A Biologically Inspired Model for Coding Sensorimotor Experience Leading to the Development of Pointing Behaviour in a Humanoid Robot

Master's Thesis

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What?

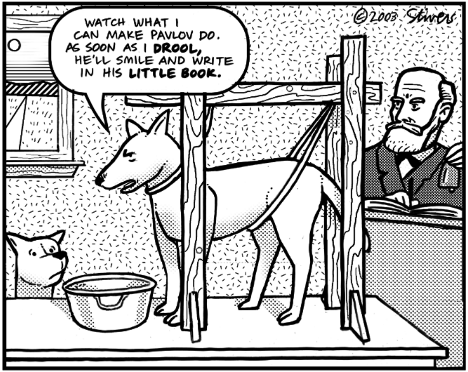
A Biologically Inspired Model for Coding Sensorimotor Experience Leading to the Development of Pointing Behaviour in a Humanoid Robot

- A Biologically Inspired Model
  - Neural networks and Hebbian learning
- Sensorimotor Experience Leading to the Development of Pointing Behaviour
  - We address questions from the developmental psychology
- Humanoid Robot
  - We use a humanoid robot (Nao) that has similar physical dimensions as a human child

Brain, Body and Behaviour

Behaviorism

- An approach to psychology that aims to explain the behaviour through experiments with animals and humans
- Concerned with observable consequences, not the internal processes

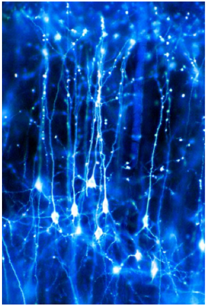


COGNITIVISM

- Explain the human behaviour in terms of underlying cognitive processes
- Gained popularity in artifical intelligence

But...

- The majority of artificial intelligence algorithms inspired by cognitivist theories were focusing on problem-solving skills
  - Unable to reproduce the complex spectrum of human behaviour (e.g.: perception, learning, emotions)
- Post-cognitivism: the role of embodiment and neural processing

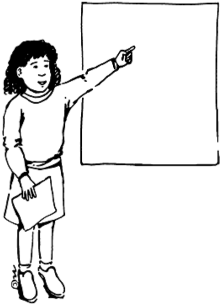


The Task

THE GOAL OF THIS THESIS

- Simulate sensorimotor learning leading to the development of attentional mechanisms
  - Robot simulates the sensory experience of a young child
  - Learning inspired by the human behaviour: body babbling
- Develop a model of sensorimotor learning based on neural networks
  - Use self-organising maps and associate them using a Hebbian learning paradigm

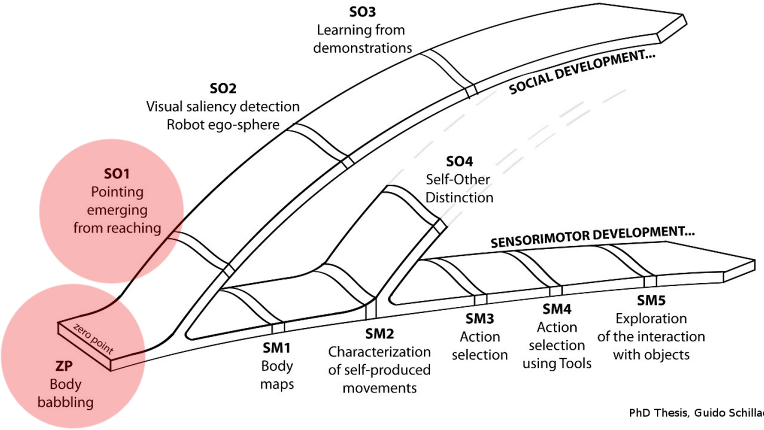
Motivation



- **Joint attention** is an important part of the development in infancy and **pointing** is one of the mechanisms used for attention manipulation

Related Work

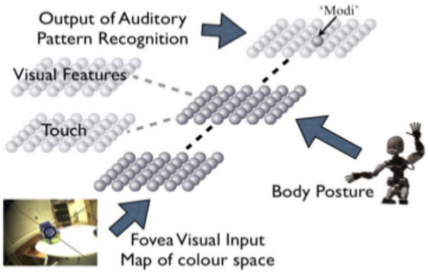
- Sensorimotor learning and simulation of experience following the theories on the human development [Schillaci, 2014]



PhD Thesis, Guido Schillaci

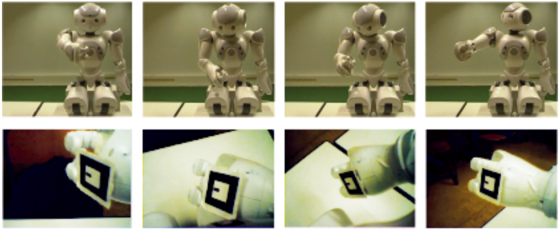
RELATED WORK

- Structured association of multiple SOMs has been adopted for mapping different modalities in Epigenetic Robotics Architecture [Morse et al., 2010]



Motor Babbling

- Self-exploration strategy employed by infants to learn internal mappings of body postures
- Implemented on a humanoid robot using a random walk strategy
  - The robot moved its left arm randomly - hands and joint positions were stored (cca. 40 min)
  - Hand was tagged with a marker



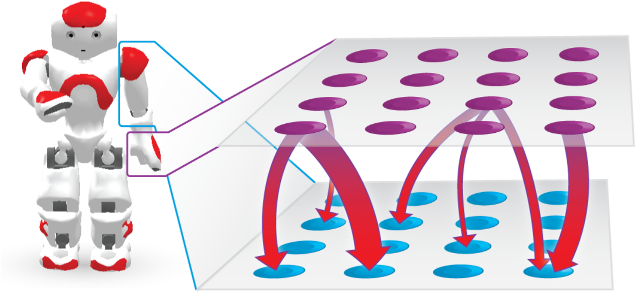
REALISATION

1. Collect data in the random motor babbling experiment
   - $74,143$ 7D data points (3D hand coordinates, 4D elbow and shoulder coordinates)
2. Train the SOM-based model on the data from the step 1.
   - 2 different models: 5×5 and 15×15 model
3. Implement both models on the humanoid robot
4. Run the experiment and use the model to determine arm positions
   - A human subject holding an object tagged with a marker

The Model

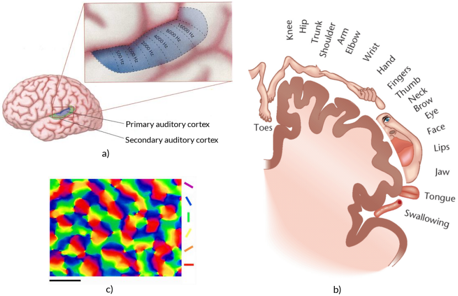
The Model

- Two 2D SOMs connected with Hebbian weights
  - We analyse two different models with a different number of neurons: 5×5 (25 neurons in each map) model and 15×15 model (225 neurons in each map)



Motivation for the model

- Biologically inspired by self-organisation observed in the brain
    - Orientation maps in V1, somatotopic maps, tonotopic organisation of the auditory cortex



SOM training I

- Training data are points obtained in the random motor babbling experiment
- $\mathbf{x_p}$ is a 3D or 4D data point corresponding to hands or joint positions
- $\mathbf{w_i}$ are weights of a neuron *i*, in the beginning initialized randomly
- Gaussian neighbourhood function:

$$h(i,j) = e^{-\frac{\left(\mathbf{w_i} - \mathbf{w_j}\right)^2}{2\pi\sigma(t)^2}} \tag{1}$$

SOM training II

- Pick a winning neuron as the one with the smallest Euclidean distance to the data point:

$$\arg\min_i ||\mathbf{x_p} - \mathbf{w_i}|| \quad (2)$$

- Adjust weights of all neurons based on the winning neuron using the learning rate $\eta(t)$ and neighbourhood function $h(i,j)$:

$$\Delta\mathbf{w_j} = \eta(t)h(i,j)(\mathbf{w_j} - \mathbf{x_p}) \quad (3)$$

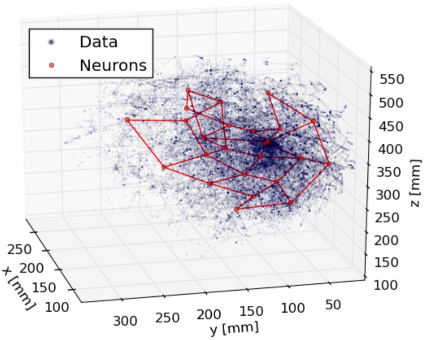
- The learning rate η and the spread of Gaussian function σ are annealed exponentially after the first half of iterations
- Hebbian weights according to activations of winning neurons:

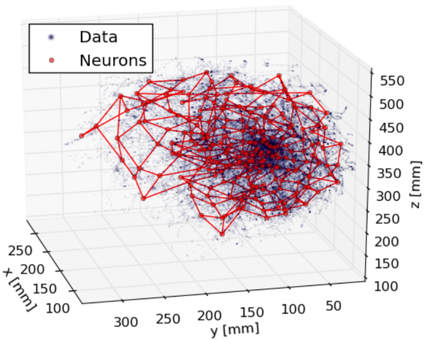
$$\Delta w_{ij} = \eta_h A_i(\mathbf{x}) A_j(\mathbf{y}) \quad (4)$$

Results

BABBLING DATA

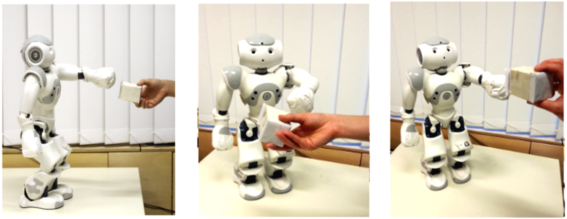
- 5×5 and 15×15 SOMs covering the hand coordinates





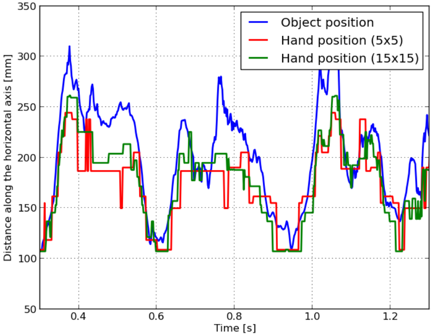
The Experiment

- 5×5 and 15×15 models implemented on the robot Nao
- Human held and randomly moved an object tagged with a marker in front of the robot for 3 min
- Every 100 ms positions of hands, joints and the marker were stored



Hand trajectories

- Comparison of hand trajectories predicted by the two models for the horizontal dimension (cca. 1 sec)



Conclusion

Conclusion

- The proposed SOM-based model exhibits pointing when implemented on a humanoid robot
  - Supports the hypothesis that pointing emerges from grasping [Kaplan and Hafner, 2006]
- Better pointing precision achieved with more neurons
- Interesting directions for the future research: spiking neurons and more complex learning rules (e.g. STDP)

FINAL WORDS

- More on this project:
  - Talk to me :)
  - Read: Kajić, I., Schillaci, G., Bodiroža, S., and Hafner, V. V. (2014). Learning hand-eye coordination for a humanoid robot using SOMs. In Proceedings of the 2014 ACM/IEEE International Conference on Human-robot Interaction, HRI 14, pages 192 - 193, New York, NY, USA. ACM.
  - Python source code online: `github.com/ikajic/cog-rob`
- More on these slides and the poster:
  - Made in LaTeX(open-source program)
  - LaTeXcode for both available online: `github.com/ikajic/uni-templates`
  - Open-source: Because sharing knowledge (for free) is important!

Kaplan, F. and Hafner, V. V. (2006).
The challenges of joint attention.
Interaction Studies, 7(2):135–169.

Morse, A., de Greeff, J., Belpaeme, T., and Cangelosi, A. (2010).
Epigenetic robotics architecture (era).
Autonomous Mental Development, IEEE Transactions on, 2(4):325–339.

Schillaci, G. (2014).
Sensorimotor learning and simulation of experience as a basis for the development of cognition in robotics.
PhD thesis.

Appendix

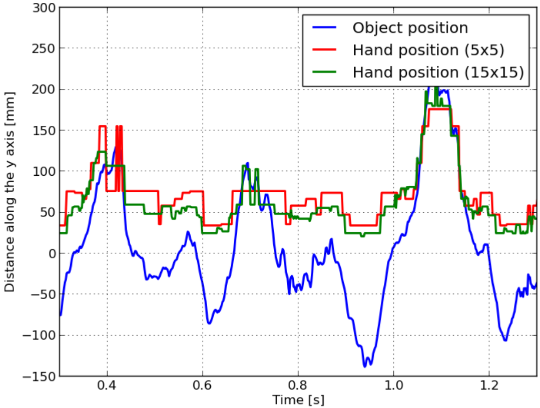
Pointing precision

- The Euclidean distance between the object and the hand
- A paired-samples t-test ($t(1400) = 76.47, p < 0.05$) showed a significant difference between two the models

	Mean (mm)	Std. Dev. (mm)
5×5	99.93	32.10
15×15	80.32	33.41

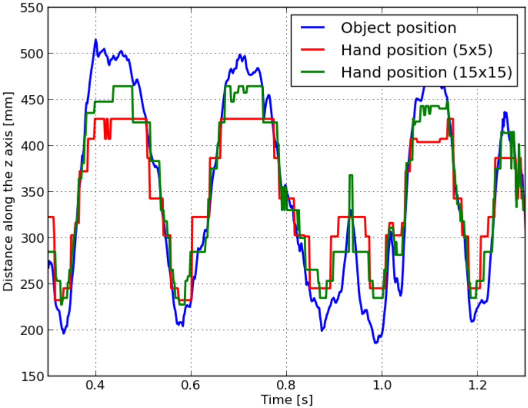
HAND TRAJECTORIES

- Comparison of hand trajectories predicted by the two models for the vertical dimension



Hand trajectories

- Comparison of hand trajectories predicted by the two models for the depth dimension



Random Body Babbling - Limitations

- Does not assume any goal directed behaviour (but there's: goal babbling)
- Inability to switch between exploration of new postures and exploitation of existing ones based on robot's learning interest
- There are more advanced exploration behaviours, but they were out of scope of this thesis

Embodied Cognition

- The idea that our cognition is influenced/shaped/determined by our experiences in the physical world
- "Thought is tightly constrained, and at the same time enabled by the body“ (Pfeifer and Bongard, 2007)
- "We propose that seeing is a way of acting. It is a particular way of exploring the environment. Activity in internal representations does not generate the experience of seeing. ” (Regan and Noe, 2001)
- Perceptual experience very often incorporates anticipated embodied interaction

SOMs are (not) Biologically Inspired

- *A Possible Embodiment of Self-Organization in a Neural Structure* (Section 3 in "Self-Organized Formation of Topologically Correct Feature Maps“ (Kohonen 1982)
- Two mechanisms:
  - Formation of activity cluster (anatomical and physiological evidence)
  - Adaptive change in input weights (limited synaptic resources)