# **Robot Brains**

Prof.dr. R. Babuška

Intelligent Control & Robotics

14 January 2011

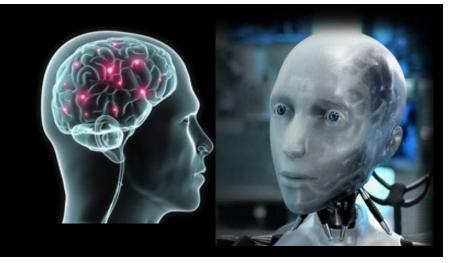


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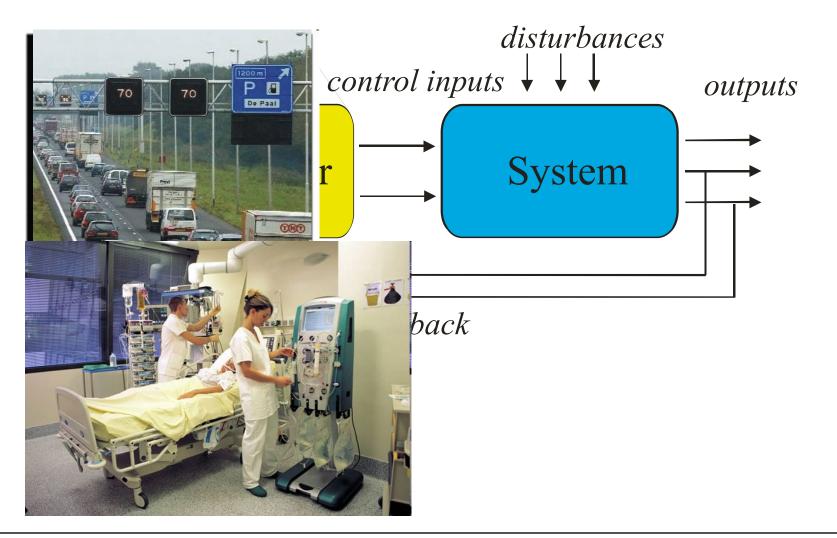
14 January 2011



- Systems and control
- Challenges in robotics
- Intelligent control

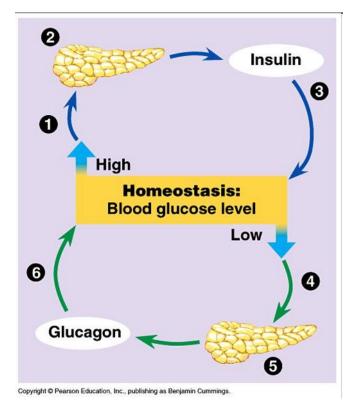


### **Automatic Control**





### **Feedback in Nature**



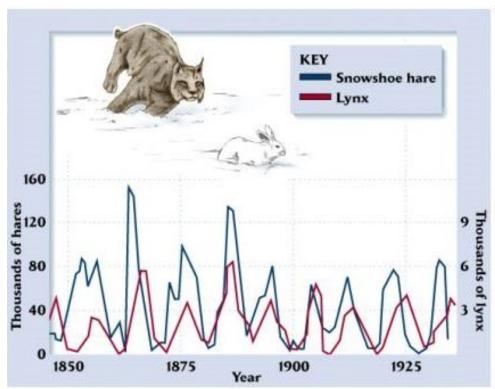
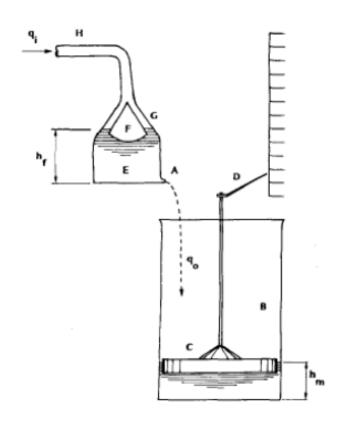
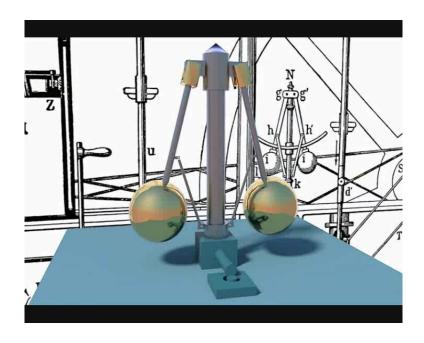


Image source: mathnathan.com



# First Man-Made Control Systems



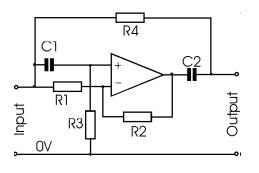


**Ancient water clock** by Ktesibios Alexandria 3<sup>rd</sup> century BC

**Steam engine** speed regulator James Watt, Scotland 1788



# **Huge Impact of Invisible Technology**





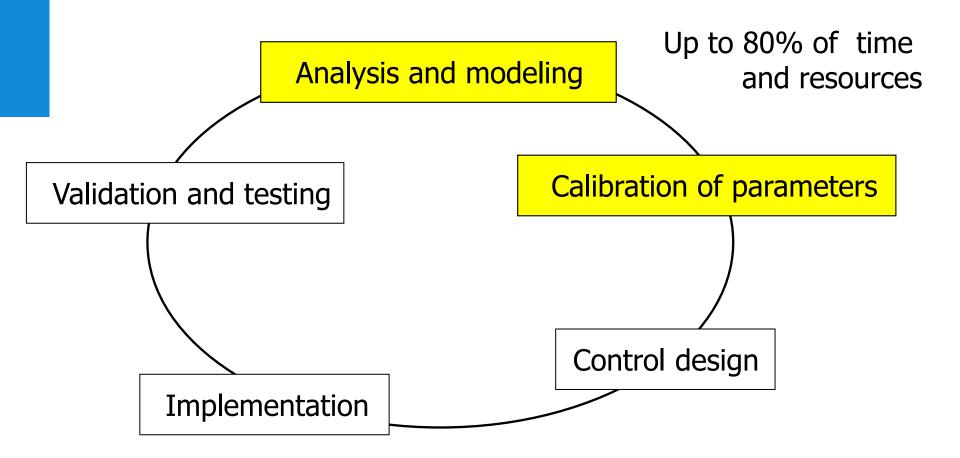








# **Model-Based Design**





### **Cornerstones of Control Research**

Mathematics

Systems approach

Control

Application domain

#### **Emphasis on provably correct design**

- stability and performance guarantees

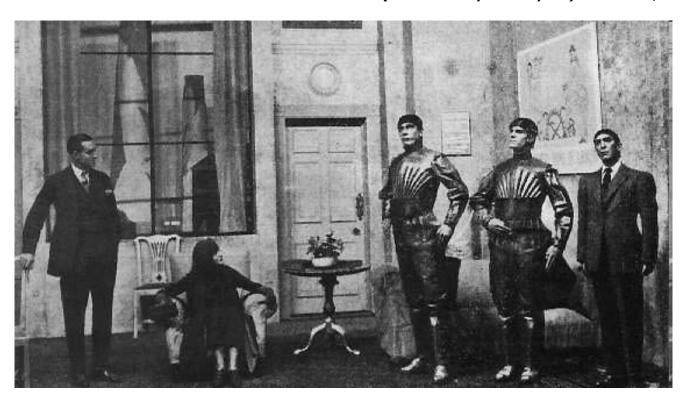




### Robot

 a mechanical system which performs tasks under human control, in collaboration with humans or autonomously

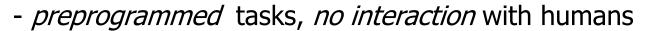
from Czech "robota" – forced labor (Karel Čapek's play R.U.R., 1921)





#### Great impact in well structured, engineered environments

- speed, accuracy, repeatability, automatic operation











Some success in **telemanipulation** and **teleroperation** 

- robots operated by humans







Challenges ahead in domestic, service and care applications

-operate autonomously and interact with humans





Challenges ahead in domestic, service and care applications

-operate autonomously and interact with humans



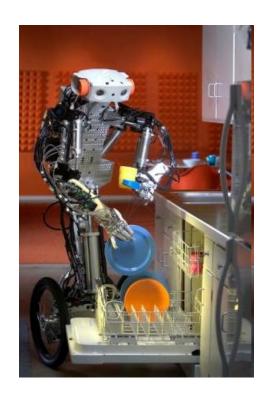


video source: youtube



Challenges ahead in domestic, service and care applications

-operate semi-autonomously and interact with humans



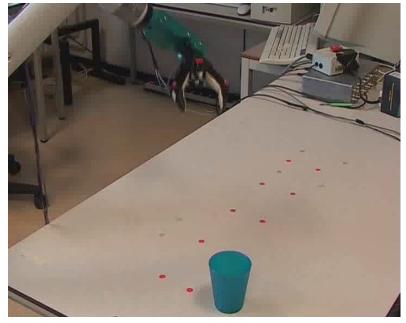




Challenges ahead in domestic, service and care applications

-operate semi-autonomously and interact with humans



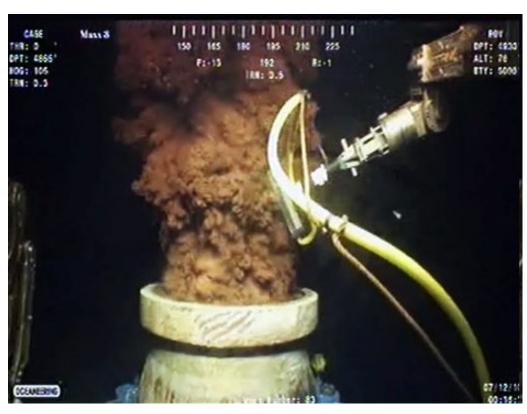


Freek Liefhebber (TNO & TU Delft)



more challenges: agriculture, deep sea, construction, ...







# **Challenges in Robotics**

- safety in human-machine interaction
- autonomy and shared autonomy (collaborate with humans)
- coping with unstructured environments



versus

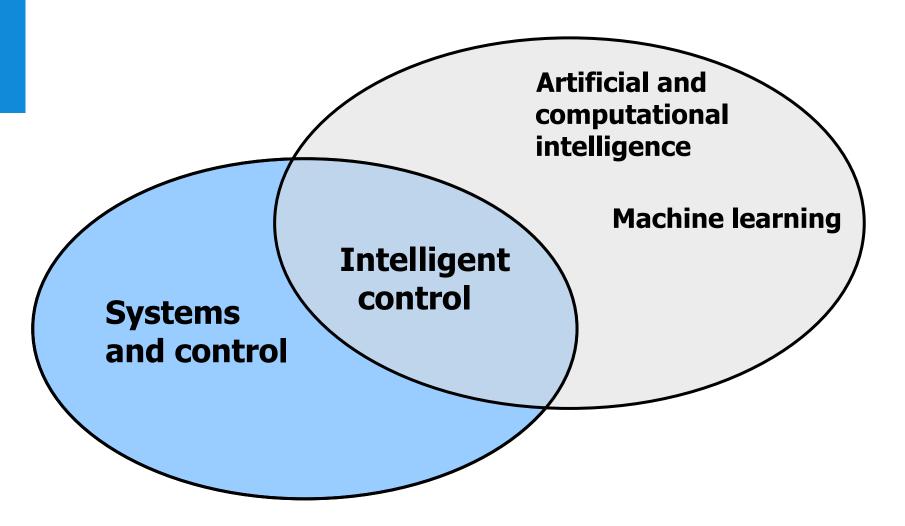




# **Intelligent Control**



# **Intelligent Control**

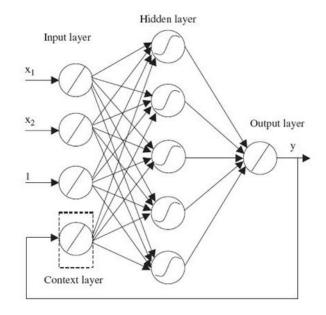




### **Alternative Representation Schemes**

Traditional control

$$y(k+1) = A(q)y(k) + B(q)u(k)$$



artificial neural networks

Inspiration in nature



#### rule-based models

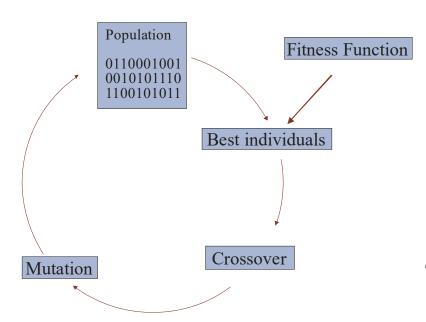
if <condition> then <conclusion>



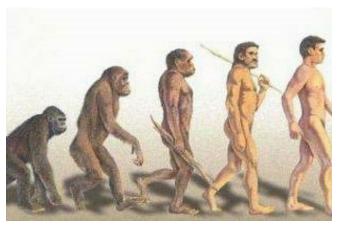
# **Optimization in Control**

Roots in maths

$$x_{opt} = \underset{X}{argmax} F(x)$$



Inspiration in nature



Genetic and evolutionary algorithms

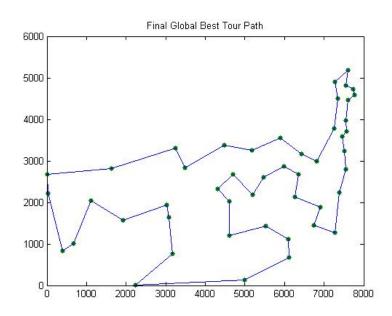


# **Optimization in Control**

#### Roots in maths

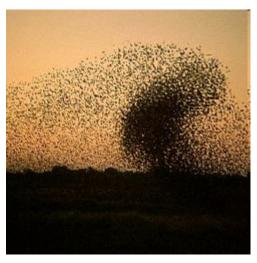
$$x_{opt} = \underset{X}{argmax} F(x)$$

#### **Swarm intelligence**



#### Inspiration in nature







# **Machine Learning**

ability to learn a *specific task* from experience, without being specifically programmed for that task

- adapt to changes in environment
- find new, better solutions
- teach by demonstration or imitation



# **Spectrum of Learning Techniques**

#### **Reinforcement learning**

(learn directly to control)

#### **Supervised learning**

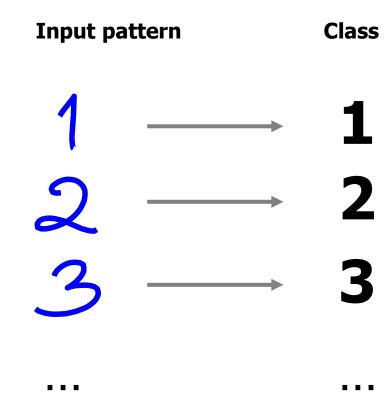
(with 'teacher')

#### **Unsupervised learning**

(without 'teacher')



### **Supervised Learning: Classification**

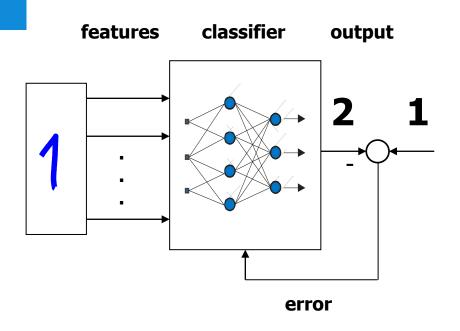


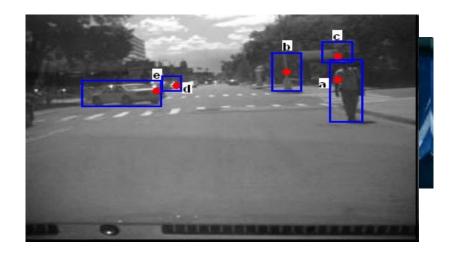


1. Collect a training set



### **Supervised Learning: Classification**





- 1. Collect a training set
- 2. Train the classifier
- 3. Use to classify new patterns



### **Construct a Robot Model from Data**



actuate motors and observe the response

Two ways to model the system:

- 1. Physical modeling
- 2. System identification



Maarten Vaandrager



# **Spectrum of Learning Techniques**

#### **Reinforcement learning**

(learn directly to control)

**Supervised learning** 

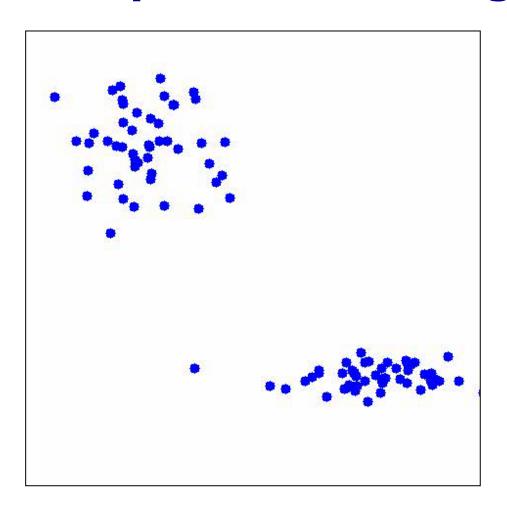
(with 'teacher')

**Unsupervised learning** 

(without 'teacher')



### **Unsupervised Learning - Clustering**



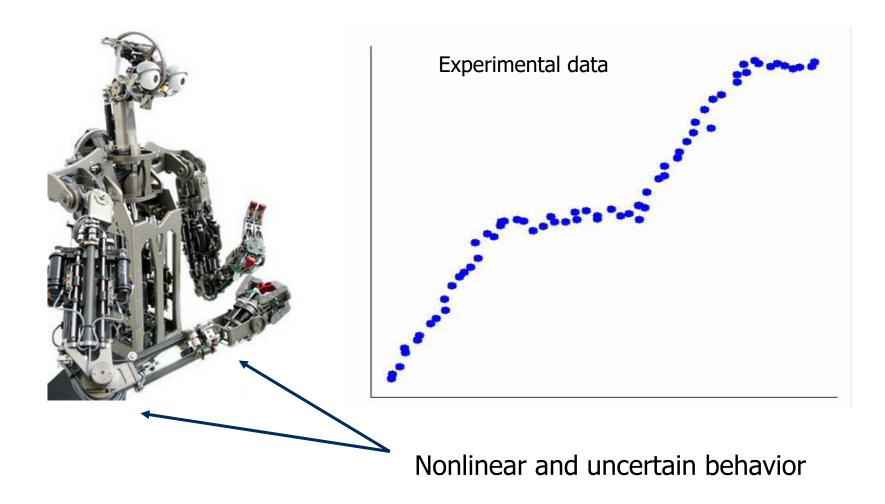
 Discover automatically groups and structures in data

#### **Applications:**

- Pattern recognition
- Robot perception, vision
- Data-driven construction of dynamic models



### **Construction of Nonlinear Models**





# **Spectrum of Learning Techniques**

#### **Reinforcement learning**

(learn directly to control)

**Supervised learning** 

(with 'teacher')

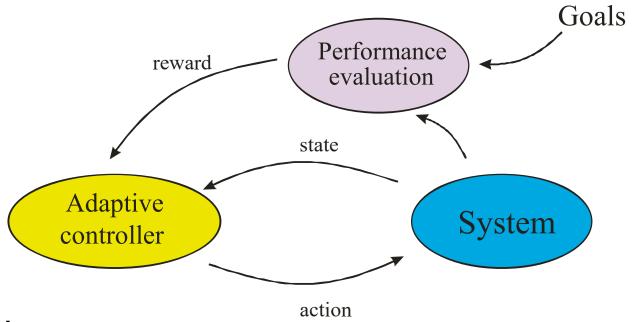
**Unsupervised learning** 

(without 'teacher')



# **Reinforcement Learning**

Inspiration - animal learning (reward desired behavior)



#### Goal:

Adapt the control strategy so that the sum of rewards over time is maximal.



# **Reinforcement Learning**

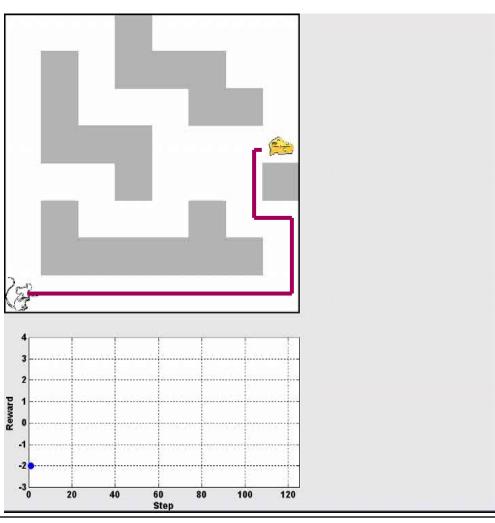
Inspiration - animal learning (reward desired behavior)







# **Example - Learning Optimal Path**



Reitiar posible (goal next of next of



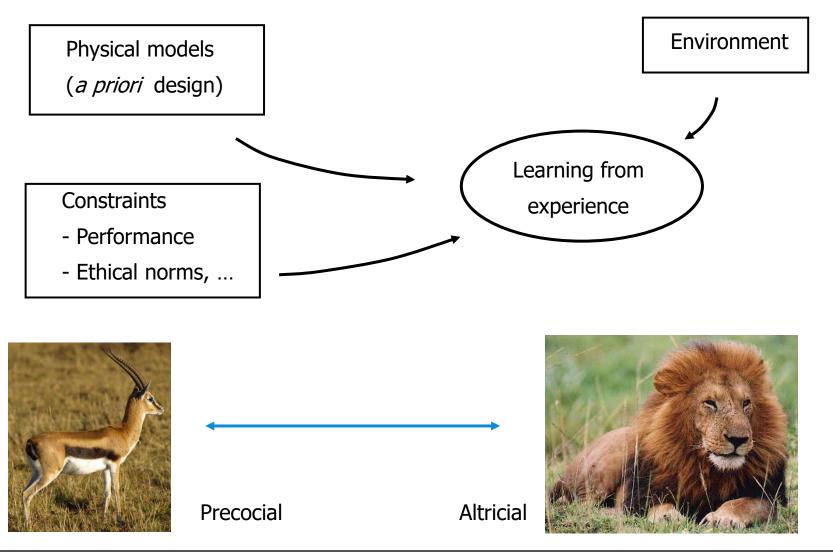
# Learning in Real World, in Real Time

Reinforcement learning using experience replay for the robotic goalkeeper

Initial trials: bad performance



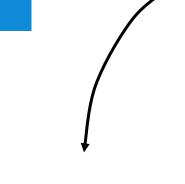
## **Long-term Research Goal**





#### **Robot Control: Traditional View**

**Task control** 



**Motion control** 

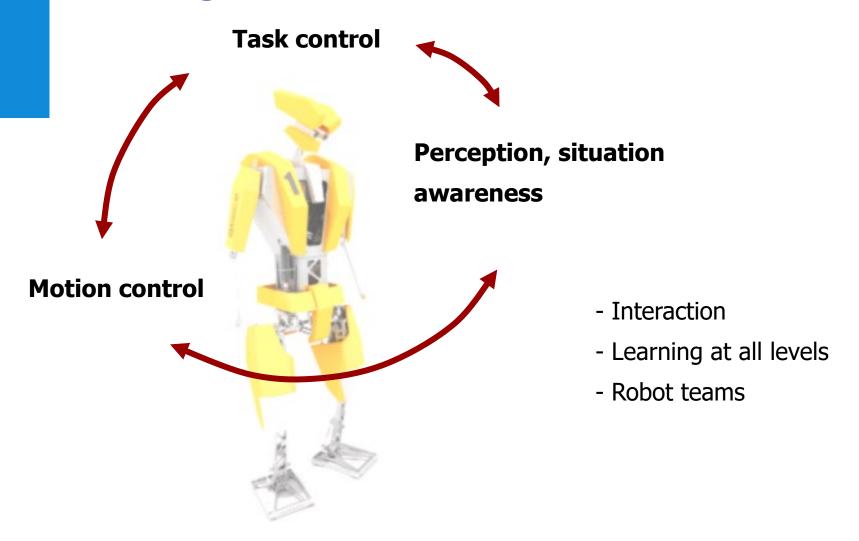




Perception, situation awareness



# **Integrated Robot Control**

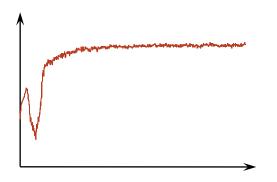


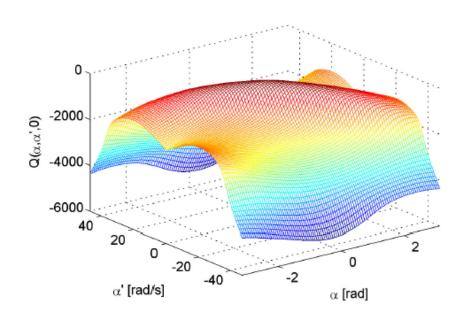


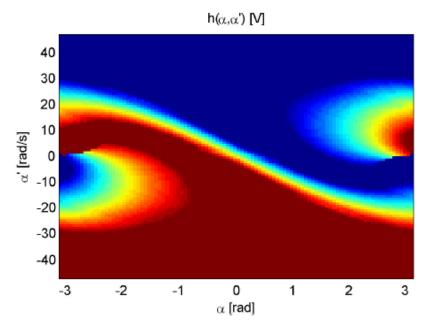
#### **Research Themes**

#### **Reinforcement Learning for Control and Planning**

- Approximation in high-dimensional continuous spaces
- Computationally effective methods
- Constrained learning and convergence

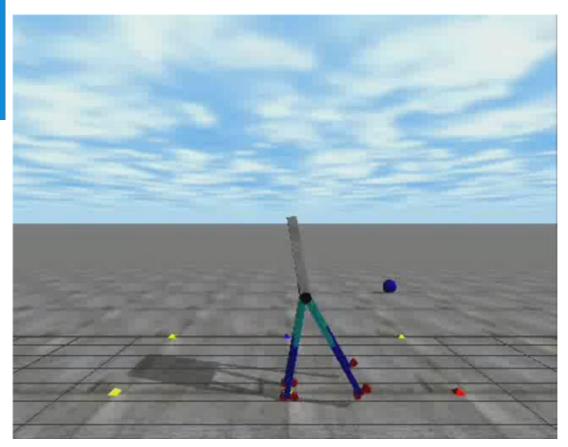


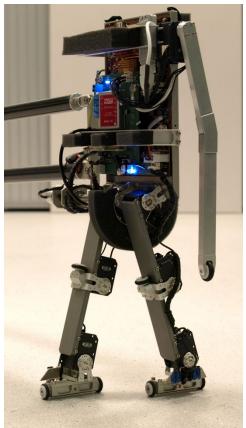






#### **Reinforcement Learning for Bipedal Locomotion**





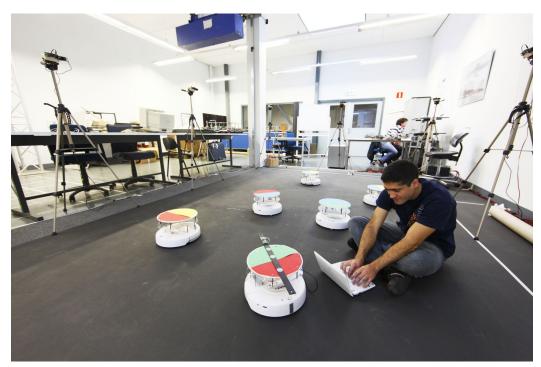
E. Schuitema (collaboration with the Biorobotics Lab, TU Delft - M. Wisse and P. Jonker).



#### **Research Themes**

#### Filtering, estimation and adaptive control

- Distributed filtering and localization
- Nonlinear adaptive methods
- Stochastic estimation



Andrea Simonetto and Tamas Keviczky



#### **Research Themes**

#### **Legged locomotion**

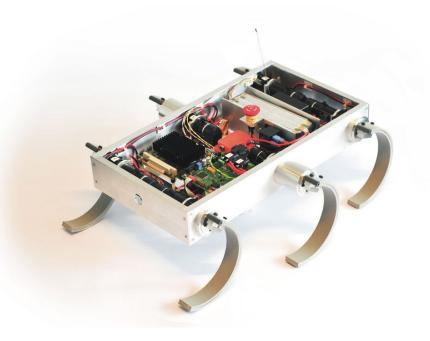
- Gait generation
- Learning and optimization

#### **Robotic manipulators**

- Task-oriented control
- Adaptive payload estimation

#### **Software and hardware**

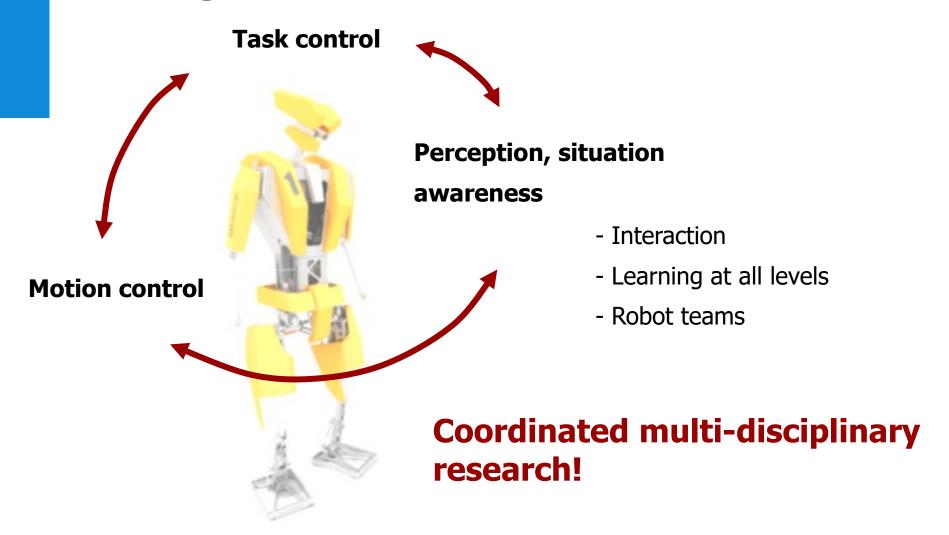
- Automatic code generation
- Development of infrastructure



Gabriel Lopes & DCSC engineering team

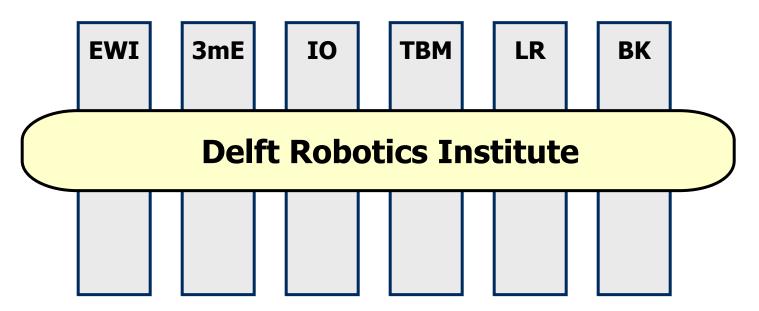


## **Integrated Robot Control**





#### **Robotics @ TU Delft**



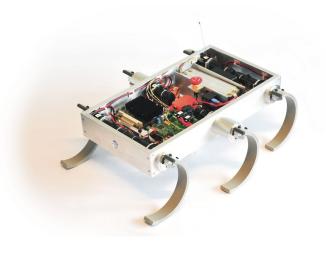
Goal: advance robotics research, education and valorization in a coordinated fashion.

Mechanics, electronics, design, control, sensing, vision, human-robot interaction, ...



## **Research Platforms**















#### **Educational Platforms**











#### **Robotics in the Dutch Context**

# dutch institute of systems and control







## **Acknowledgements**

- University board
- Dean of 3mE, Prof. Marco Waas
- Rector Magnificus, Prof. Karel Luyben
- My teachers, mentors, colleagues and students



# **Special Thanks to**

Henk Verbuggen (emeritus professor)





# **Biggest Thanks to**

#### Dana, Markéta and Míša







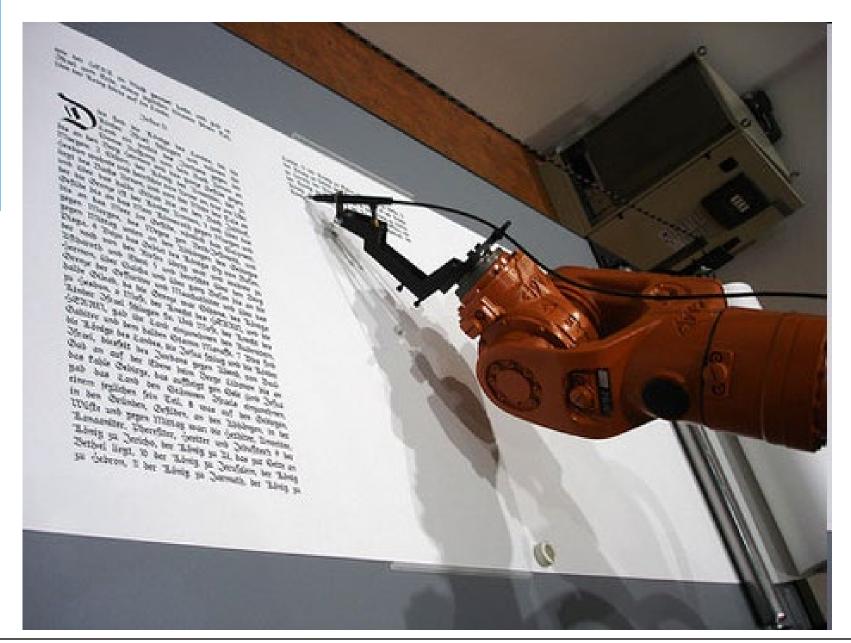


## **Hard Disk Read/Write Head Control**

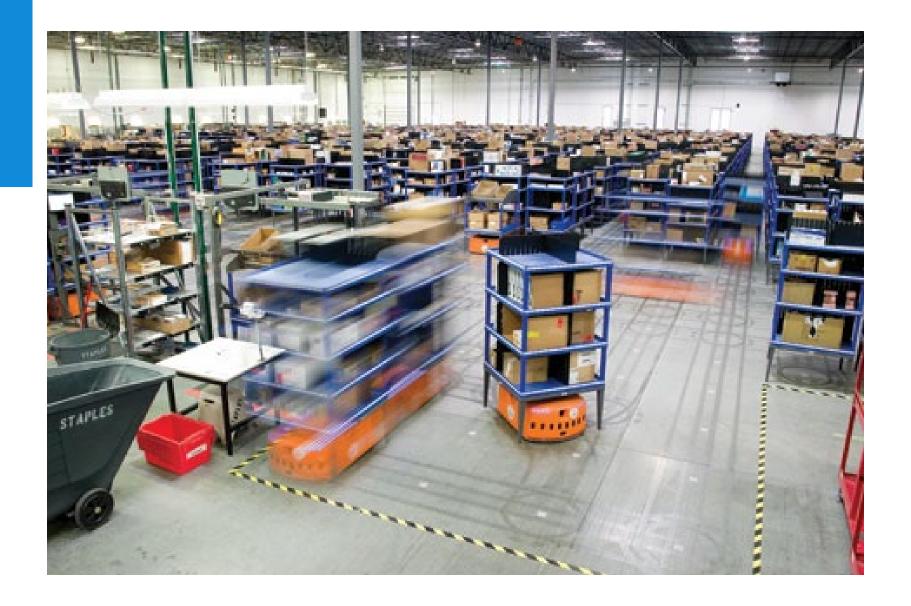


- high-speed, high-precision positioning of the arm
- closed system, little interaction with environment









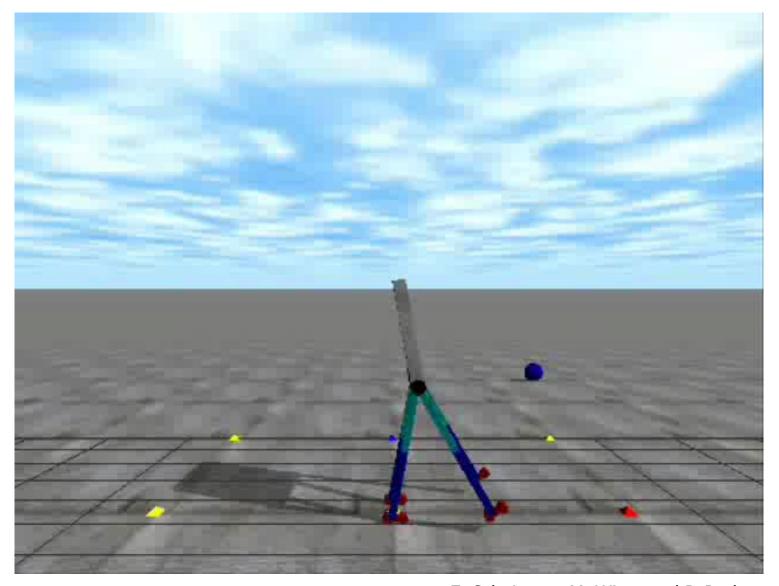


# **Harvesting Robot**



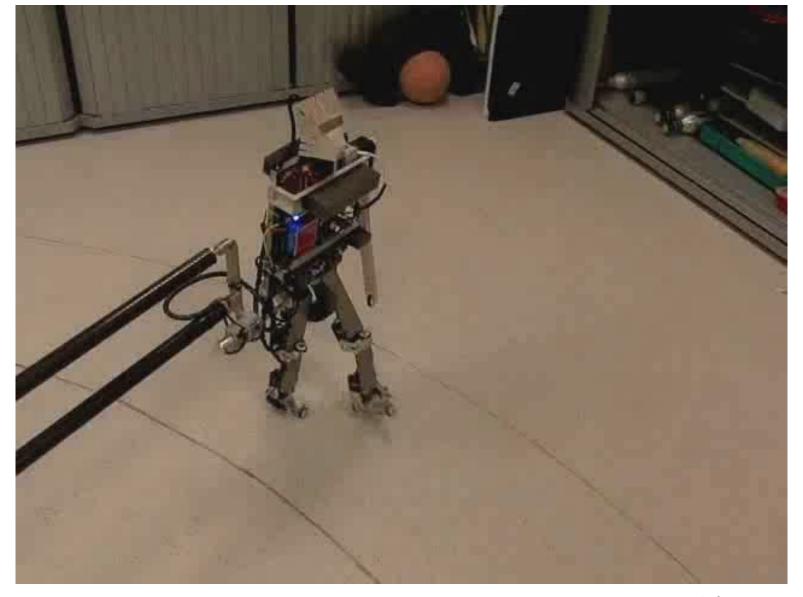
- high-speed, highprecision, gentle handling
- open system, interaction with environment is crucial





E. Schuitema, M. Wisse and P. Jonker





E. Schuitema





RHex project, USA



# **Possible Convergence Curve**

