INTERPRETATION OF SPONTANEOUSLY PROVIDED TACTILE INSTRUCTIONS

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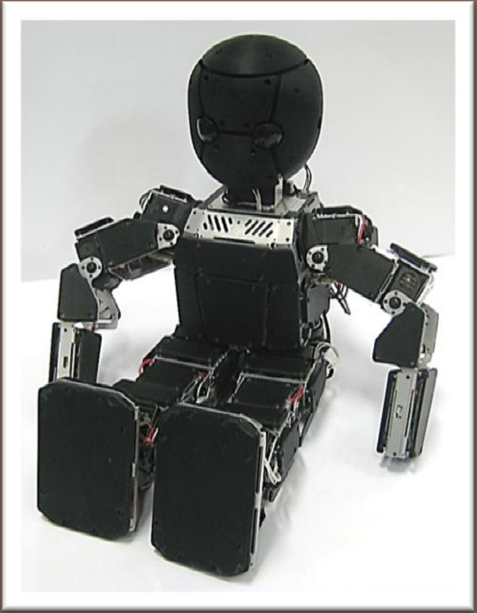
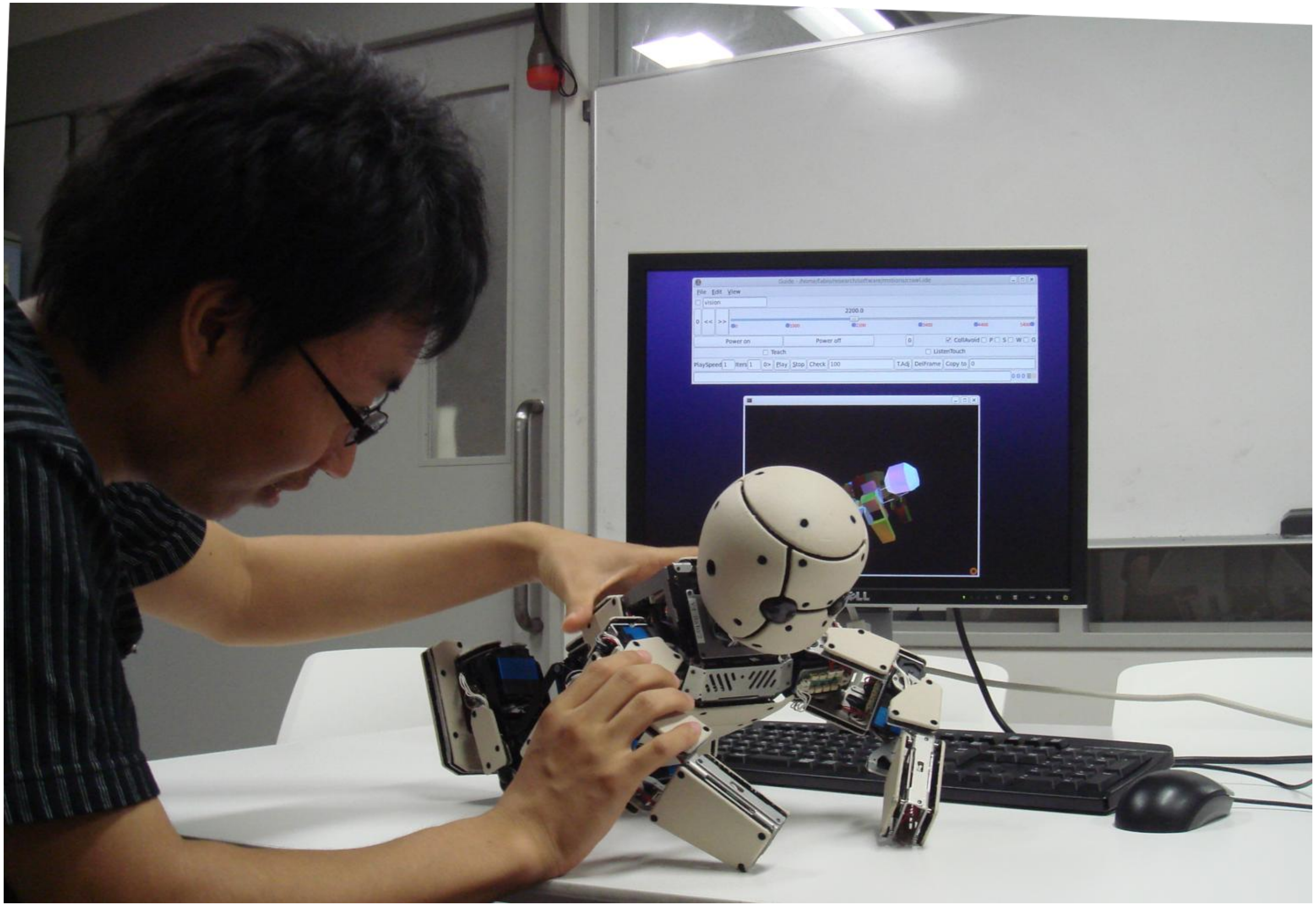


Outline

- Teaching by touching
  - Tactile instructions as a communication mean
    - Difficulties
  - Proof of concept implementation
    - Experiment
  - Analysis of the data collected
- Design policies for building touch interpretation algorithms
- Klinokinesis based control
- Analysis of natural looking movements

Part 1

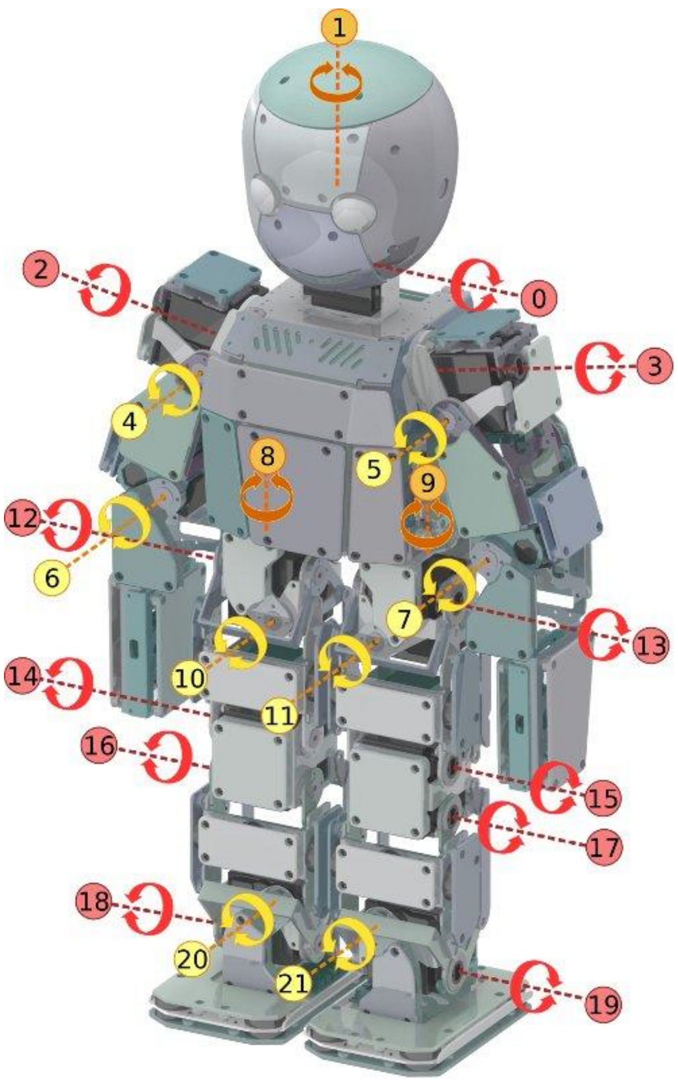
- Teaching by touching



Why humanoids?

- They can use tools and infrastructures already available for humans
- They can convey non-verbal information: ease communication
- They can become a model for understanding humans

Difficulties



- Developing motions for humanoids with high number of DOFs (≥20) is

difficult

Continuous state space
連続状態

Continuous action space
連続行動

Time continuous
連続時間

Highly dimensional spaces
高次元空間

離散でも

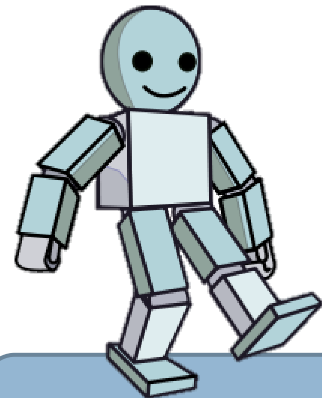
- Automatic learning is often impossible

Transfer of knowledge

1. **Task known** beforehand:

Programmer's knowledge

プログラマの知識



Robot's controller

Programmer's knowledge included in the control algorithms

Examples:

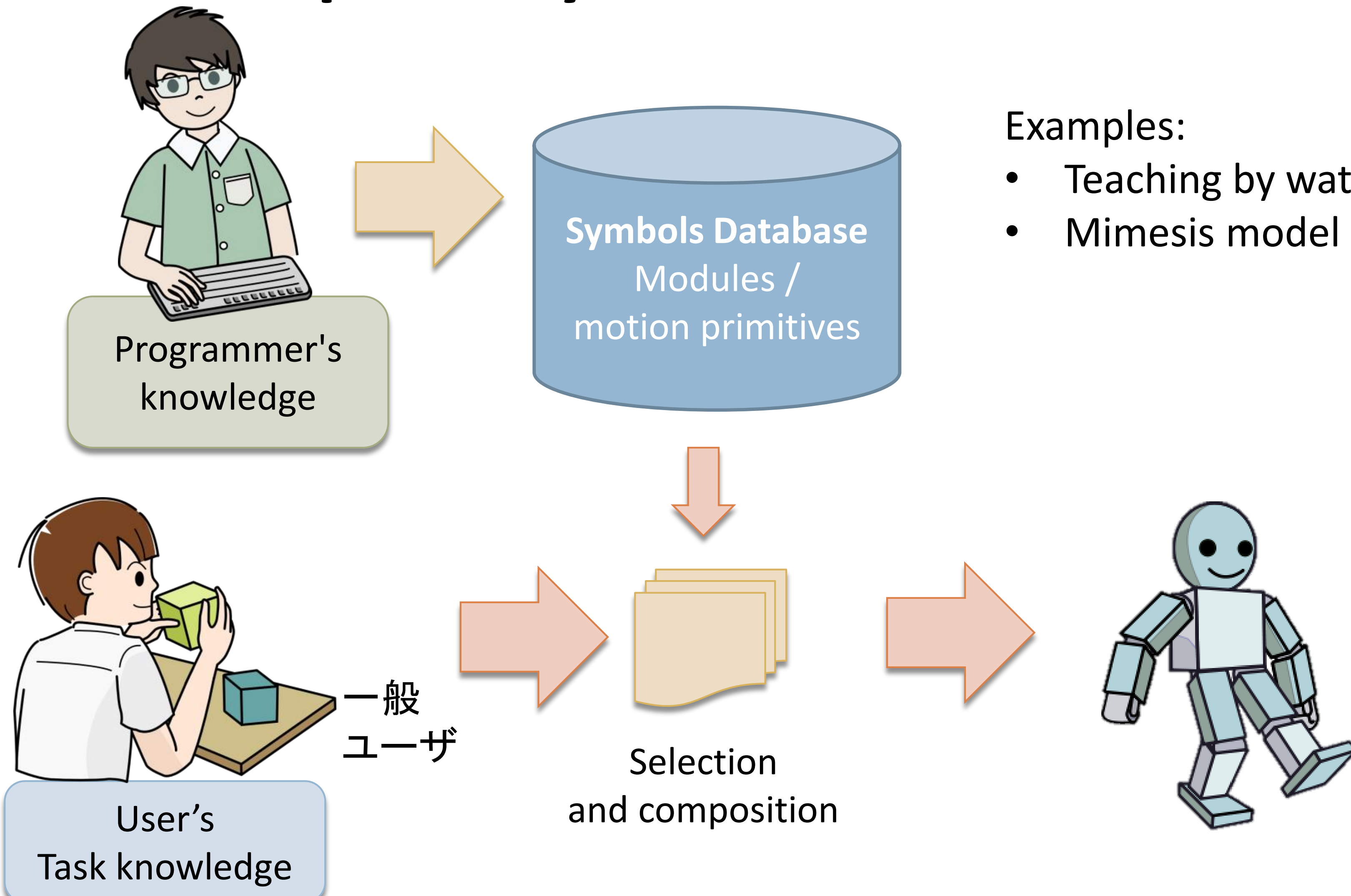
- **Visual servoing**
- **ZMP**
- **CPG connections**
- **Design of the state/action space**

Transfer of knowledge

2. Task **partially known** beforehand:

Examples:

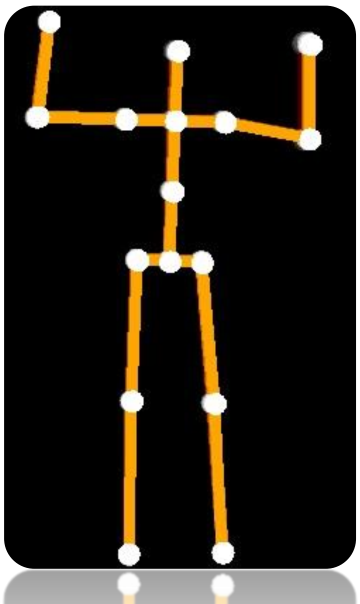
- Teaching by watching
- Mimesis model



Transfer of knowledge

3. Task **unknown** beforehand:

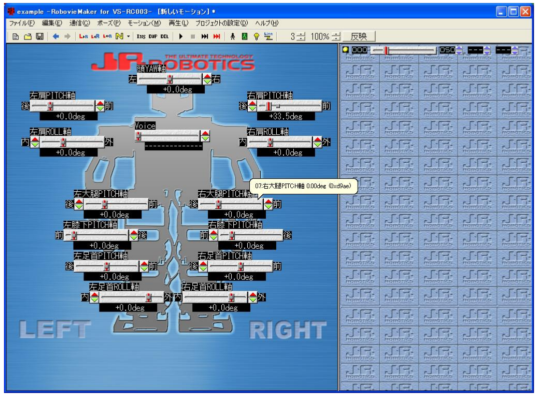
The user executes the motion by him/herself

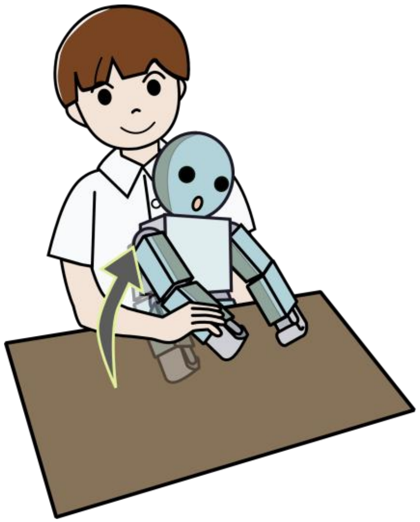


Examples:

- Motion retargeting

The user makes the robot execute the motion

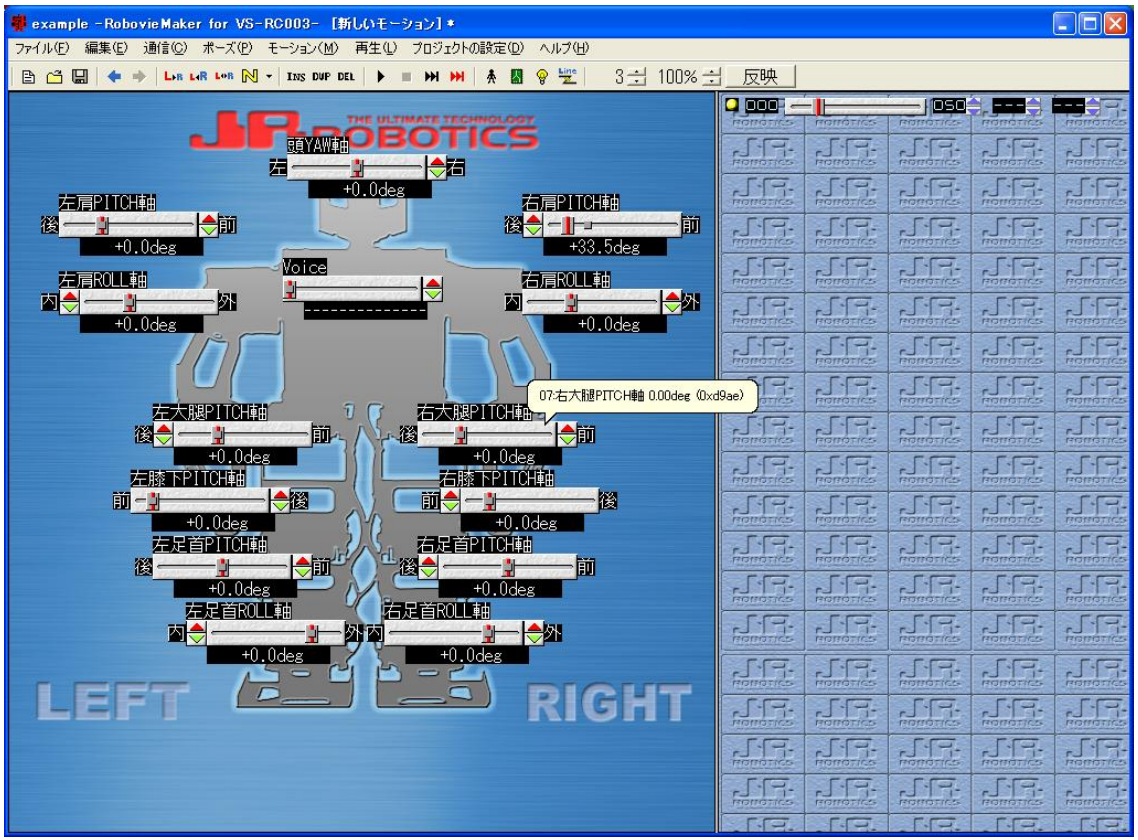




Examples:

- Motion editor
- Kinestetic demonstration (teaching and playback)

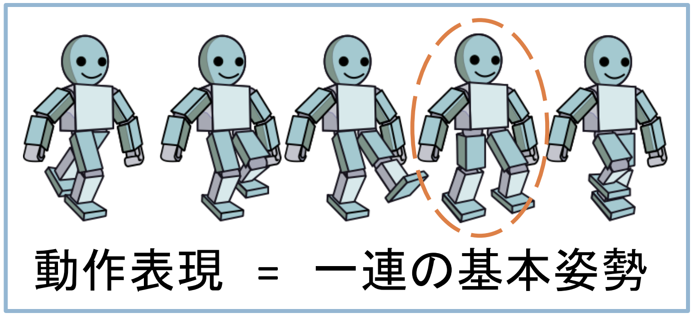
Commercial motion editors

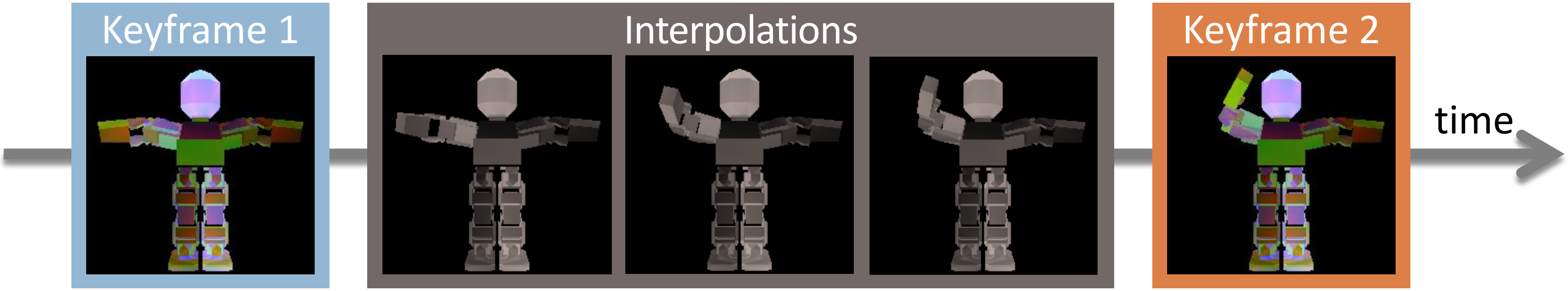


- Movement defined by **keyframes**
- The user needs to set the position of each joint at each **keyframe**.
- *Time consuming* and *unintuitive*

Keyframe based motion description

- Motion is a sequence of "important postures" defined for certain times
- The postures at intermediate in between are obtained by **interpolation**

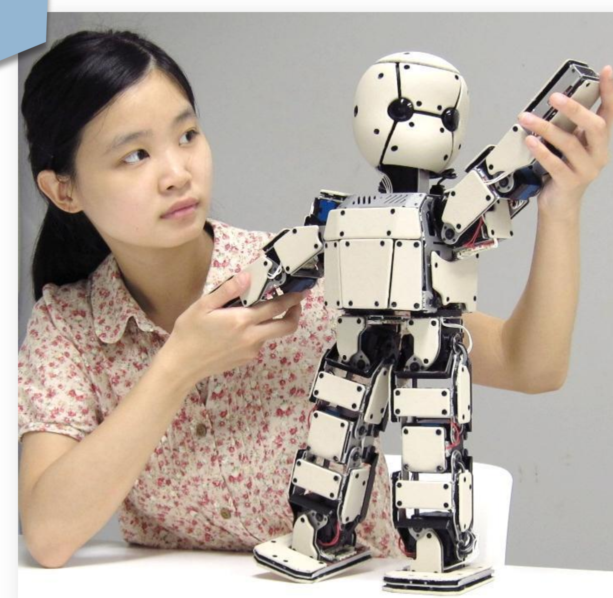




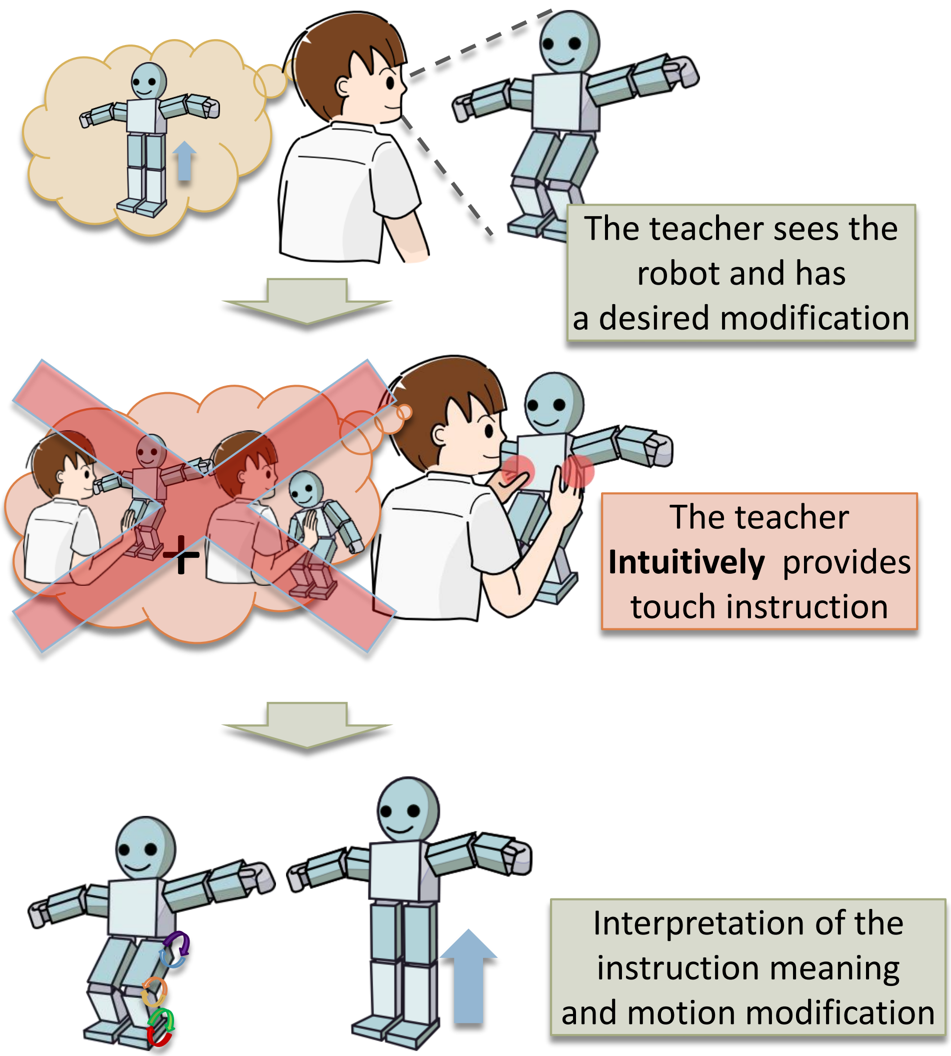
Touch as a communication mean

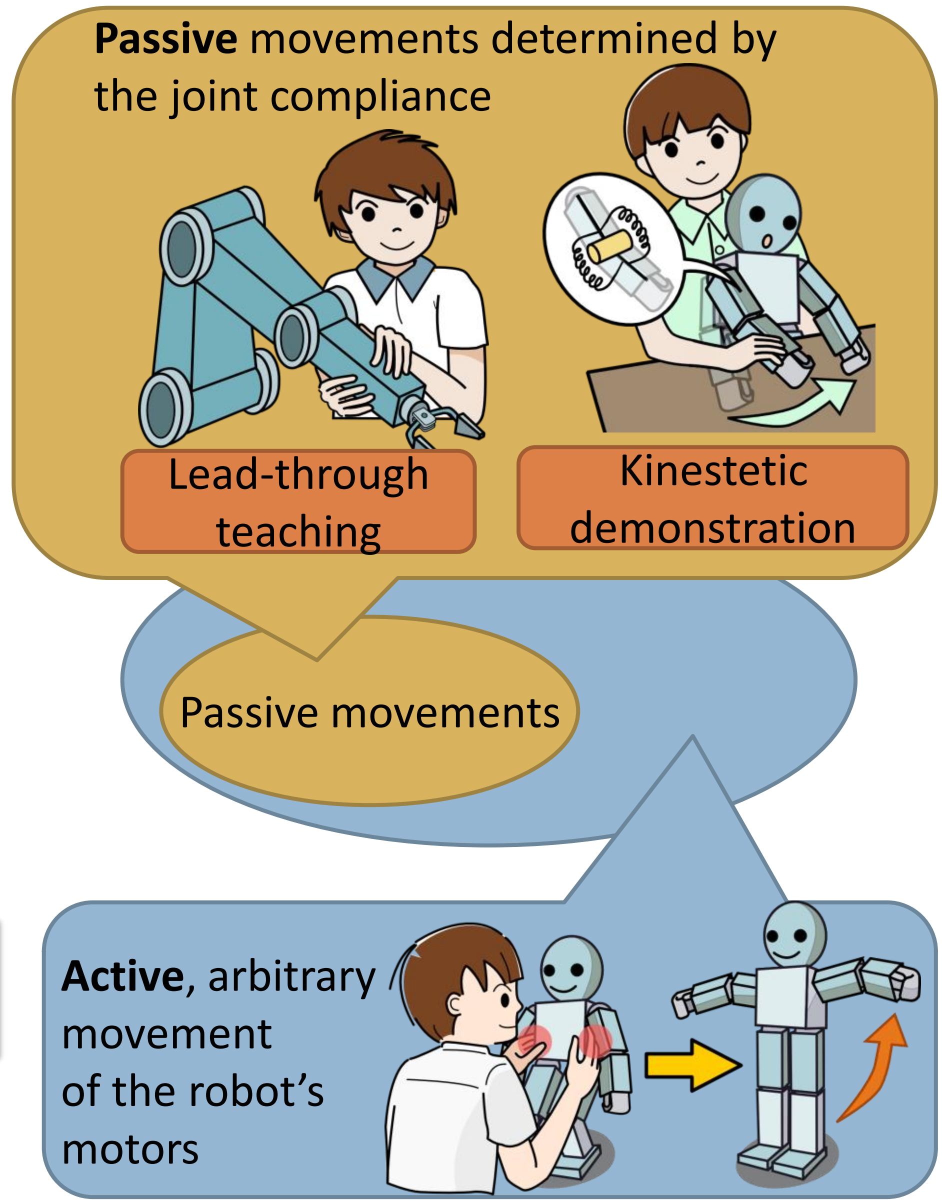
Human - human motion teaching

Human – robot motion teaching



Tactile protocol

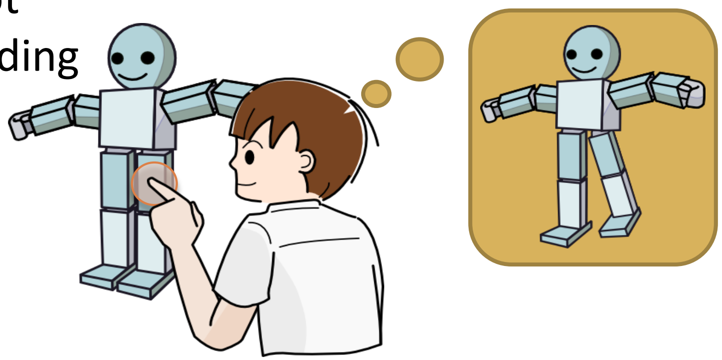




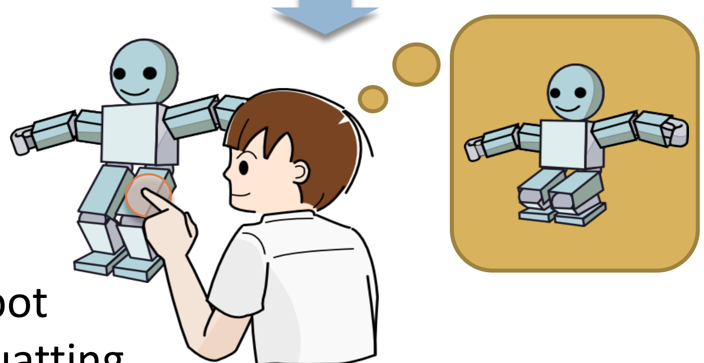
Interpretation of tactile instructions

Context dependence

Robot standing

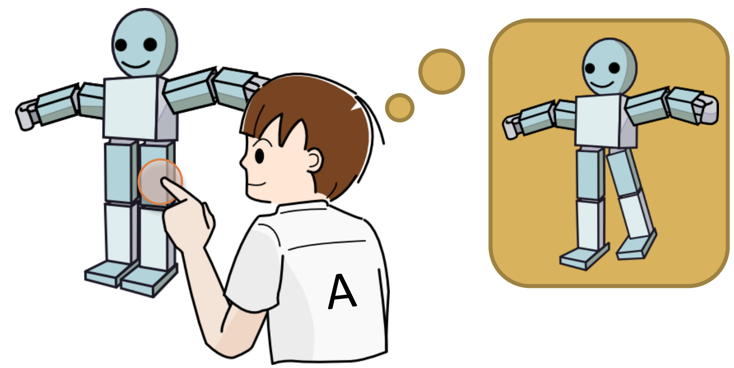


Same touch, different meanings depending on the **robot's posture**

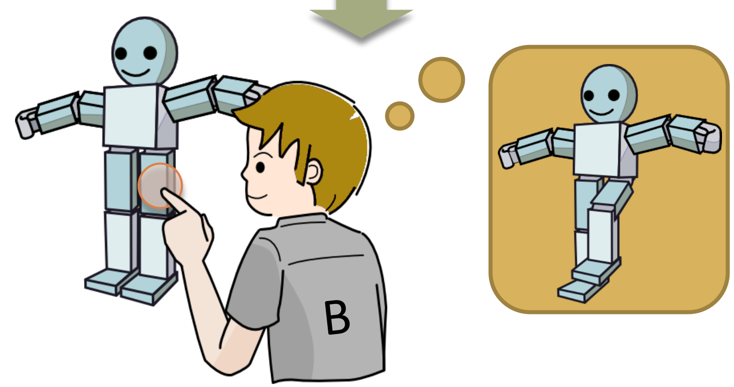


Robot squatting

User dependence

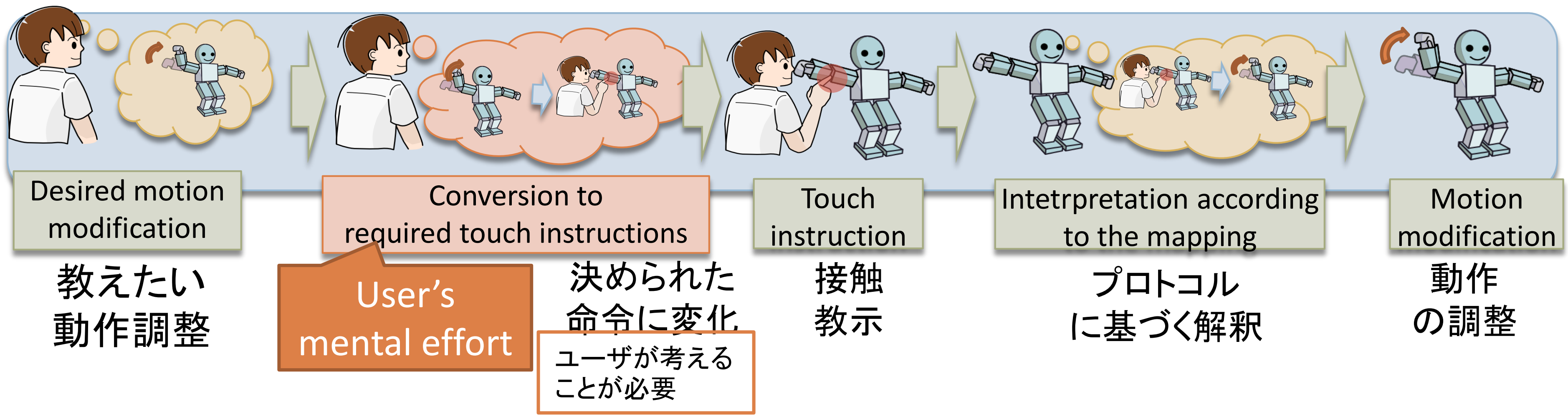


Same touch, different meanings depending on the **user**

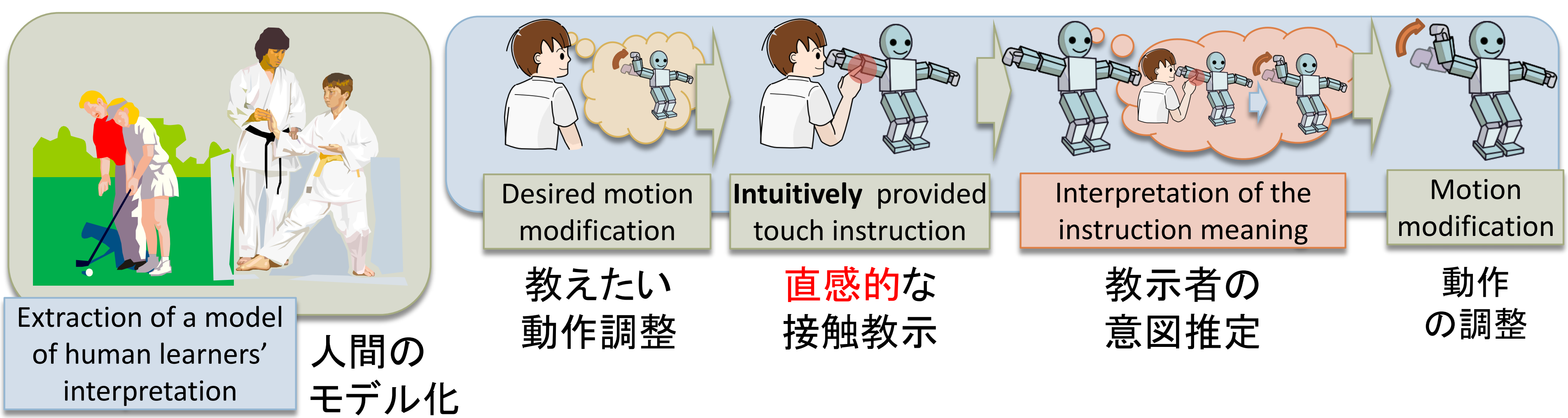


Interpretation:possible approaches

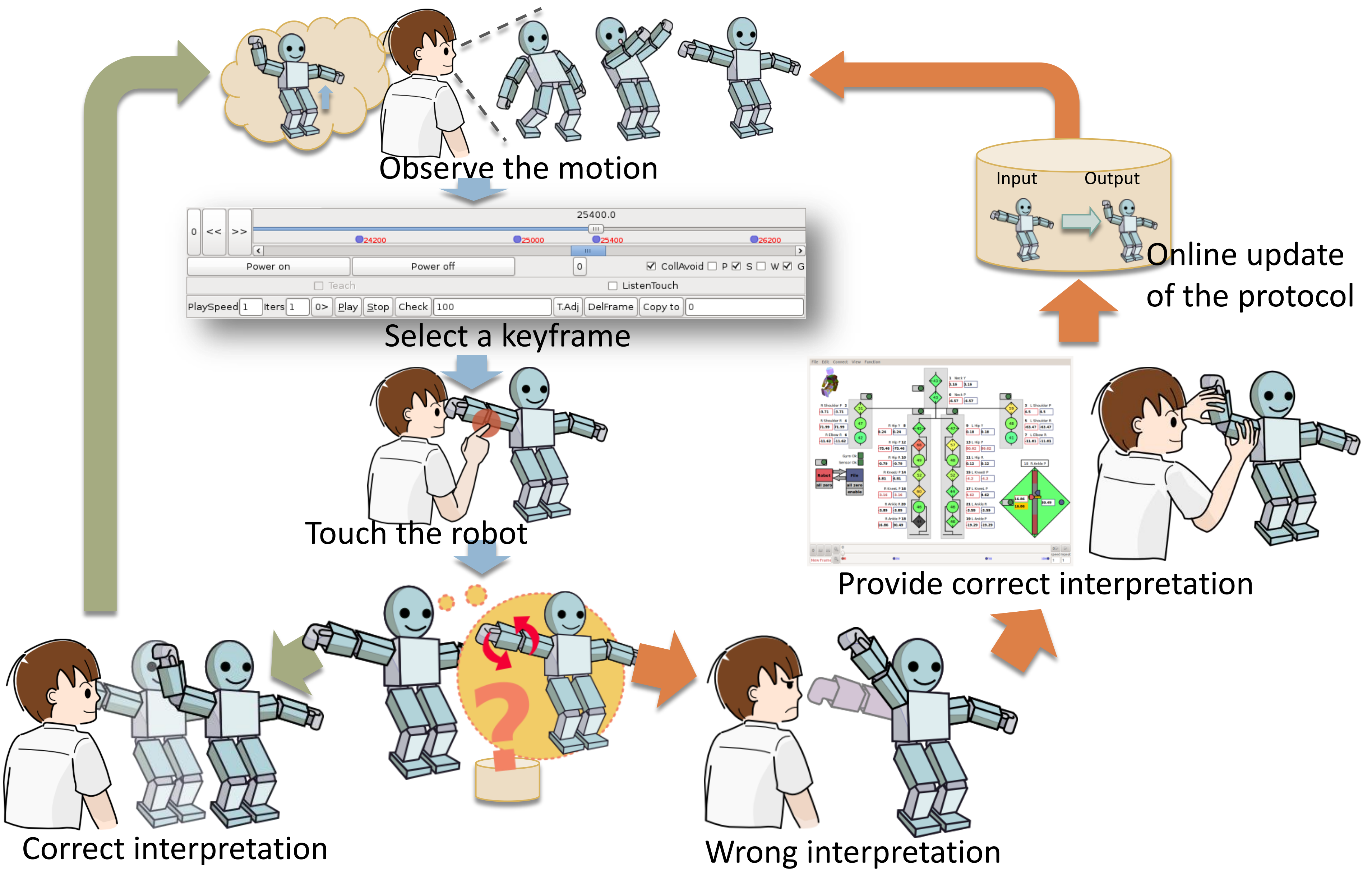
1) Fixed protocol　あらかじめ決められたプロトコル



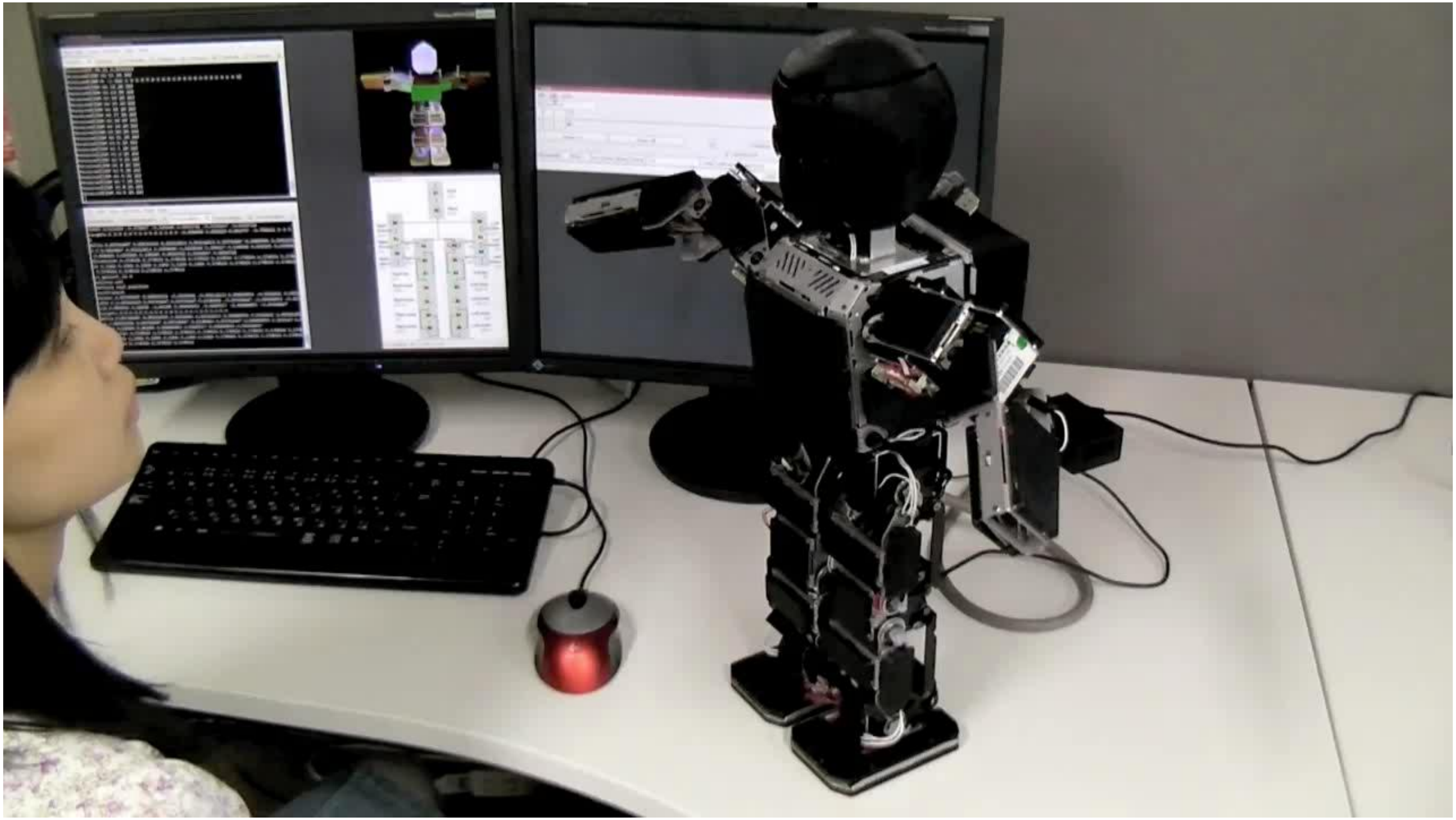
2) Human interpretation modeling　人間の学習者のモデル化に基づくプロトコル



Motion development



Teaching a new instruction

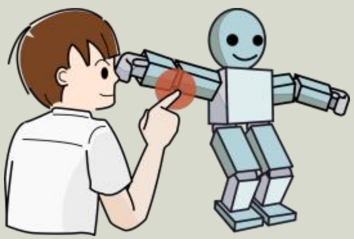


Learning algorithm

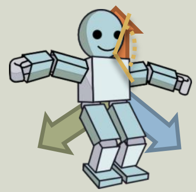
Input

Touch instruction + context

Touch sensor values:
A vector of continuous values in the range [0,1]



-Posture:
Joint potentiometer values
- Orientation:
Accelerometer values



Learning by *Kernel regression*:
non-parametric (instance based)
local learning

$$M_* = \sum_{i=1}^{E} \omega(I_*, I_i) M_i$$

Number of examples

Current sensory input

i-th example sensory input

Posture change for current sensory input

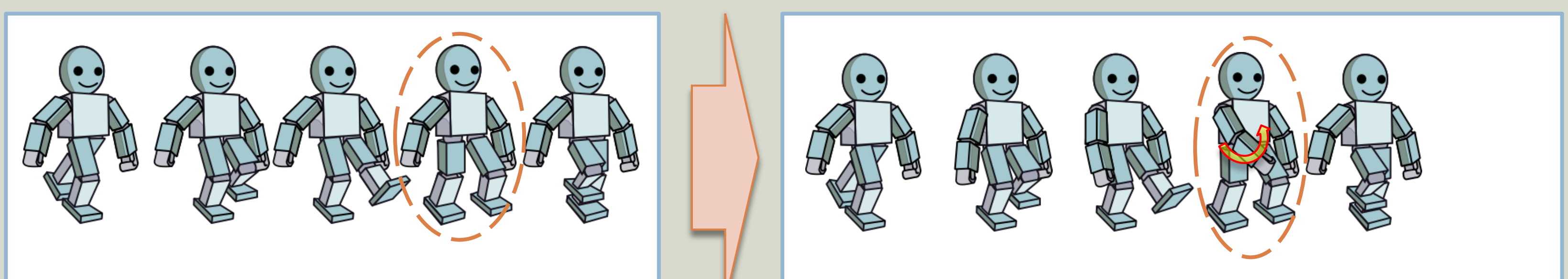
Kernel function

Posture change of i-th example

Output

Motion modification

A modification of the posture assumed by the robot at the time it is touched



Kernel function

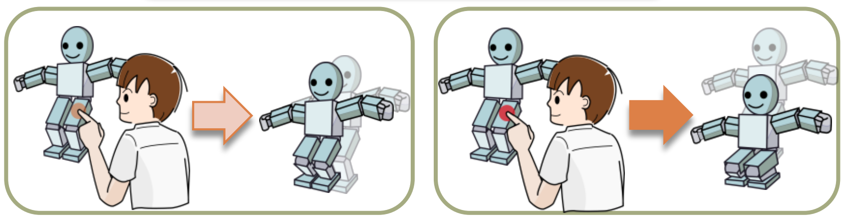
$$\omega(I_*, I_i) = \begin{cases} 0 \quad 3 & if\ \exists s : s \in \Psi_i \wedge s \notin \Psi_* \\ \dfrac{\prod_{s\in\Psi_i} \bar{I}_*^{(s)} / \bar{I}_i^{(s)} \quad 1}{1+\sqrt{\|\tilde{I}_* - \tilde{I}_i\|_2^2 + \sum_{s:\notin\Psi_i} (\bar{I}_*^{(s)})^2} \quad 2} & otherwise \end{cases}$$

Touch sensor data

Set of sensors pressed

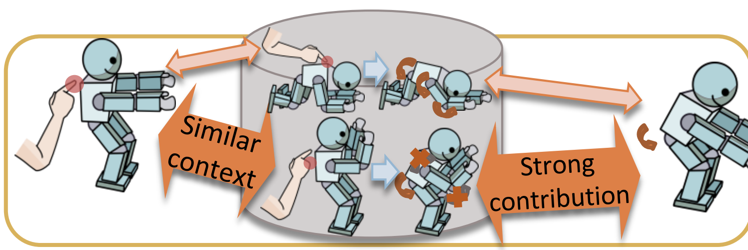
Sensory information except touch sensors

1



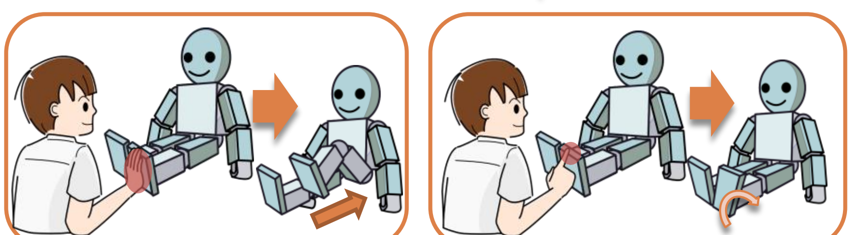
Stronger push → bigger effect

2



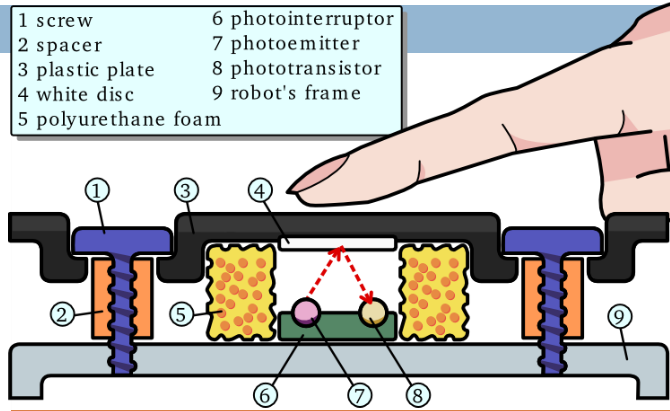
Closer context → stronger contribution to the output

3



Only a subset of sensors is pushed → ignore

Experimental setup



M3 Neony: body covered with 90 optical tactile sensors

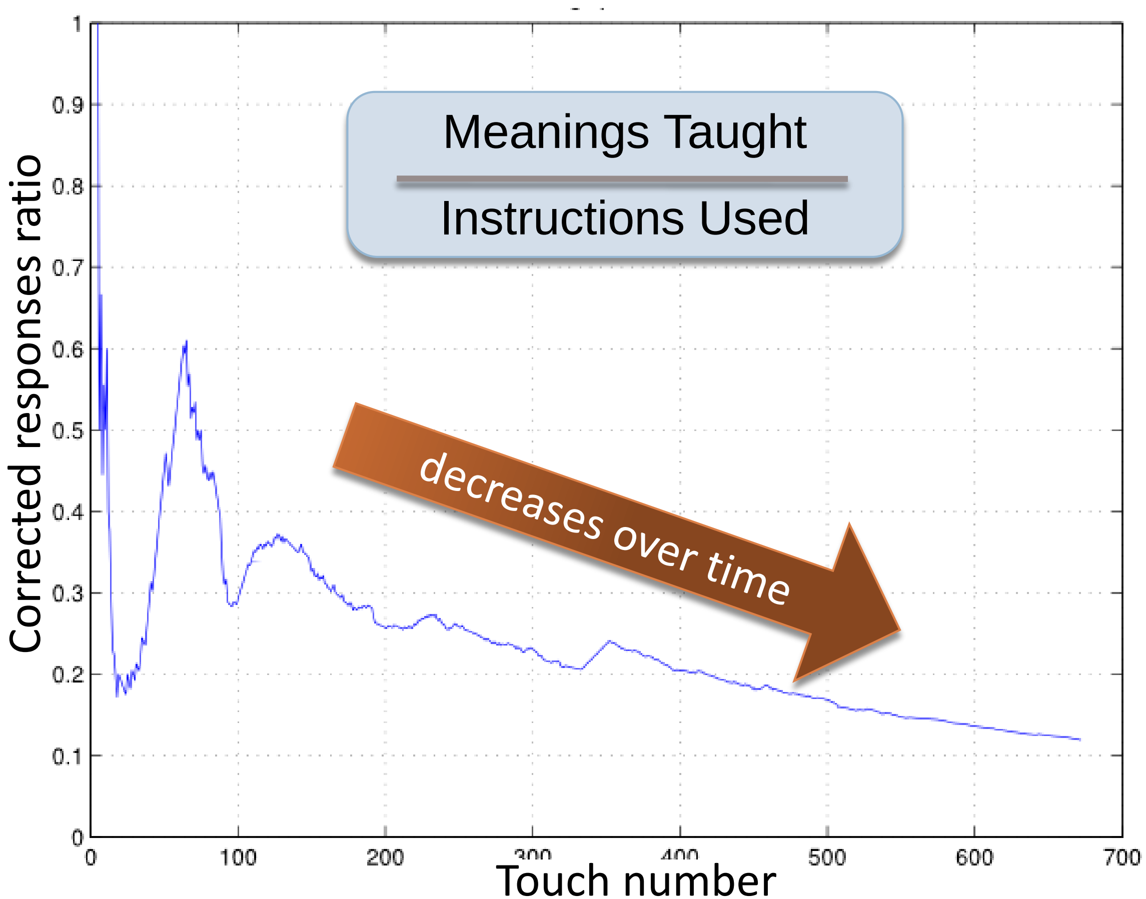
Subjects:

- engineering students
- age 23-25
- 3 males, 1 female
- no knowledge on TbT

Task:
Development of algorithm exercise

Results

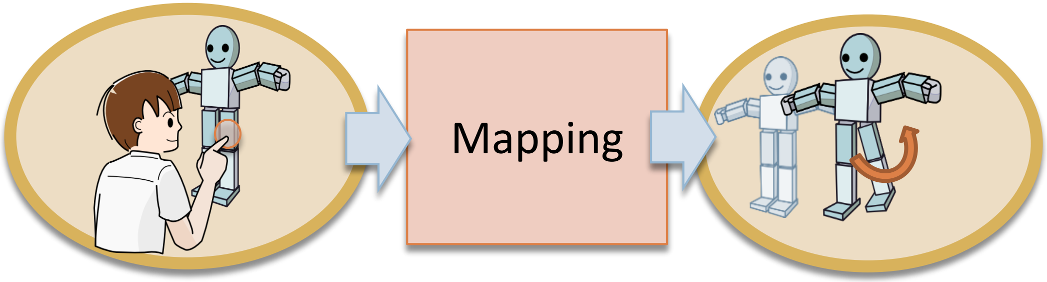
- On average
  - 96 instructions (min 60 – max 157)
  - 867 touches (min 436 – max 2332)
  - 6 hours (min 4:20 – max 7:30)



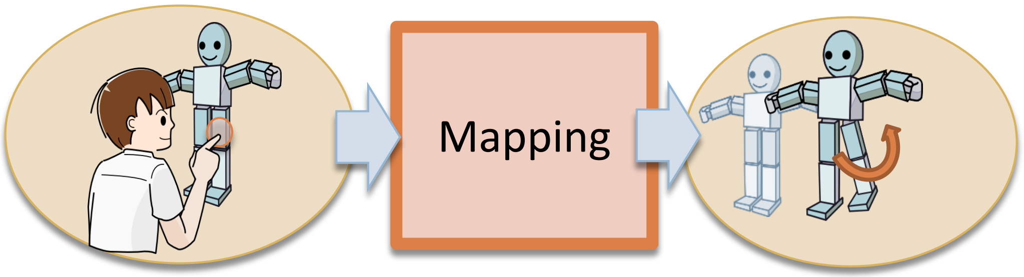
The system correctly learns how to interpret the touches and the user needs to teach less and less the meaning of the touches

Data analysis

- Study **how humans use touch** to communicate

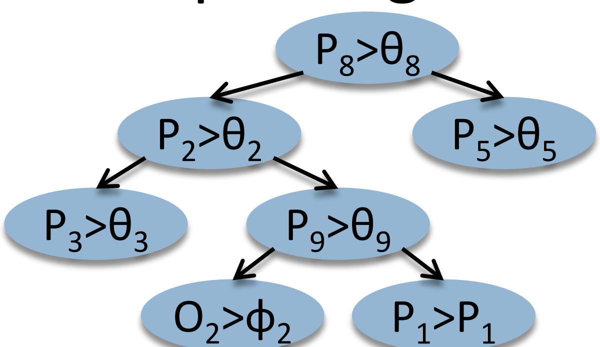


- Study the properties of the mapping
  - Design policies for interpretation algorithms

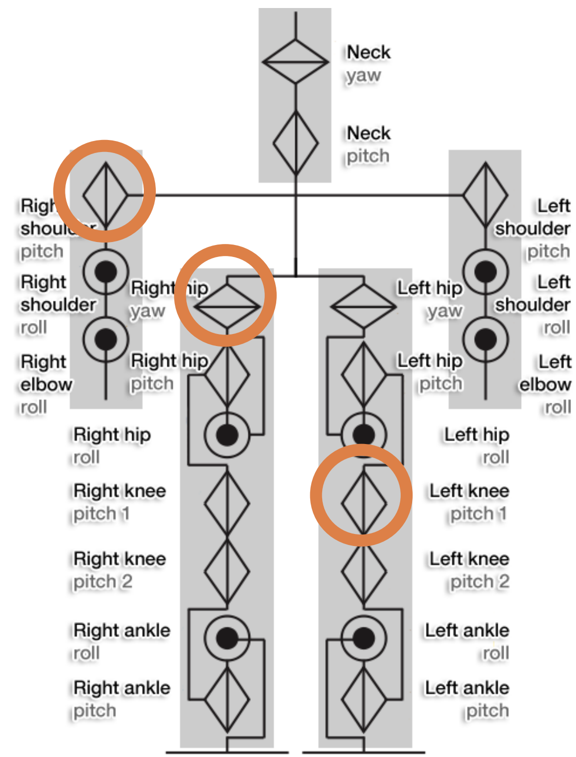


Mapping linearity

- Linear (ridge) regression generalizes very poorly
  - Errors often 2 orders of magnitude w.r.t. Kernel regression
- Regression trees can improve the situation, exploiting the context



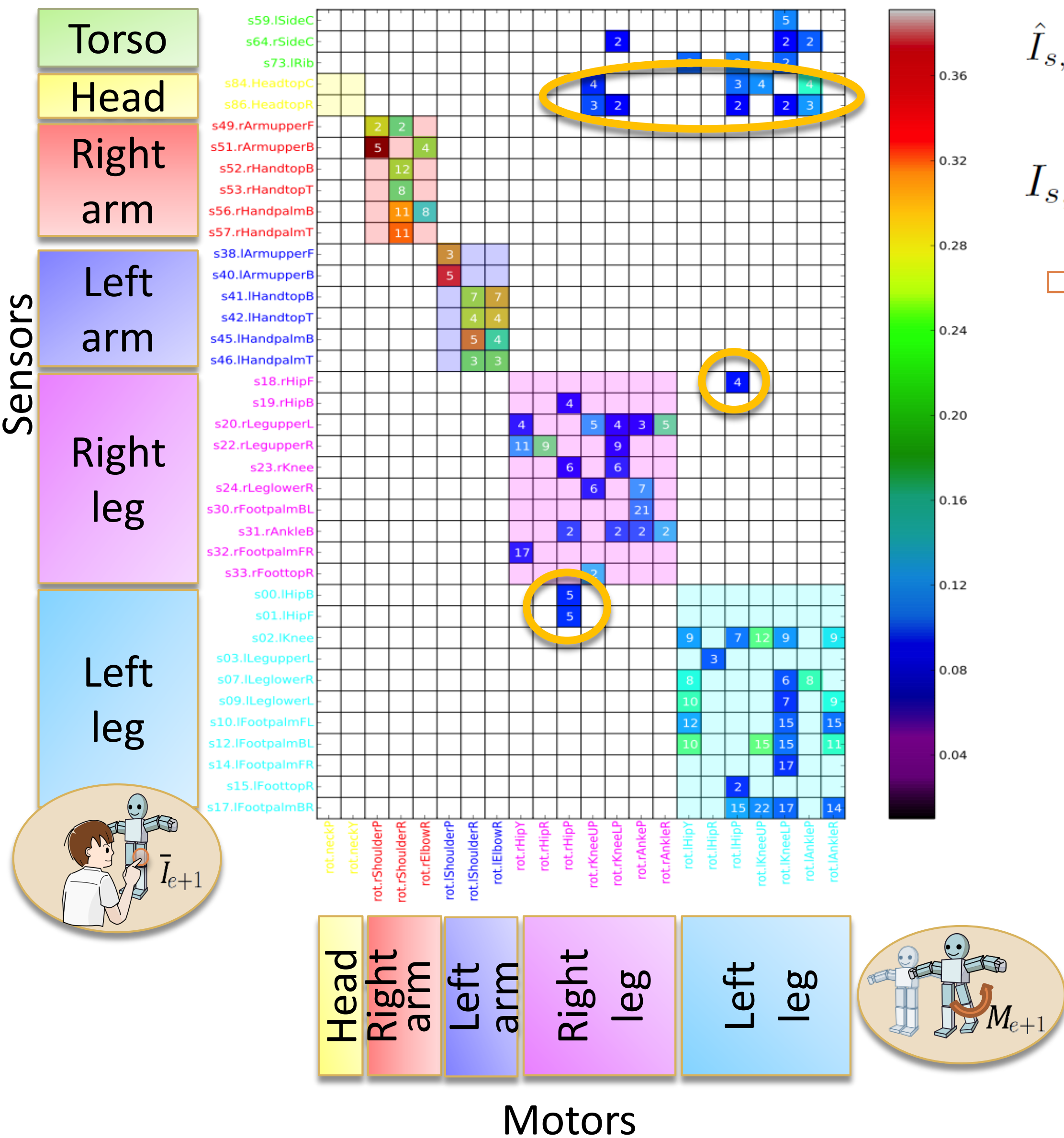
- Posture (potentiometers)
- Orientation (accelerometers)



1

Context that mostly influence the mapping:
rotation of the joints near the torso

Mapping structure



$$\hat{I}_{s,m} = \sum_{\sigma}\sum_{\mu} p_{s,m}(\sigma,\mu)\log_2\left(\frac{p_{s,m}(\sigma,\mu)}{p_s(\sigma)p_m(\mu)}\right)$$

$$I_{s,m} = \frac{\hat{I}_{s,m}}{\sqrt{H_s H_m}}$$

- Generally mutual information is high for sensors and motors of the same limb
- For high level behaviors,

  ex: *push the head = squat*

  high mutual information between different parts

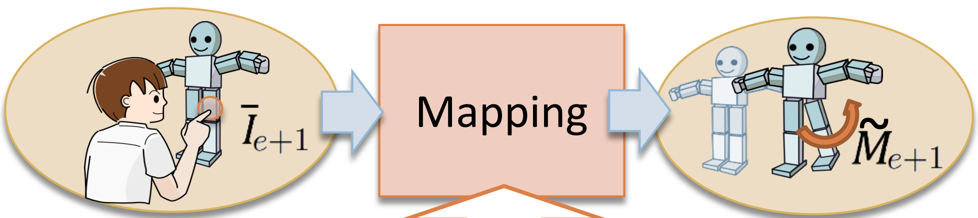
2

Mapping algorithms
- can assume a higher probability for motors of the same limb
- must allow inter-limb associations

Mapping sparsity

Very high Gini index for inputs and outputs

	Subject 1	Subject 2	Subject 3	Subject 4
$avg_{1\le i\le E} < G(\bar{I}_i) >$	0.96	0.90	0.98	0.92
$avg_{1\le i\le E} < G(M_i) >$	0.82	0.78	0.87	0.70



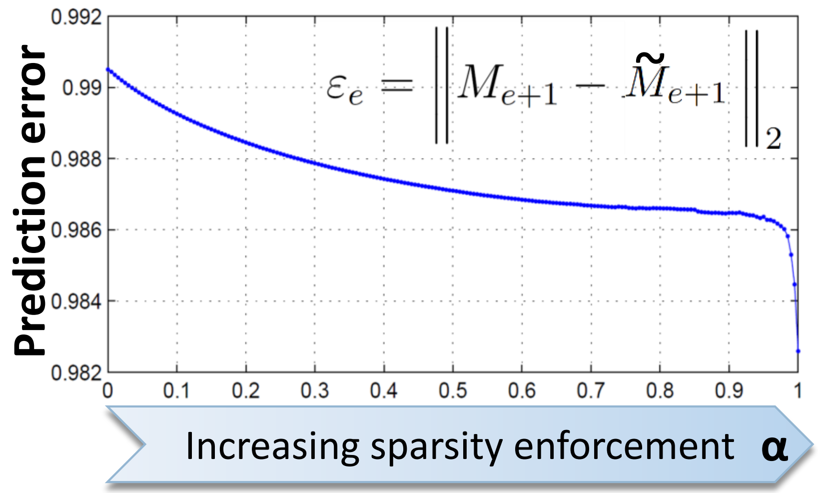
Given the couples $(\bar{I}_i, M_i)$ for 1≤i ≤e predict the result M_{e+1} from $\bar{I}_{e+1}$

$$\tilde{M}_{e+1} = B_e \begin{bmatrix} 1 \\ \bar{I}_{e+1} \end{bmatrix} \text{ with rows } {B_e}^{(k)} = [{b_e}^{(k)} \quad {\beta_e}^{(k)}]$$

chosen by **Elastic net regularization**

$$\frac{1}{2N}\sum_{i=1}^{e}\left(M_i^{(k)} - b_e^{(k)} - \beta_e^{(k)}\bar{I}_i\right)^2 + \lambda\left[(1-\alpha)\frac{1}{2}\|\beta_e^k\|_2^2 + \alpha\|\beta_e^k\|_1\right]$$

Friedman, Hastie, Tibshirani, Regularization paths for generalized linear models via coordinate descent, J. of Statistical Software, 33(1), 2010.

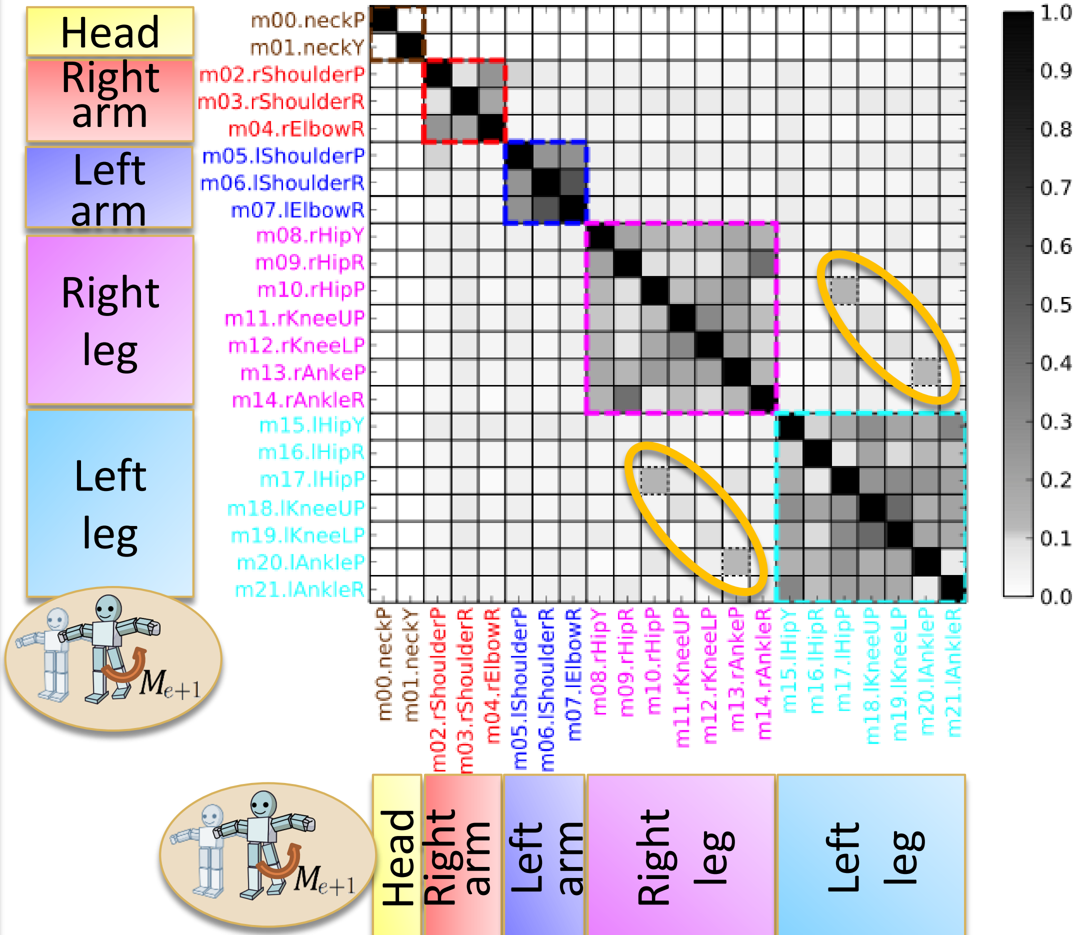


The mapping between inputs $\bar{I}_i \in \mathbb{R}^n$ and outputs $M_i \in \mathbb{R}^m$ can be improved enforcing sparsity

3

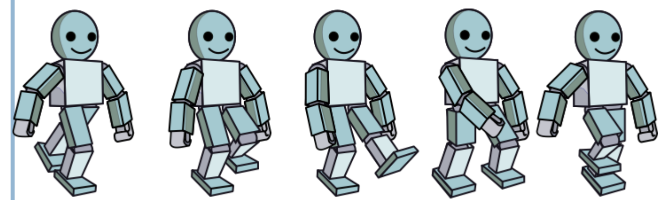
Motion Primitives in Motor responses

Motion responses ("edits of a single posture")



Motion primitives

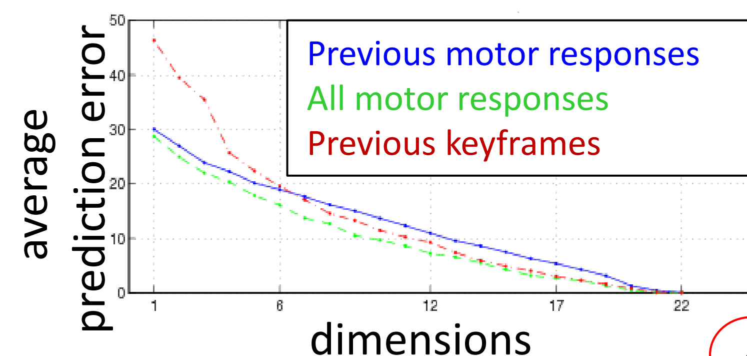
Keyframes ("whole motion")



Motion primitives

"Keyframe-derived" motion primitives and "motor response-derived" motion primitives are very similar

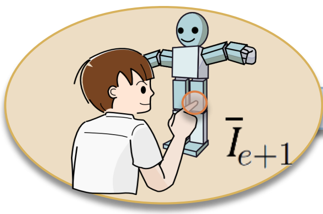
"We can use "seen keyframes" for improving the mapping



4

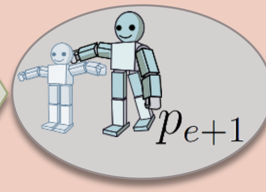
Keyframes selection

Mapping

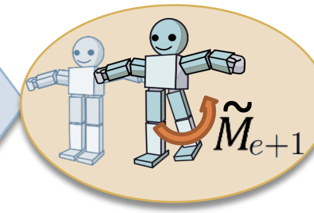


Initial prediction

$$p_{e+1} = B_e \begin{bmatrix} 1 \\ \bar{I}_{e+1} \end{bmatrix}$$



Projection on span <F₁,..,F_k>



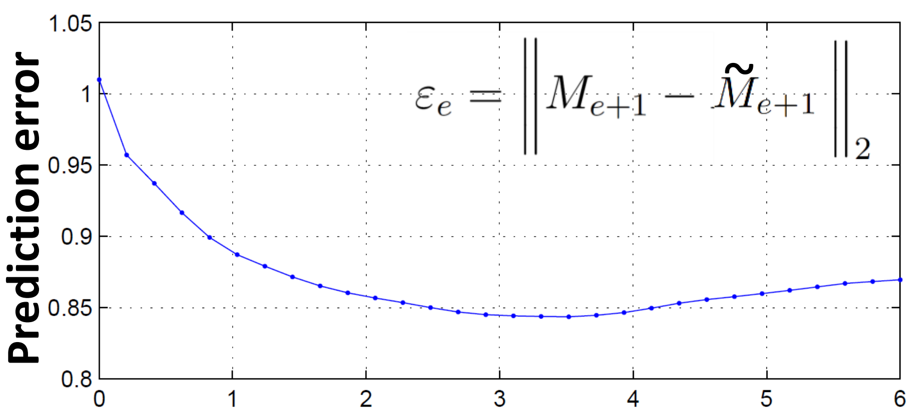
$$\tilde{M}_{e+1} = \Gamma_{e+1}\rho_{e+1}$$

$$\Gamma_{e+1} = \begin{bmatrix} F_1 & \dots & F_K \end{bmatrix}$$

chosen by minimizing

$$\|p_{e+1} - \Gamma_{e+1}\rho_{e+1}\|_2^2 + \gamma\|\rho_{e+1}\|_1$$

H. Lee, A. Battle, R. Raina, and A. Y. Ng. Efficient sparse coding algorithms. NIPS, 2007.

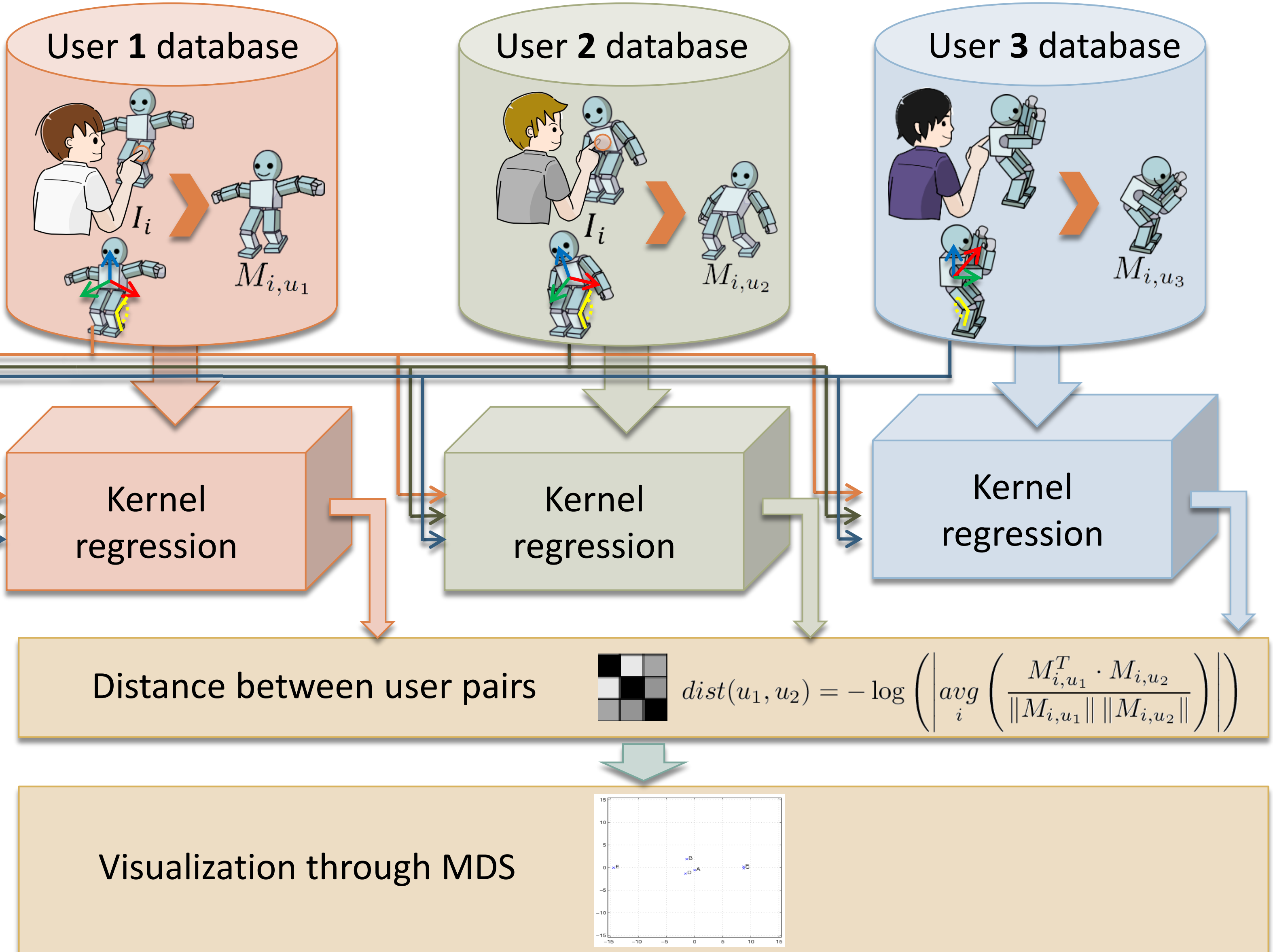


Increasing sparsity enforcement γ

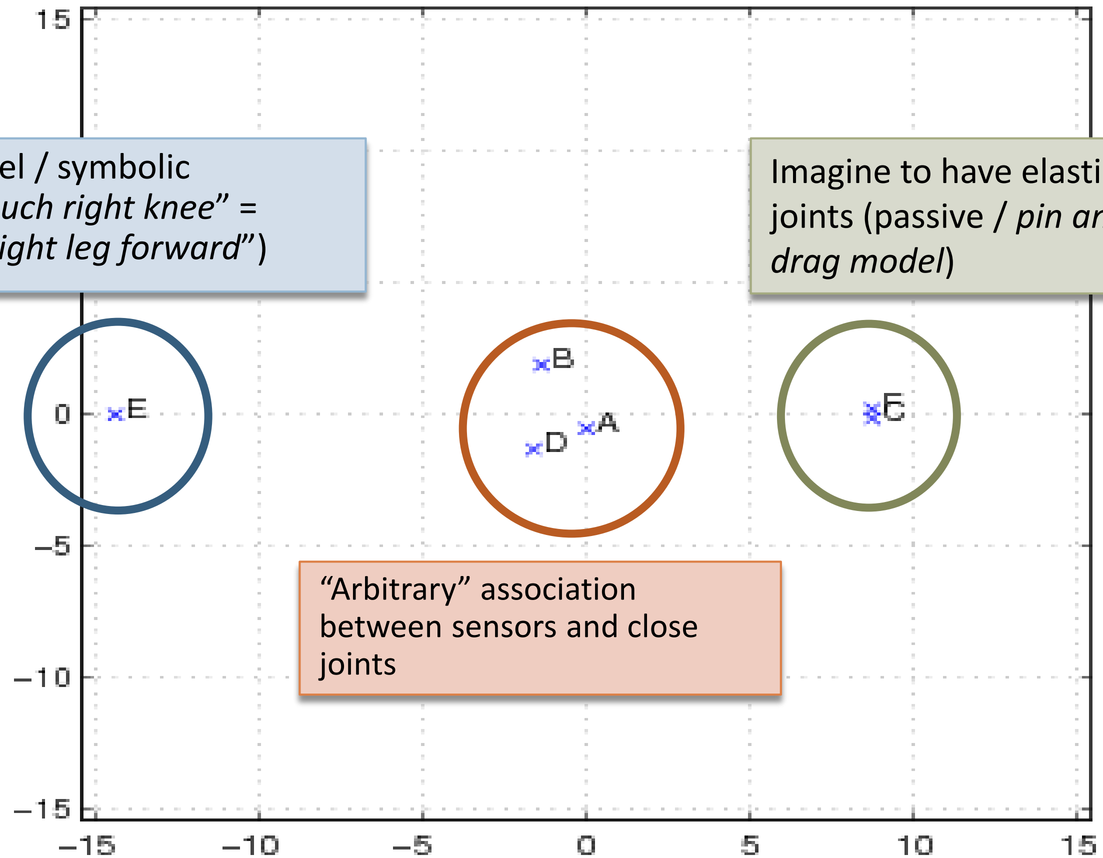
- Projecting on a subset of keyframes (instead of the whole) can further improve the performance

5

User dependency



Different levels of abstraction



high-level / symbolic (e.g. *"touch right knee"* = *"move right leg forward"*)

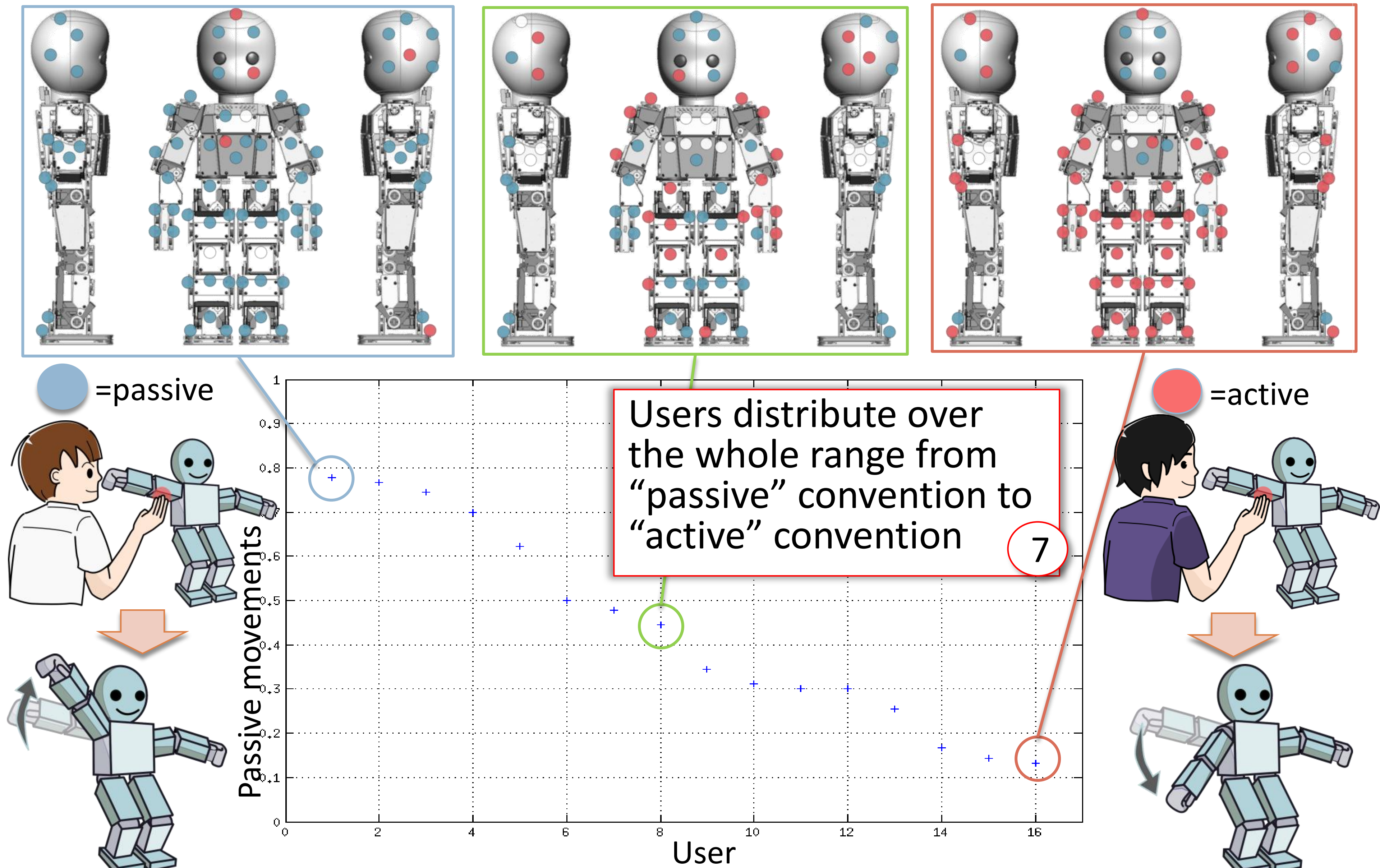
Imagine to have elastic joints (passive / *pin and drag model*)

"Arbitrary" association between sensors and close joints

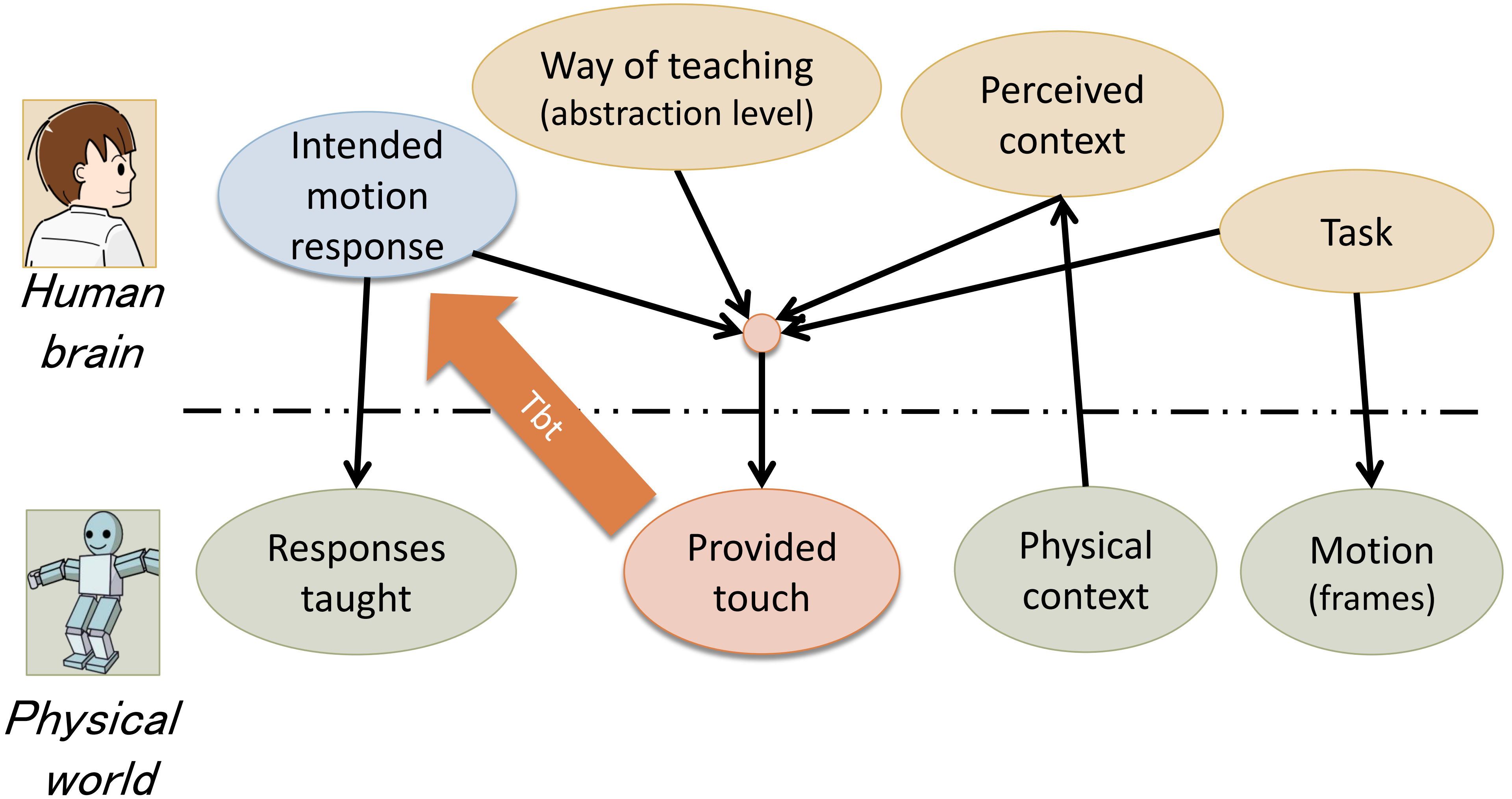
Different people tend to associate different "abstraction levels" to touch instructions

6

Active - passive



TbT: A conceptual schema



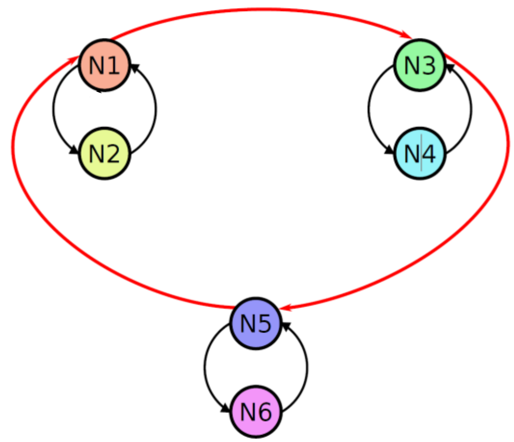
TbT analysis: Conclusions

- Context and user dependence
- Motion responses involve with high probability joints of the touched limb
  - Need the possibility of modeling exceptions and inter-limb mappings
  - Can assume sparse movements have high probability
- Motion responses can be composed by motor primitives
  - With good probability they can be derived from combining **few** frames

Predictability of CPG's behavior: Oscillator type

Plenty of oscillators types:

- Sinusoidal (*Morimoto et al. 06*)
- Hopf/adaptive Hopf(*Righetti et al. 06*)
- Rayleigh (*De Pina Filho et al. 05*)
- Van der Pol (*Veskos et al. 05*)
- FitzHugh-Nagumo (*Collins et al 94*)
- Hopfield (*Mathayomchan et al 02*)
- Matsuoka (*Inada et al 03, Inoue et al 04*)
- …



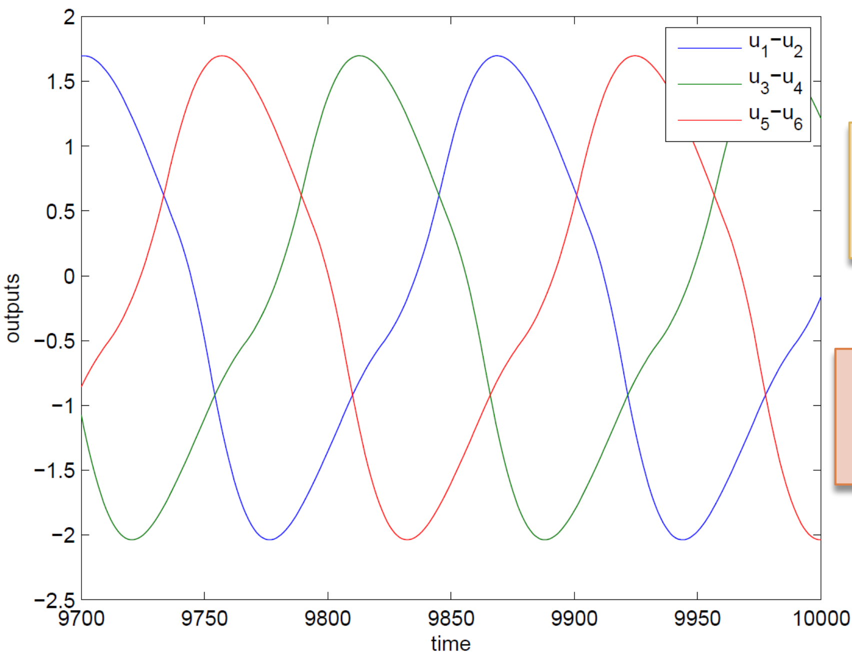
$$\tau_u \dot{u}_i = -u_i - \beta v_i - \sum w_{ij}[u_j]^+ + c_i$$

$$\tau_v \dot{v}_i = -v_i + [u_i]^+$$

$$\tau_u = 0.2,\ \tau_v = 0.4, \beta = 2.5, c = 2$$

$$W = \begin{bmatrix} 0 & 2.5 & 0 & 0 & 0 & 0 \\ 2.5 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 2.5 & 0.5 & 0 \\ 0 & 0 & 2.5 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0 & 0 & 2.5 \\ 0 & 0 & 0 & 0 & 2.5 & 0 \end{bmatrix}$$

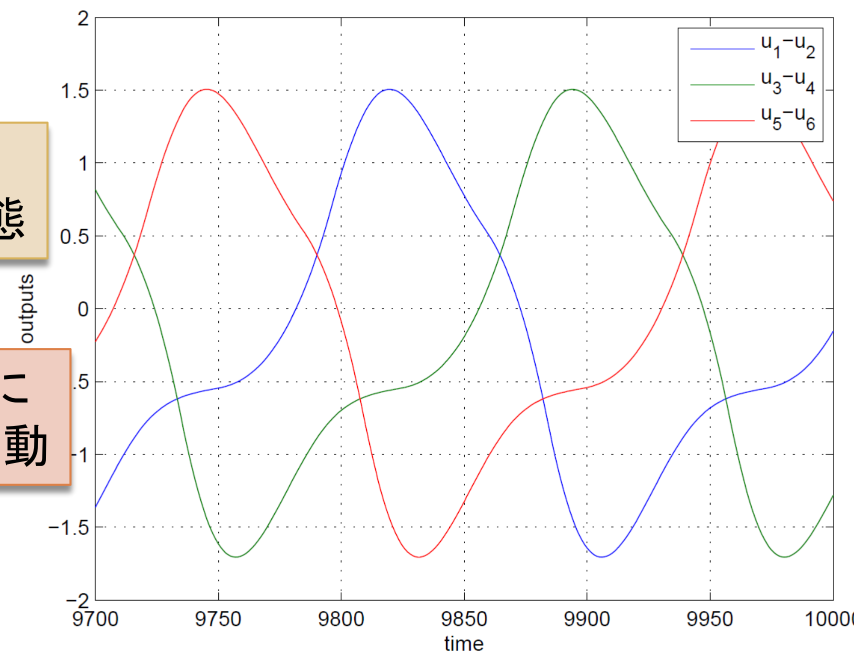
$$u = [0.0999, 0.5046, 0.7471, -0.7059, -0.9883, 0.9757]^T$$
$$v = [0.0768, 0.5865, 0.6040, 0.1839, 0.2886, 0.4419]^T$$



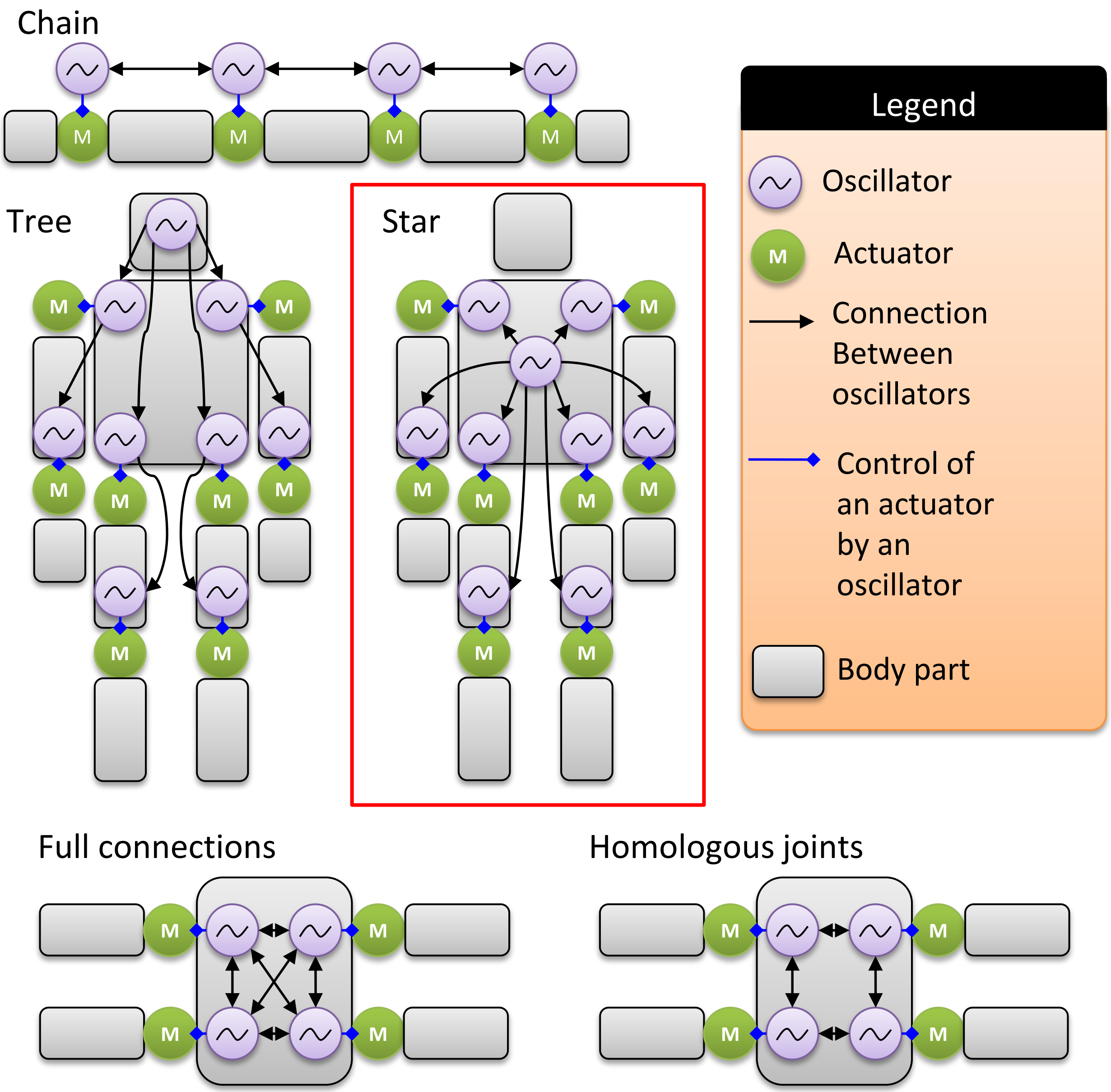
異なる
初期状態

根本的に
異なる行動

$$u = [0.8981, -0.6008, -0.0319, 0.5365, -0.4061, 0.9221]^T$$
$$v = [0.4888, 0.2295, 0.0564, 0.5740, 0.3706, 0.3309]^T$$



Generality of generable movements
CPG network structure



- Literature presents a great variety of network structures
- They can be summarized in 5 types
- The structure determines the types of motions that can be generated

CPG[神経振動子]の相互接続によって出力の一般性が増す

System setup

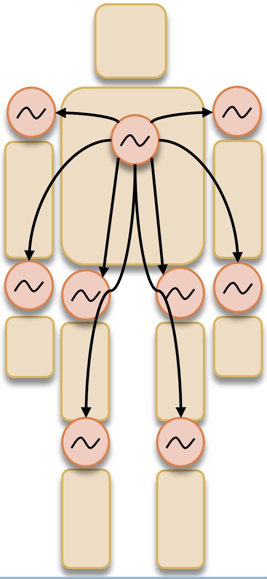
Neuron model:
Hopf oscillator

$$\dot{x}_i = \gamma_i(\mu_i - r_i^2)x_i - \omega_i y_i + \sum_j W_{ij} x_j$$

$$\dot{y}_i = \gamma_i(\mu_i - r_i^2)y_i - \omega_i x_i$$

$$r_i = \sqrt{x_i^2 + y_i^2}$$

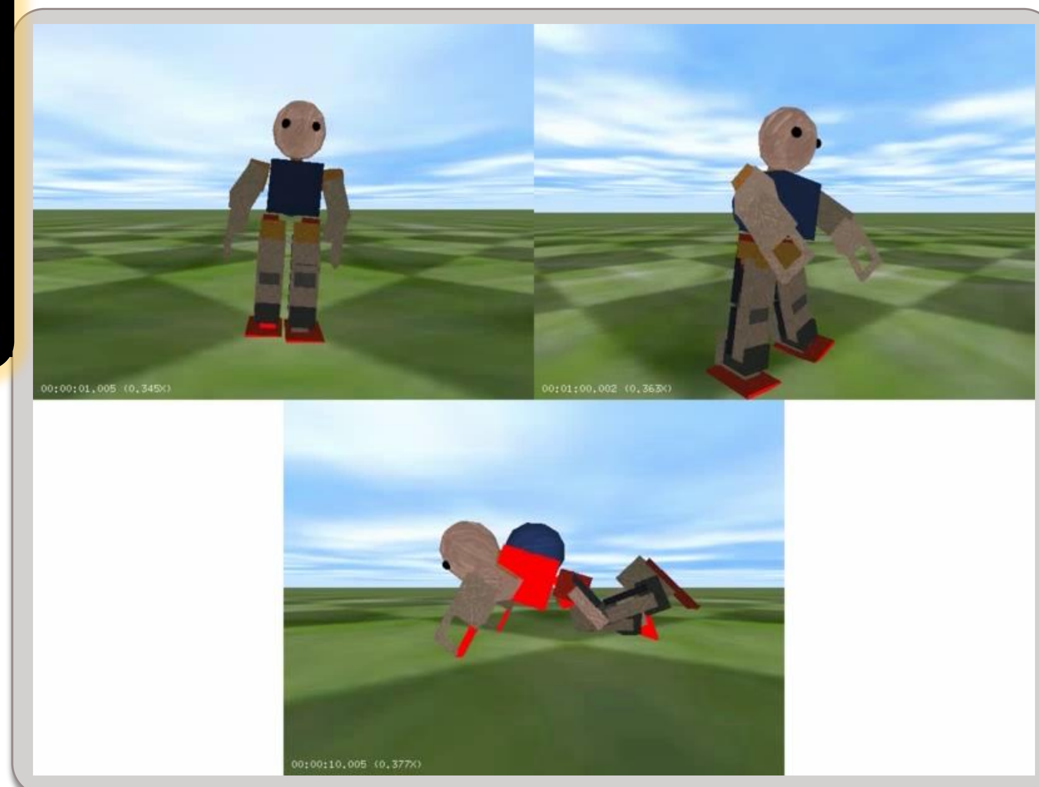
Configuration:
Star
("clock" oscillator)



Collision prevention:
Enclosing convex
Polyhedra

実体より大きい
凸多面体で近似する

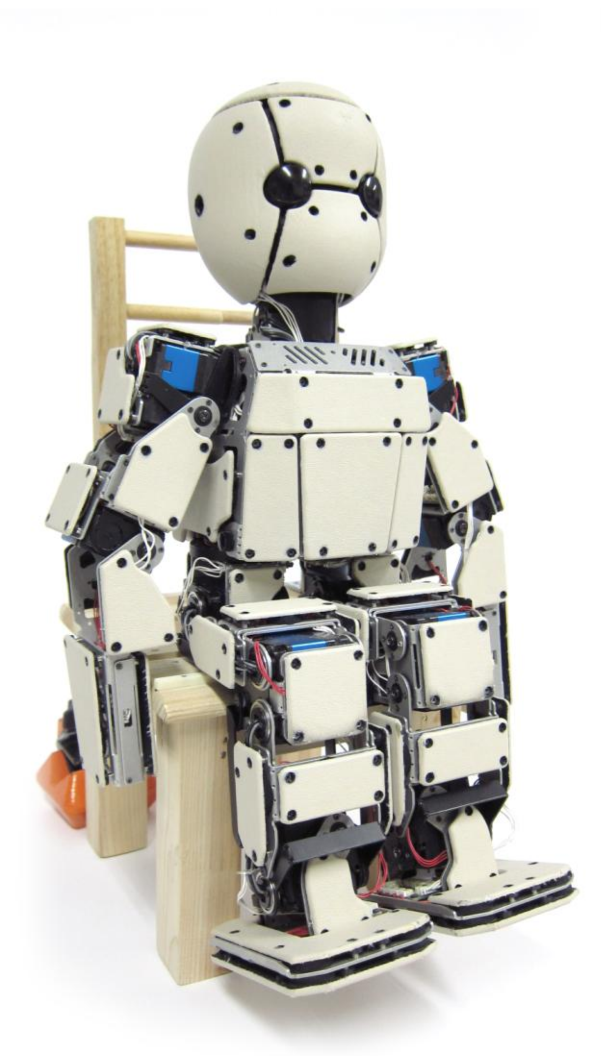
Motion examples



Research topic 1

- Distinguish between different type of touches
  - Self – User – Environment touch
- Probabilistic model of the self – environment touches
  - Identification of user’s touches as highly improbable touches due to other reasons

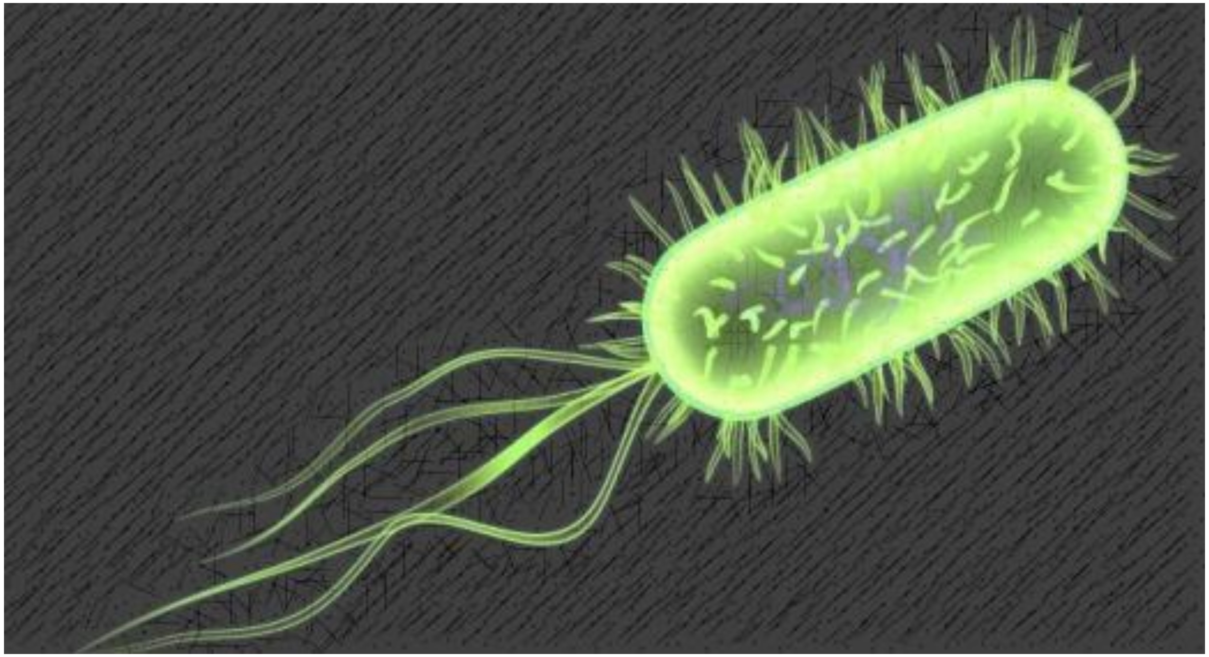
Questions ?

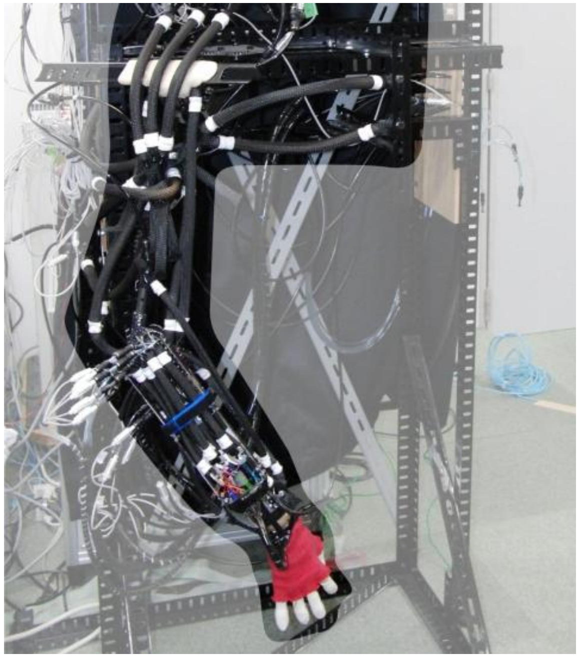


End of part 1

Part 2

- Klinokinesis based control



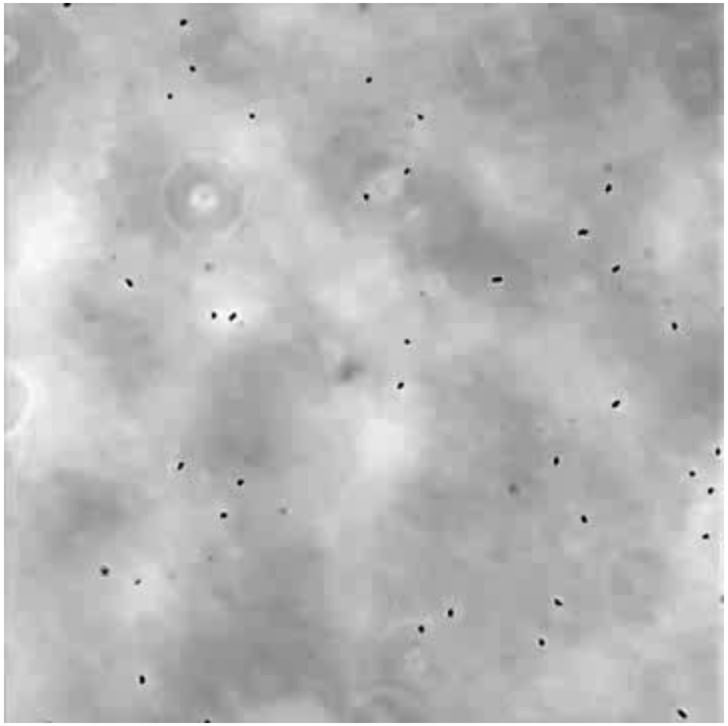


Klinokinesis

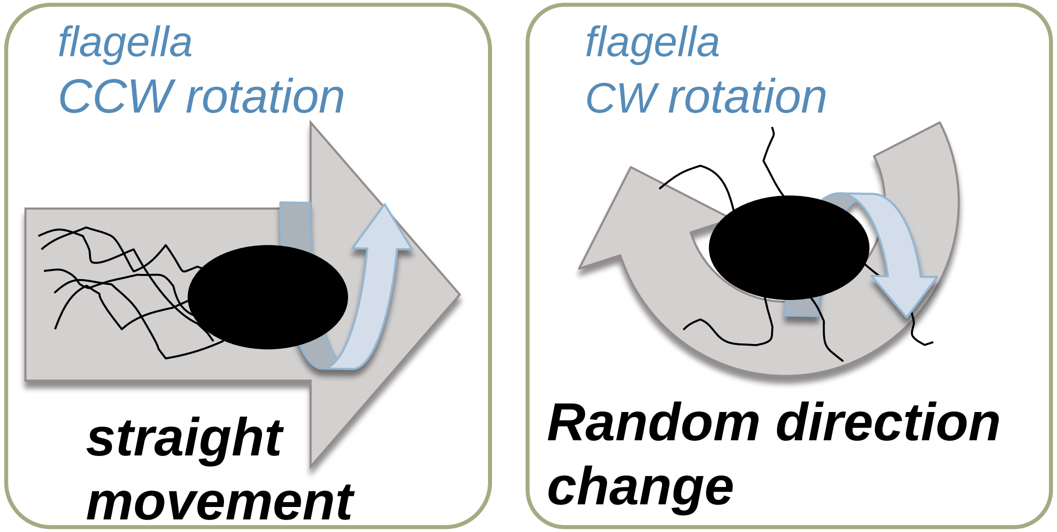
“if conditions are improving, keep on in the same direction, otherwise try a new direction”

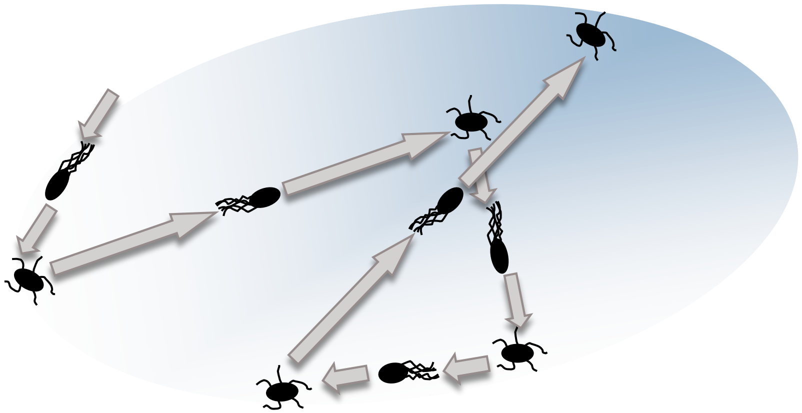
Dusenbery DB, Performance of basic strategies for following gradients in two dimensions,

Journal of Theoretical Biology, 2001



http://www.youtube.com/watch?v=EZ5ATNJfuCs





A minimalistic behavioral rule

Previous motor command

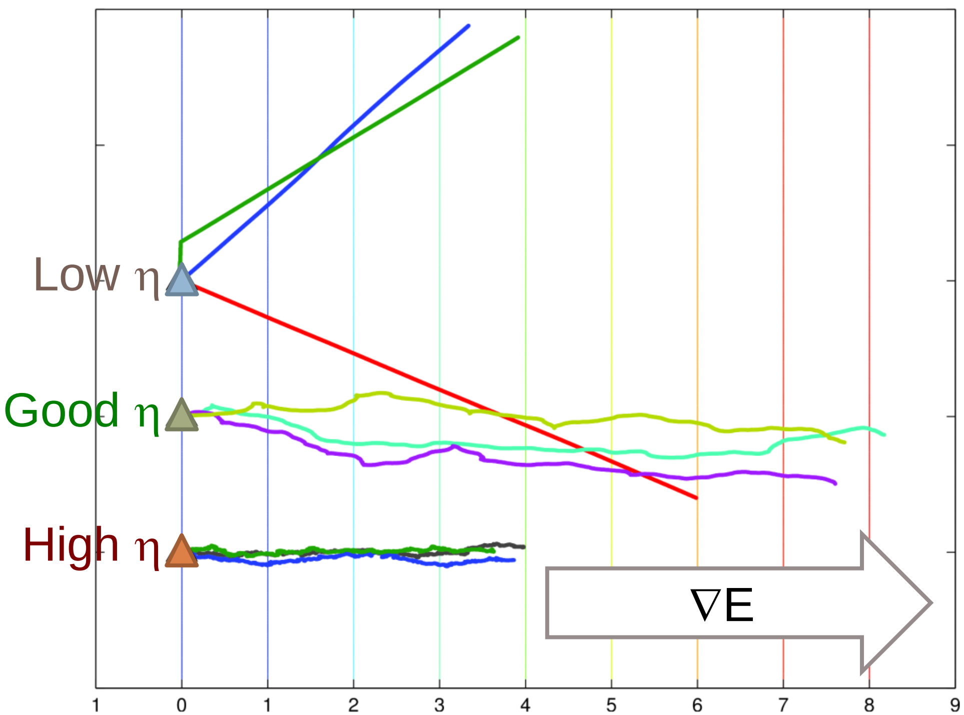
If conditions are improving

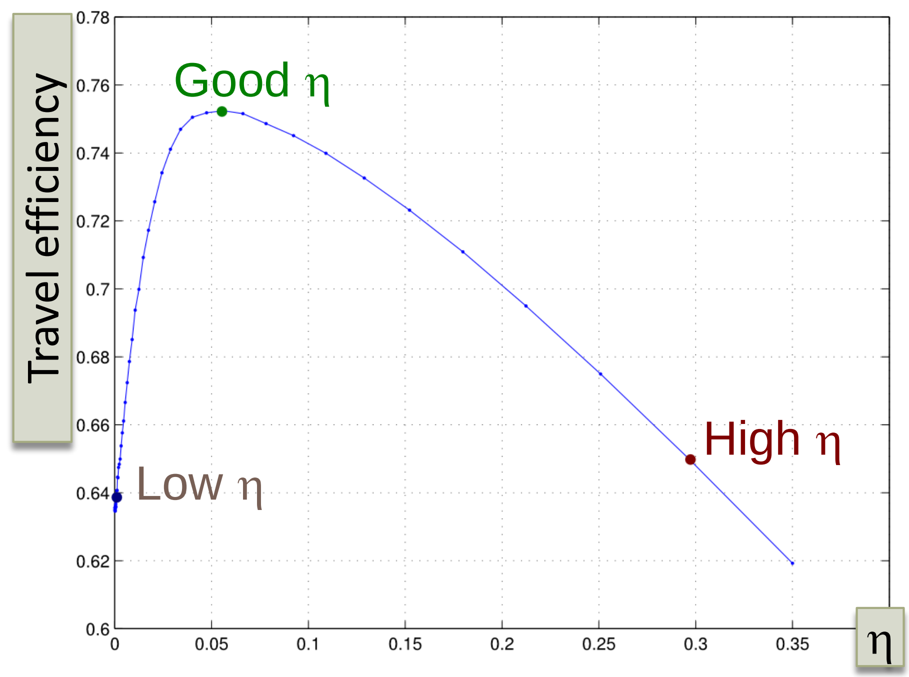
$$u_{t+1}^{(i)} = \begin{cases} u_t^{(i)} + \eta R & if\ \Delta E_t \geq 0 \\ random\ selection & otherwise \end{cases}$$

Next motor command

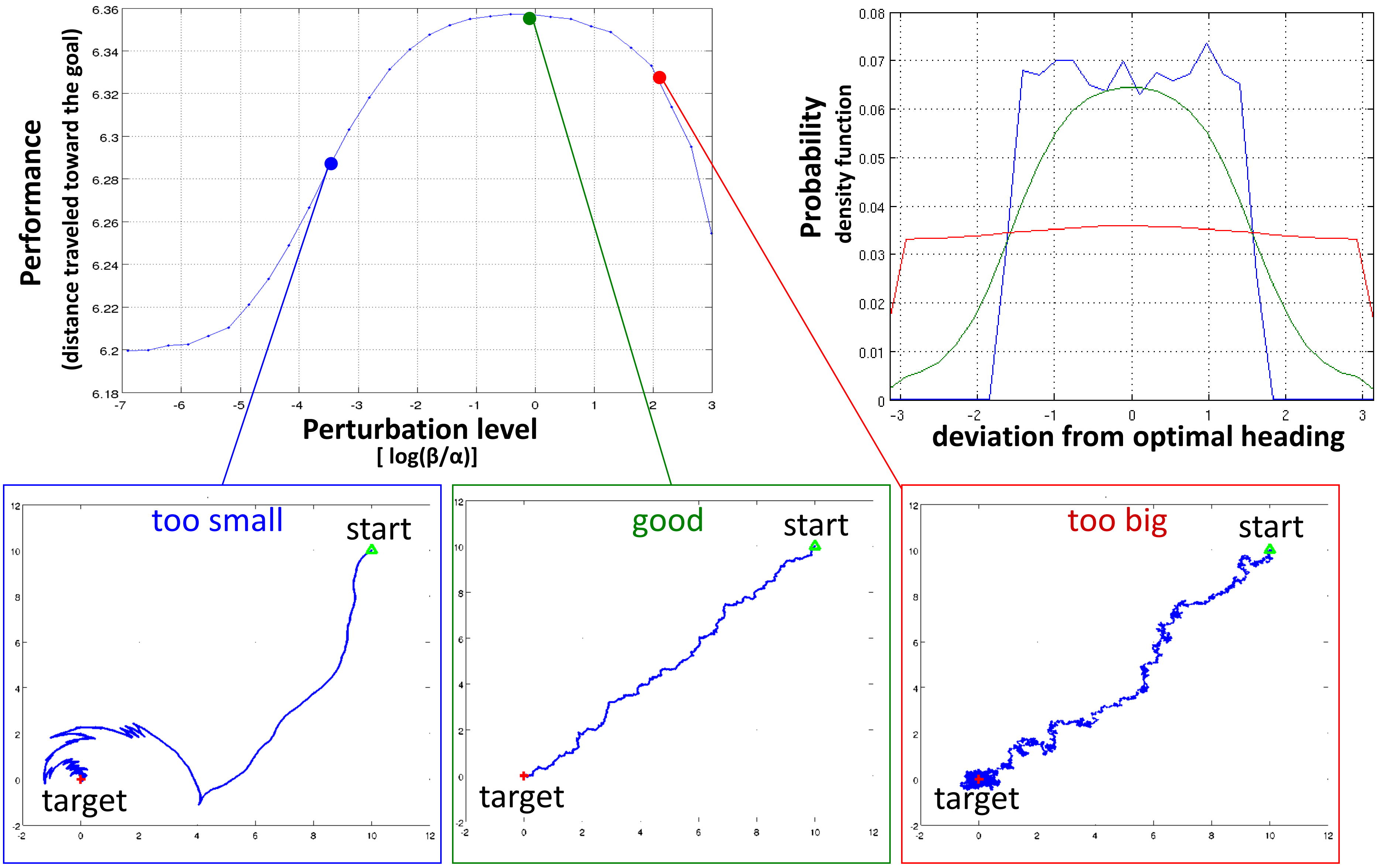
A new random motor command

"if conditions are improving, keep on in the same direction, otherwise try a new direction"

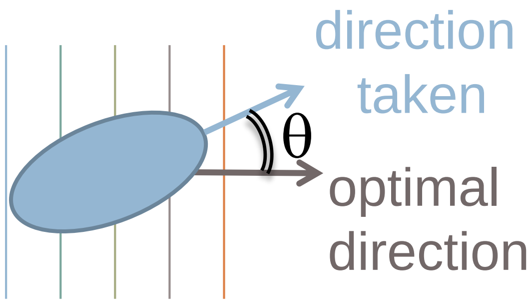




Performance increase by random perturbations



Analysis of the effect of η



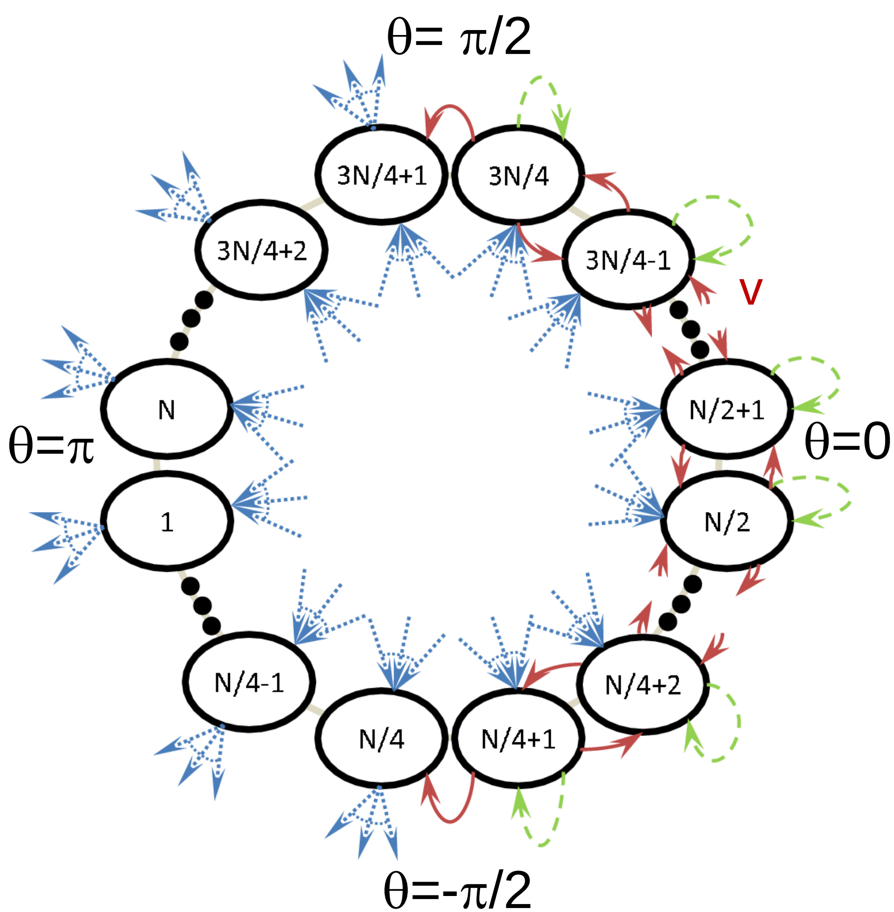
$$\theta_{t+1} = \begin{cases} \theta_t + \boxed{\eta\mathcal{U}(-1,1)} & if\ \Delta E > 0 \\ \boxed{\mathcal{U}(-\pi,\pi)} & otherwise \end{cases}$$

Probability distribution:
a Fredholm eq. of the II type

$$\begin{aligned} p(\theta) &= \int_{-\pi/2}^{\pi/2} K(\theta,\phi)p(\phi)d\phi + \frac{1-\int_{-\pi/2}^{\pi/2} p(\phi)d\phi}{2\pi} \\ &= \frac{1}{2\pi} + \int_{-\pi/2}^{\pi/2} (K(\theta,\phi) - \frac{1}{2\pi})p(\phi)d\phi \end{aligned}$$

No closed form!

Markov Chain Model



η tradeoff

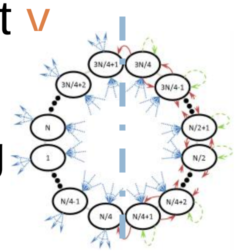
Long-term behavior

Stationary distribution:

$$p_{i,\infty} = \begin{cases} \frac{24(N+4)v}{N(8+6N+N^2+96v)} & if\ i = \frac{N}{4} \vee i = \frac{3N}{4}+1 \\ \frac{-48i^2+48i(N+1)-12N-9N^2}{N(8+6N+N^2+96v)} & if\ \frac{N}{4}+1 \le i \le \frac{3N}{4} \\ \frac{96v}{N(8+6N+N^2+96v)} & otherwise \end{cases}$$

Derivative w.r.t v

>0 for states corresponding to -π/2<θ<π/2



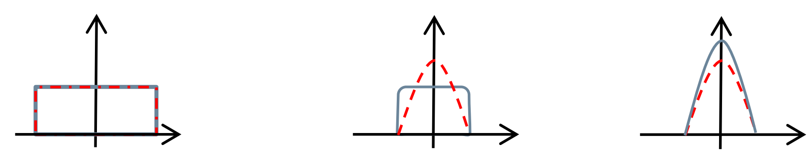
<0 for states corresponding to -π/2<θ<π/2

Short-term behavior

Difference equations

$$p_{i,t+1} = \begin{cases} vp_{i+1,t} + g & if\ i = \frac{N}{4} \\ (1-2v)p_{i,t} + vp_{i+1,t} + g & if\ i = \frac{N}{4}+1 \\ (1-2v)p_{i,t} + v(p_{i+1,t} + p_{i-1,t}) + g & if\ \frac{N}{4}+2 \le i \le \frac{3N}{4}-1 \\ (1-2v)p_{i,t} + vp_{i-1,t} + g & if\ i = \frac{3N}{4} \\ vp_{i-1,t} + g & if\ i = \frac{3N}{4}+1 \\ g & otherwise \end{cases}$$

Convergence to the stationary distribution sped up by increasing v



Low v (η)

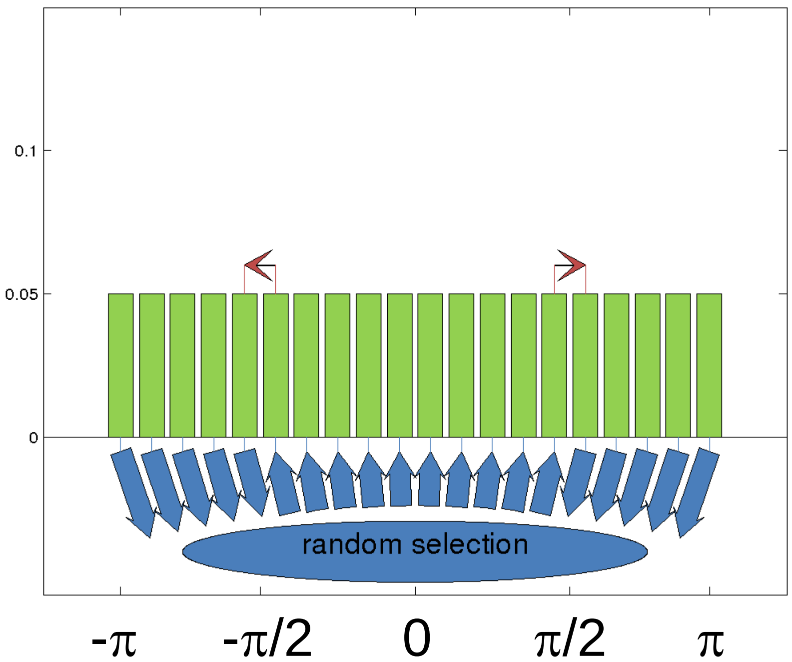
Lower probabilities for bad directions

at t→∞

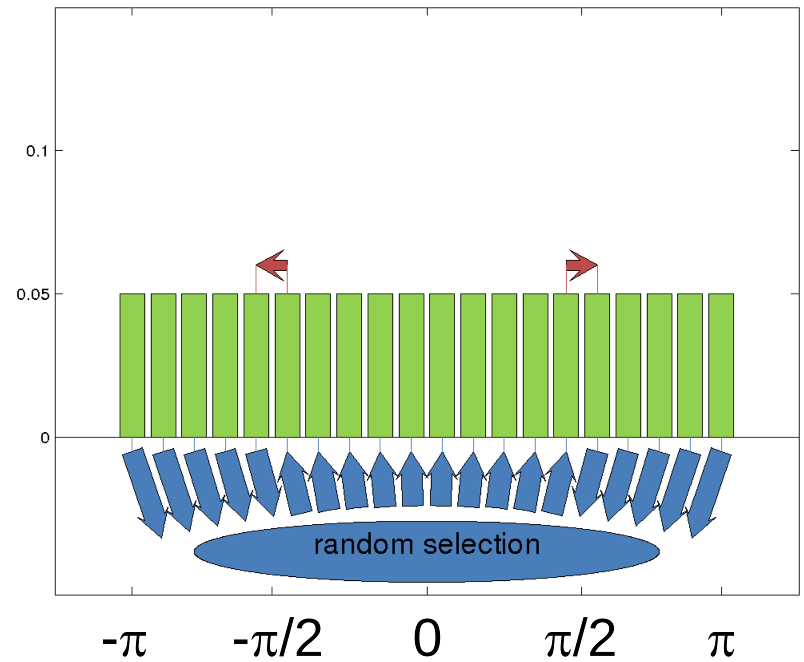
Shorter time for achieving high probability of good directions

High v (η)

Directions probability, t=0

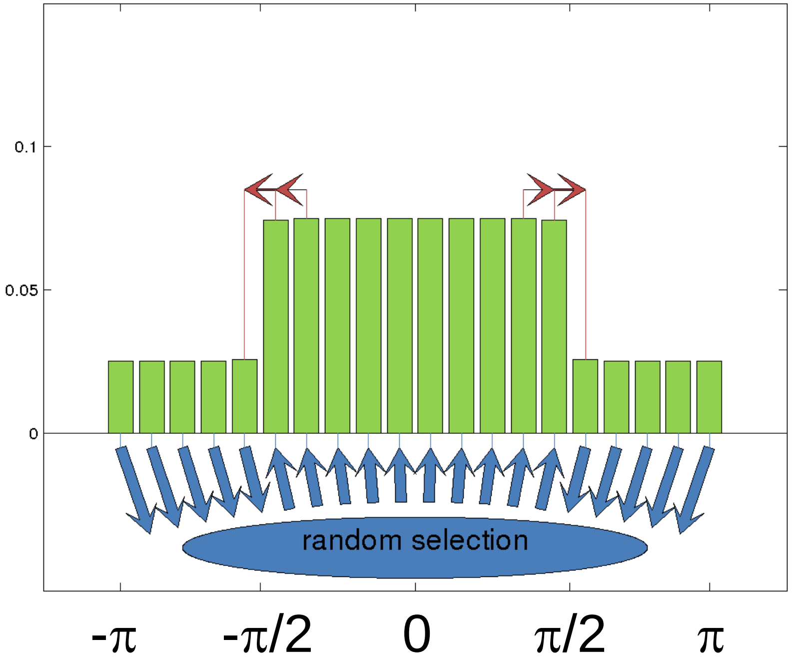


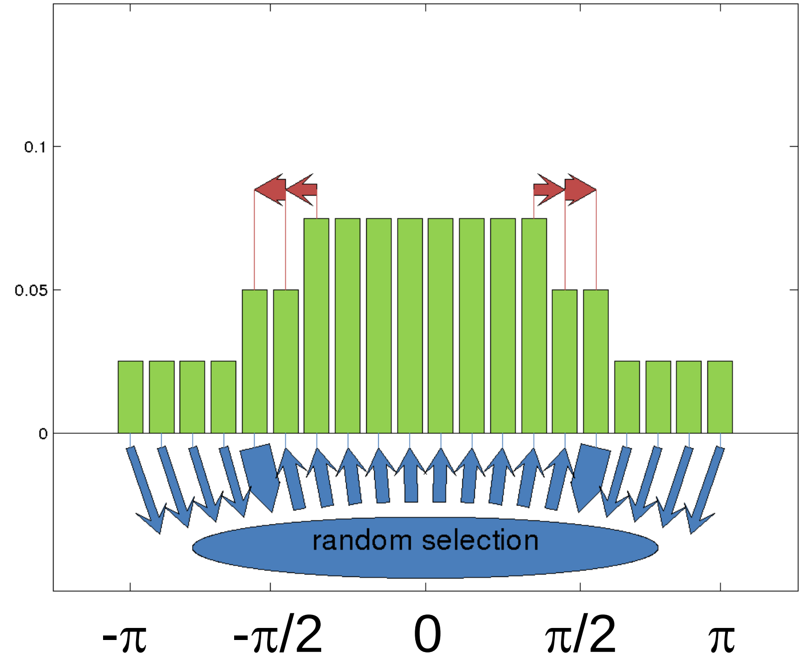
Low η
v=1/64



High η
v=1/2

Directions probability, t=1

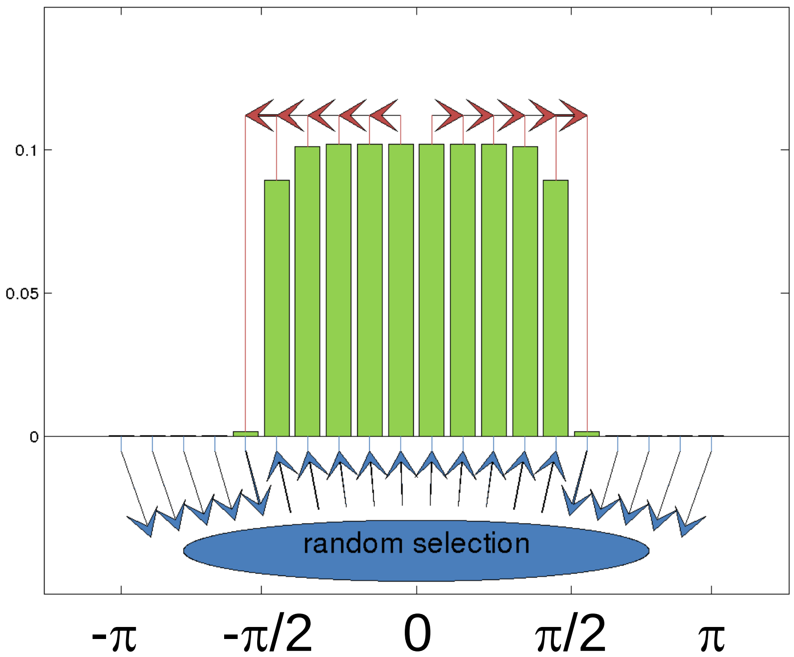




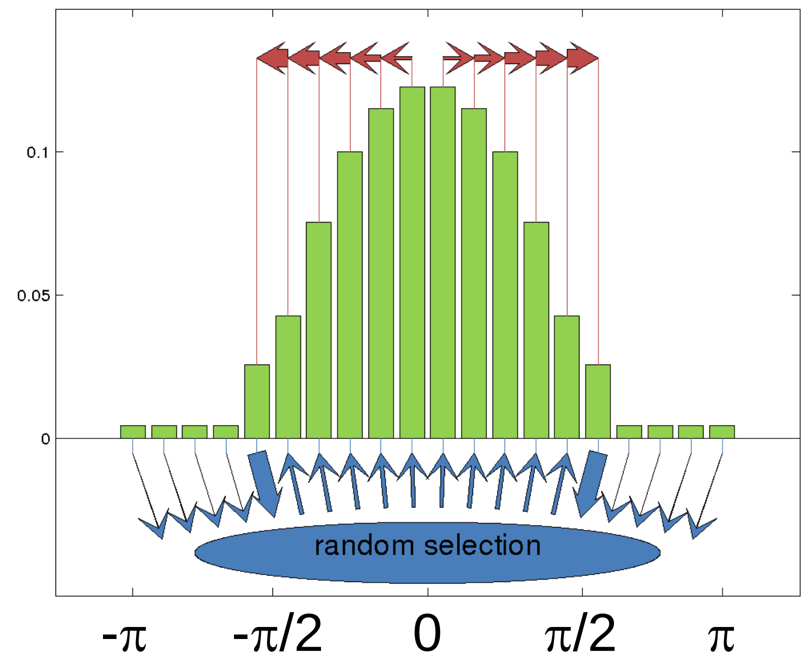
Low η
v=1/64

High η
v=1/2

Directions probability, t=10

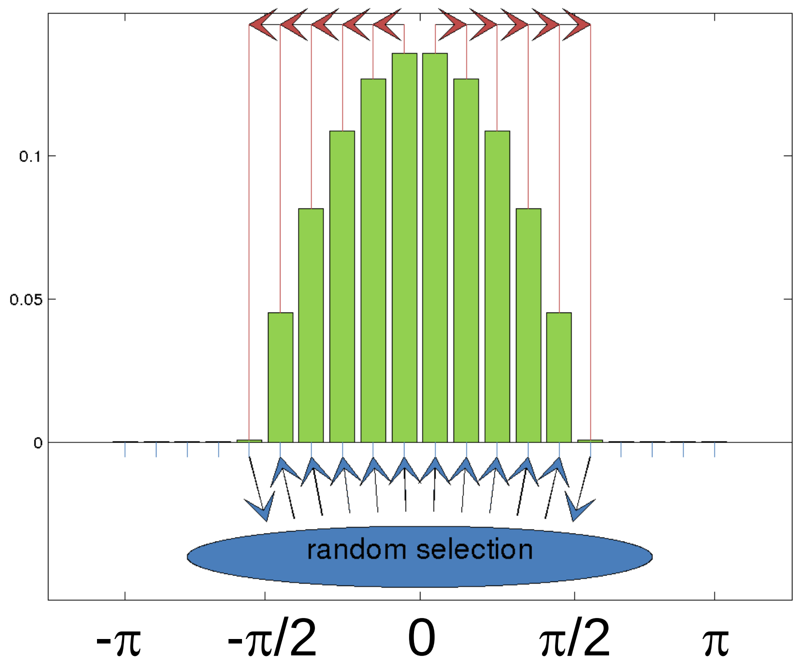


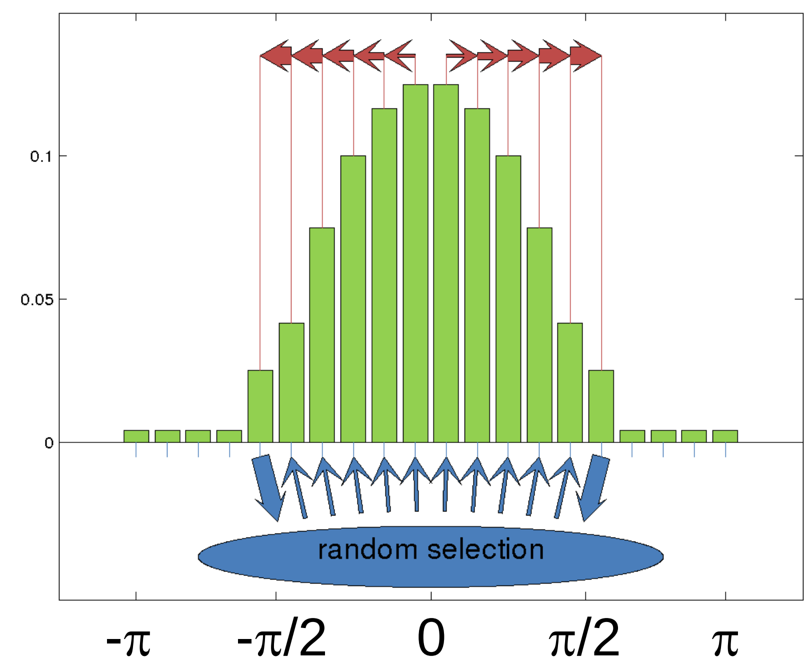
Low η
v=1/64



High η
v=1/2

Directions probability, $t=10^4$

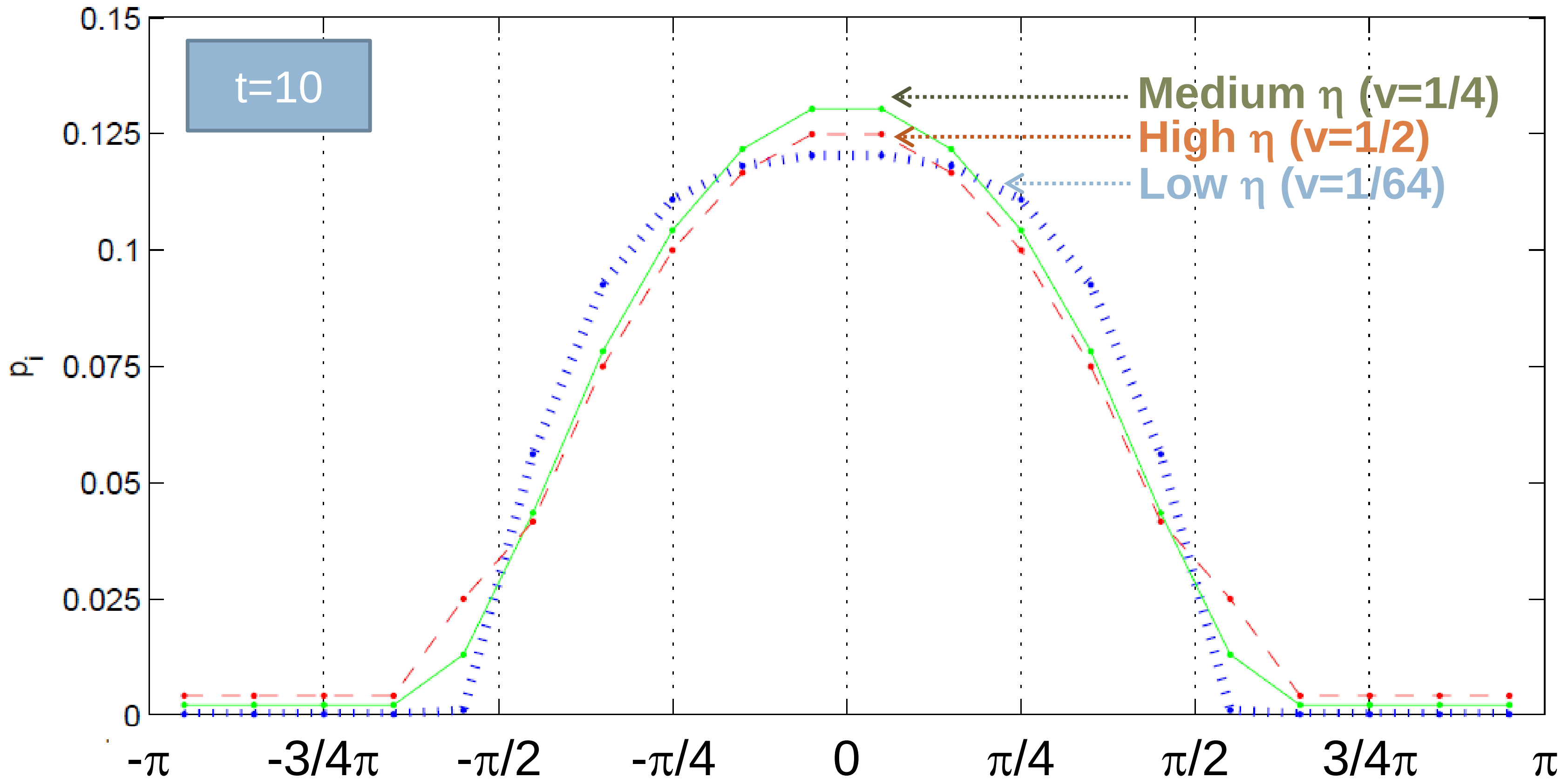




Low η
v=1/64

High η
v=1/2

Choosing η

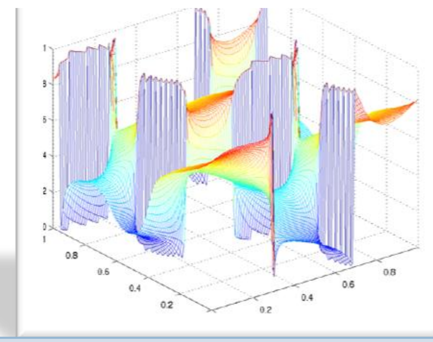


- The optimal value for η depends not only on the problem, but also on the time available for the task
- Whatever η>0 is sufficient to have a distribution with a peak in the optimal direction

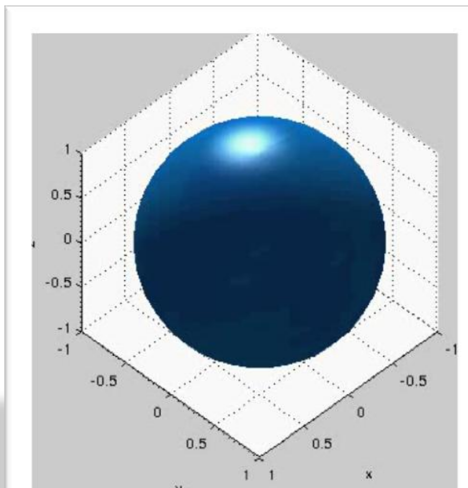
Features of MBR (Minimalistic Behavioral Rule)

$$u_{t+1}^{(i)} = \begin{cases} u_t^{(i)} + \eta R & if\ \Delta E_t \geq 0 \\ random\ selection & otherwise \end{cases}$$

- Extremely simple:
  - A single parameter η with low sensitivity
  - No model required
  - Minimal memory requirements
  - A single binary input
- Works with a wide variety of systems
  - Systems with non-linearities
  - System with delays
  - Systems with time-variant dynamics
- Works in n-dimensional spaces



Nonlinear dynamics

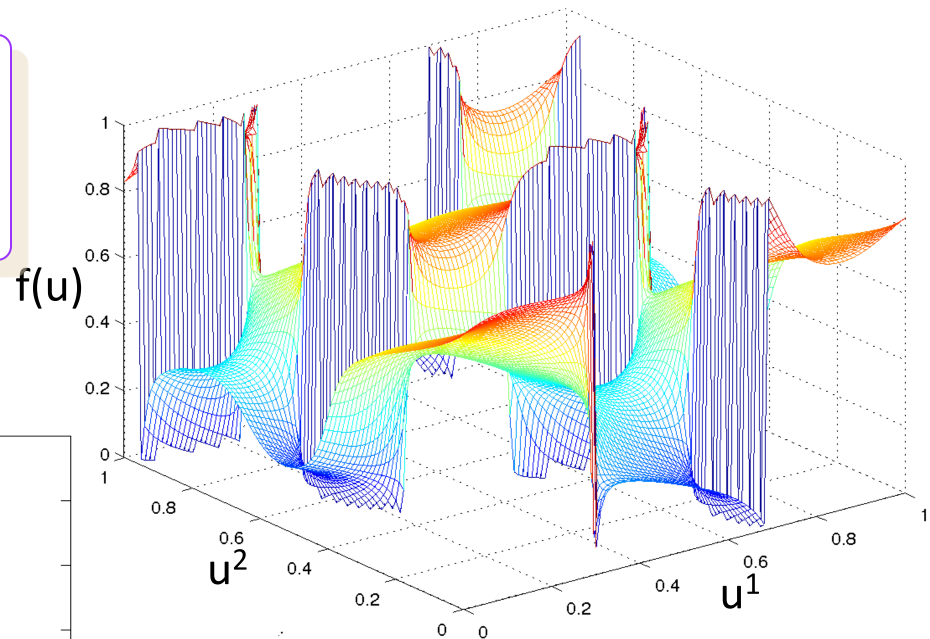


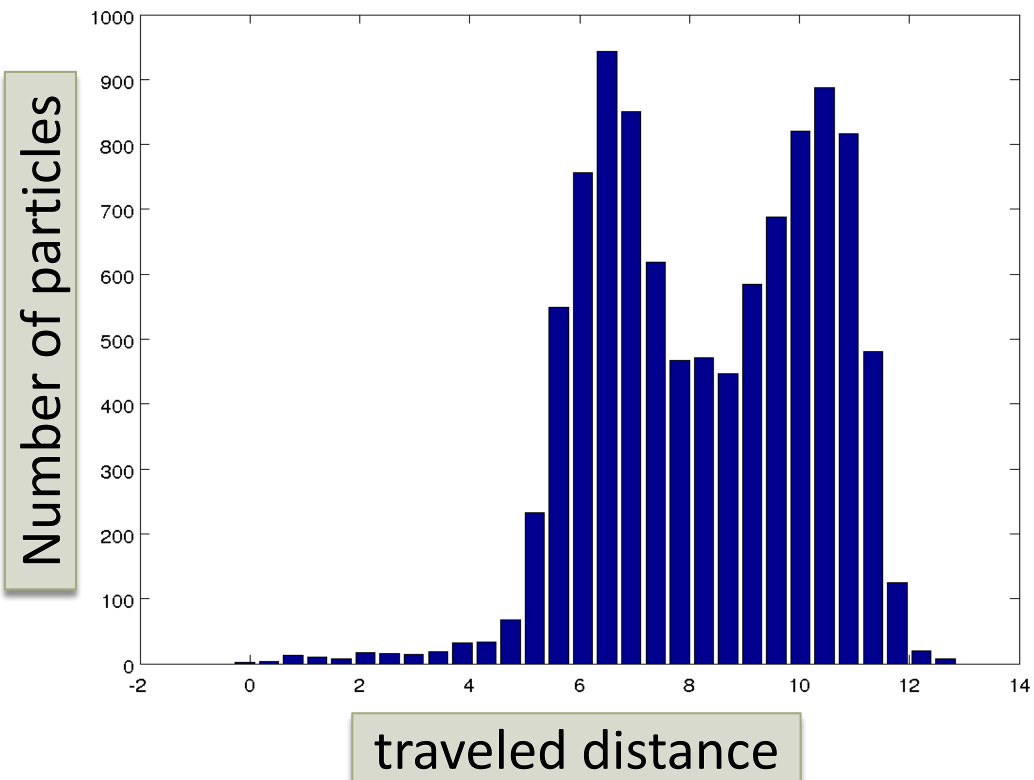
Probability of the directions taken in a 3D space

Non-linear system

$$x^i_{t+1} = x^i_t + s \cdot f^i(u_t)$$

$$f^i(u) = \frac{1}{\pi} \arctan\left(\frac{(sin(2\pi u + \xi^i))^T Q^i sin(2\pi u + \xi^i)}{(sin(2\pi u + \zeta^i))^T P^i sin(2\pi u + \zeta^i)} \right)$$



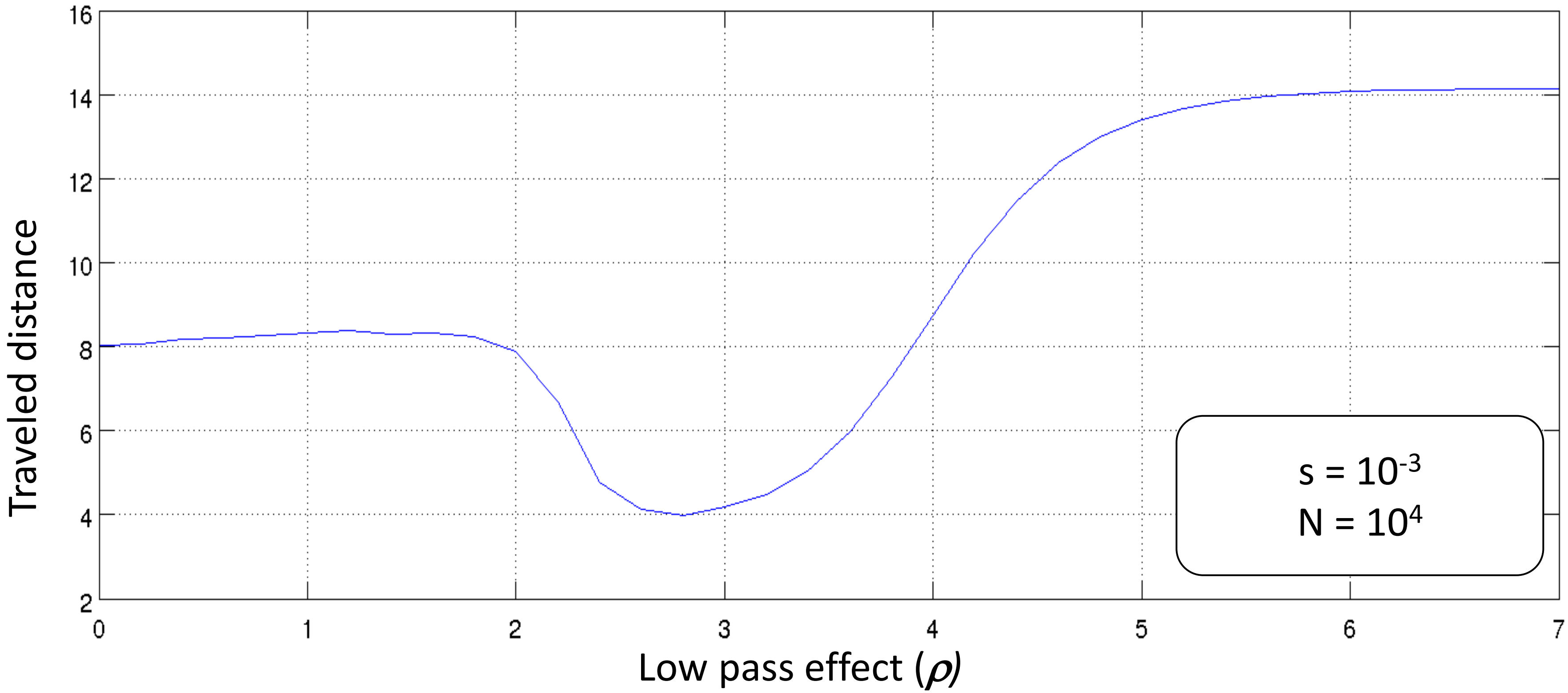


Delays

Low-pass system dynamics

$$v_t = (1 - 10^{-\rho})v_{t-1} + 10^{-\rho}u_t$$

$$x_{t+1} = x_t + v_t$$

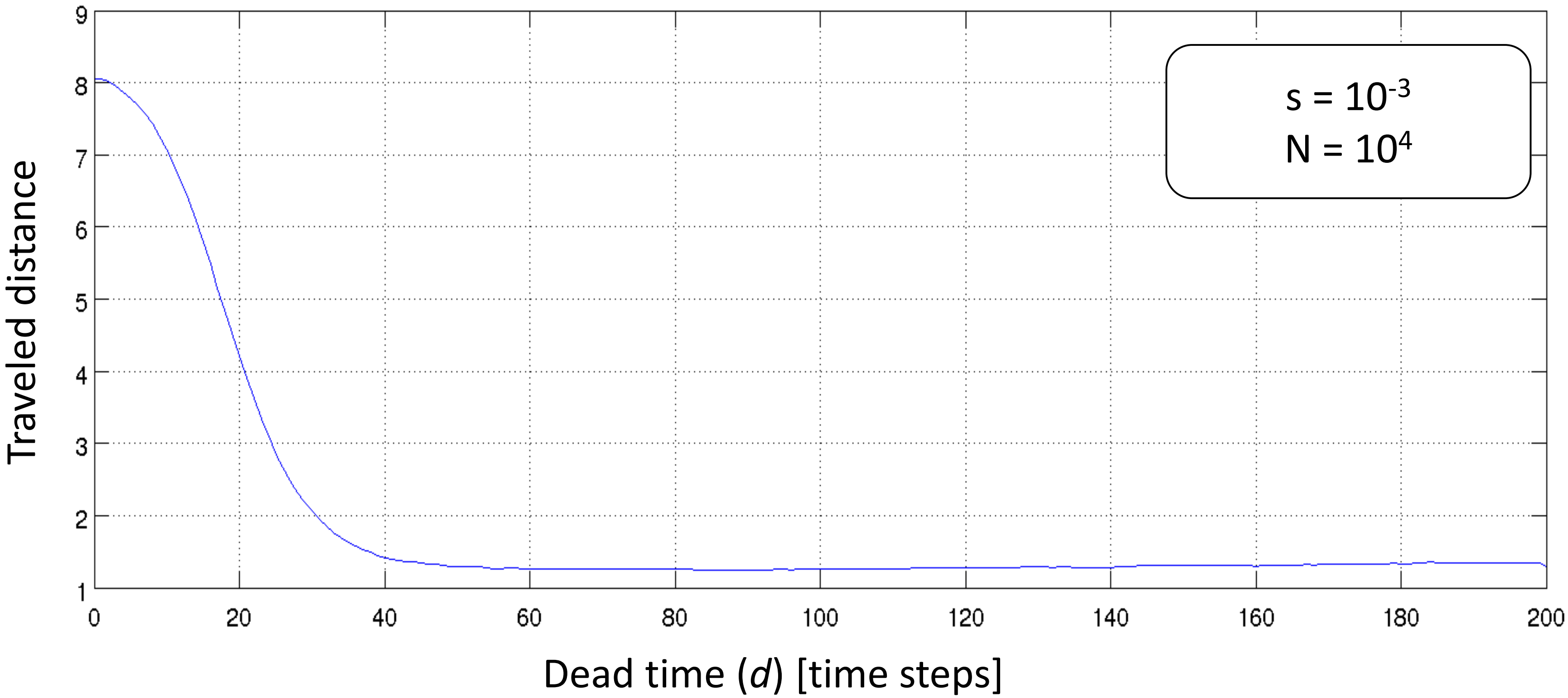


Dead time

Dead time in the system dynamics

Dead time system dynamics

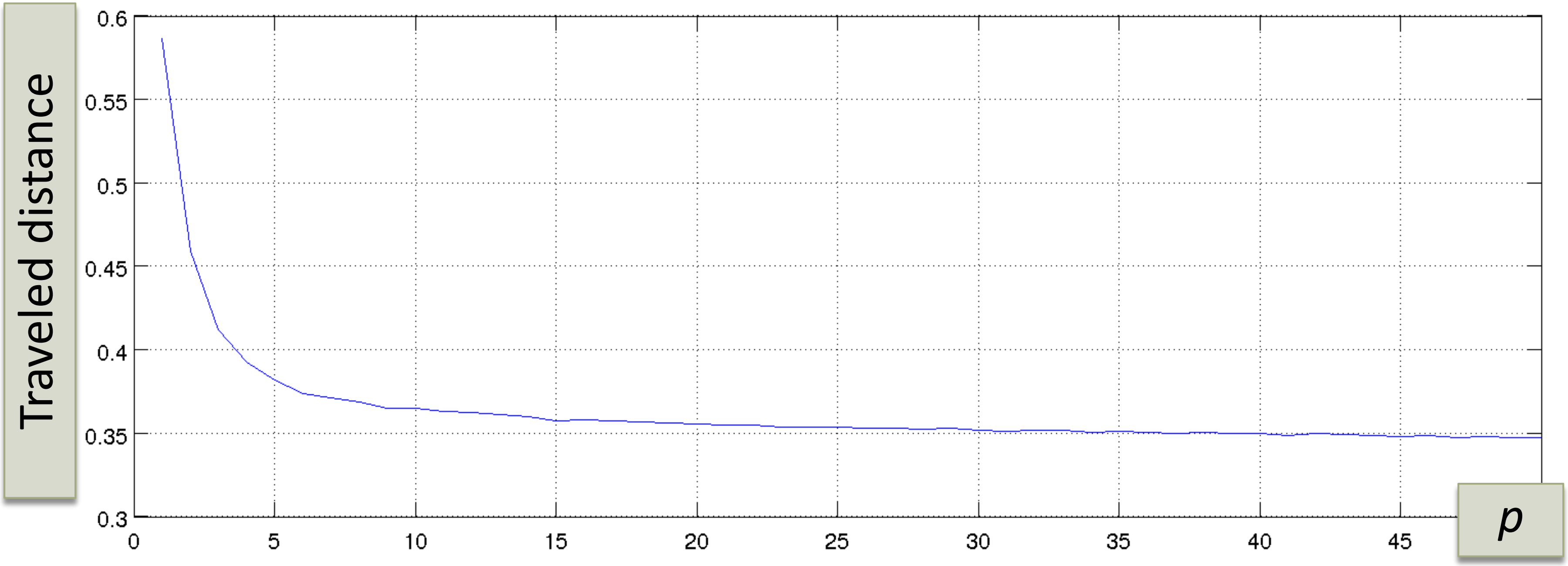
$$x_{t+1} = x_t + u_{t-d}$$



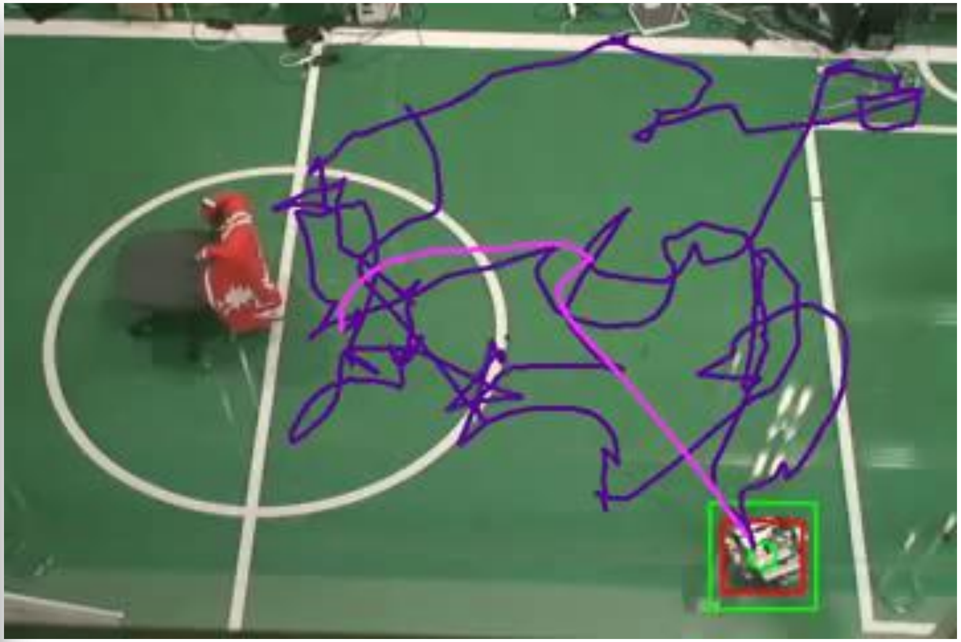
High dimensional spaces

$$x_0 = [-1, 0, \ldots, 0]^T \in \mathbb{R}^p$$
$$x_{t+1} = x_t + s \cdot u_t$$

Space dimensions (p)



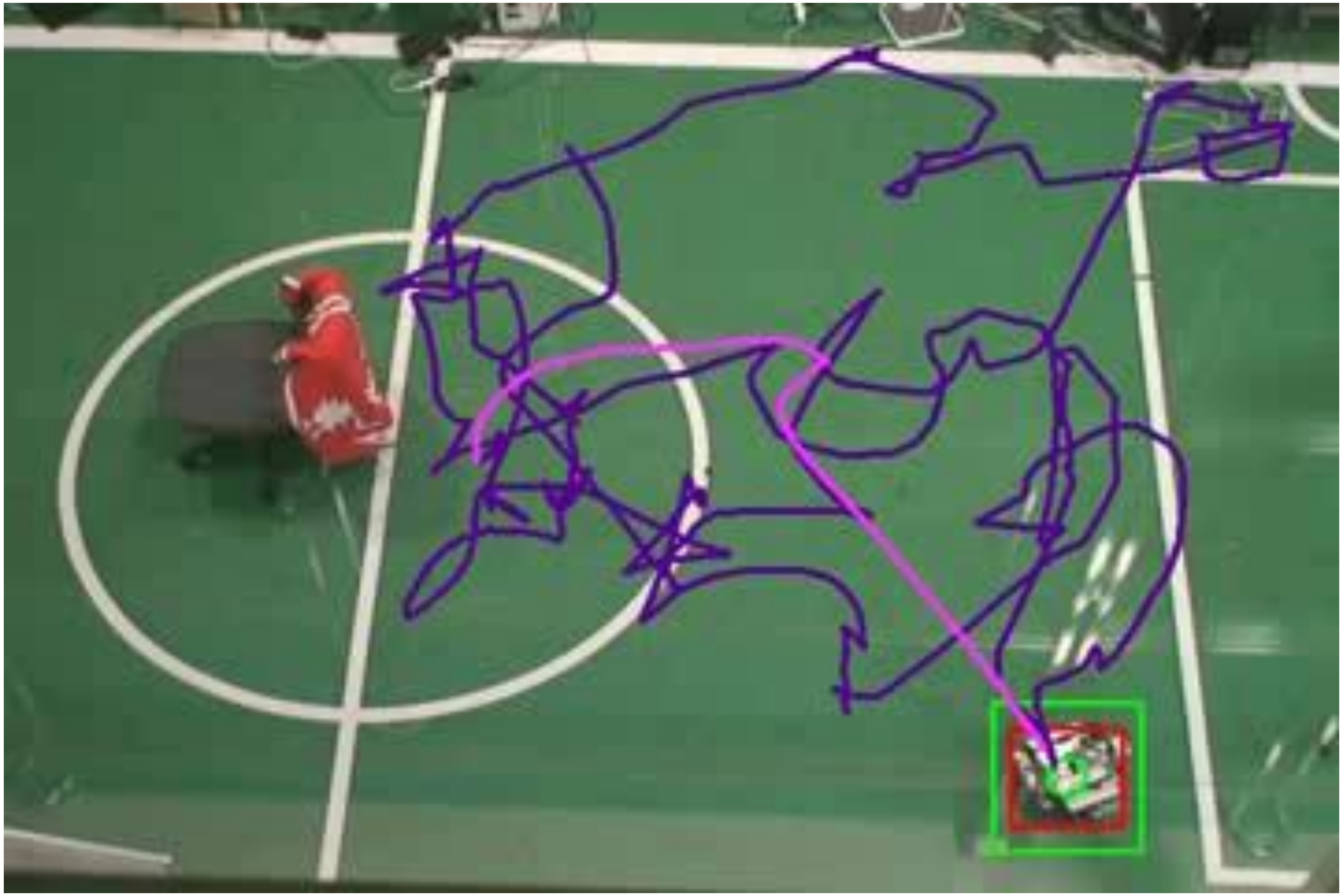
Applications – mobile robot reaching



Task: reach a red object

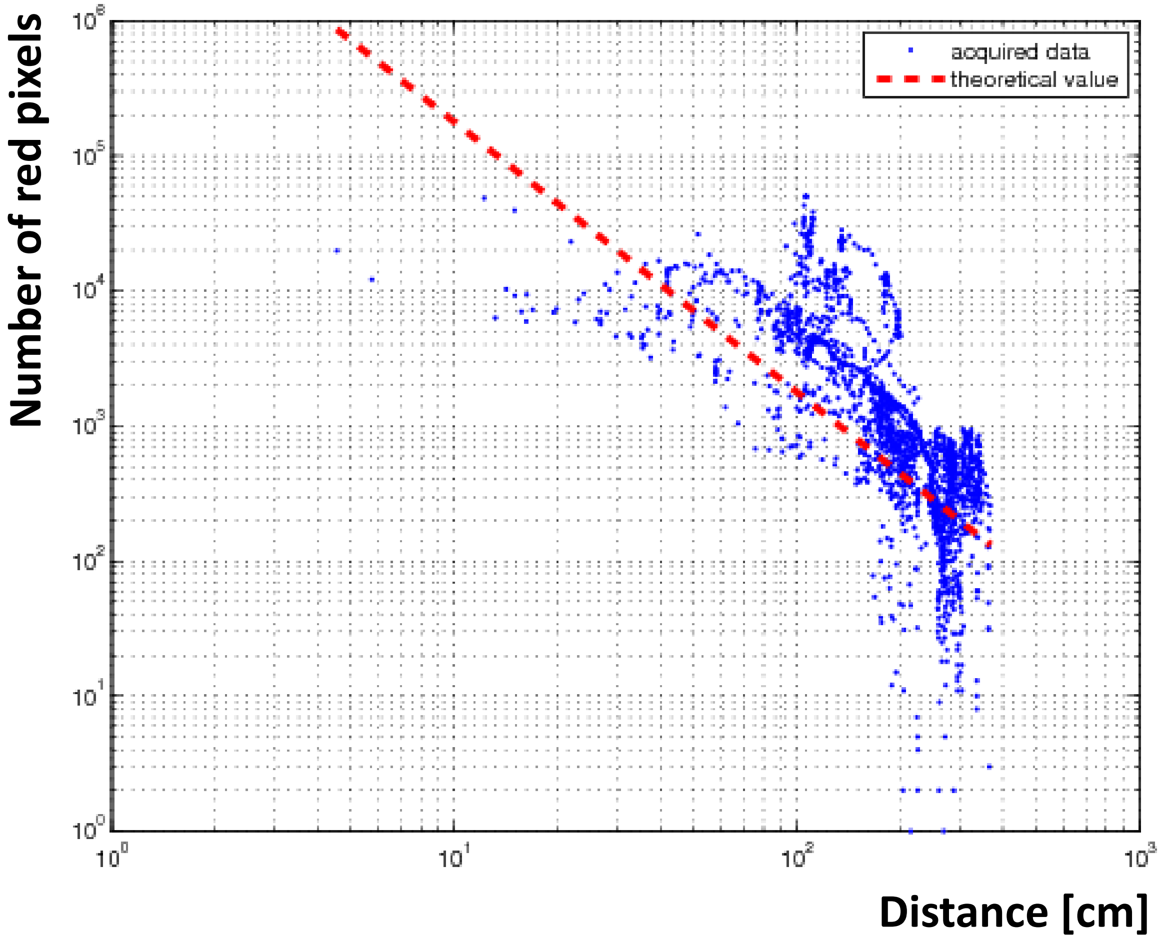
Hardware:
- Real World Interface B12 (Synchro Drive)
- 640 × 480 Logitech webcam on an omnidirectional mirror

Navigation



Advantages

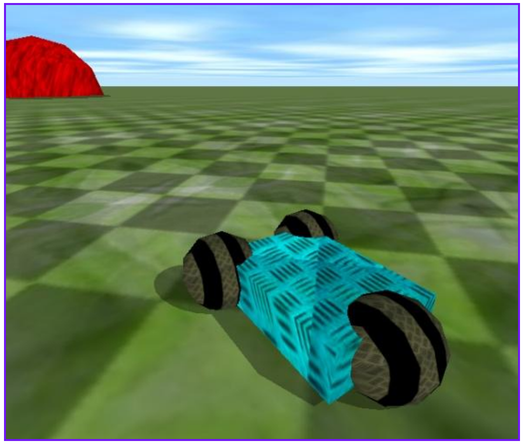
- No robot model required
- Minimal computational requirements
- Limited input information required
- Robustness to noisy information



Robustness to hardware damage

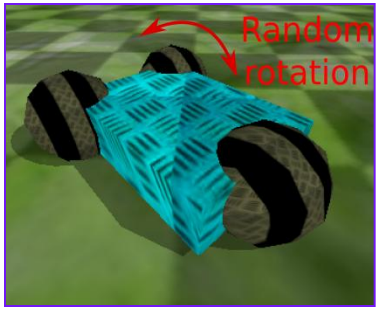
- No model of the robot
  - The robot can change during runtime!

Robot: simulated mobile robot with two independent wheels and an omnidirectional camera
Task: reach a red hemisphere
Sensory information: number of red pixels in the camera image

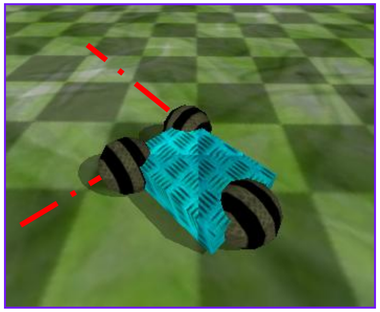


4 simulated hardware faults

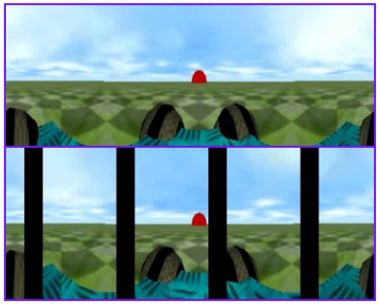
Change in the size of a wheel



Uncontrollability of a wheel



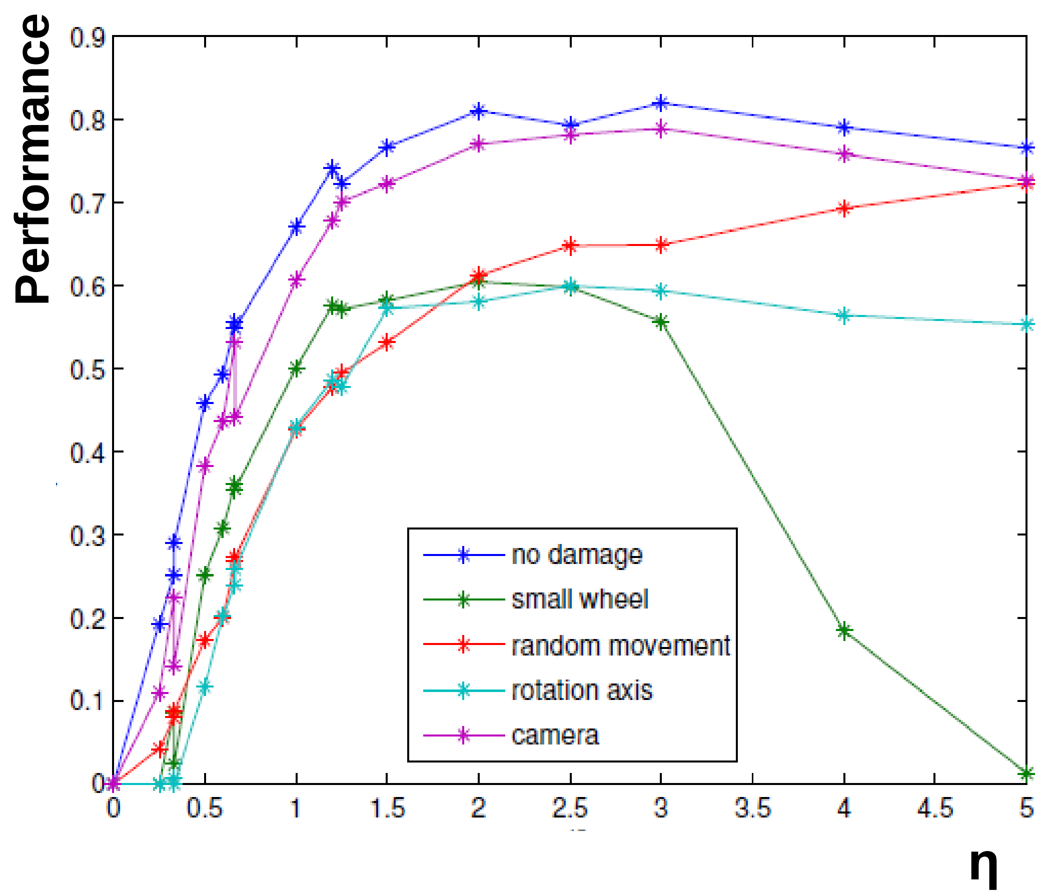
Change of the rotation axis of a wheel



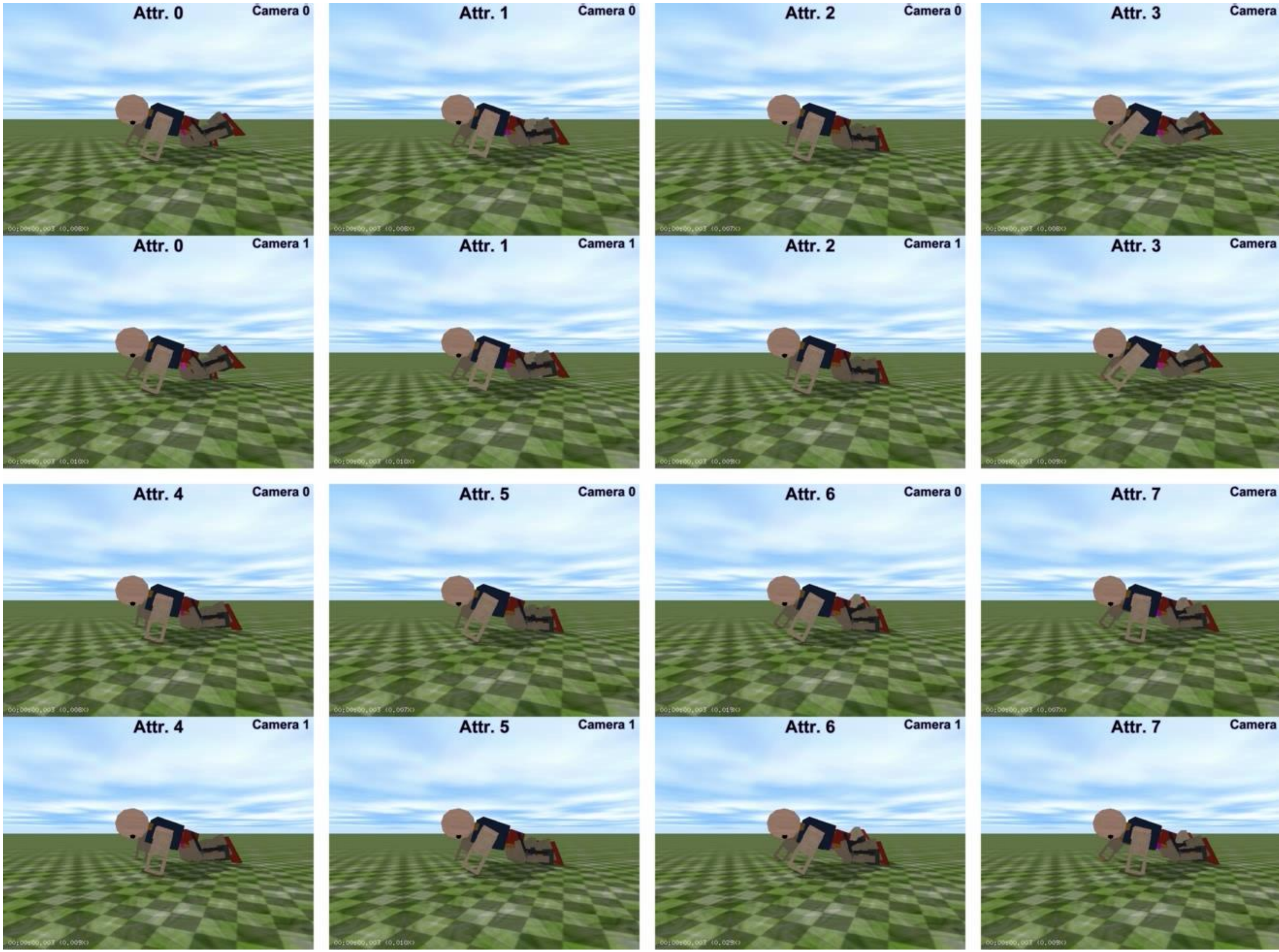
Obscuration of 20% of the camera

Results

- The robot is able to reach the target in all the cases
- An optimal ratio between the noise and the signal exists
- This ratio depends on the hardware and environment conditions



Movement in a parameter space



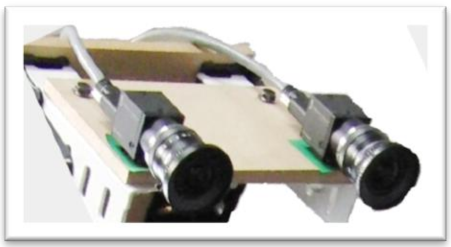
Applications – humanoid robot

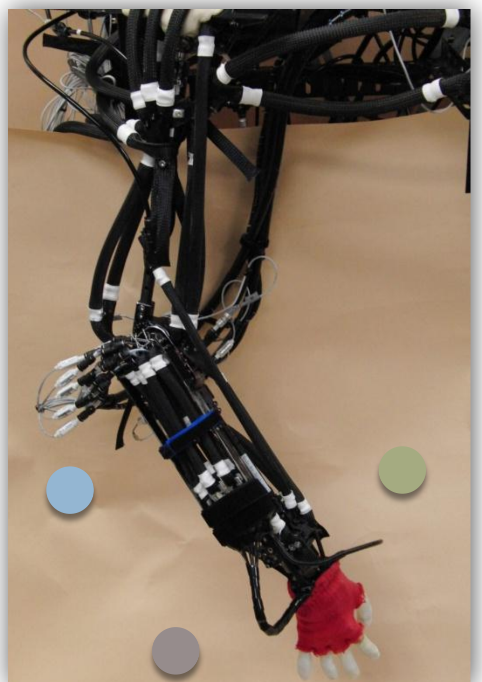
MBR used to control the parameters of a CPG network

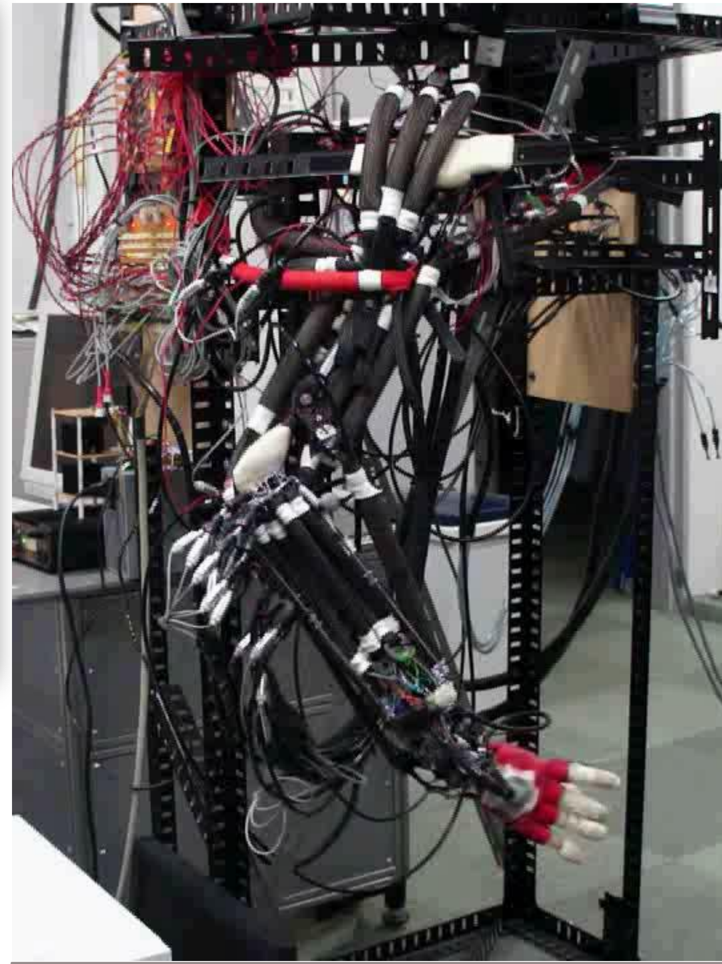
Task: maximize the crawling speed

Applications – pneumatic robot arm

Hardware:
- pnematic robot arm
  17 actuators, 7DOFs
- 2x FL2-08S2 camera
  with EMVL-316 CCTV lens

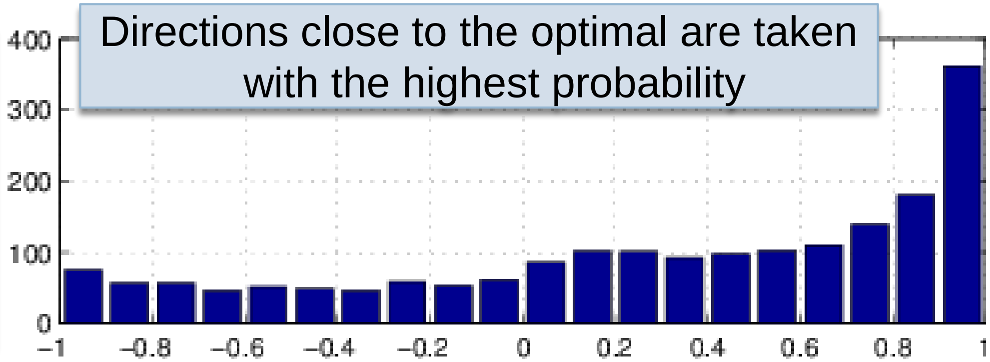






Task: reach 3 virtual targets

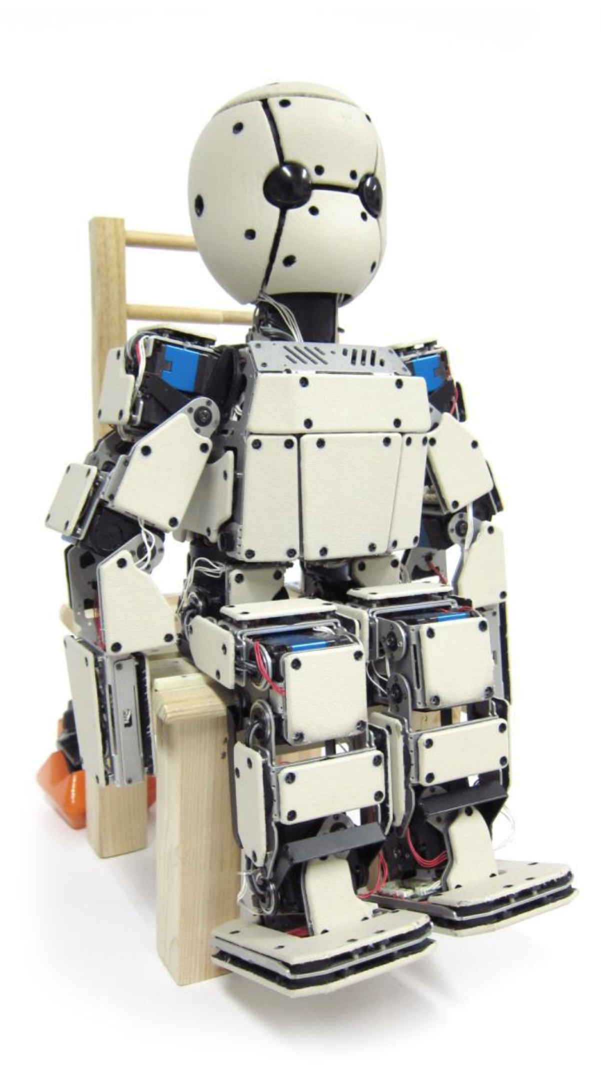
Directions close to the optimal are taken with the highest probability



Frequency

cos(θ)

Questions ?



Thank you