

# Homeokinesis

A new principle to back up evolution with learning

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This presentation does not contain any  
complex Maths

Not suitable for consumption by Pure Mathematicians

## Overall motto: Non goal-directed learning

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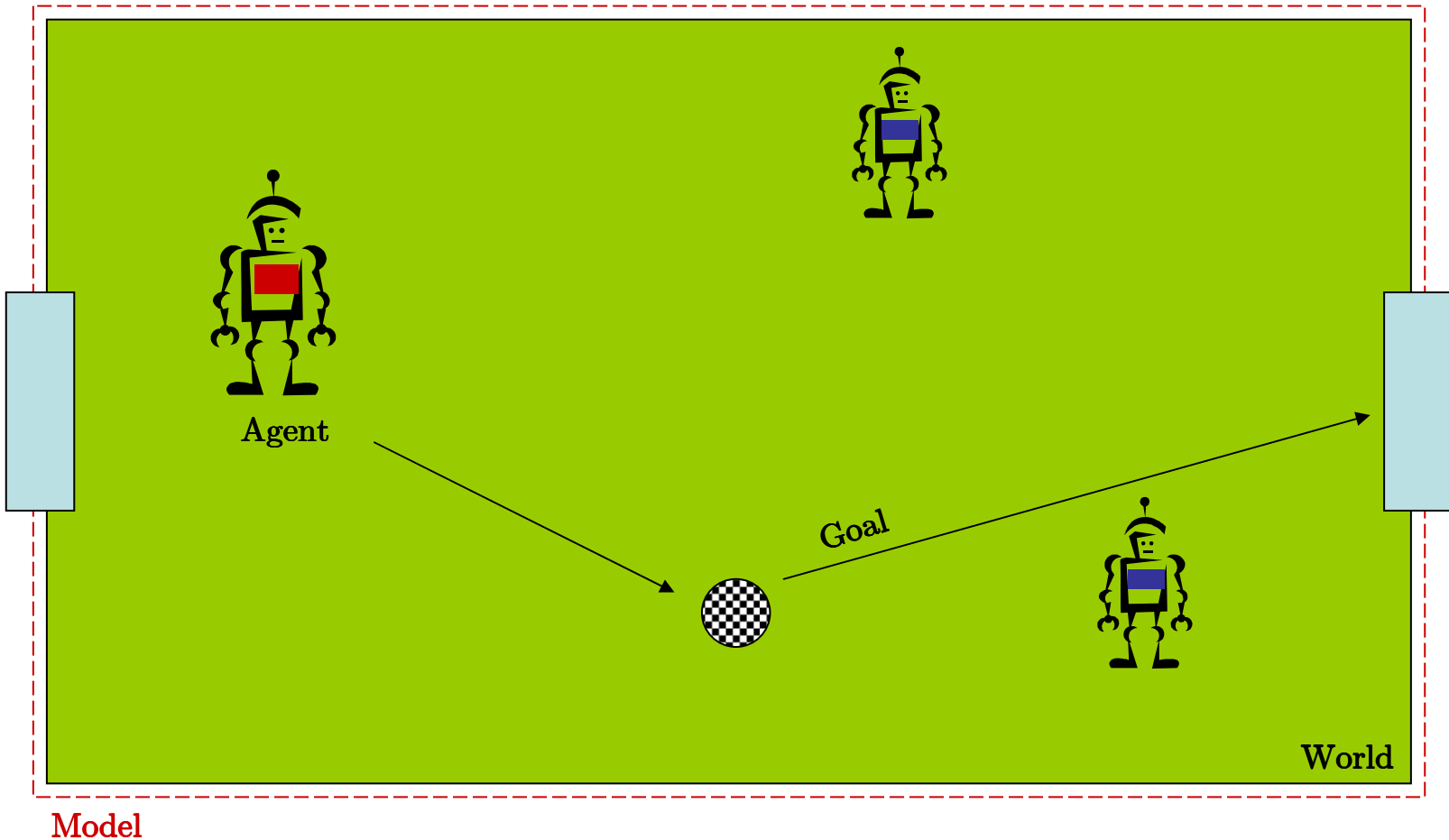
- Relatively new approach – central paper published in 1999, recently received some more attention
- Non goal-directed learning
- Models biological evolution (to some degree)
- Allows for self-organised AI agents

... but first, let's look at a few basic things.

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# A few basic things about AI

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## A few words on learning...

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- Learning is a topic in many sciences...
  - Psychology...
  - Biology...
  - Mathematics...
  - Physics...
  - Computer Science...

... and there are several different concepts:

- Reinforcement Learning
  - Supervised Learning
  - Autonomous Learning
    - Trial and Error...

## Learning in AI

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- So why are we so keen on learning?
  - Artificial Evolution
  - Autonomous agents
  - Self-organisation
  - Model nature – „let evolution do the work“
  - *In vivo* evolutionary robotics

# Different types of learning

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- Supervised Learning
  - Use a **training set**: Map example inputs to desired outputs
  - **Regression or classification**
  - Learner can predict values for new, unknown input objects
  - cf. **Concept Learning** in humans
  
  - **Distinguishing feature**: Manual, human-prepared training examples
  - **Issues**: Manual training required, generalisation difficult

# Different types of learning

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- Reinforcement Learning
  - Agent learns a **policy** of how to act given an observation
  - Feedback provided by the environment (world) in form of **rewards** and **punishments**
  - Inspired by Psychology (animal learning)
  - Agent tries to maximise the reward and avoid punishments
  
  - **Distinguishing feature:** Action/Reward mapping
  - **Issues:** Little generalisation, large sample space required

# The complexity barrier

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- So far, only fairly simple successful examples, e.g.
  - Wall following in a maze
  - Picking up objects
  - In simulation only (!)
- The real world is an extremely complex system
- Central issue:

We require specific learning goals.

... so why is this?

## The necessity of specific learning goals

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- For a self-organised, evolving robot, the fitness function is critical to its success
- Supervised learning requires a teacher and explicit, goal-directed input
- Reinforcement learning requires finding the right distribution of rewards
  
- i.e. we require explicit formulation of goals to drive evolution.

We want something better.

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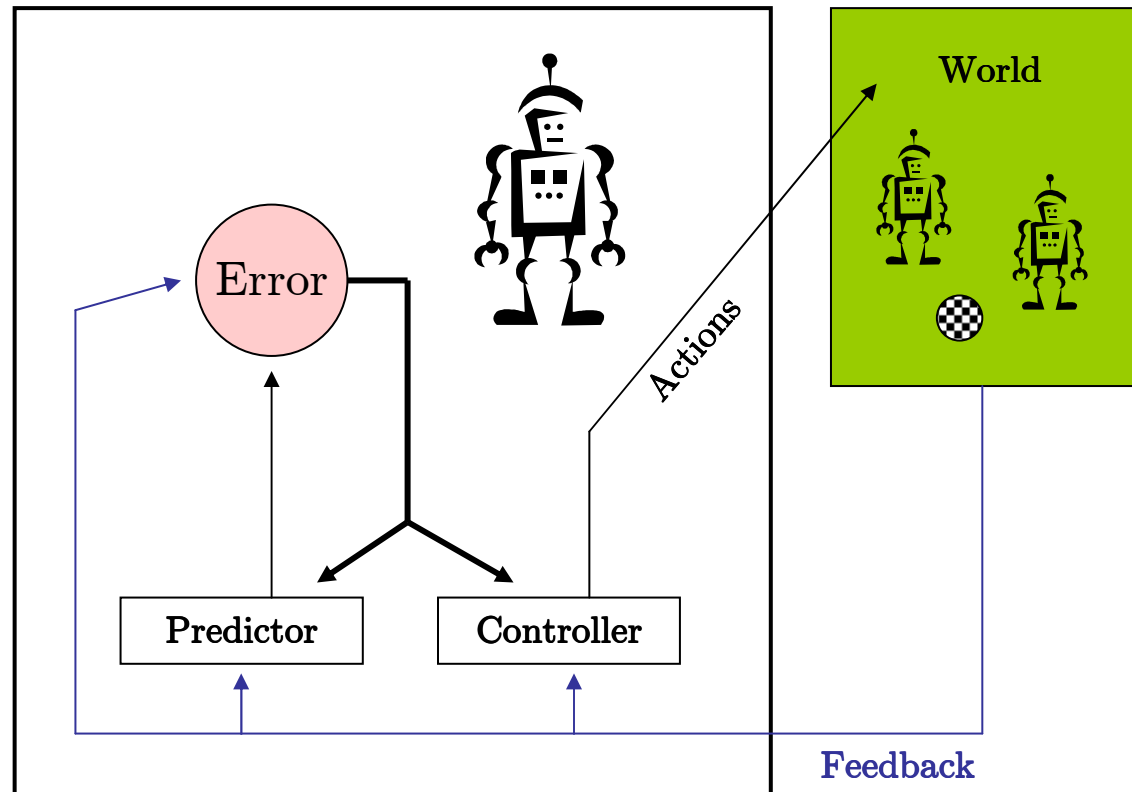
## Getting to a better model of learning

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- Agent should learn general principles
- Similar to biological evolution: Learn behaviours that make sense in the environment ... or die.
- Give the agent an adaptive model of its own behaviour
- Adapt the controller so that the model understands its own behaviour

# Getting to a better model of learning

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**Example 1:**  
**Linear control of a stochastic dynamic system**

## Generic example (1)

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- Consider a mass-less particle with friction under the influence of a harmonic force plus noise:

$$x'(t) = \underbrace{F(x)}_{\text{Force}} + \underbrace{\xi(t)}_{\text{Noise}}$$

$\xi(t)$  is white Gaussian noise with mean  $\langle \xi(t) \rangle = 0$  and correlation function (N.B.:  $\delta(t - t') = 0$  if  $t \neq t'$ ,  $\delta(0) = 1$ )

$$\langle \xi(t)\xi(t') \rangle = \sigma^2 \delta(t - t')$$

← Dirac delta

- Model understands the systematic behaviour of the system ... but **not** the noise.

## Generic example (2)

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- The model is a predictor for the value at some future point in time, evaluating

$$x_t^{(pred)}(t + \tau)$$

- It is of linear complexity, hence

$$x_t^{(pred)}(t + \tau) = ax(t)$$

- Using a mean squared error function, we get

$$E = \frac{1}{2} \left( x_t^{(pred)}(t + \tau) - x(t + \tau) \right)^2$$

## Generic example (3)

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- Assume that  $a = e^{-\kappa\tau}$  (i.e. model adapts quicker than controller)

- Average over the noise:

$$E = \sigma^2 \frac{1 - e^{-2\kappa\tau}}{4\kappa\tau}$$

- This decays monotonically

... so we can use learning by gradient descent.

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## Example 2: Non-linear emergence of control

# Non-linear emergence of control (1)

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- Example: **Braitenberg vehicle**

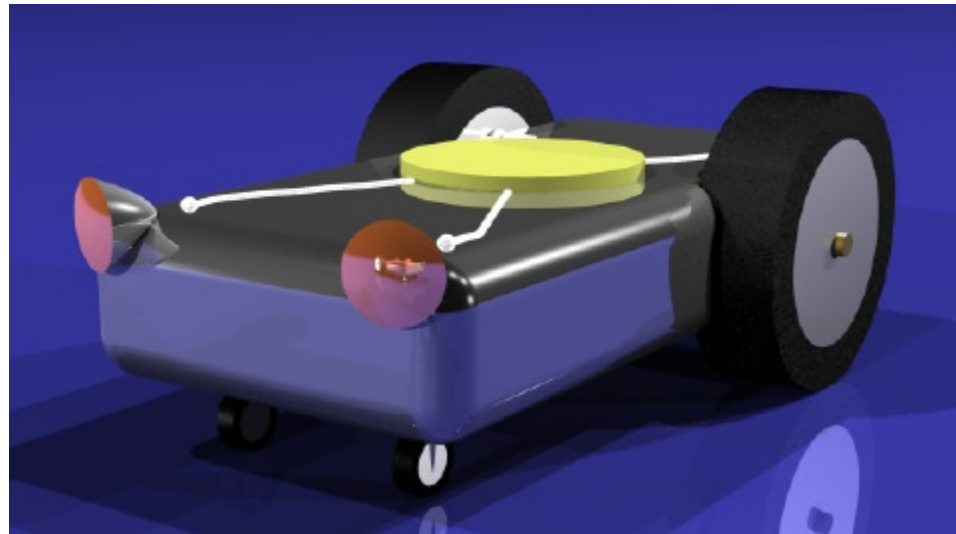


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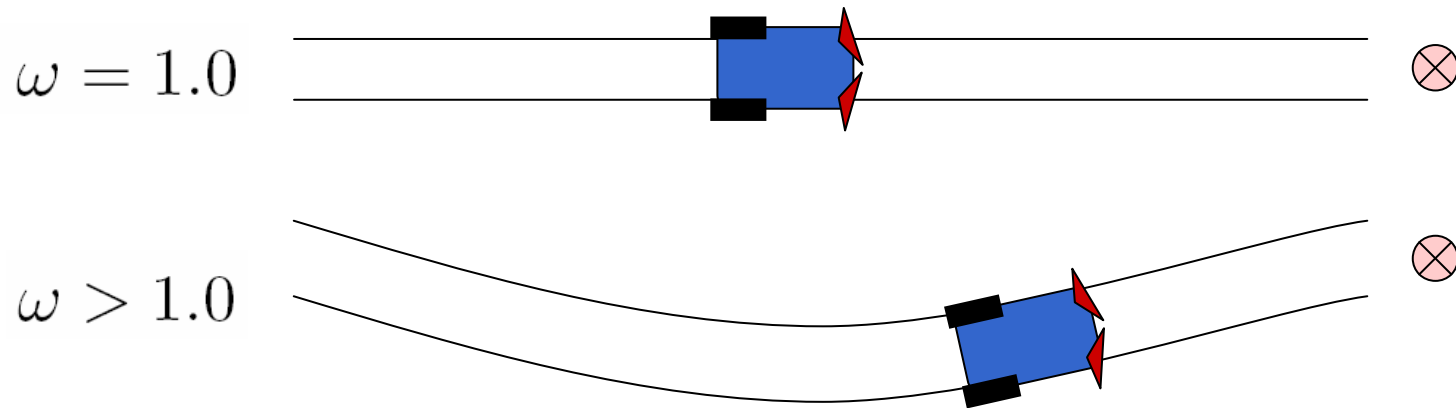
<http://people.cs.uchicago.edu/~wiseman/vehicles/vehicle.jpg>

- 2 light sensors, 2 wheels

## Non-linear emergence of control (1)

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- Assume coupling of strength  $\omega$  on right wheel
- Move light source along  $x$  axis
- Vehicle starts off at some  $y$  position
- Vehicle moves at constant distance,  $s$  and speed,  $c = 1$



## Non-linear emergence of control (2)

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- Angular velocity  $\phi'$  depends on sensor readings and coupling strength
- Equations of motion:

$$\begin{aligned}x' &= \cos \phi \\y' &= \sin \phi \\ \phi' &= s(\omega s_l(y, \phi) - s_r(y, \phi))\end{aligned}$$

- Sensor readings:

$$s_{l,r} \approx \frac{1}{s^2} \left( 1 + \frac{2R}{s} \cos(\alpha + \phi + \gamma) \right)$$

## Non-linear emergence of control (3)

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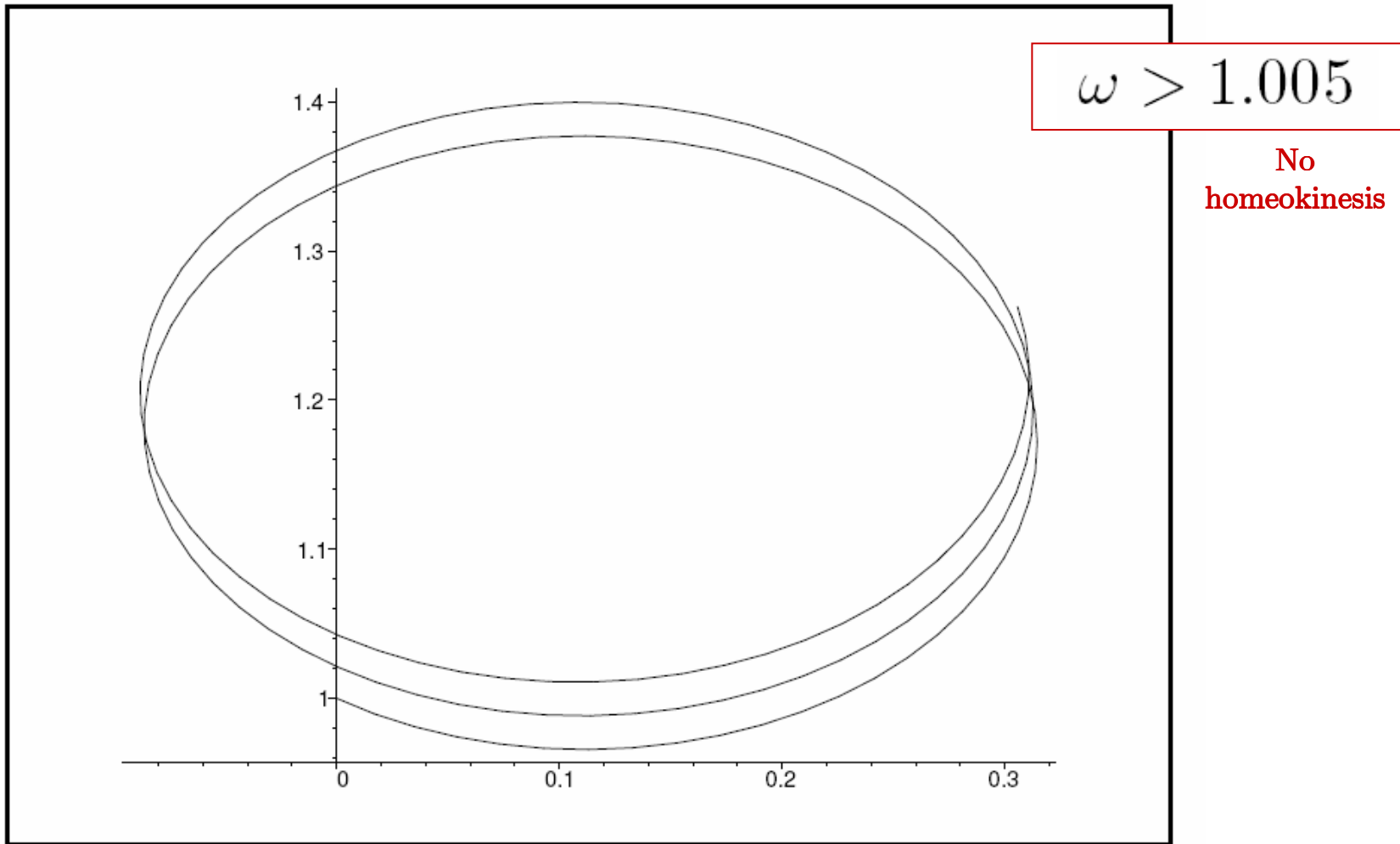


Image source:

<http://www.informatik.uni-leipzig.de/~der/Veroeff/wienfin3.ps>

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## Non-linear emergence of control (4)

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- N.B.: The robot knows **nothing** about itself
- Want to detect and counterbalance coupling effect:  
*„Learn about your weaknesses and compensate“*
- Evolution does **not** create perfect individuals!
  
- We need to have some way of intergrating learning with the system:
  - Use prediction error as learning signal

## Non-linear emergence of control (5)

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- We want to work out  $\omega$  (for our model)
- Use trivial predictor: Always propose  $s'_{l,r} = 0$
- Prediction error ( $E$ ) is change of sensor value in  $\tau$
- Minimise  $E$  by gradient descent ...

... complement equations of motion with

$$\omega' = -\frac{1}{\theta} \frac{\partial}{\partial \omega} E(y, \phi; \omega)$$

where  $\theta$  is a time constant

## Non-linear emergence of control (6)

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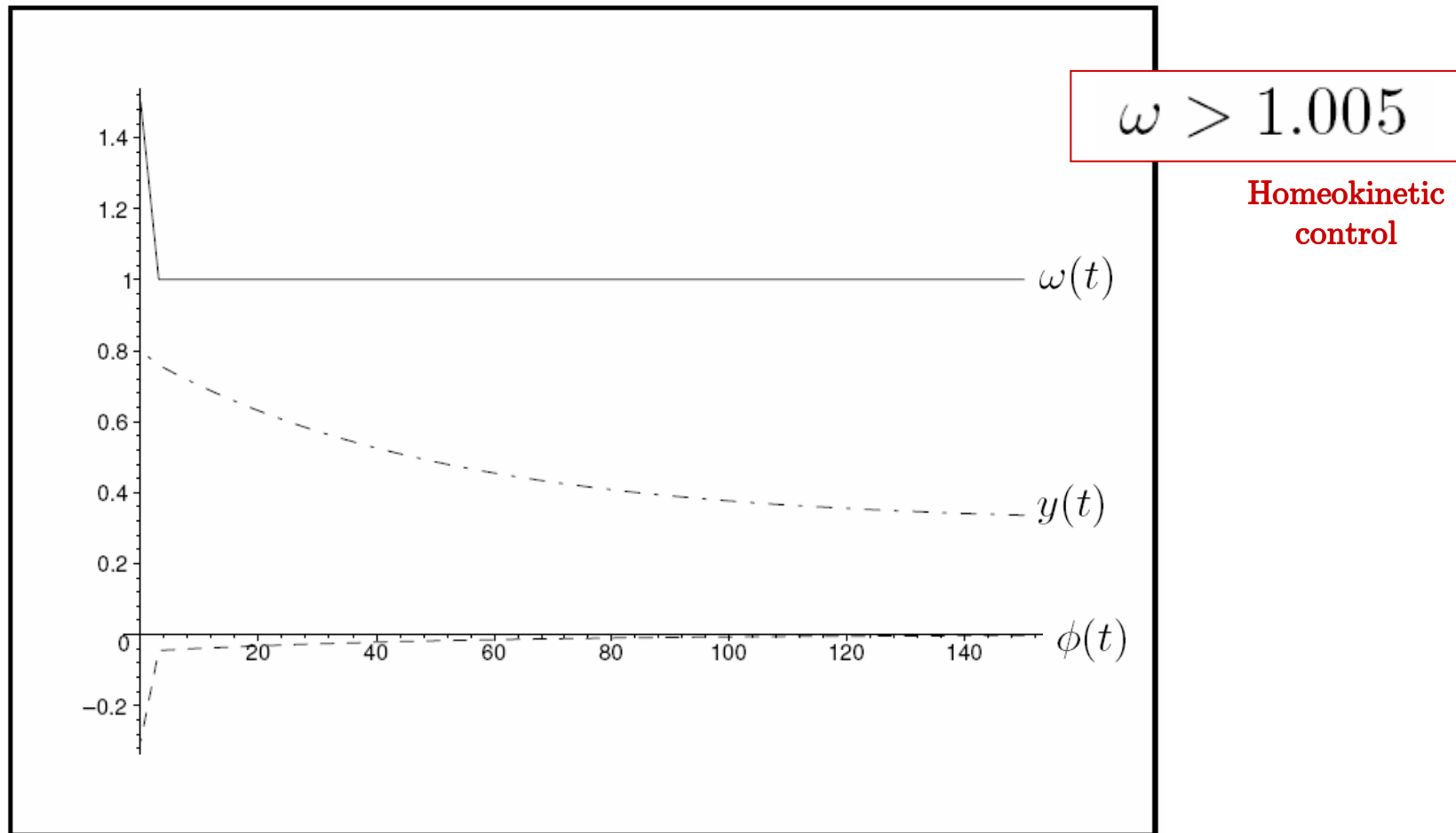


Image (modified) from:

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## Non-linear emergence of control (7)

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- Stable light-following behaviour
- Adapts to maintain sensor values  
(cf. physiological values in homeostasis)

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# The homeokinetic principle

## The homeokinetic principle

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- cf. Homeostasis: Try to maintain physiological values at a certain level
- Here: Try to maintain a smooth controlled behaviour, i.e. keep the agent in a kinetic state
- Mode learnt decided by predictor complexity and environmental conditions
- Learning signal derived from misfit between real behaviour and model prediction, i.e. how well the agent understands the world

## ... and the complexity barrier?

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- Complex nonlinear problems: Task decomposition
  - Indep. behaving functional units
  - „Expert“ systems
- The components are independent and self-organised

## Criticism

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- Isn't the error function just a weaker form of a negative fitness function?
- Limits imposed on predictor by error function
- Complexity of component systems

*"I would be interested to know whether the control theorists have looked at this in a more mathematically acceptable fashion - it is not a good idea to expect to do anything interesting with nonlinear dynamic systems without biting the foundational bullet."*

## Applications & Demos

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- Self-organised systems
  - Emerging motion patterns in humanoids
  - Der et al., 1999-2008
  
- Emergent cooperativity in a chain of mobile robots
  - Emerging cooperative behaviour of chained robots
  - Der et al., 2008

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Thank you!