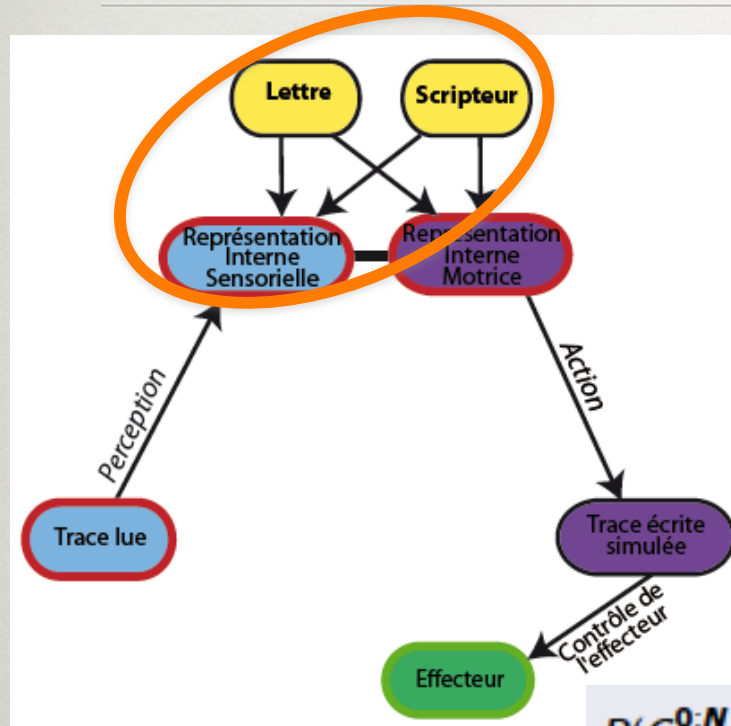


COMMON FEATURES FOR BOTH REPRESENTATIONS

$$\frac{dx}{dt}(t) = 0 \quad \vee \quad \frac{dy}{dt}(t) = 0$$



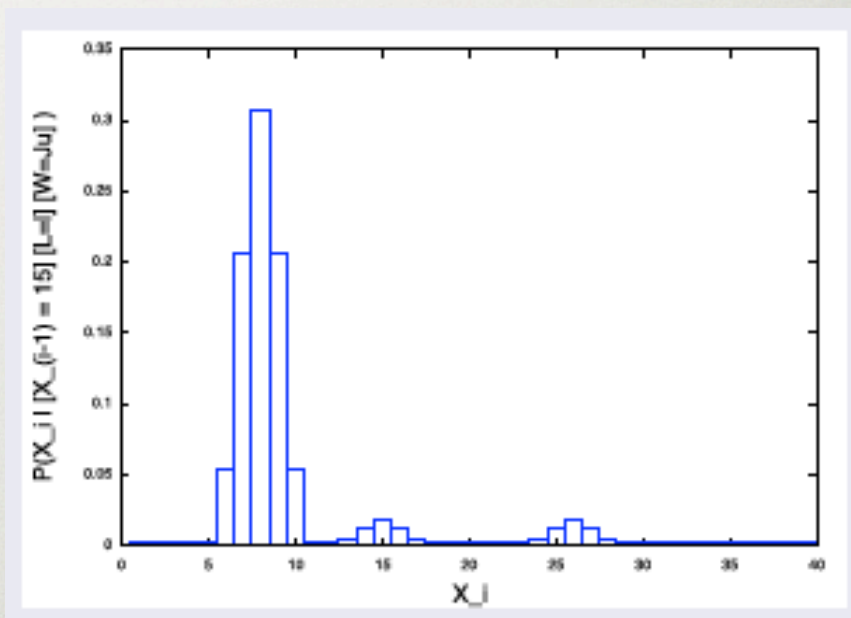
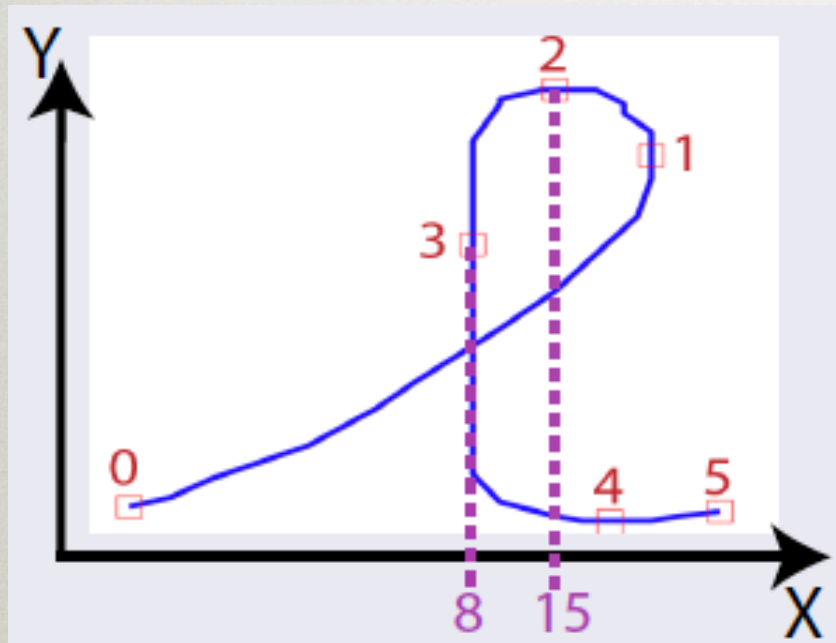
HERE COME THE PROBABILITIES



$$\begin{aligned}
 & P(C_L^{0:N} | L W) \\
 &= P(C_L^{0:N} | L W) P(L) P(W) \\
 &= \left(\begin{array}{c} \left(\begin{array}{cc} P(C_{Lx}^0 | L W) & P(C_{Ly}^0 | L W) \\ P(C_{Lx}^0 | L W) & P(C_{Ly}^0 | L W) \end{array} \right) \\ \prod_{n=1}^N \left(\begin{array}{cc} P(C_{Lx}^n | C_{Lx}^{n-1} L W) & P(C_{Ly}^n | C_{Ly}^{n-1} L W) \\ P(C_{Lx}^n | C_{Lx}^{n-1} L W) & P(C_{Ly}^n | C_{Ly}^{n-1} L W) \end{array} \right) \\ P(L) P(W) \end{array} \right)
 \end{aligned}$$

LEARNING SUCCESSION OF CONTROL POINTS

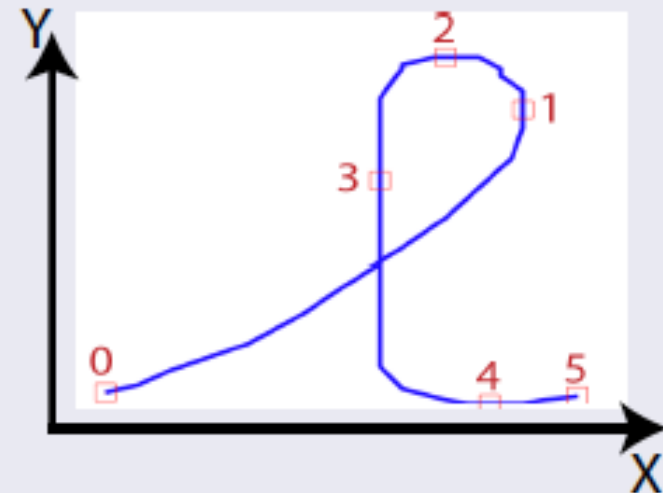
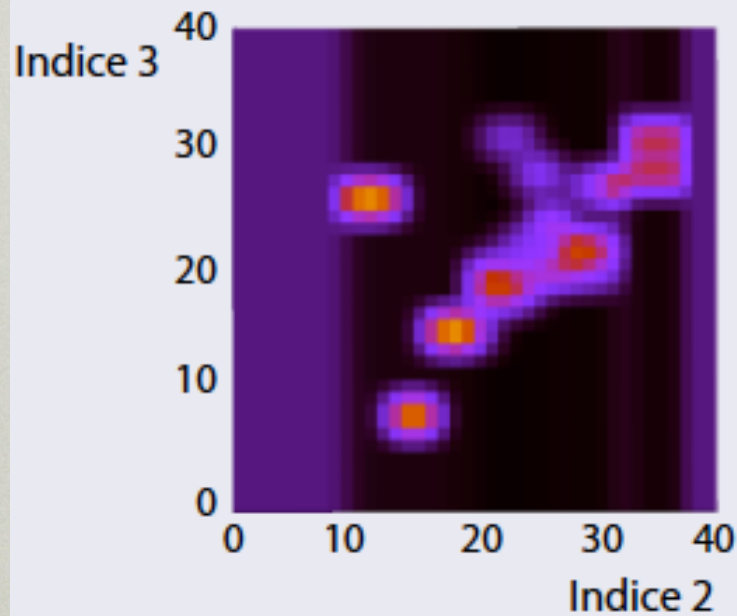
$$P(C_{Lx}^3 \mid [C_{Lx}^2 = 15] [L = l] [W = \textit{Julienne}]) = \frac{p_i + \alpha}{N + k\alpha}$$



LEARNING SUCCESSION OF CONTROL POINTS

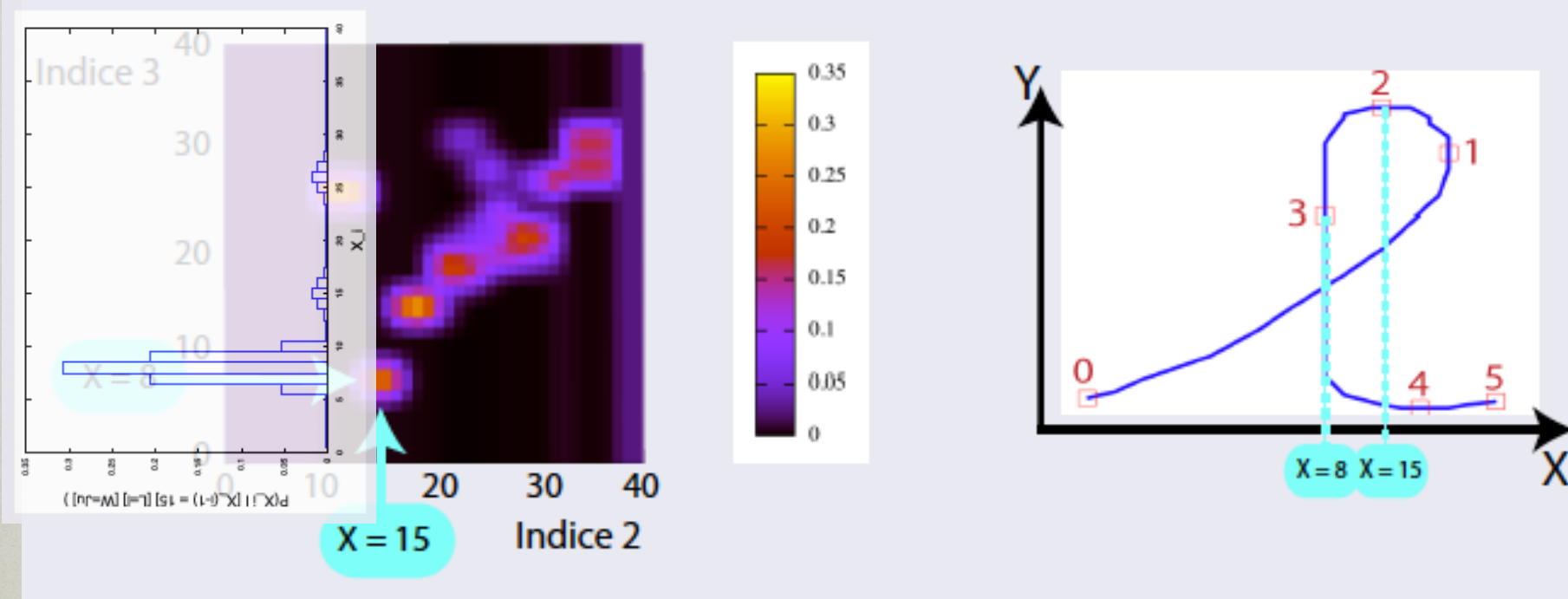
$$P(C_{Lx}^3 | C_{Lx}^2 [L = 1] [W = \textit{Julienne}])$$

(2)



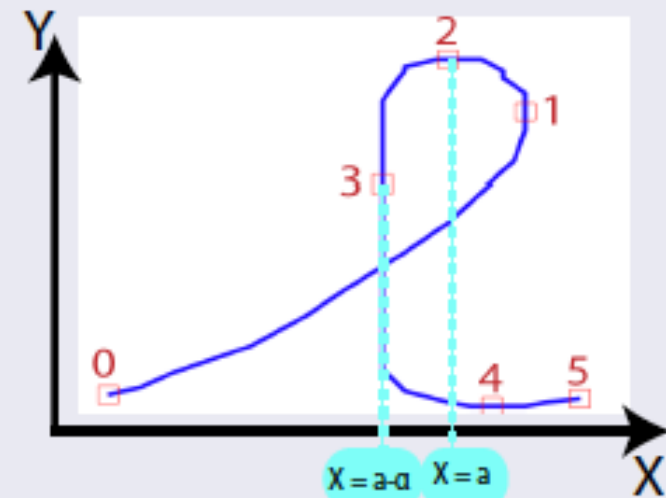
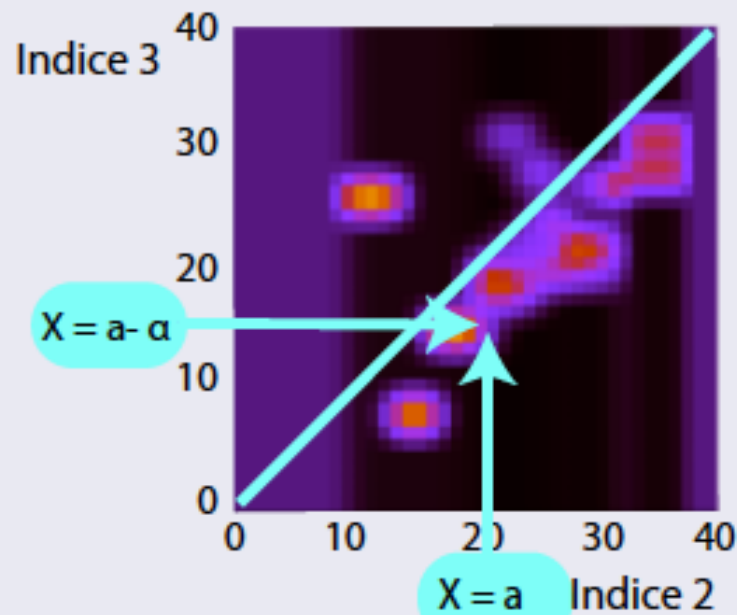
LEARNING SUCCESSION OF CONTROL POINTS

$$P(C_{Lx}^3 | C_{Lx}^2 [L = 1] [W = \textit{Julienne}]) \quad (2)$$



LEARNING SUCCESSION OF CONTROL POINTS

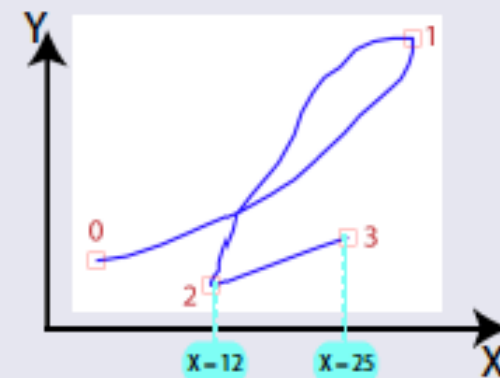
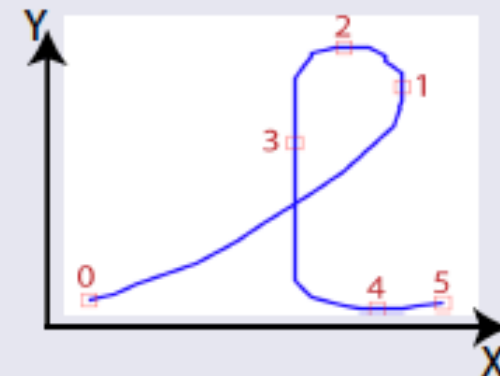
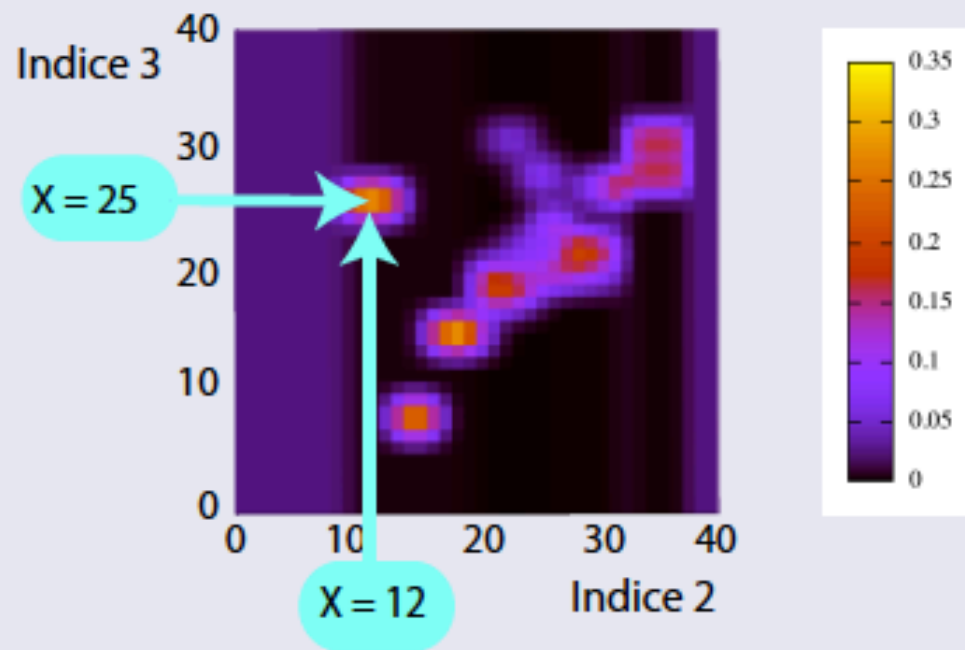
$$P(C_{Lx}^3 \mid C_{Lx}^2 [L = I] [W = \textit{Julienne}]) \quad (2)$$



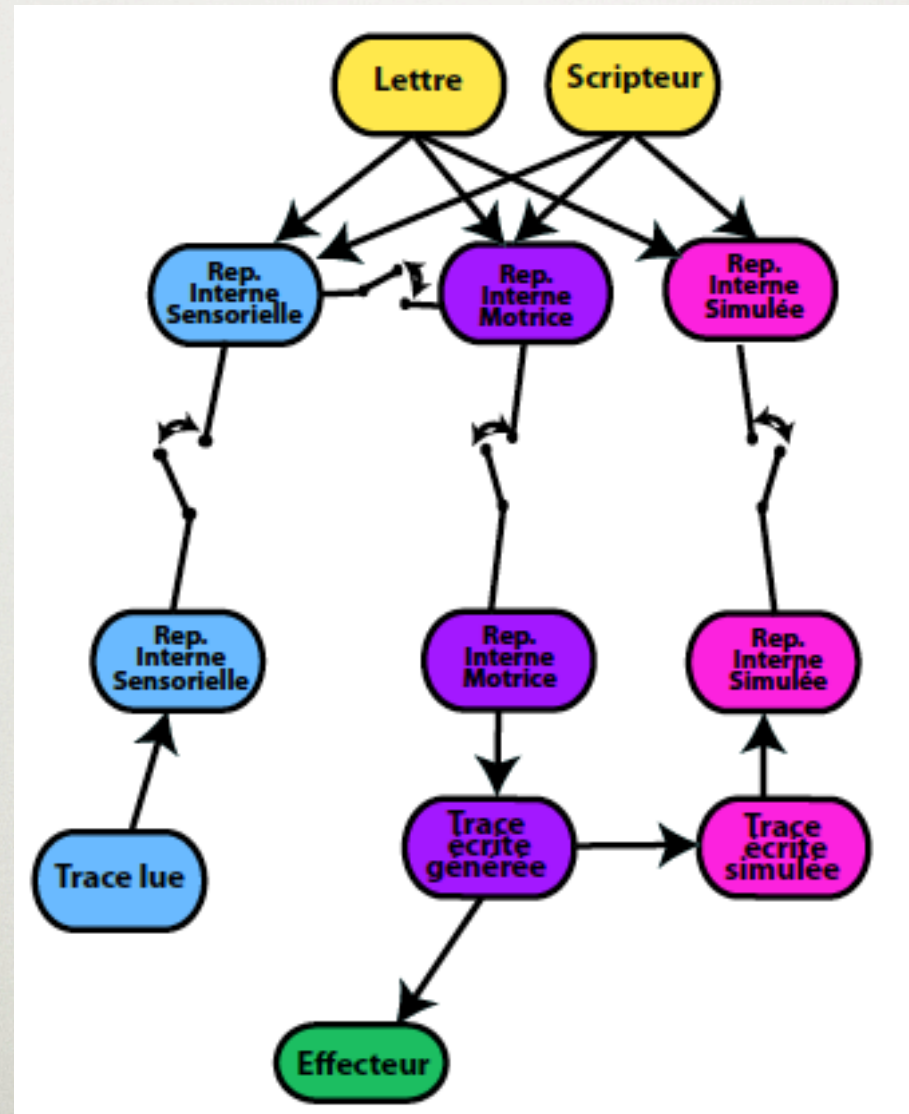
LEARNING SUCCESSION OF CONTROL POINTS

$$P(C_{Lx}^3 | C_{Lx}^2 [L = l] [W = \textit{Julienne}])$$

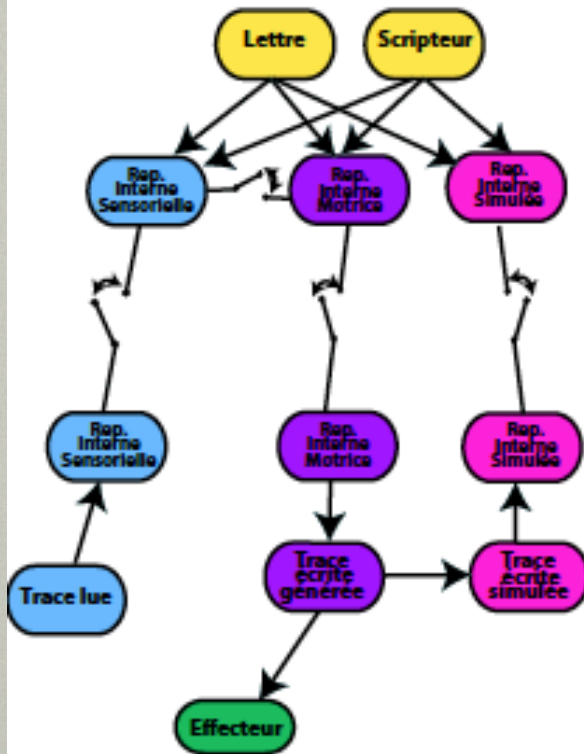
(2)



BAP MODEL



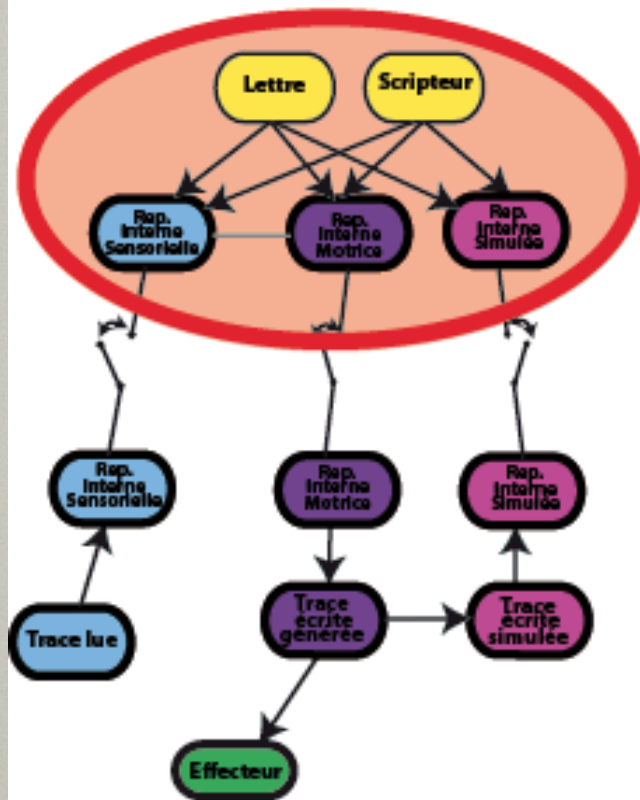
BAP MODEL



$$P \begin{pmatrix} C_{LV} & C_{LP} & C_{LS} & C_V & \lambda_P & \lambda_V & \lambda_S & \lambda_I & E \\ C_P & C_S & V & P & L & W & S & & \end{pmatrix}$$

$$= \begin{pmatrix} P(C_{LV} | L W) P(C_{LP} | L W) P(C_{LS} | L W) \\ P(L) P(W) P(\lambda_I | C_{LV} C_{LP}) \\ P(\lambda_V | C_{LV} C_V) P(C_V | V) P(V) \\ P(\lambda_P | C_{LP} C_P) P(P | C_P) P(E | P) \\ P(\lambda_S | C_{LS} C_S) P(C_S | S) P(S | P) \end{pmatrix}$$

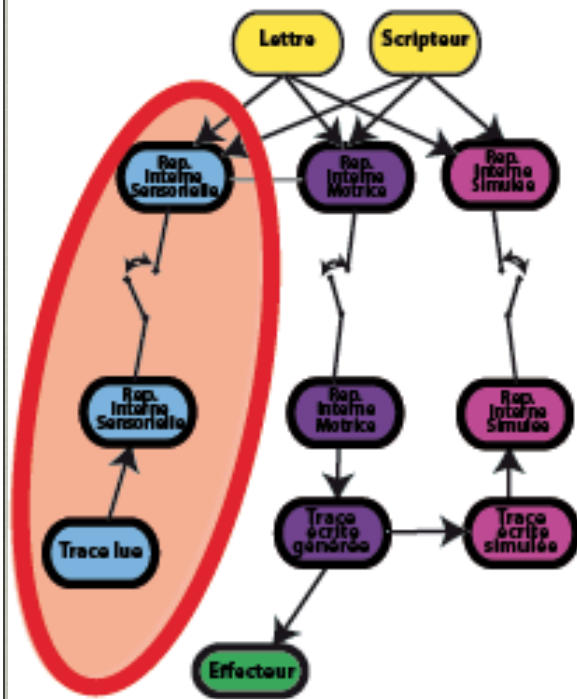
BAP MODEL



$$P \left(\begin{array}{cccccccccc} C_{LV} & C_{LP} & C_{LS} & C_V & \lambda_P & \lambda_V & \lambda_S & \lambda_I & E \\ C_P & C_S & V & P & L & W & S \end{array} \right)$$

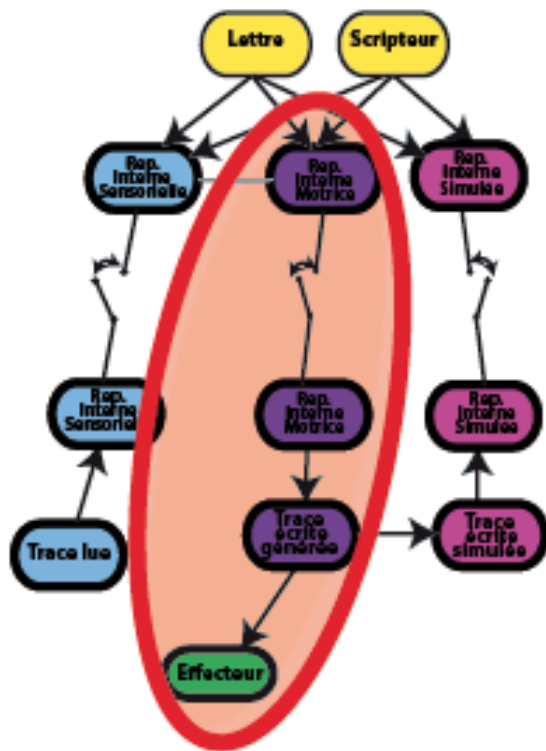
$$= \left(\begin{array}{l} P(C_{LV} | L W) P(C_{LP} | L W) P(C_{LS} | L W) \\ P(L) P(W) P(\lambda_I | C_{LV} C_{LP}) \\ P(\lambda_V | C_{LV} C_V) P(C_V | V) P(V) \\ P(\lambda_P | C_{LP} C_P) P(P | C_P) P(E | P) \\ P(\lambda_S | C_{LS} C_S) P(C_S | S) P(S | P) \end{array} \right)$$

BAP MODEL



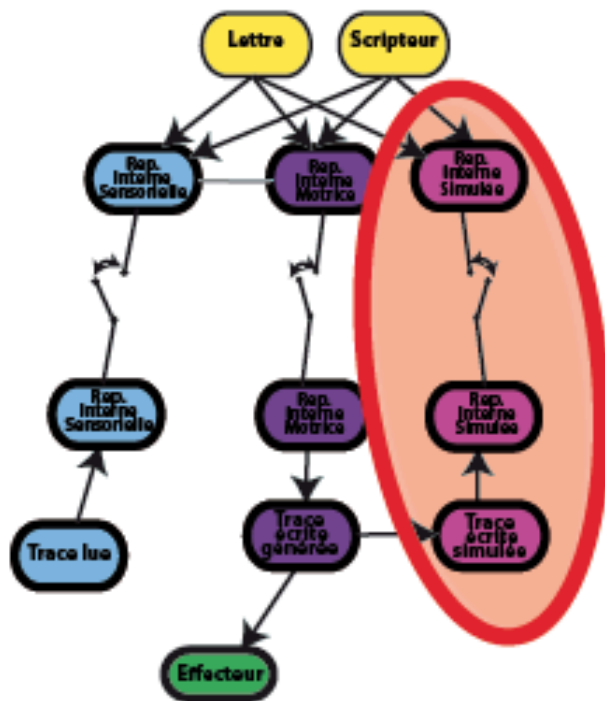
$$P \begin{pmatrix} C_{LV} & C_{LP} & C_{LS} & C_V & \lambda_P & \lambda_V & \lambda_S & \lambda_I & E \\ C_P & C_S & V & P & L & W & S \end{pmatrix} \\
 = \begin{pmatrix} P(C_{LV} | L W) P(C_{LP} | L W) P(C_{LS} | L W) \\ P(L) P(W) P(\lambda_I | C_{LV} C_{LP}) \\ P(\lambda_V | C_{LV} C_V) P(C_V | V) P(V) \\ P(\lambda_P | C_{LP} C_P) P(P | C_P) P(E | P) \\ P(\lambda_S | C_{LS} C_S) P(C_S | S) P(S | P) \end{pmatrix}$$

BAP MODEL



$$P \left(\begin{array}{cccccccccc} C_{LV} & C_{LP} & C_{LS} & C_V & \lambda_P & \lambda_V & \lambda_S & \lambda_I & E \\ C_P & C_S & V & P & L & W & S \end{array} \right) \\
 = \left(\begin{array}{l} P(C_{LV} | L, W) P(C_{LP} | L, W) P(C_{LS} | L, W) \\ P(L) P(W) P(\lambda_I | C_{LV}, C_{LP}) \\ P(\lambda_V | C_{LV}, C_V) P(C_V | V) P(V) \\ P(\lambda_P | C_{LP}, C_P) P(P | C_P) P(E | P) \\ P(\lambda_S | C_{LS}, C_S) P(C_S | S) P(S | P) \end{array} \right)$$

BAP MODEL



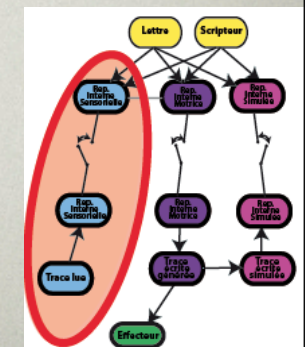
$$P \left(\begin{array}{cccccccccc} C_{LV} & C_{LP} & C_{LS} & C_V & \lambda_p & \lambda_v & \lambda_s & \lambda_l & E \\ C_p & C_s & V & P & L & W & S \end{array} \right)$$

$$= \left(\begin{array}{l} P(C_{LV} | L, W) P(C_{LP} | L, W) P(C_{LS} | L, W) \\ P(L) P(W) P(\lambda_l | C_{LV}, C_{LP}) \\ P(\lambda_v | C_{LV}, C_V) P(C_V | V) P(V) \\ P(\lambda_p | C_{LP}, C_p) P(P | C_p) P(E | P) \\ P(\lambda_s | C_{LS}, C_s) P(C_s | S) P(S | P) \end{array} \right)$$

LETTER RECOGNITION

KNOWING THE SCRIPTER

$$P(L \mid [V_X^{0:M} = v_x^{0:M}] [V_Y^{0:M} = v_y^{0:M}] [W = w] [\lambda_V = 1])$$



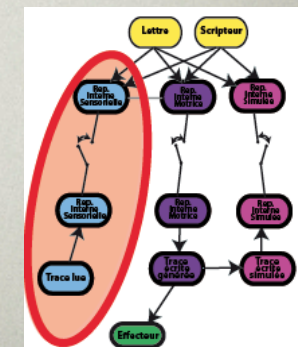
LETTER RECOGNITION

KNOWING THE SCRIPTER

$$P(L \mid [V_X^{0:M} = v_x^{0:M}] [V_Y^{0:M} = v_y^{0:M}] [W = w] [\lambda_V = 1])$$

$$\propto \begin{pmatrix} P([C_{LV_x}^0 = f(v_x^{0:M}, v_y^{0:M})] \mid L [W = w]) \\ P([C_{LV_y}^0 = f(v_x^{0:M}, v_y^{0:M})] \mid L [W = w]) \\ P([C_{LV_{\dot{x}}}^0 = f(v_x^{0:M}, v_y^{0:M})] \mid L [W = w]) \\ P([C_{LV_{\dot{y}}}^0 = f(v_x^{0:M}, v_y^{0:M})] \mid L [W = w]) \end{pmatrix}$$

$$\prod_{n=1}^N \begin{pmatrix} P([C_{LV_x}^n = f(v_x^{0:M}, v_y^{0:M})] \mid [C_{LV_x}^{n-1} = f(v_x^{0:M}, v_y^{0:M})] L [W = w]) \\ P([C_{LV_y}^n = f(v_x^{0:M}, v_y^{0:M})] \mid [C_{LV_y}^{n-1} = f(v_x^{0:M}, v_y^{0:M})] L [W = w]) \\ P([C_{LV_{\dot{x}}}^n = f(v_x^{0:M}, v_y^{0:M})] \mid [C_{LV_{\dot{x}}}^{n-1} = f(v_x^{0:M}, v_y^{0:M})] L [W = w]) \\ P([C_{LV_{\dot{y}}}^n = f(v_x^{0:M}, v_y^{0:M})] \mid [C_{LV_{\dot{y}}}^{n-1} = f(v_x^{0:M}, v_y^{0:M})] L [W = w]) \end{pmatrix}$$

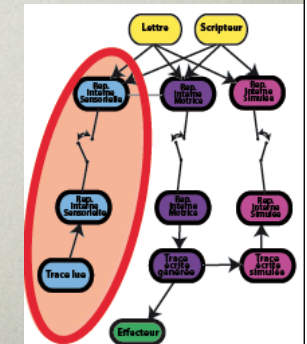


LETTER RECOGNITION

KNOWING THE SCRIPTER

	a	b	c	d	e	f	g	h	k	l	m	n	o	p	q	r	s	u	v	w	y	z	?
a	0.95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.05
b	0	0.72	0	0	0.05	0	0	0.12	0.03	0.05	0	0	0	0	0	0	0	0	0	0	0	0	0.03
c	0	0	0.92	0	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0	0	0	0.03
d	0.03	0	0	0.94	0	0	0	0	0	0	0	0	0	0	0.03	0	0	0	0	0	0	0	0
e	0	0	0	0	0.87	0	0	0	0	0	0	0	0	0	0	0.10	0	0	0	0	0	0	0.03
f	0	0	0	0	0	0.97	0	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
g	0	0	0	0	0	0	0.90	0	0	0	0	0	0	0	0.10	0	0	0	0	0	0	0	0
h	0	0.03	0	0	0	0.03	0	0.91	0	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0
k	0	0	0	0	0	0	0	0	0.97	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0
l	0	0.10	0	0	0	0	0	0.08	0	0.82	0	0	0	0	0	0	0	0	0	0	0	0	0
m	0	0	0	0	0	0	0	0	0	0	0.97	0	0	0	0	0	0	0	0	0.03	0	0	0
n	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
o	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
p	0	0	0	0	0	0	0	0	0	0	0	0	0	0.94	0	0	0.03	0	0	0	0	0	0.03
q	0	0	0	0	0	0	0.15	0	0	0	0	0	0	0	0.85	0	0	0	0	0	0	0	0
r	0	0	0	0	0	0	0	0	0	0	0	0.03	0	0.03	0	0.86	0	0.05	0.03	0	0	0	0
s	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
u	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
v	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
w	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.95	0.05

93,36%



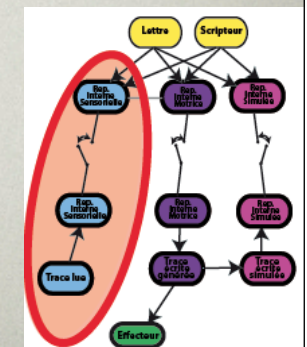
SCRIPTER RECOGNITION

KNOWING THE LETTER

$$P(W \mid [V_X^{0:M} = v_x^{0:M}] [V_Y^{0:M} = v_y^{0:M}] [L = l] [\lambda_V = 1])$$

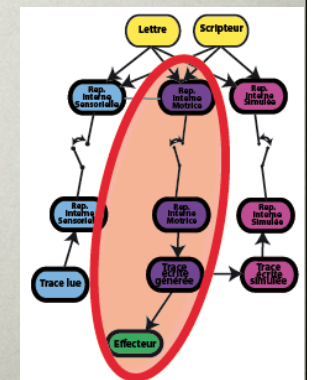
	Estelle	Julienne	Jean-Louis	Christophe
Estelle	0.76	0.03	0.07	0.14
Julienne	0.02	0.80	0.07	0.11
Jean-Louis	0	0	1	0
Christophe	0.10	0.14	0.13	0.62

79,5%

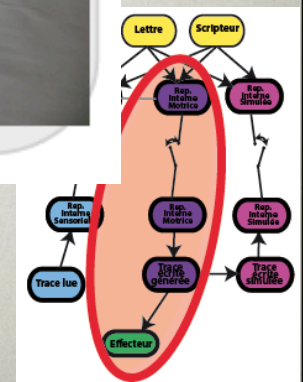
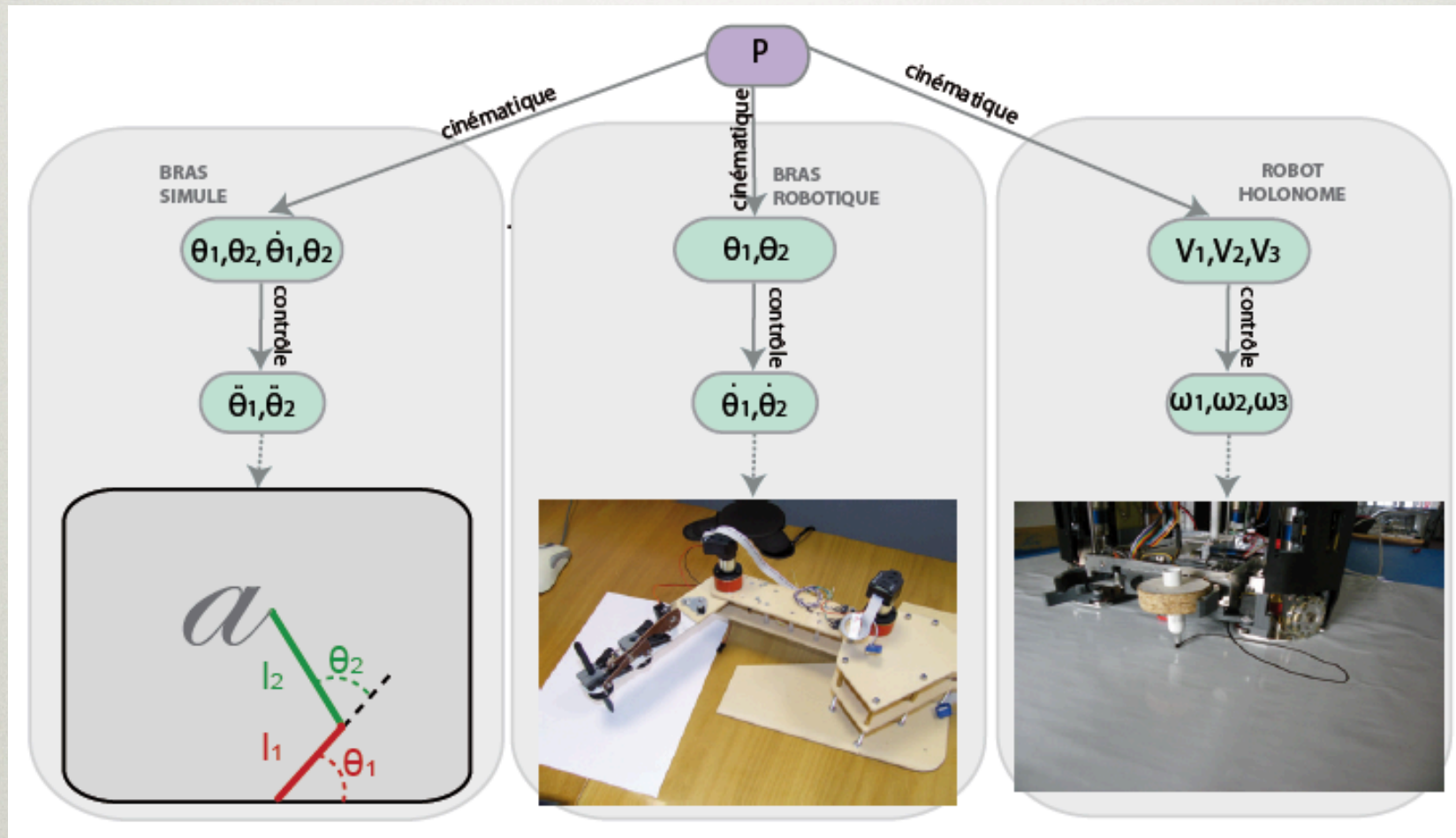


MOTOR CONTROL

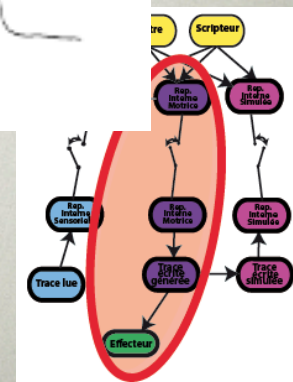
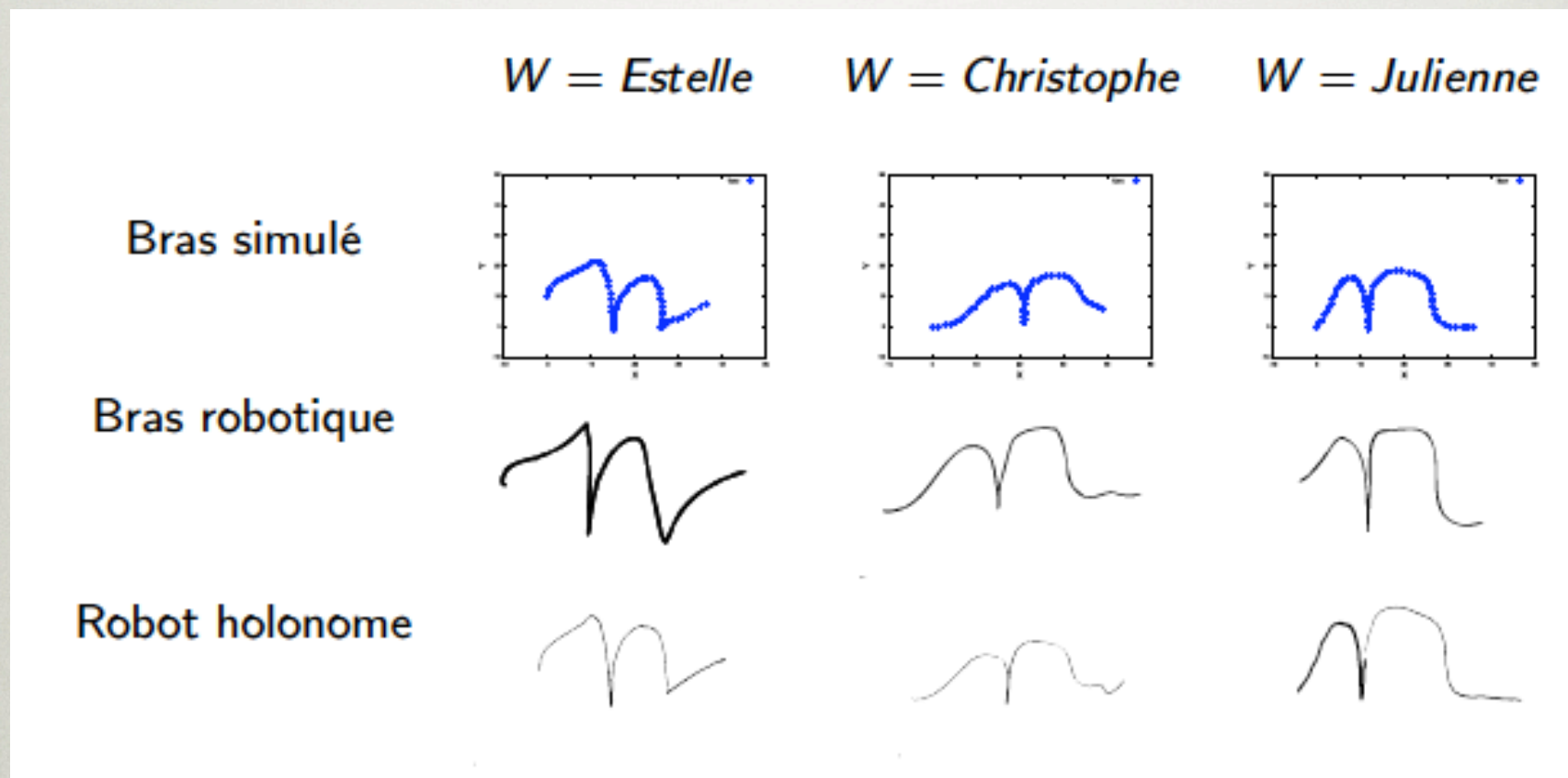
$$P(\ddot{\theta}_1^{0:T} \ \ddot{\theta}_2^{0:T} \mid [L = l] [W = w] [\lambda_P = 1])$$



MOTOR EQUIVALENCE

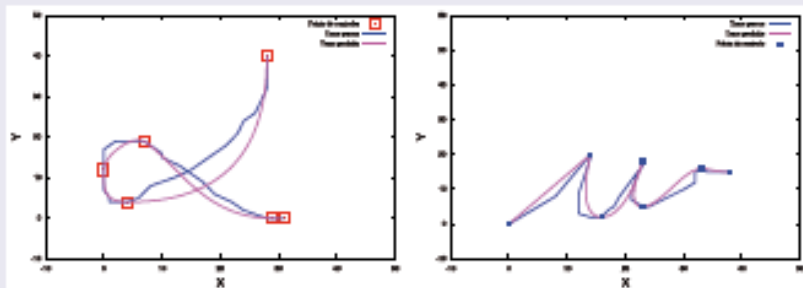
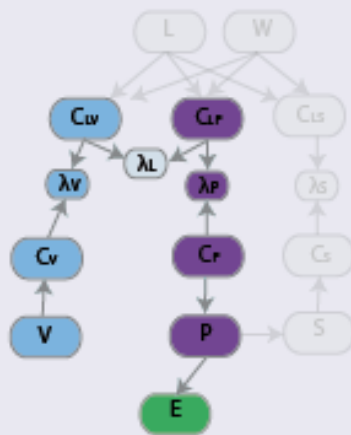


MOTOR EQUIVALENCE



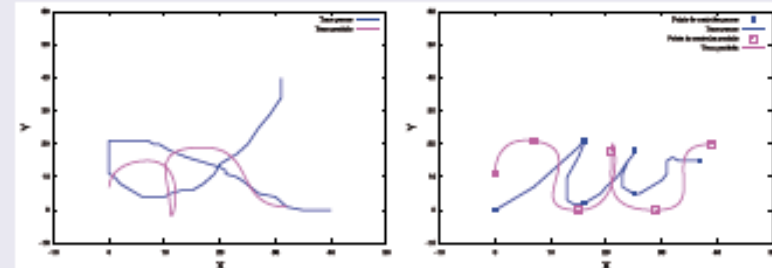
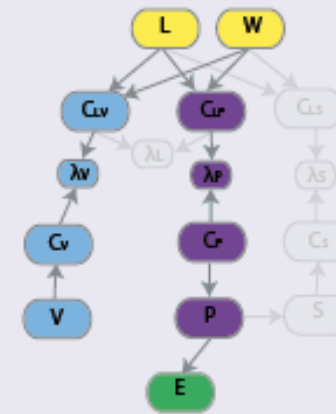
COPY

$$P(\theta_1^{0:T} \theta_2^{0:T} | V_x^{0:M} V_y^{0:M} [\lambda_V = 1] [\lambda_I = 1] [\lambda_P = 1])$$

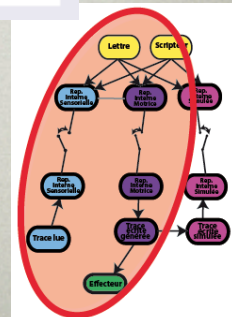


Trace copy

$$P(\theta_1^{0:T} \theta_2^{0:T} | V_x^{0:M} V_y^{0:M} [\lambda_V = 1] [\lambda_P = 1] [W = w])$$

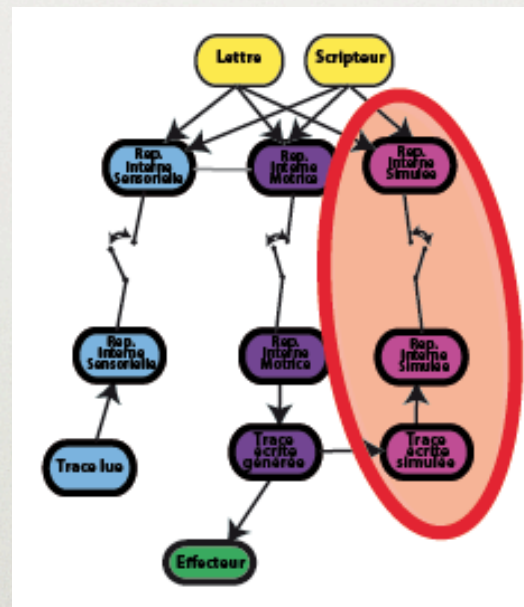


Letter copy

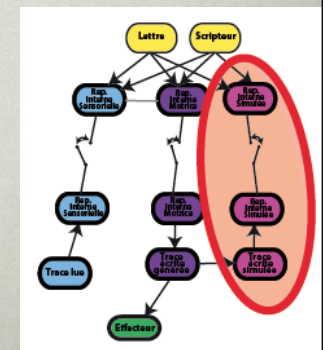
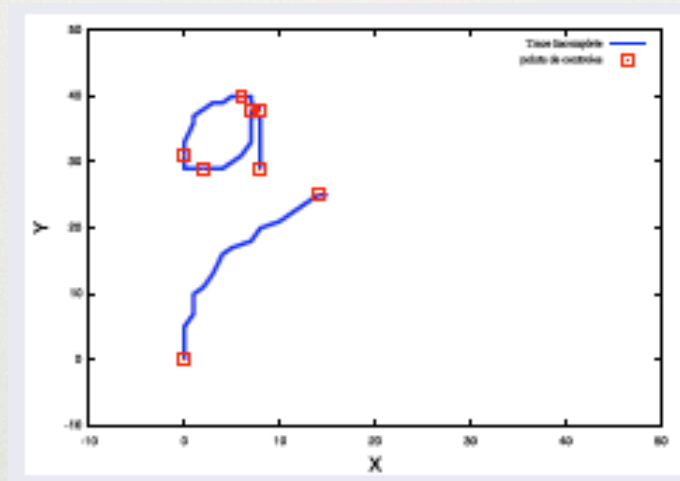


LETTER RECOGNITION WITH MOTOR SIMULATION

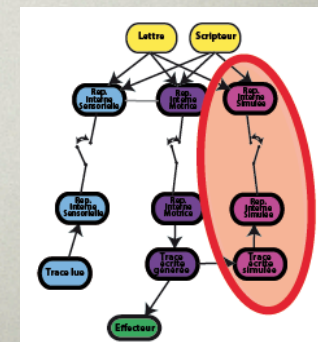
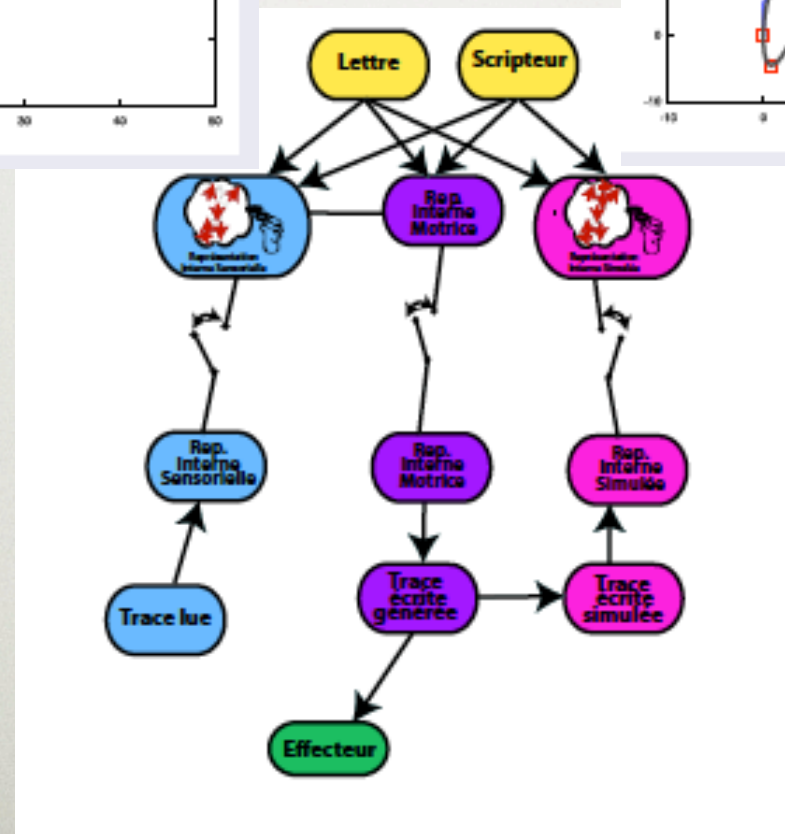
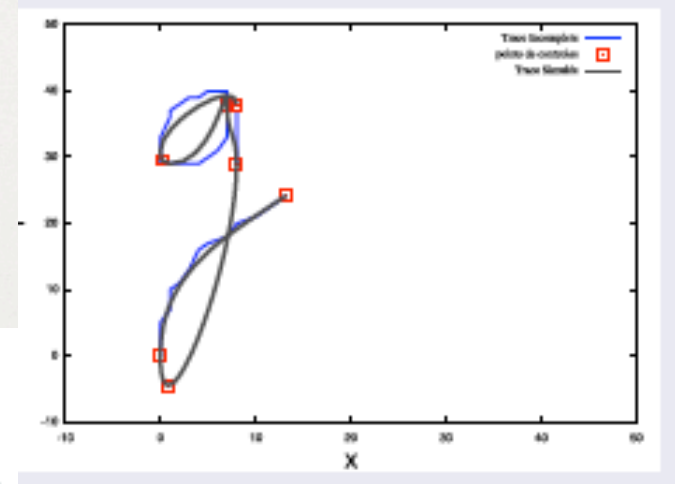
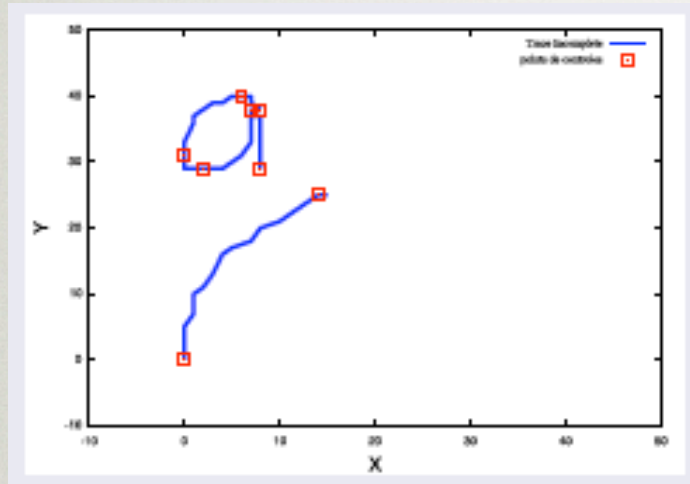
$$P(L | [V_X^{0:M} = v_x^{0:M}] [V_Y^{0:M} = v_y^{0:M}] [W = w] [\lambda_V = 1] [\lambda_L = 1] [\lambda_P = 1] [\lambda_S = 1])$$



LETTER RECOGNITION WITH MOTOR SIMULATION

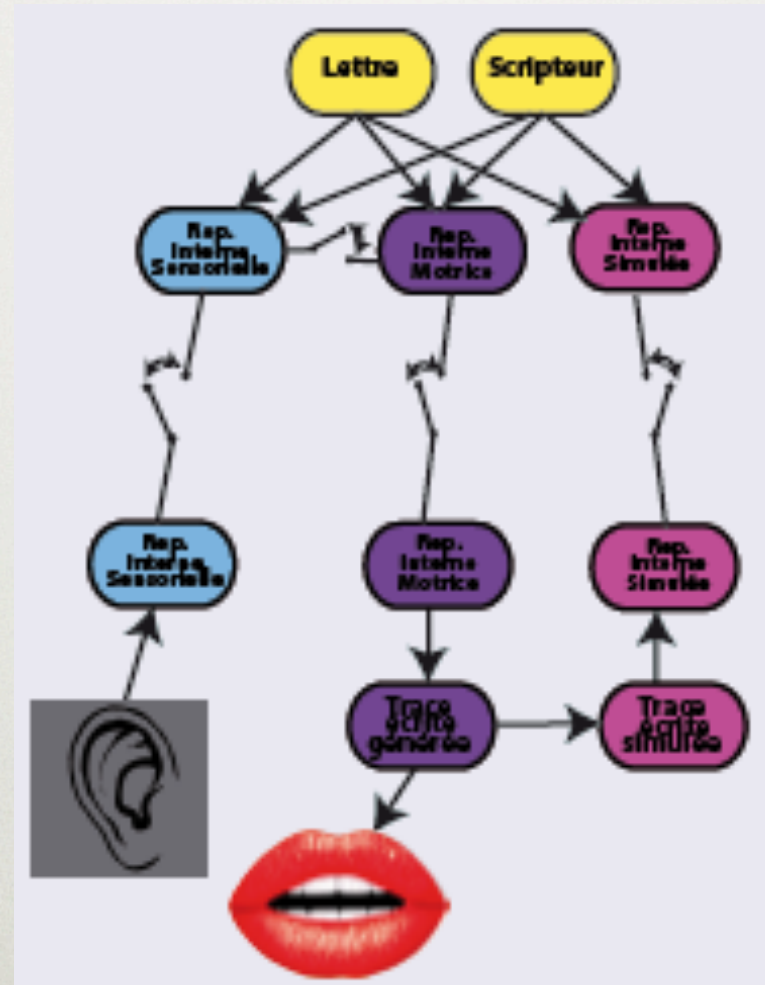


LETTER RECOGNITION WITH MOTOR SIMULATION



PERSPECTIVES (2)

BACK TO SPEECH PERCEPTION AND PRODUCTION



OVERVIEW

- HOW TO SURVIVE (PERCEIVE, REASON, LEARN, DECIDE AND ACT) WITH INCOMPLETE INFORMATION ?
- PROBABILITY AS AN ALTERNATIVE TO LOGIC
- HOW TO DEVELOP BETTER ARTIFACTS USING BAYESIAN REASONING?
- BIOLOGICAL PLAUSIBILITY OF BAYESIAN REASONING AT A MACROSCOPIC LEVEL?
- BIOLOGICAL PLAUSIBILITY OF BAYESIAN REASONING AT A MICROSCOPIC LEVEL?

AMOEBE

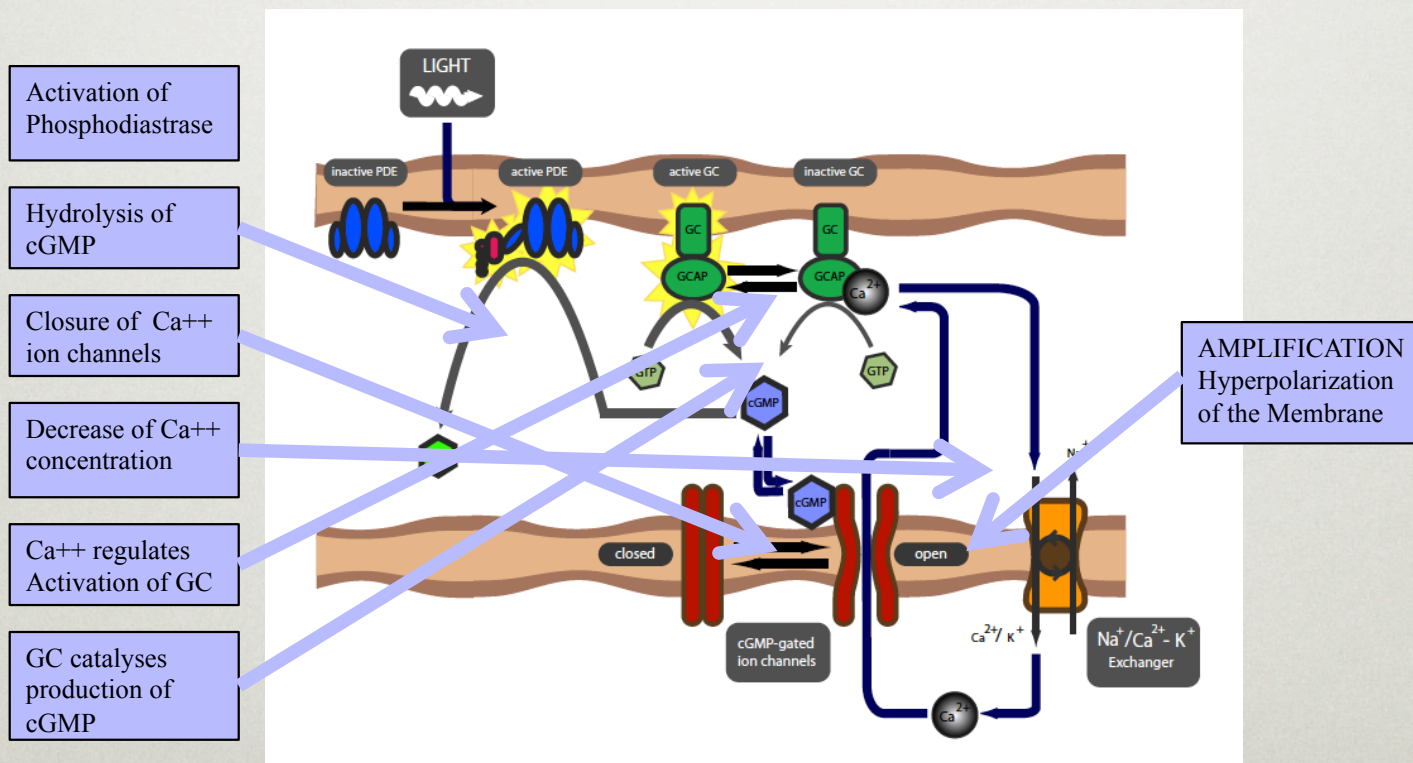
HOW IS IT PERFORMING PROBABILISTIC INFERENCE?



CELL SIGNALING

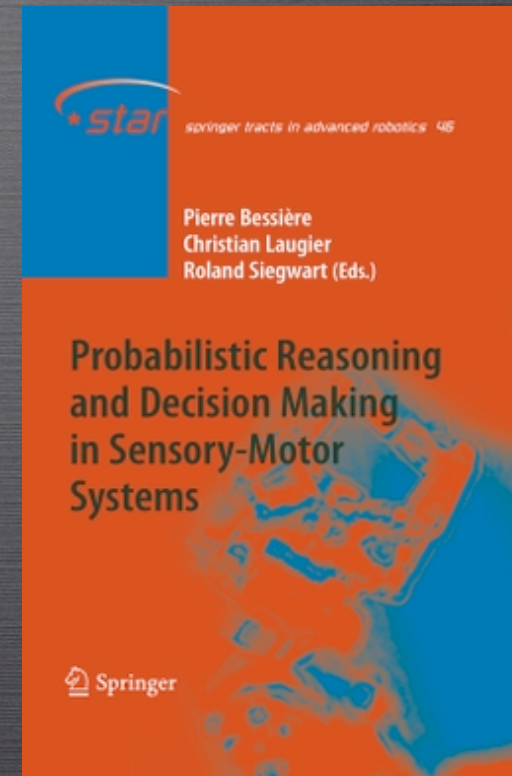
MICROSCOPIC LEVEL

Probabilistic inference by the biochemical mechanisms of phototransduction



WANT TO KNOW MORE?

BAYESIAN-PROGRAMMING.ORG



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