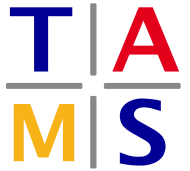




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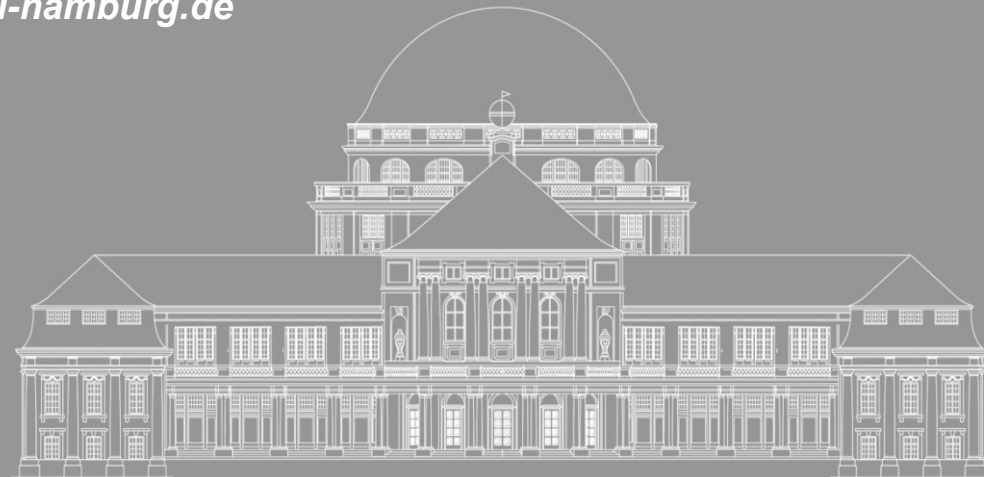


Department of Informatics
Intelligent Robotics WS 2016/17

28.11.2016

Neural Models for Multi-Sensor Integration in Robotics

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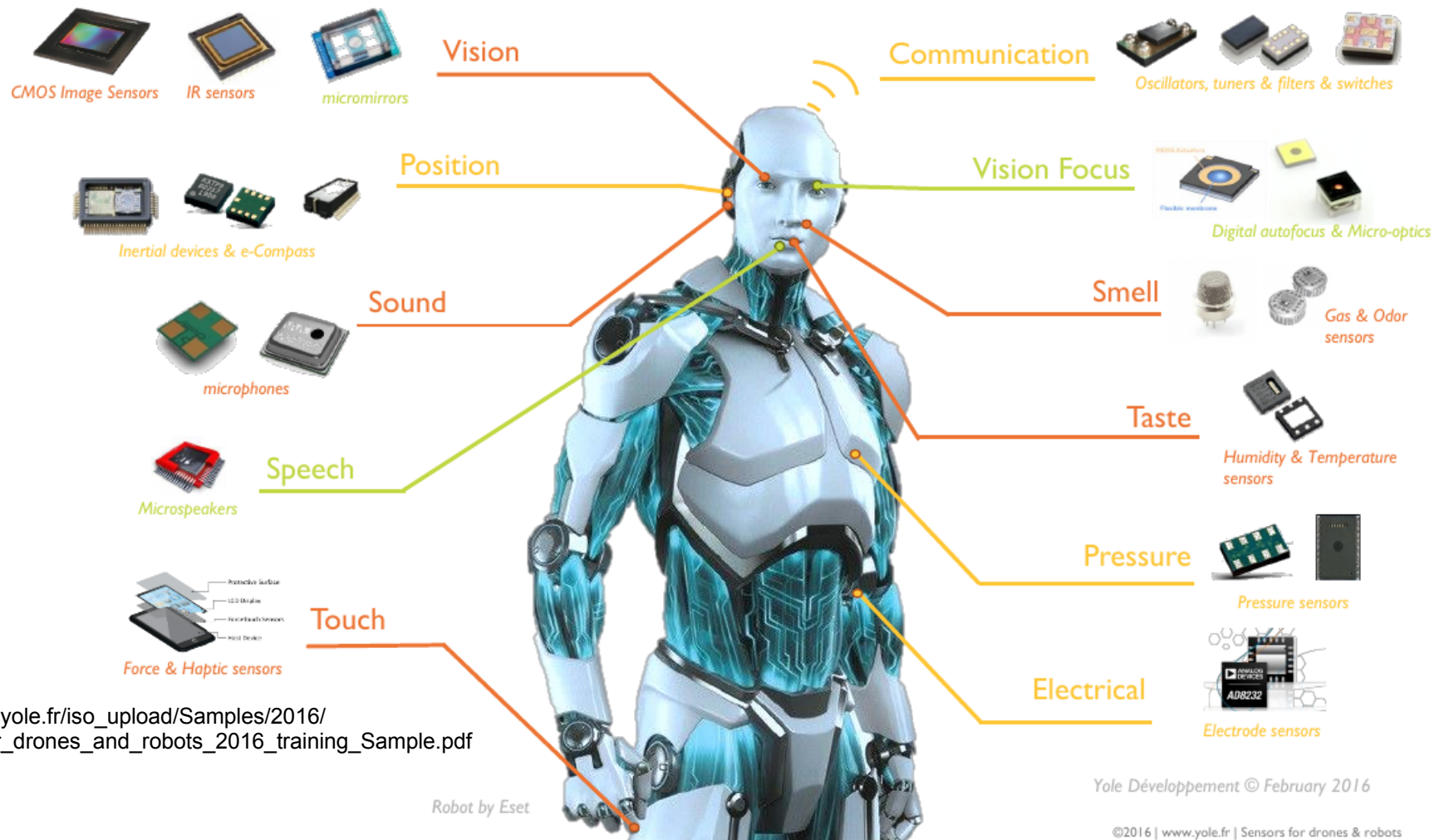


Outline

- **Multi-sensor Integration:**
 - Definitions, benefits, possible approaches
- **Neurally inspired sensor integration and fusion**
 - Ideas, benefits and drawbacks
- **Case: Robot control by Hierarchical Neural Network**
 - Robot and model description, results
- **Case: Sensor fusion for estimating robot heading**
 - Robot and model description, results
- **Current Research at our HRI Lab**
- **Summary**

Multi-Sensor Integration - Definition

Multi-sensor integration - Sensor fusion - Modality - Multi-modal integration



http://www.yole.fr/iso_upload/Samples/2016/Sensor_for_drones_and_robots_2016_training_Sample.pdf

Robot by Eset

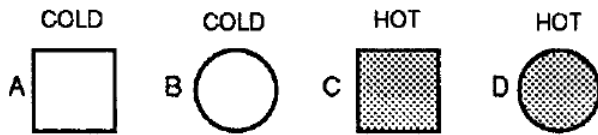
Yole Développement © February 2016

©2016 | www.yole.fr | Sensors for drones & robots

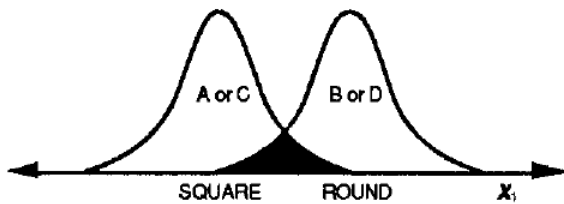
Multiple sensors – Benefits

The motivation behind usage of multiple sensors

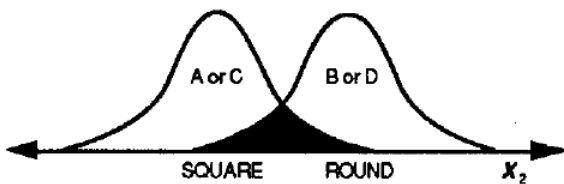
- Providing redundant information (increased reliability and availability)
- Providing complementary information (increasing dimensionality i.e. coverage)



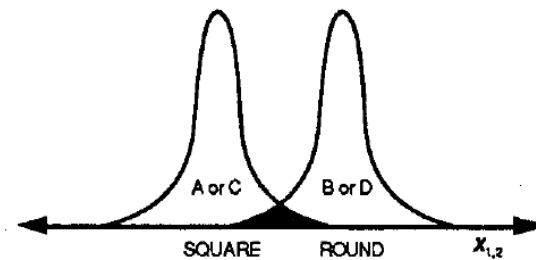
(a) Four objects.



(b) Sensor 1.



(c) Sensor 2.

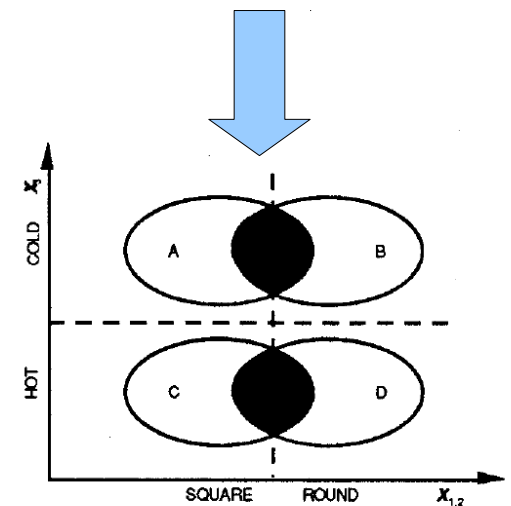


(d) Sensors 1 and 2.

Redundant information of the two shape sensors improves precision in distinction of shape

[1] Luo and Kay, 1990

Complementary information from additional heat sensor makes distinction possible



(e) Sensors 1, 2, and 3.

Different approaches of MSI/Fusion

Estimation methods	Non-recursive: <ul style="list-style-type: none">•Weighted Average•Least Squares Recursive: <ul style="list-style-type: none">•Kalman Filtering•Extended Kalman Filtering
Classification methods	<ul style="list-style-type: none">•Parametric Templates•Cluster Analysis•Learning Vector Quantization (LVQ)•K-means Clustering•Kohonen Feature Map•ART, ARTMAP, Fuzzy-ART Network
Inference methods	<ul style="list-style-type: none">•Bayesian Inference•Dempster-Shafer Method•Generalized Evidence Processing
Artificial intelligence methods	<ul style="list-style-type: none">•Expert System•Adaptive Neural Network•Fuzzy Logic

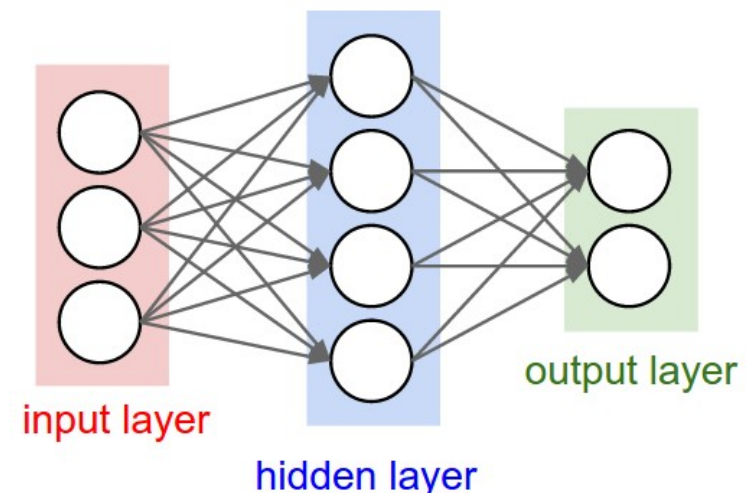
[2] Luo, Chih-Chen Yih and Kuo Lan Su, 2002

Multi-sensor integration with NNs

- Biologically inspired solution for MSI
- The brain as an integration model
- Benefits of using neural architectures:
 - Unified framework
 - Strong generalization abilities
 - Adaptability
- Drawbacks of using neural architectures:
 - Training procedure
 - Unclear causality



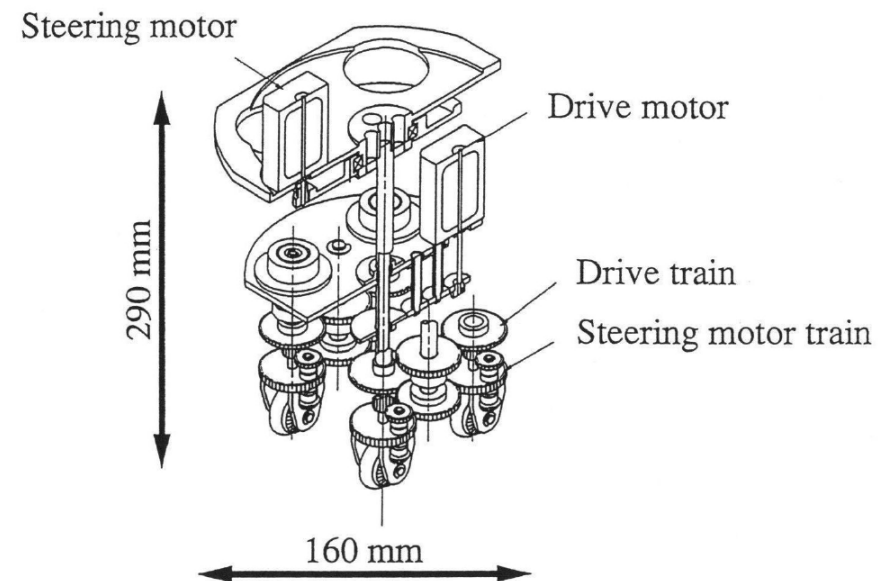
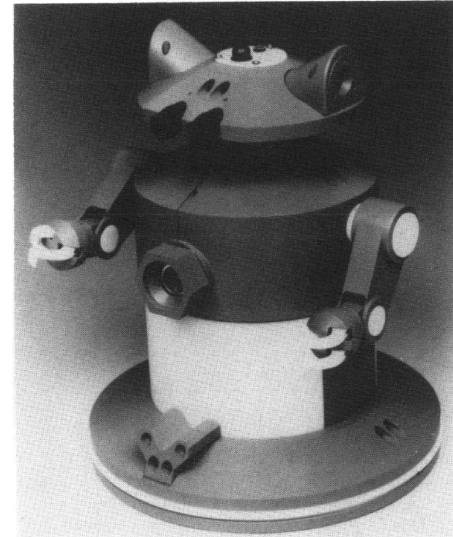
<http://www.autismmind.com/>



http://cs231n.github.io/assets/nn1/neural_net.jpeg

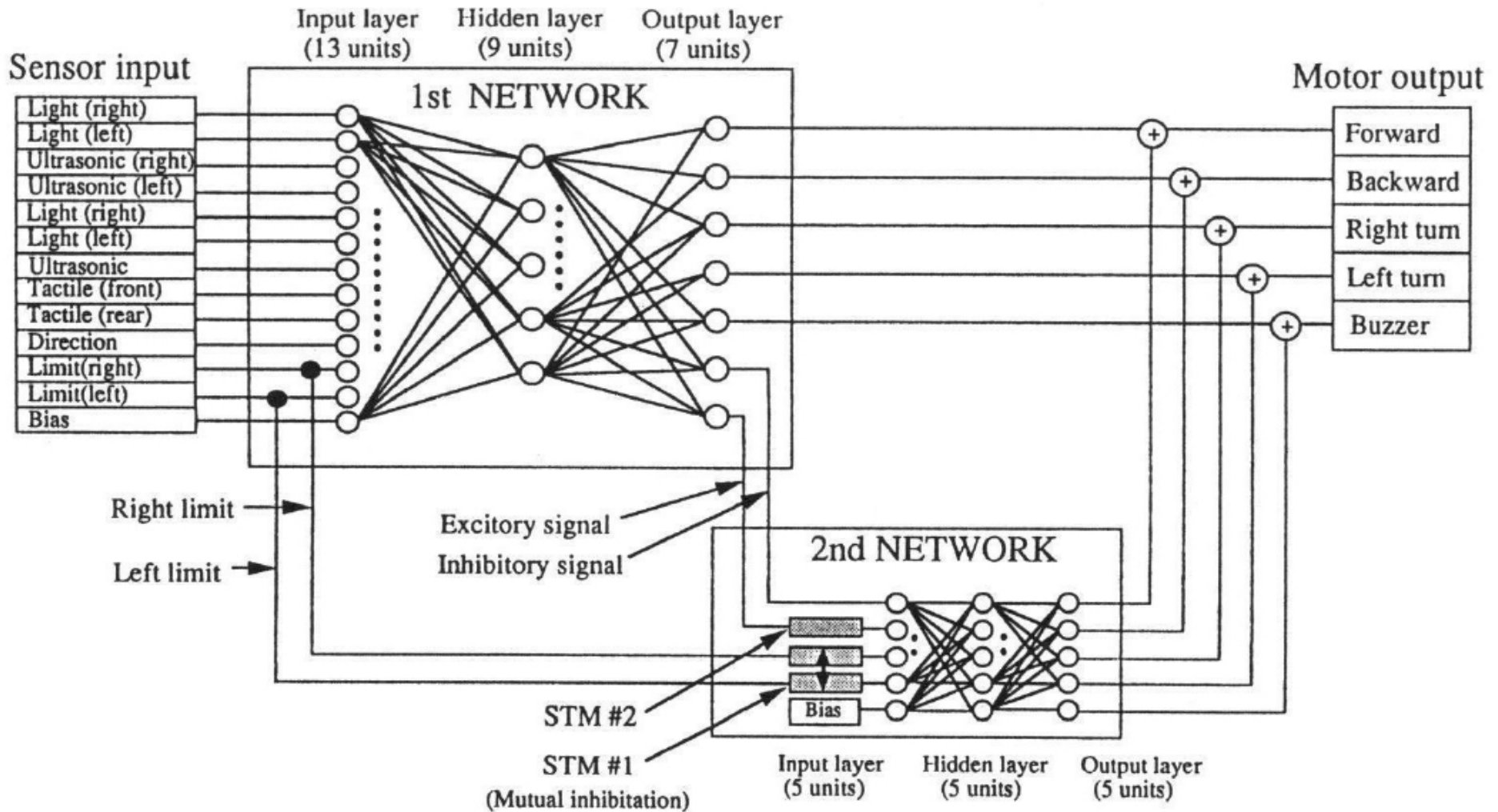
Robot control by Hierarchical NN

- Autonomous mobile robot equipped with 12 sensors of different types: **ultrasonic** sensors, **infrared** sensors, **tactile** sensors, **limit** sensors
- Locomotion:
 - 4 wheels aligned in same direction
 - Steering motor for heading
 - Drive motor for moving



[3] Nagata et al. 1990

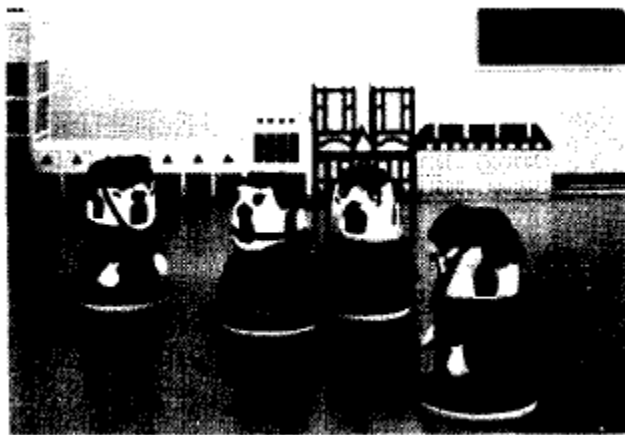
The network model for robot control



[3] Nagata et al. 1990

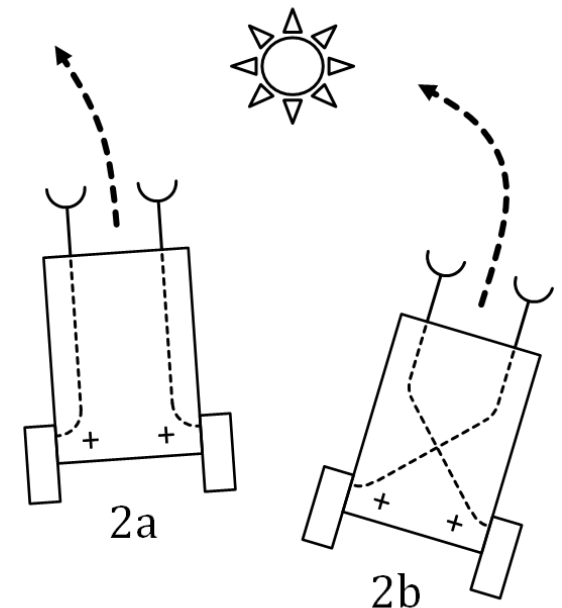
Emergent behavior of the robot

- **Training algorithm:** modified version of the backpropagation algorithm (pseudo-impedance control)
- **Training patterns:** obtained from running a simulation, only a subset of all possible 4096 patterns is needed
- **Behavior:** depending on the training patterns used, two different behaviors of the robots emerge (cops and robbers)



[3] Nagata et al. 1990

Comparison with
Braitenberg vehicles

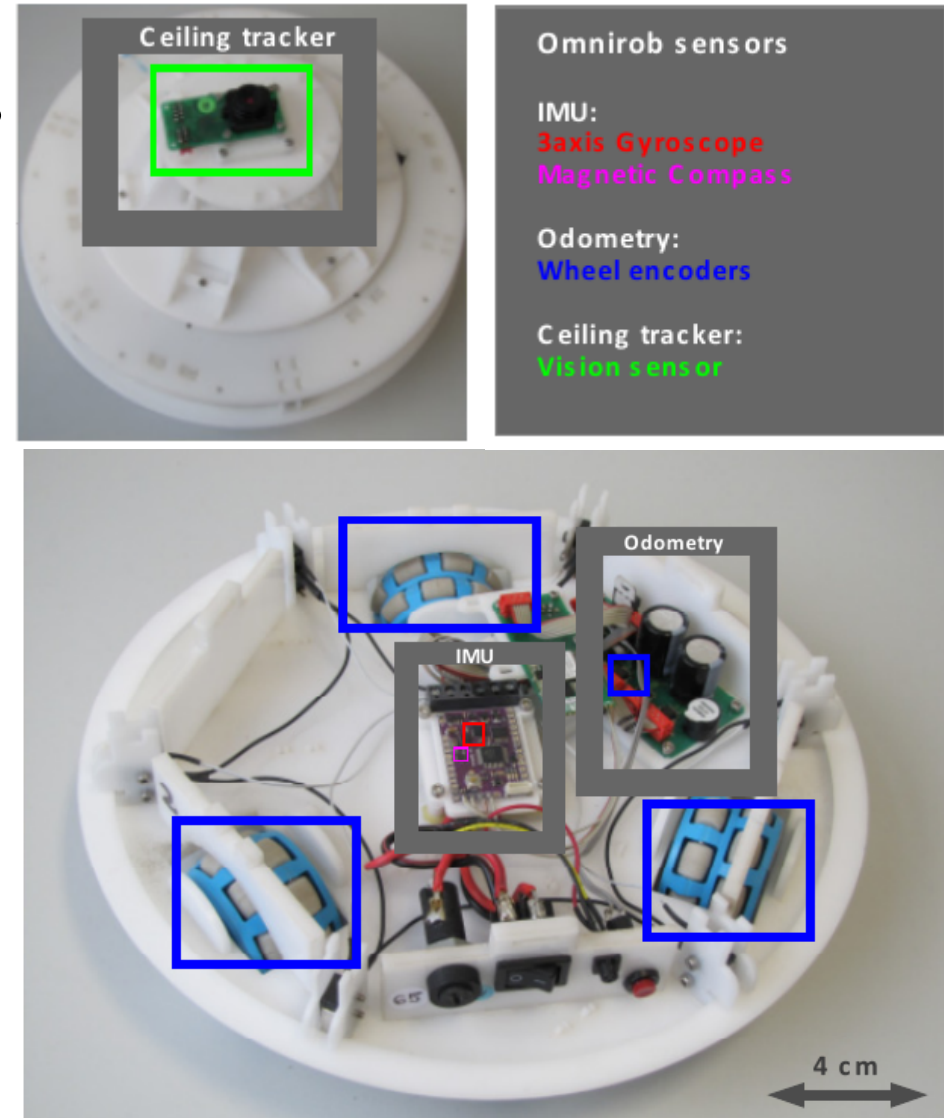


Thomas Schoch – www.retas.de

Sensor fusion for estimating robot heading

- Robot equipped with 4 different sensors for estimating direction: **gyroscope**, **compass**, **wheel encoder** and **camera**
- **Biologically inspired** sensor fusion model
- Based on the principles of **cortical** processing such as **localization**, **distributed processing** and **recurrency**

[4] Axenie and Conradt, 2013

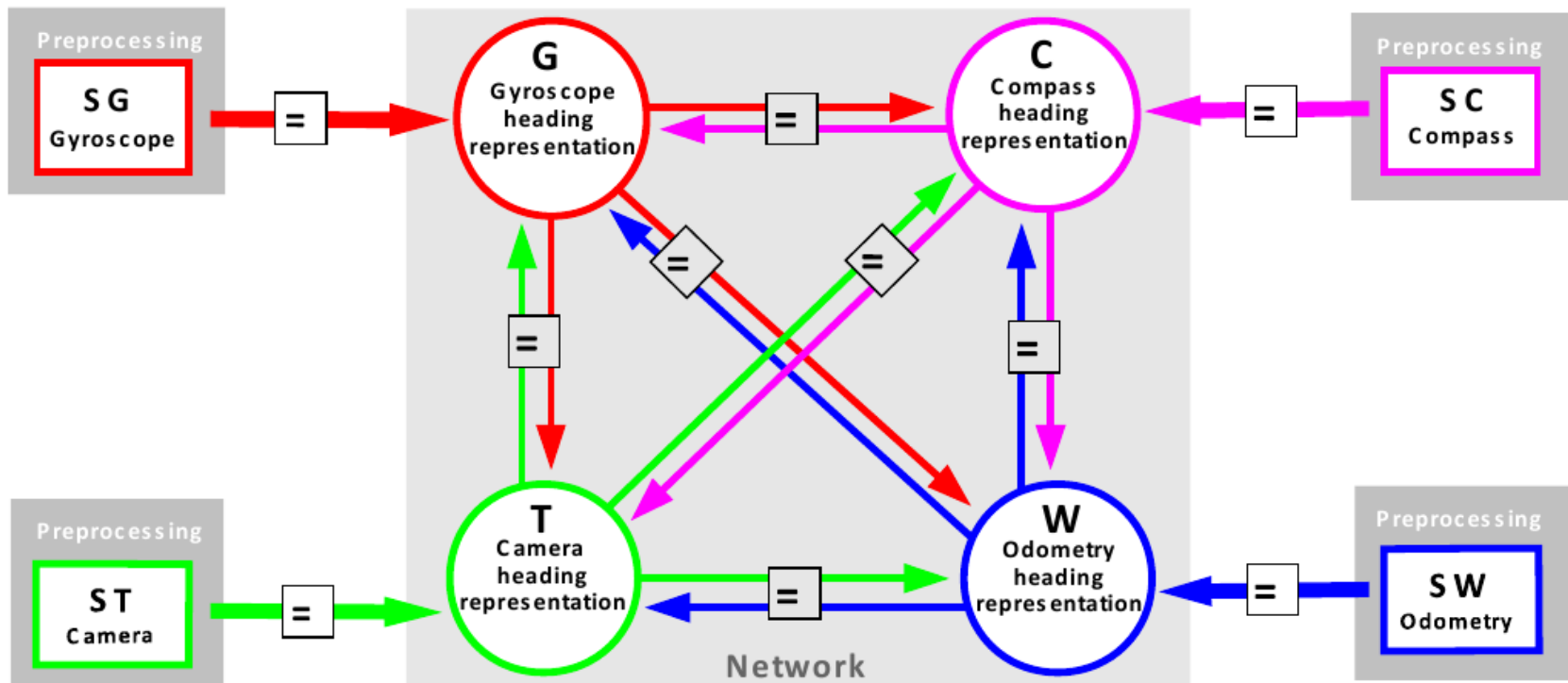


Recurrent graph network for sensor fusion

Network of four **fully connected nodes** which **mutually influence** each other

Information in nodes is encoded by **neural population code**

The network **pushes** all representations **towards an equilibrium state**



[4] Axenie and Conradt, 2013

The network dynamics

$\eta(t)$ – update rate at time t

E – mismatch between node m_i and m_j

[4] Axenie and Conradt, 2013

Generic update rule:

$$m_i(t+1) = m_i(t) - \eta(t) \cdot E_{m_i, m_j}(t), \quad E_{m_i, m_j}(t) = m_i(t) - f_{m_i, m_j}(t) \quad (1)$$

$$\eta_{i,j}(t+1) = \eta_{i,j}(0) \cdot \frac{\sum_{k=1}^{N-\{i\}} E_{m_i, m_k}(t)}{N \cdot E_{m_i, m_j}(t)} \quad (2)$$

← network's belief (numerator)

Example update rules for the Gyroscope (G) node:

$$G(t+1) = (1 - \eta_{G,C}(t)) \cdot G(t) + \eta_{G,C}(t) \cdot C(t), \quad (3)$$

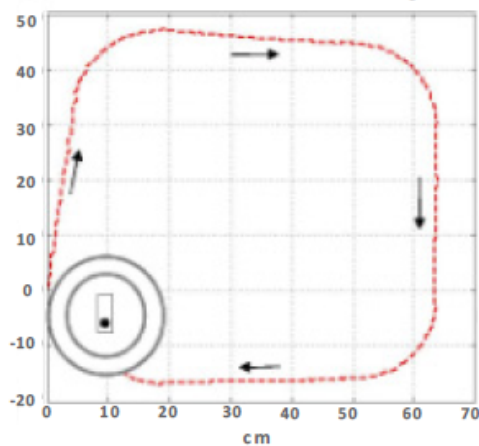
$$G(t+1) = (1 - \eta_{G,W}(t)) \cdot G(t) + \eta_{G,W}(t) \cdot W(t), \quad (4)$$

$$G(t+1) = (1 - \eta_{G,T}(t)) \cdot G(t) + \eta_{G,T}(t) \cdot T(t), \quad (5)$$

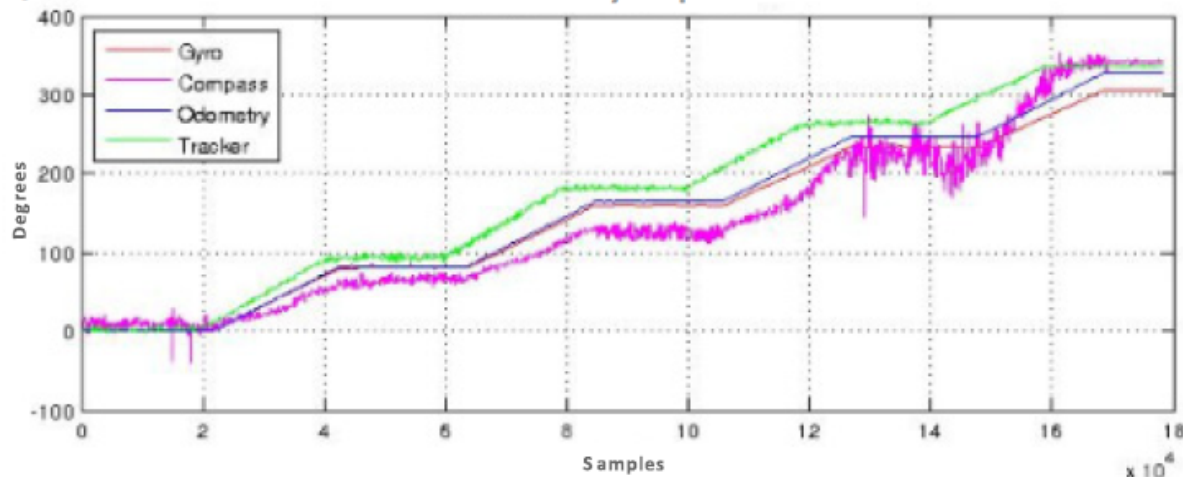
$$G(t+1) = (1 - \eta_{G,SG}(t)) \cdot G(t) + \eta_{G,SG}(t) \cdot SG(t), \quad (6)$$

Experimental results of the model

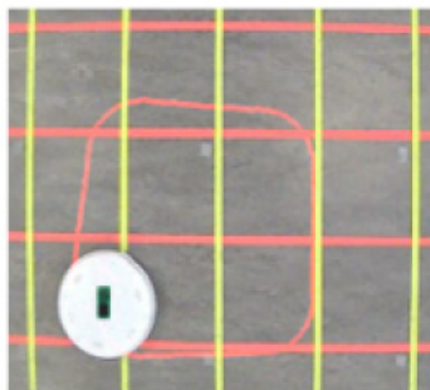
Robot reference trajectory



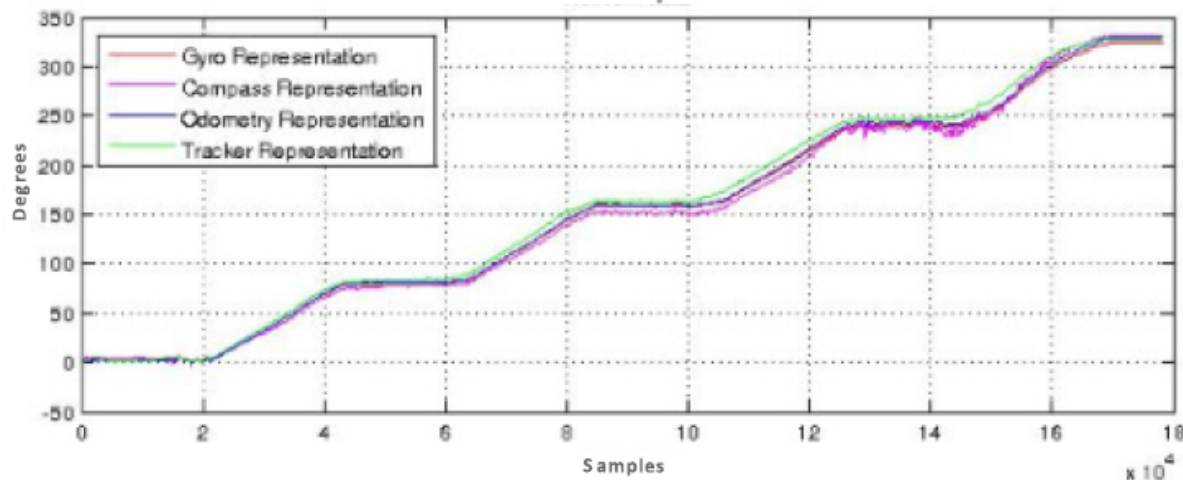
Sensory inputs



Robot real trajectory



Network internal representations

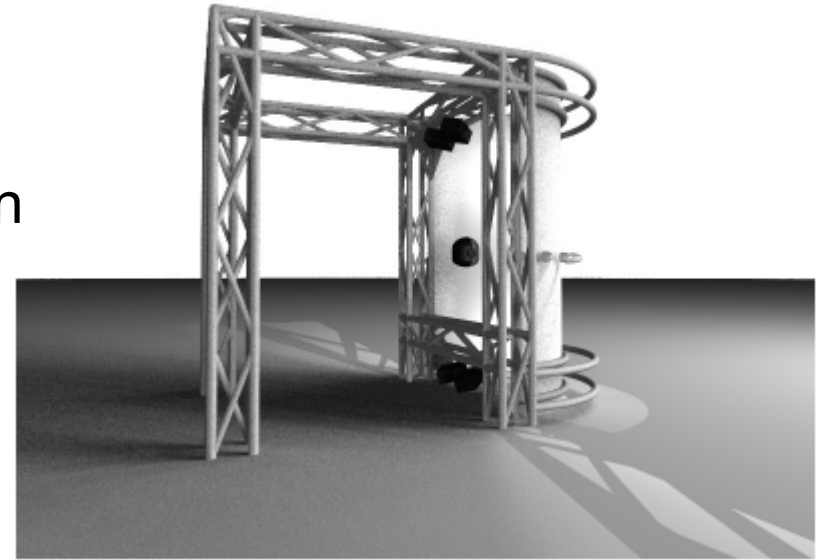


[4] Axenie and Conradt, 2013

Experiments in the HRI Lab at WTM

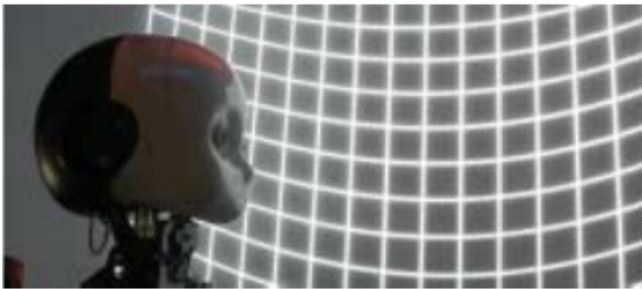
The HRI Lab at Knowledge Technology Department

- Allows for experiments with models for multi-modal (**audio-visual**) sensory integration
- **Compromise** between the advantages of **real world** and **simulation**



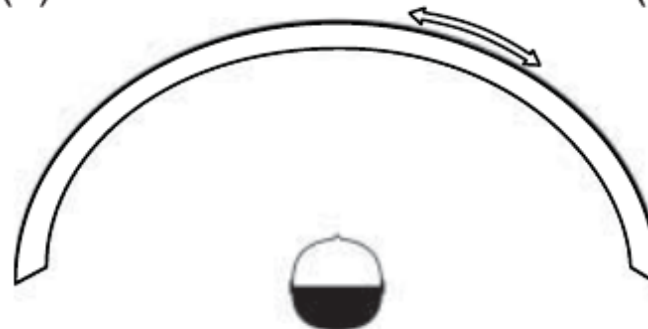
[5] Bauer et al. 2013

(a)



[6] Bauer et al. 2015

(b)



(c)



Experiments in the HRI Lab at WTM

Video of the HRI Lab



Neuronal models for MSI – Summary

Conclusions:

- Neurally inspired models have **strong generalization** abilities. Their **adaptability** allows for dealing with **unknown** and **changing environments**
- Their advantages come with the price of **training** and **complexity** of the sensor-actuator relationship, bringing **causality** which is sometimes **hard to interpret** and **not predictable**

Questions?

Thank you for the attention

Literature

- 1) Luo, Ren C., and Michael G. Kay. "A tutorial on multisensor integration and fusion." Industrial Electronics Society, 1990. IECON'90., 16th Annual Conference of IEEE. IEEE, 1990.
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- 3) Nagata, Shigemi, Minoru Sekiguchi, and Kazuo Asakawa. "Mobile robot control by a structured hierarchical neural network." IEEE Control Systems Magazine 10.3 (1990): 69-76.
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- 5) Bauer, Johannes, and Stefan Wermter. "Learning multi-sensory integration with self-organization and statistics." Ninth international workshop on neural-symbolic learning and reasoning NeSy. Vol. 13. 2013.
- 6) Bauer, Johannes, Jorge Dávila-Chacón, and Stefan Wermter. "Modeling development of natural multi-sensory integration using neural self-organization and probabilistic population codes." Connection Science 27.4 (2015): 358-376.