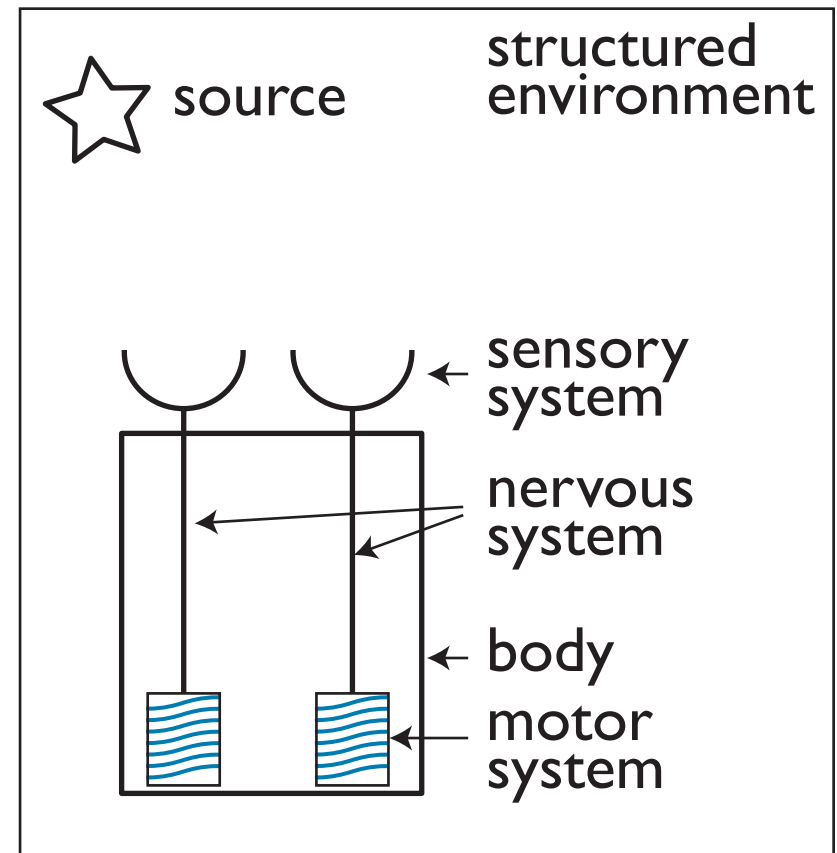


Attractor dynamics approach to behavior generation: vehicle motion

Gregor Schöner, INI, RUB

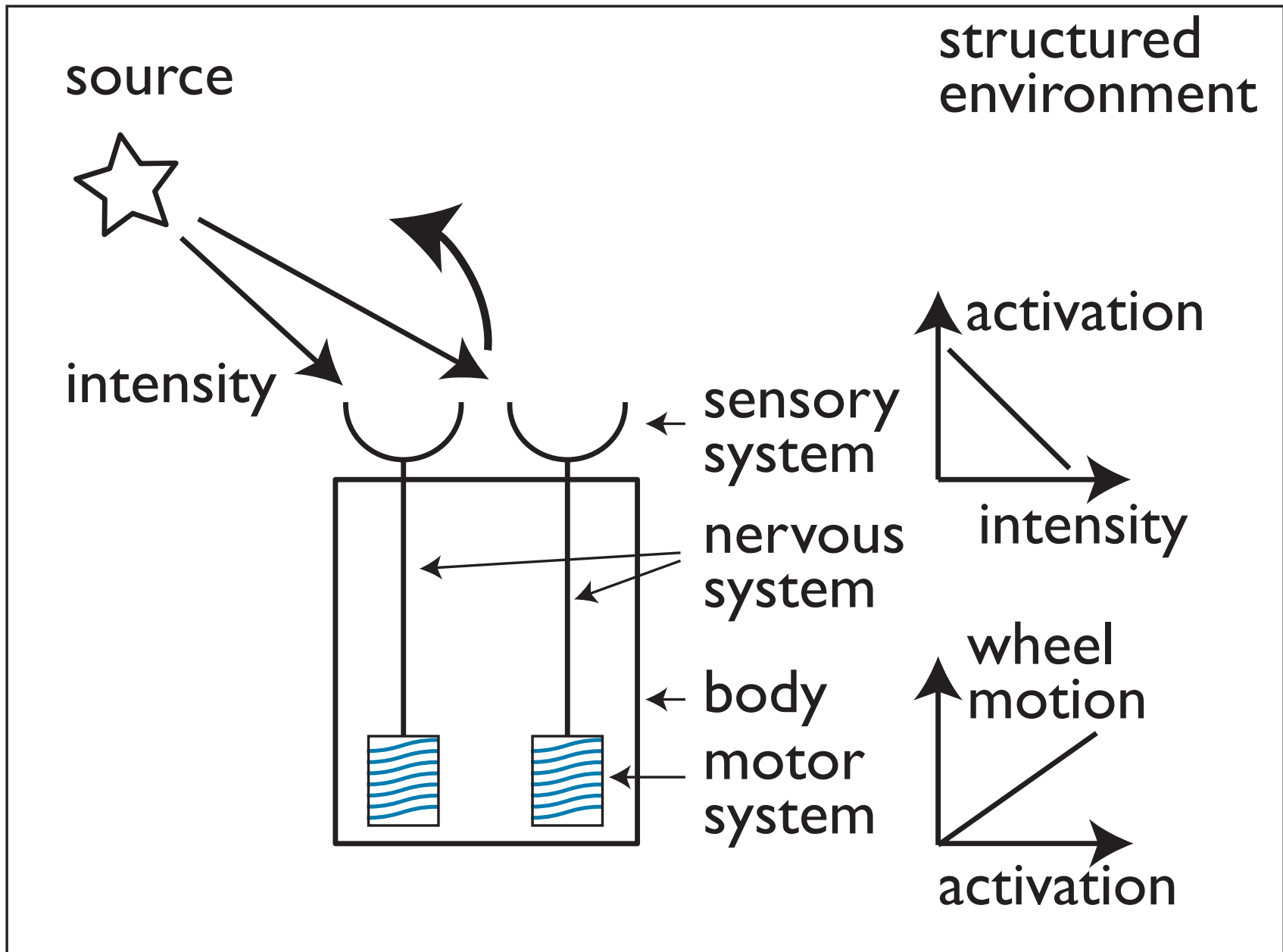
Embodied nervous system

- effectors
- sensors
- a nervous system
- a body
- situated in a structured environment
- => emergent behavior



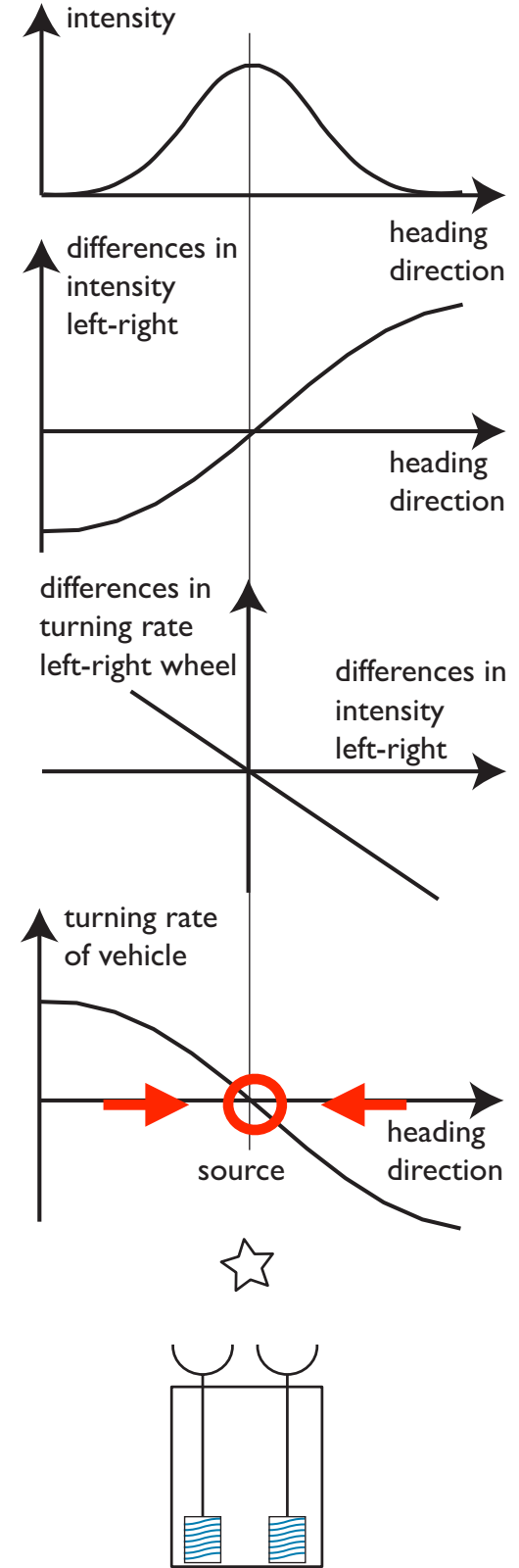
Braitenberg vehicle

Emergent behavior: taxis



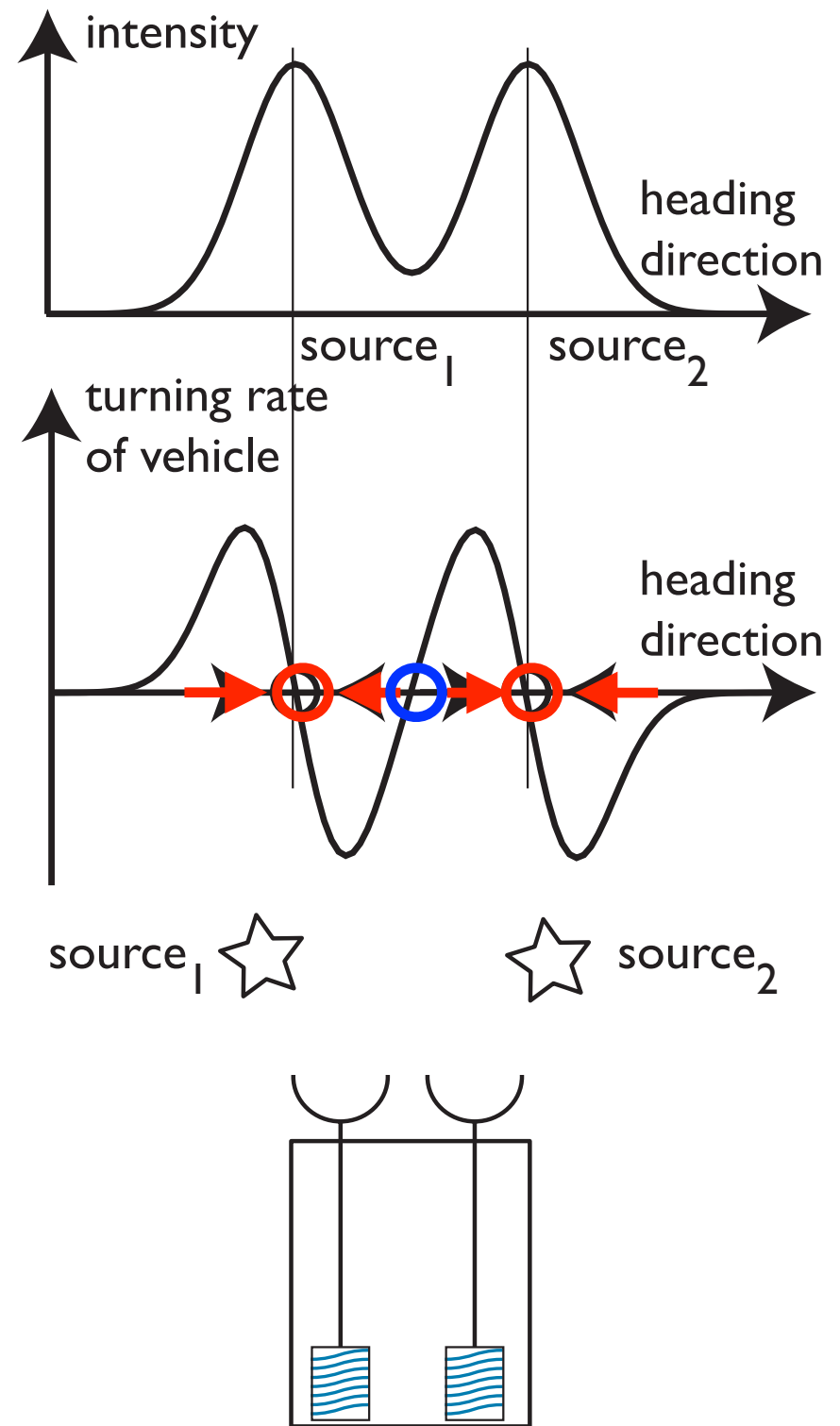
Emergent behavior: this is a dynamics

- feedforward nervous system
- + closed loop through environment
- => (behavioral) dynamics



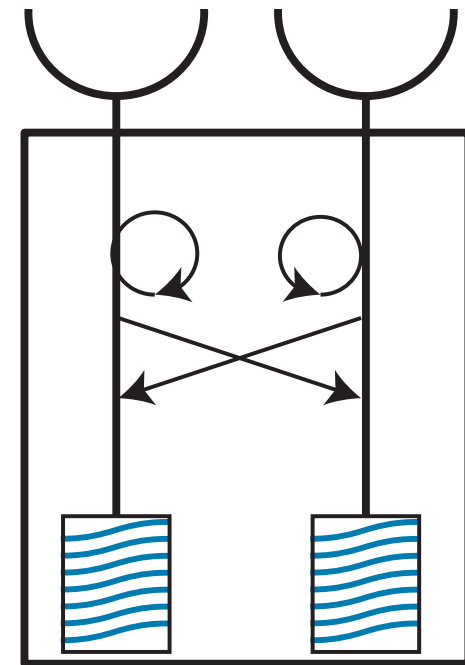
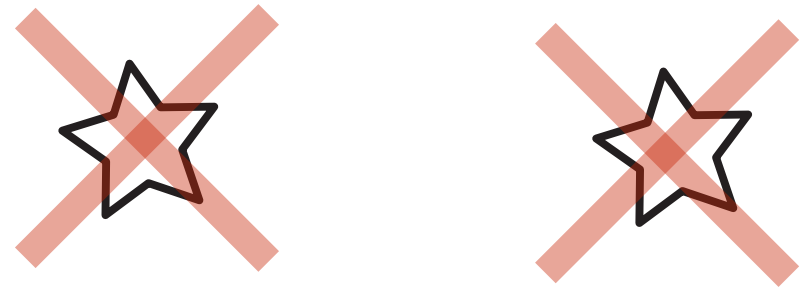
Complex environment => complex dynamics

- bistable dynamics for bimodal intensity distribution
- => nonlinear dynamics makes selection decision



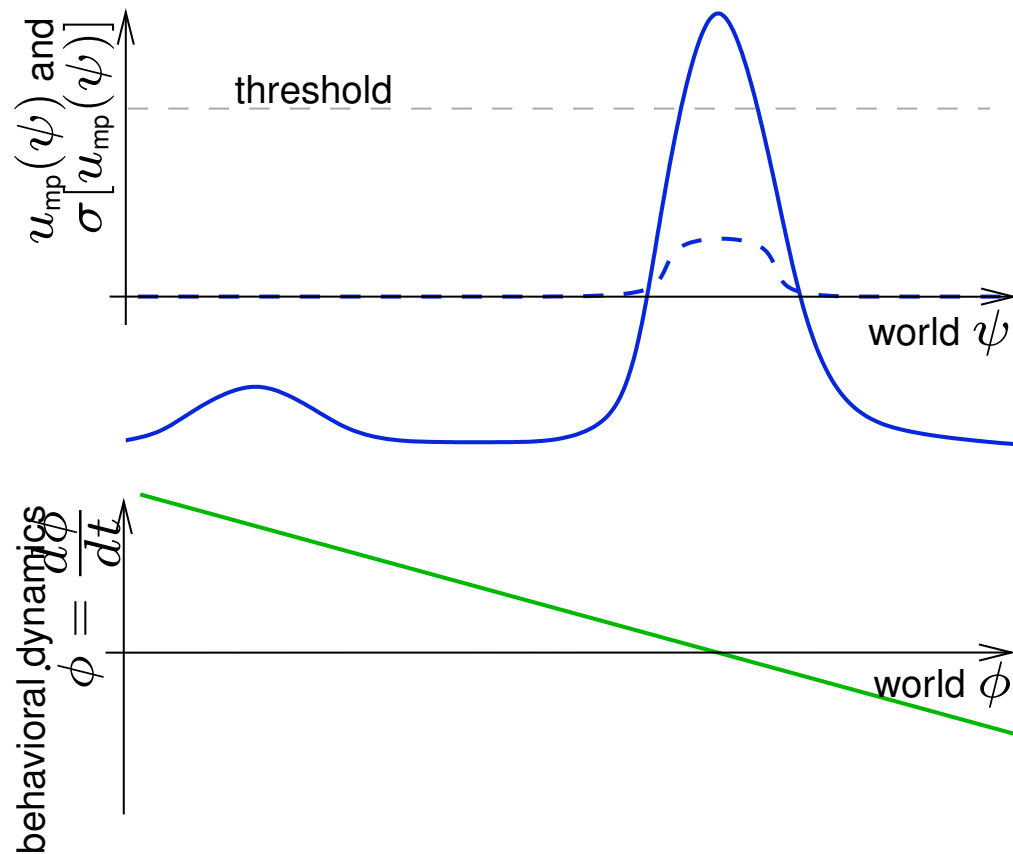
Neural dynamics

- “inner dynamic state” of the nervous system that is independent of body or sensors: activation dynamics=neural dynamics
- can create cognitive competences such as “mental selection” (e.g., selective attention), or working memory



Neural and behavioral dynamics

- couple peak in direction field into dynamics of heading direction as an attractor

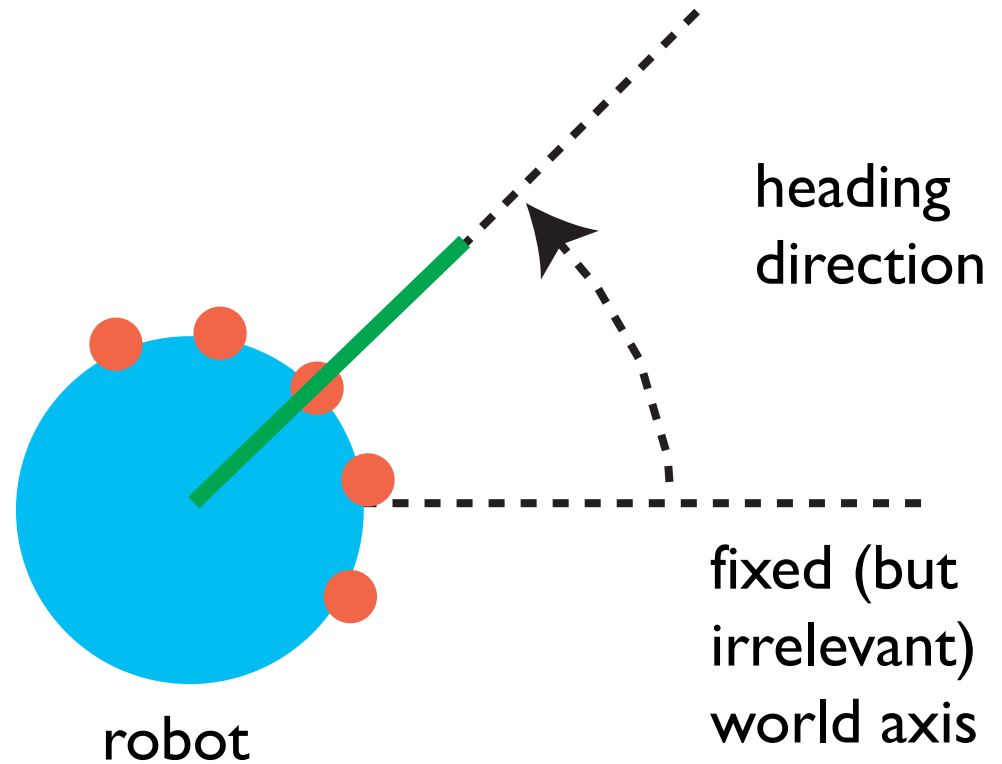


Basic ideas of attractor dynamics approach

- behavioral variables
- time courses from dynamical system:
attractors
- tracking attractors
- bifurcations for flexibility

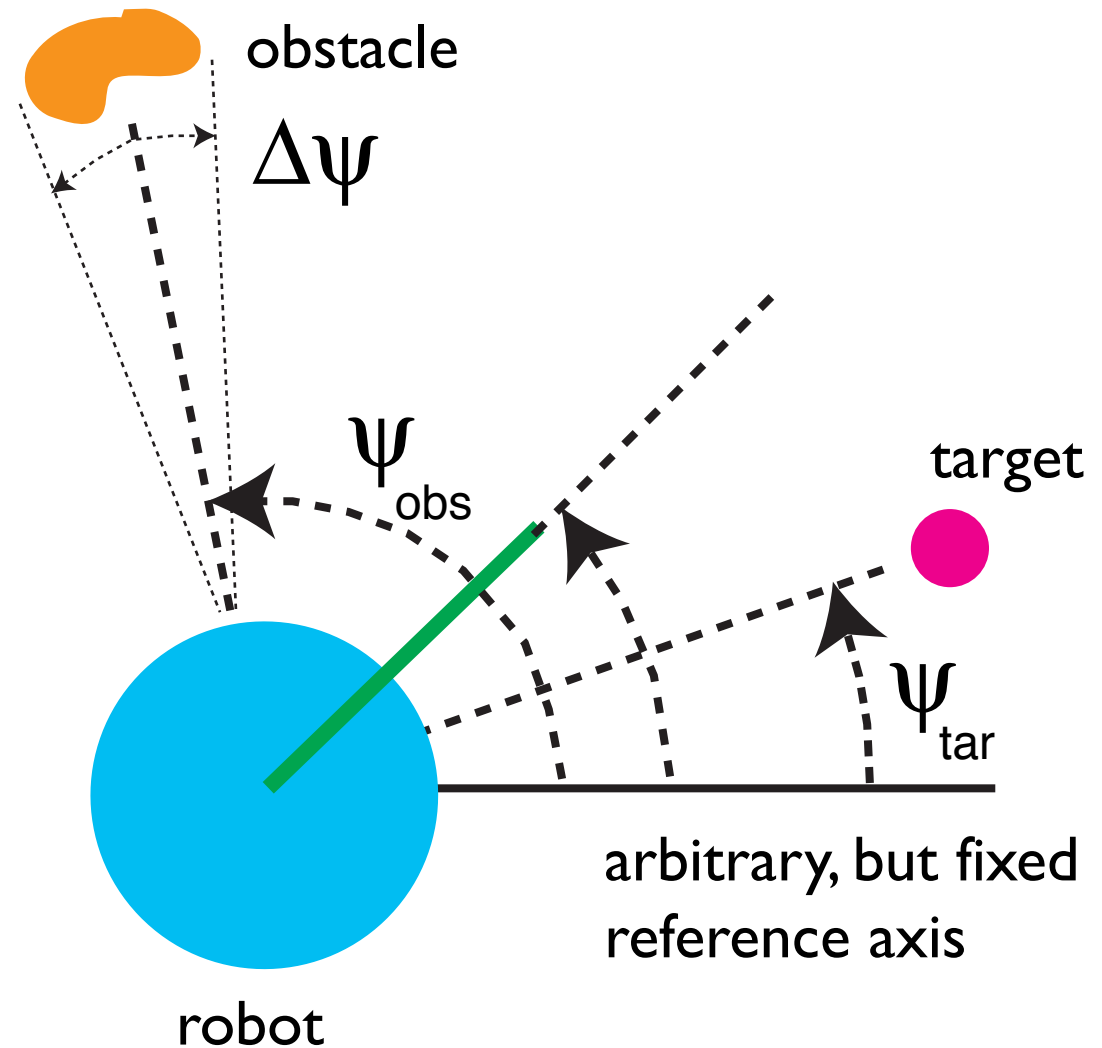
Behavioral variables: example

■ vehicle moving in
2D: heading
direction



Behavioral variables: example

- constraints:
obstacle avoidance
and target
acquisition



Behavioral variables

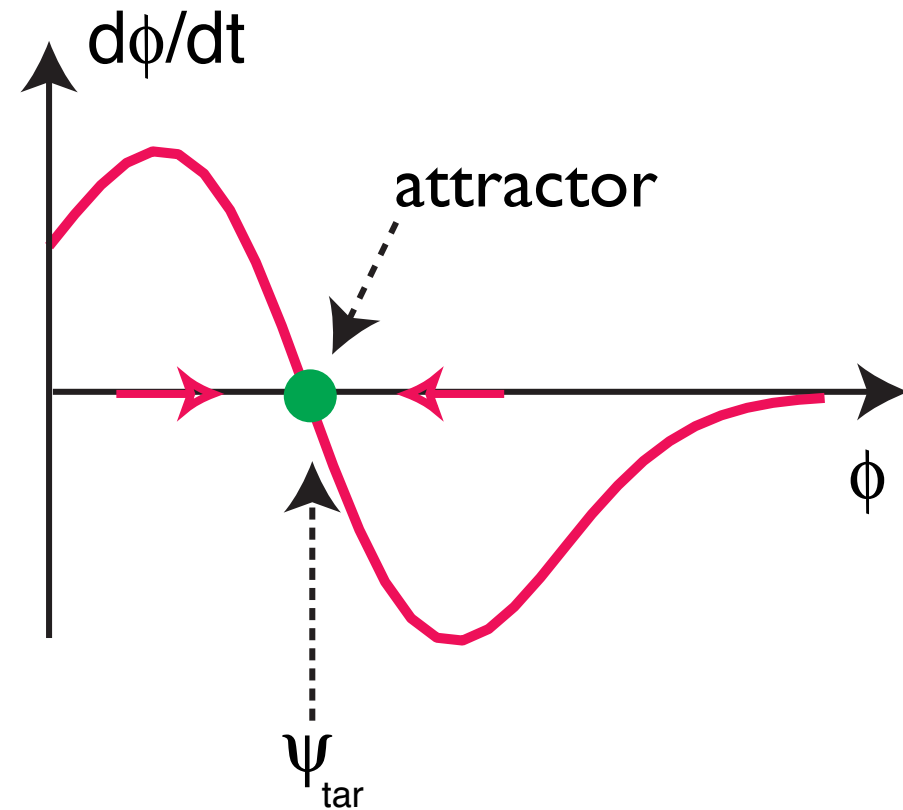
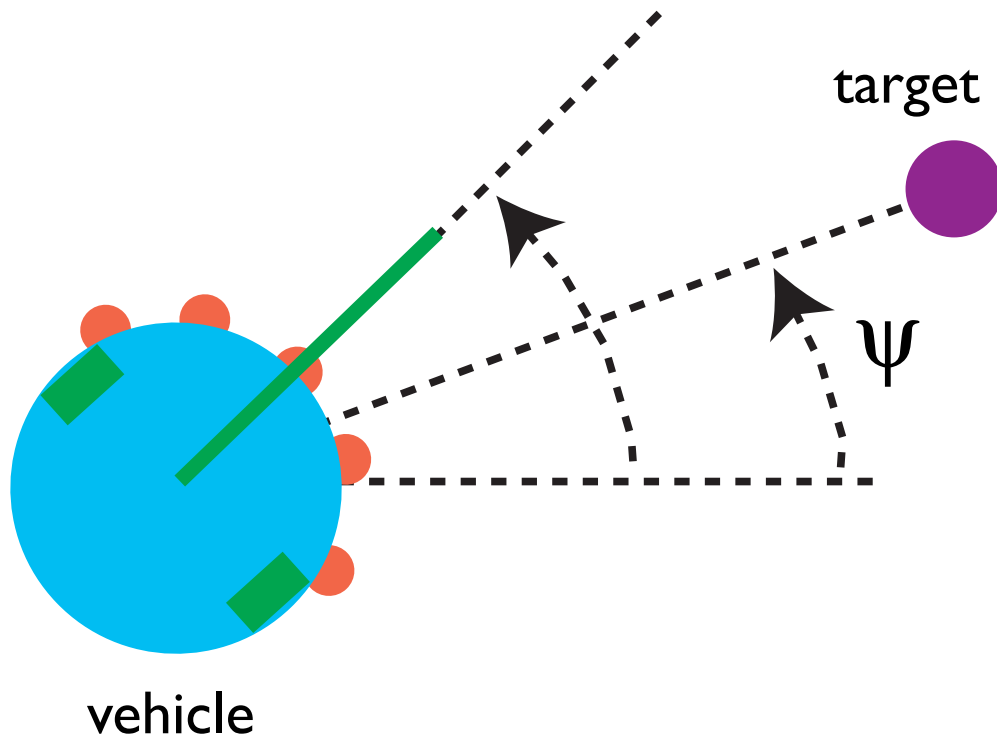
- describe desired motor behavior
- “enactable”
- express constraints as values/value ranges
- appropriate level of invariance

Behavioral dynamics

- generate behavior by generating time courses of behavioral variables
- generate time course of behavioral variables from attractor solutions of a (designed) dynamical system
- that dynamical system is constructed from contributions expressing behavioral constraints

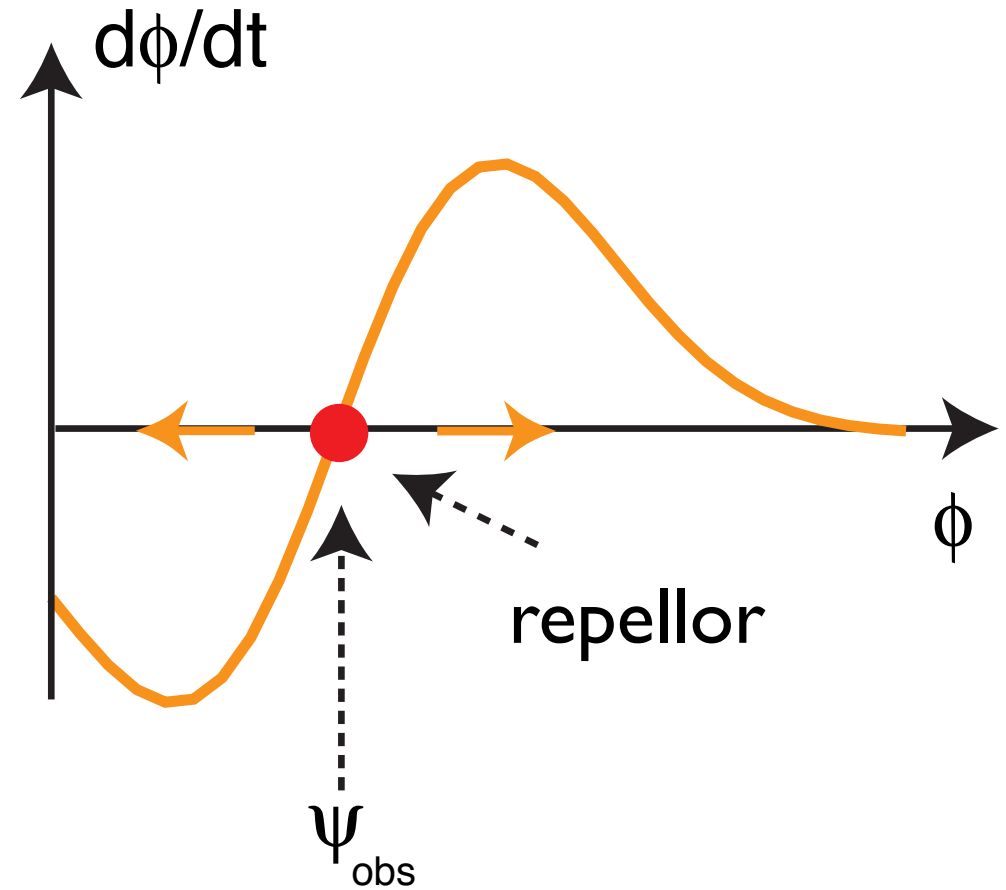
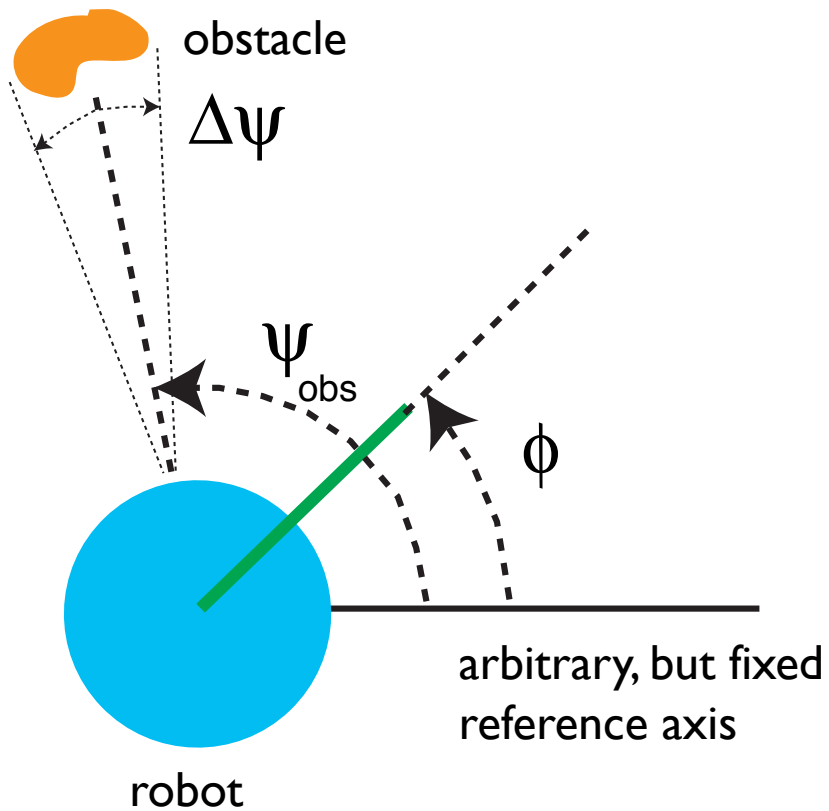
Behavioral dynamics: example

■ behavioral constraint: target acquisition



Behavioral dynamics: example

■ behavioral constraint: obstacle avoidance



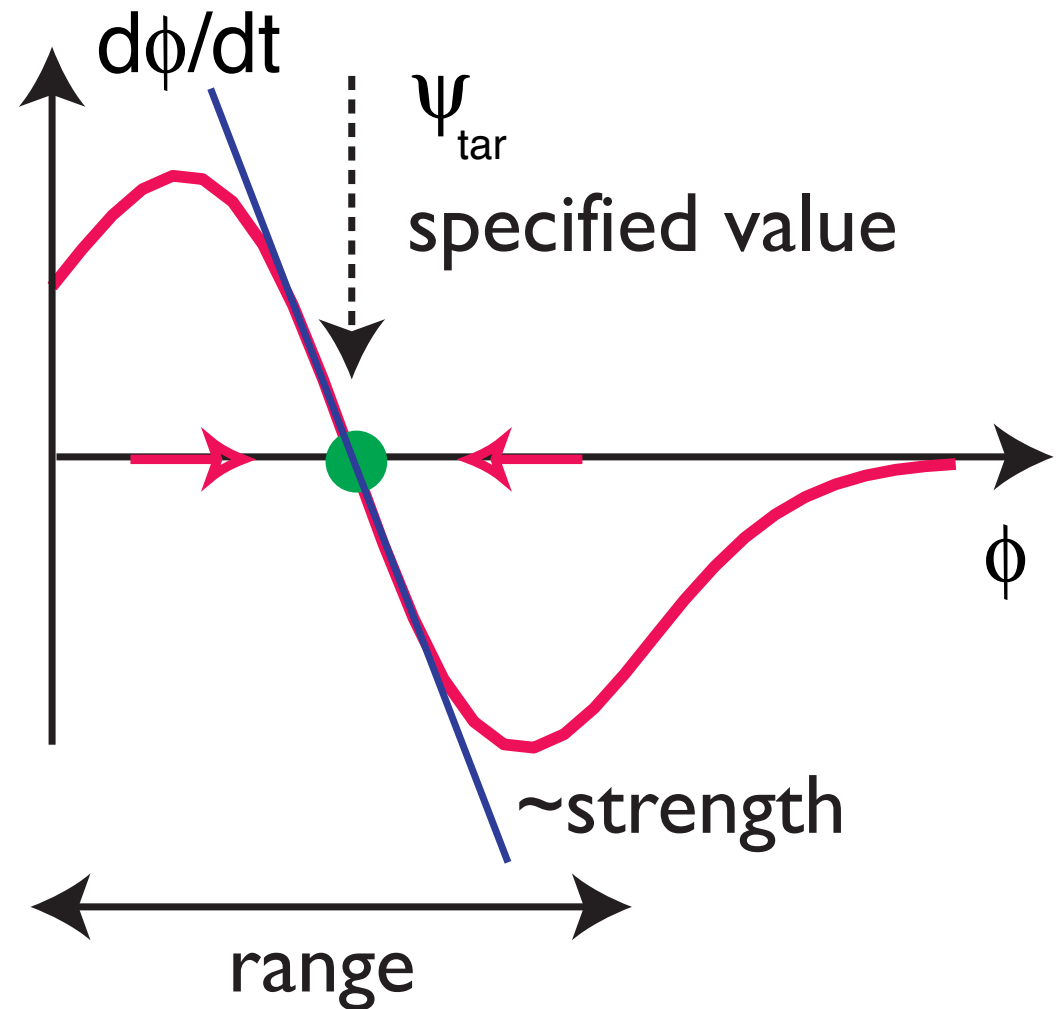
Behavioral dynamics

■ each contribution is a “force-let” with

■ specified value

■ strength

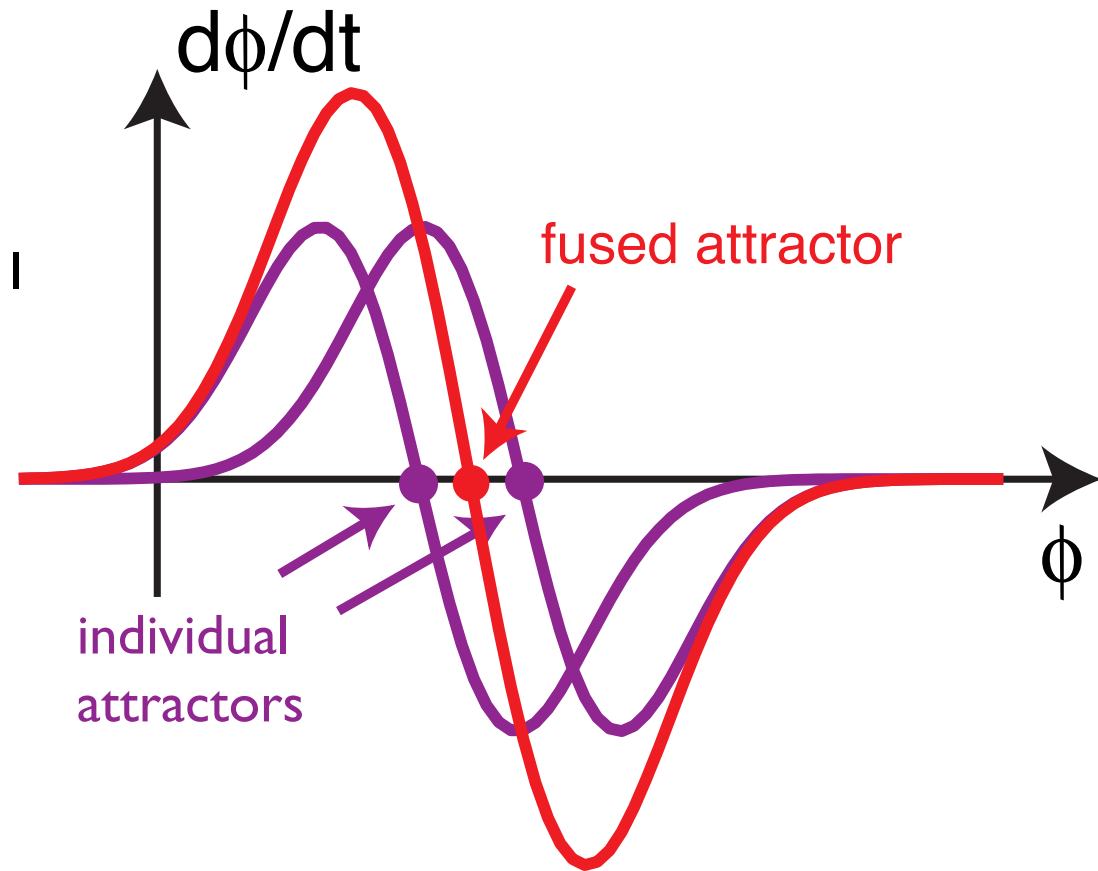
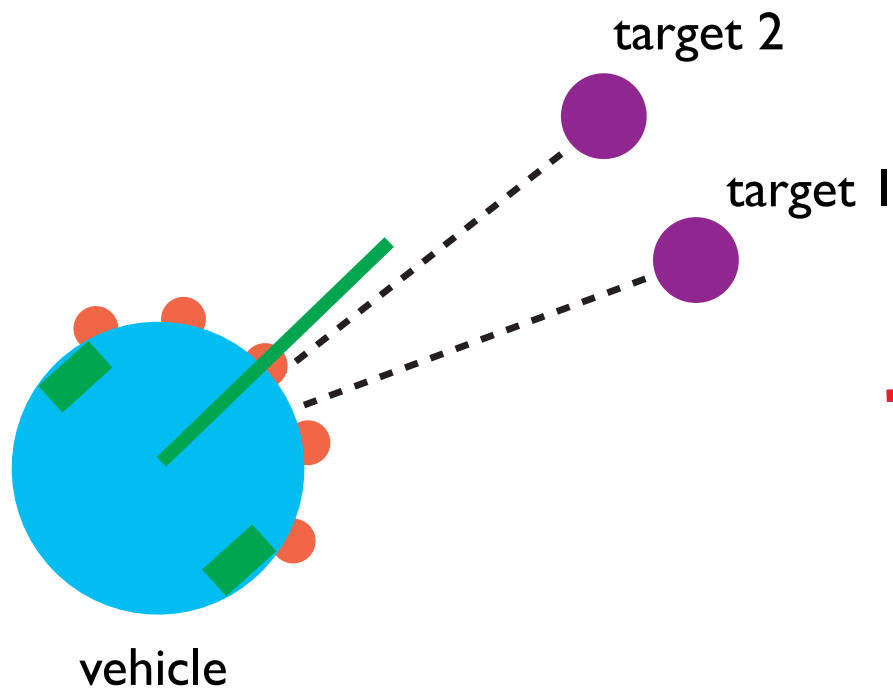
■ range



Behavioral dynamics

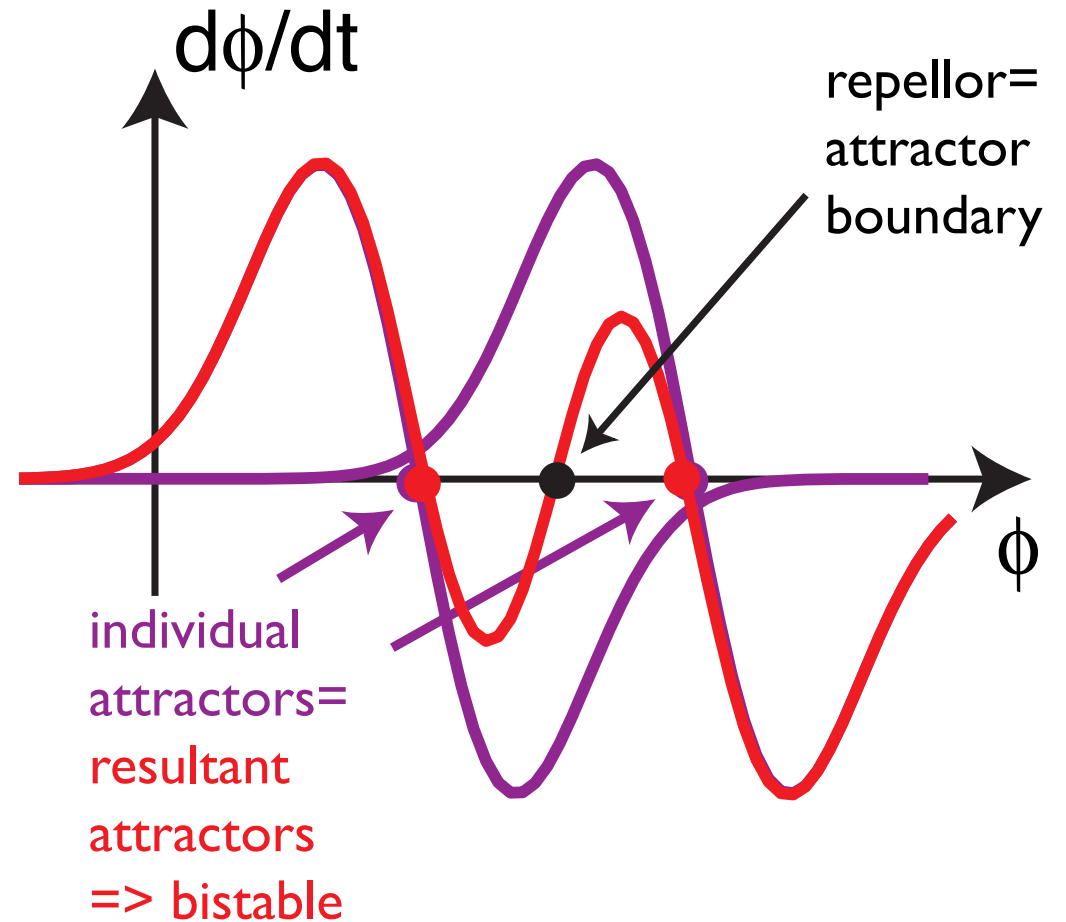
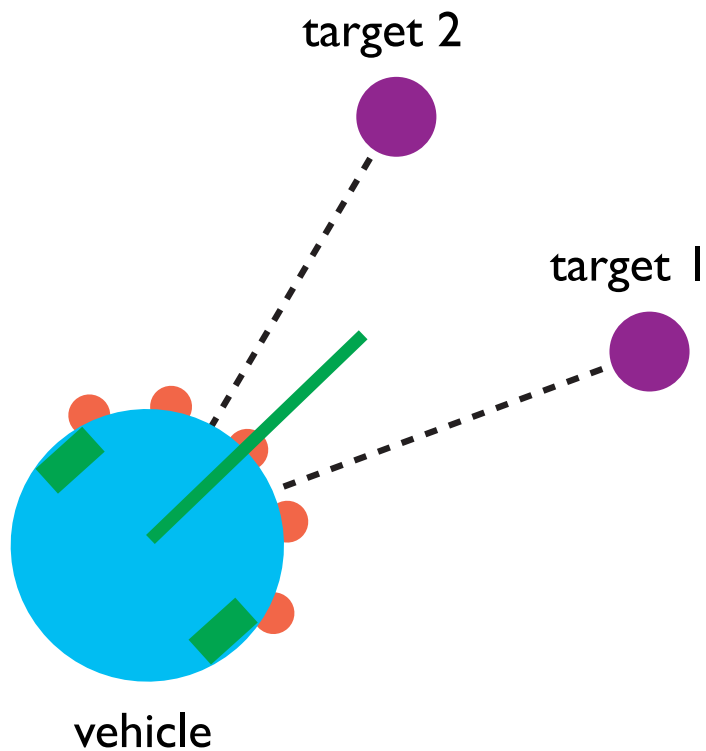
■ multiple constraints: superpose “force-lets”

■ fusion



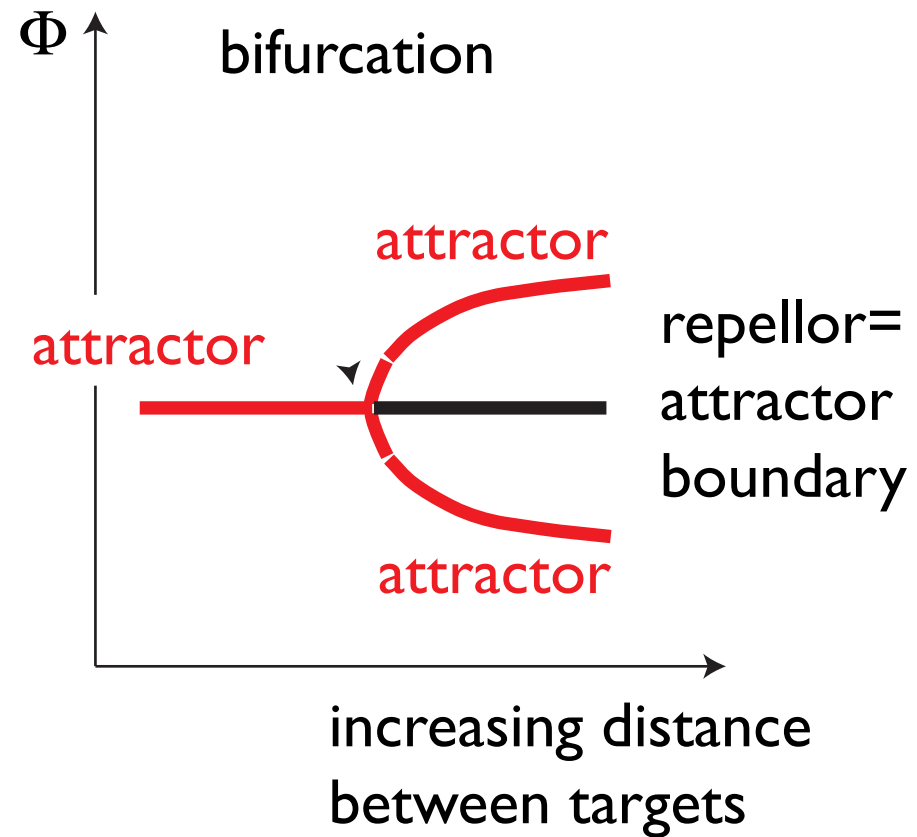
Behavioral dynamics

■ decision making



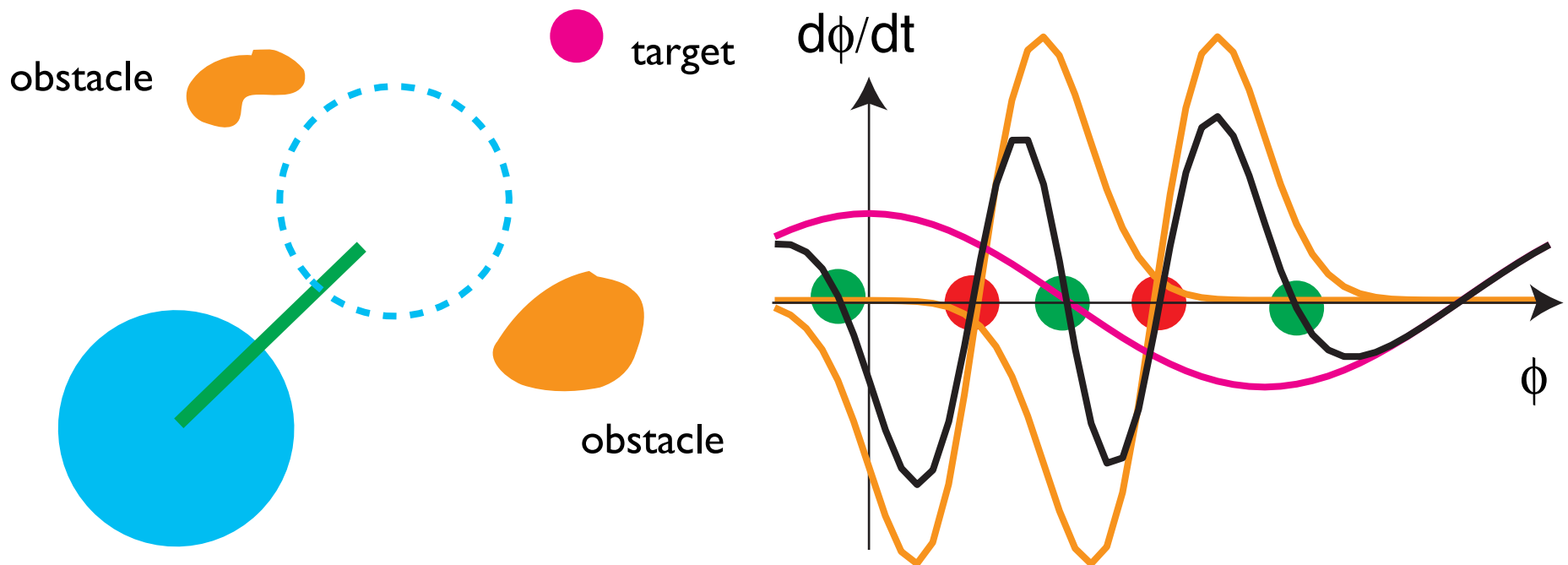
Behavioral dynamics

- Bifurcations switch between fusion and decision making



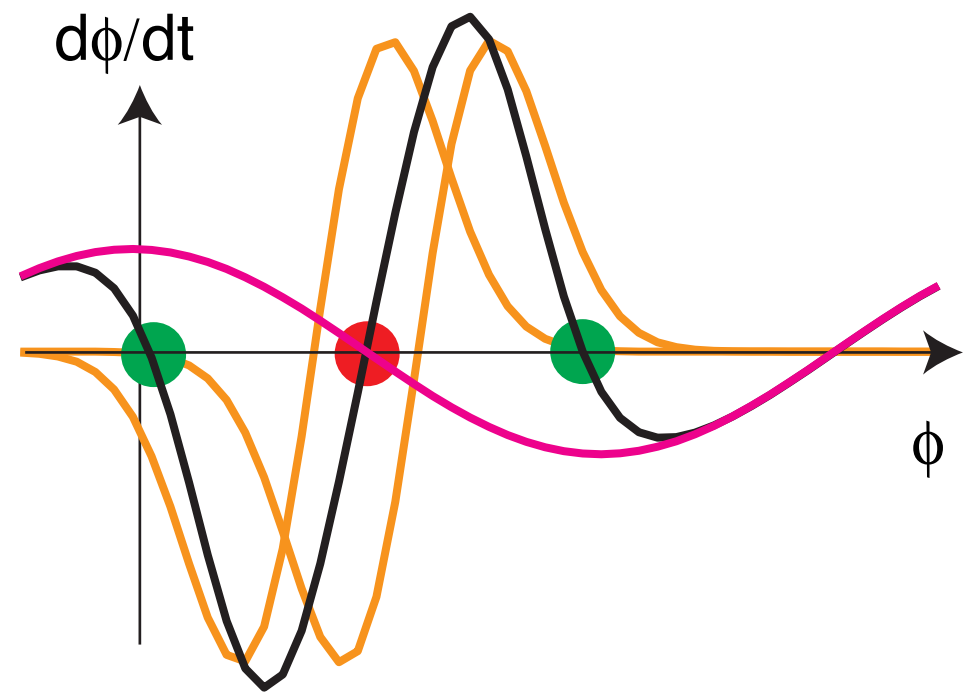
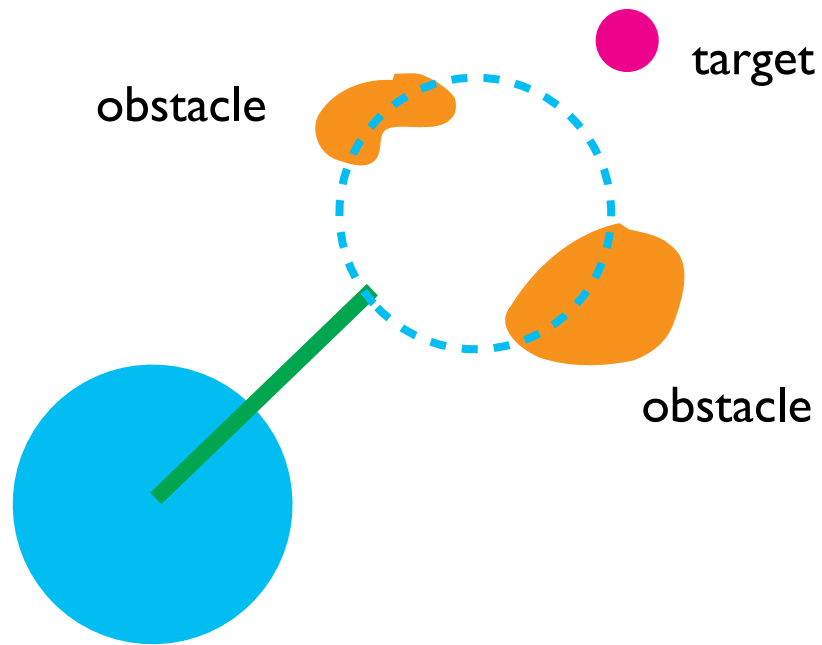
Behavioral dynamics

- an example closer to “real life”: bifurcations in obstacle avoidance and target acquisition
- constraints not in conflict



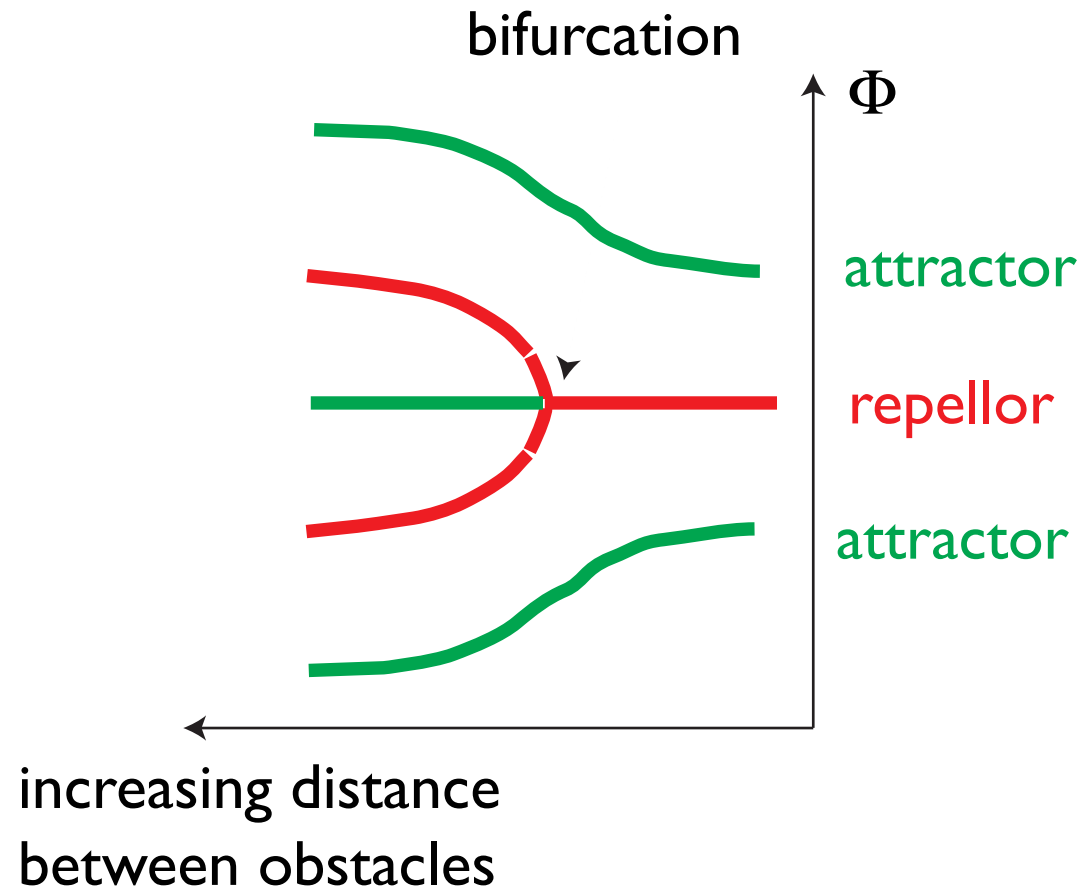
Behavioral dynamics

■ constraints in conflict



Behavioral dynamics

- transition from “constraints not in conflict” to “constraints in conflict” is a bifurcation

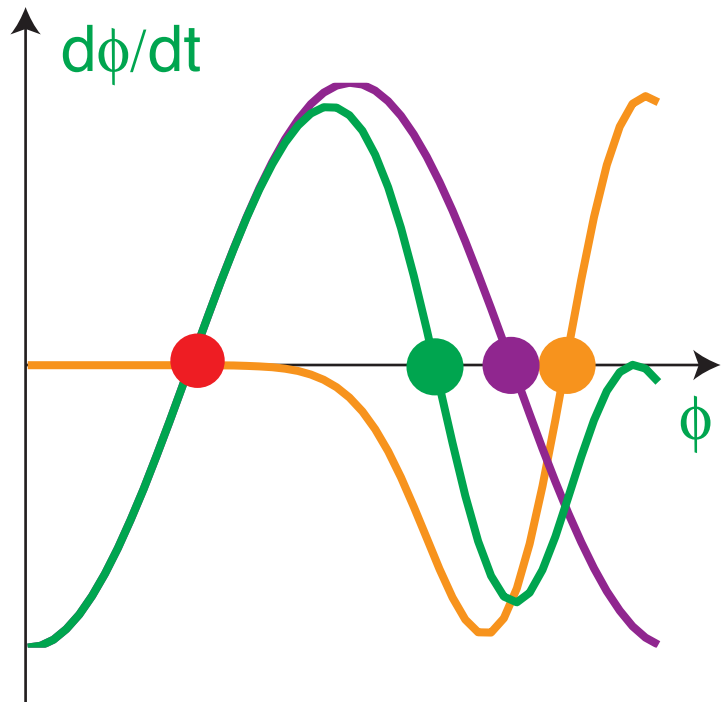
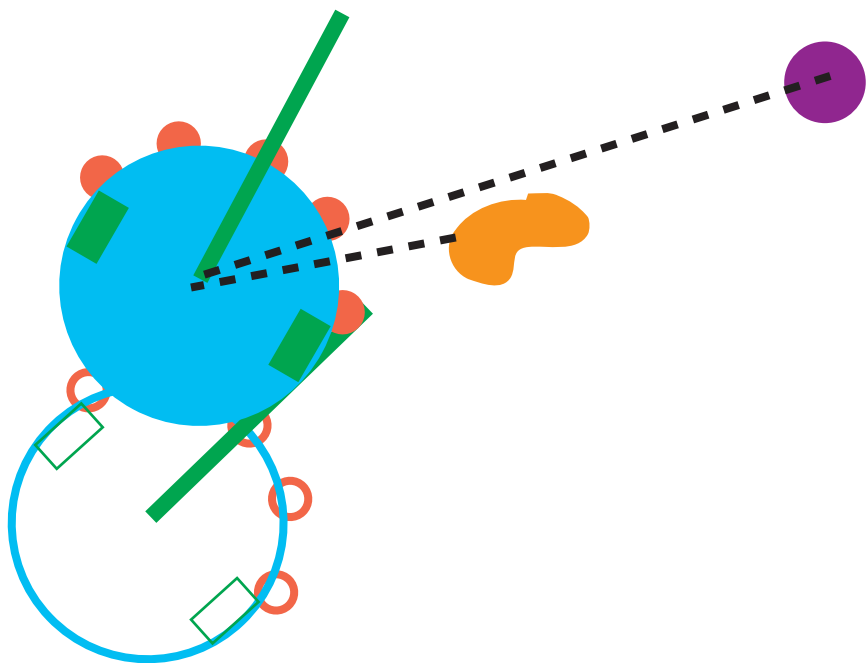
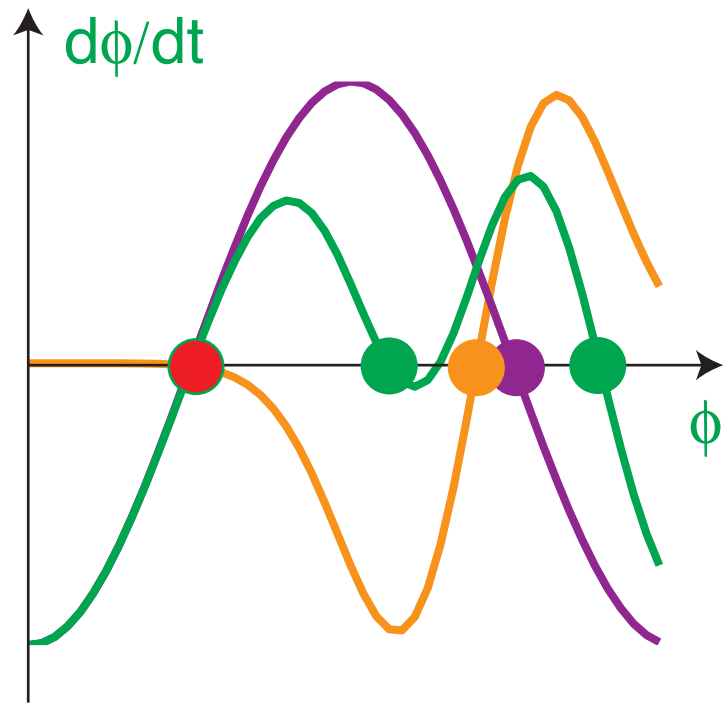
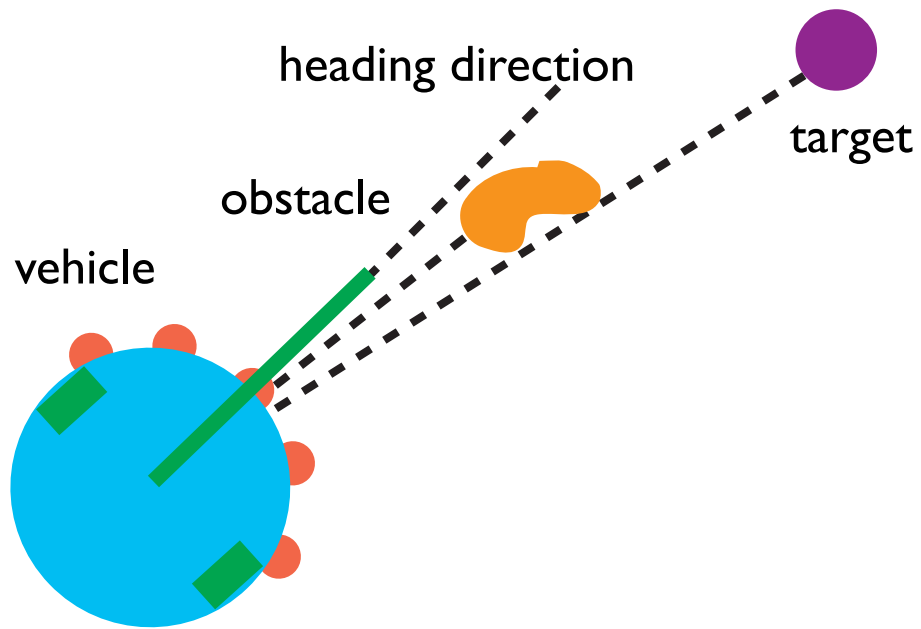


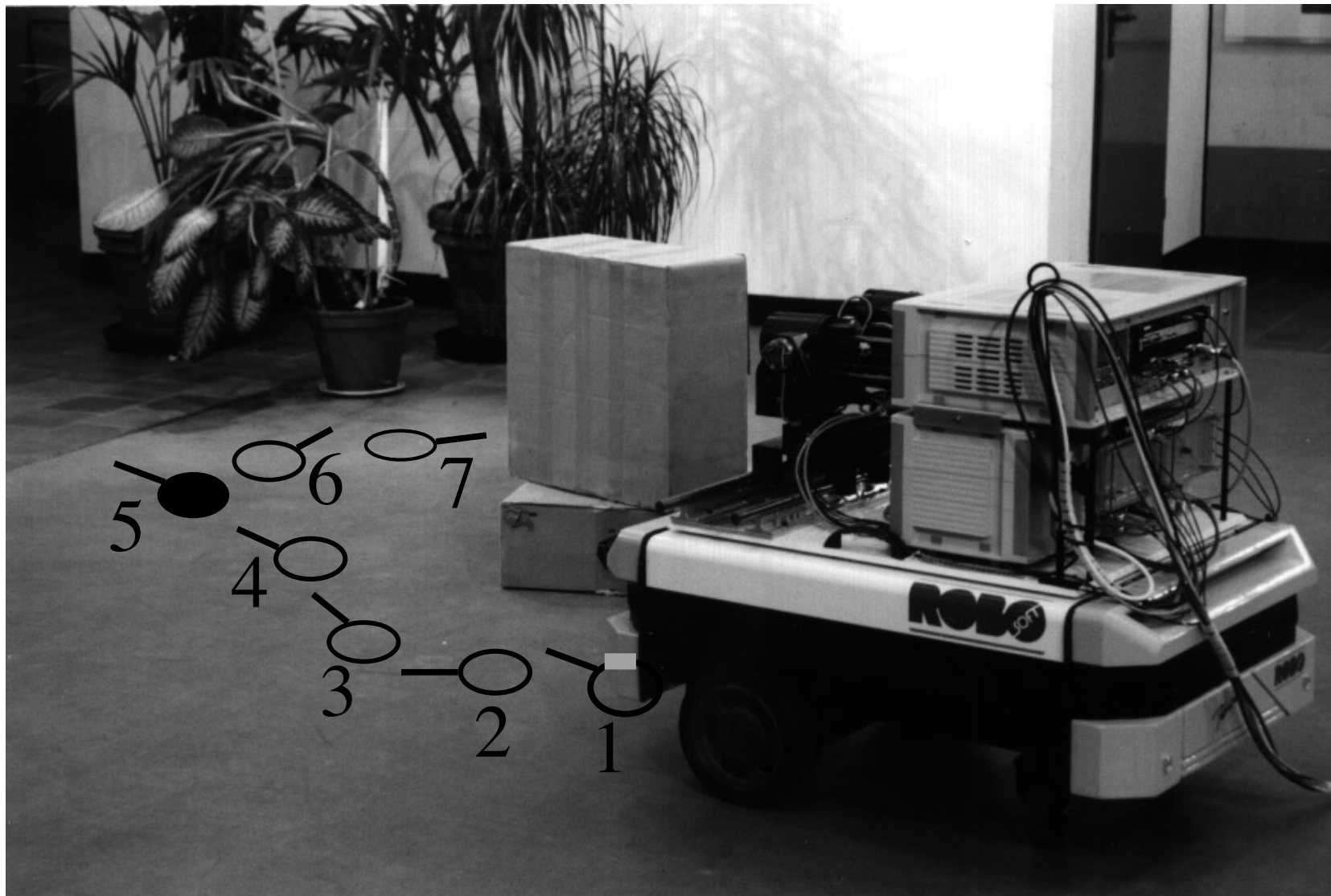
Behavioral dynamics

- Such design of decision making is only possible because system “sits” in attractor.
- This reduces the difficult design of the full flow (ensemble of all transient solutions) of non-linear dynamical systems to the easier design of attractors (bifurcation theory).

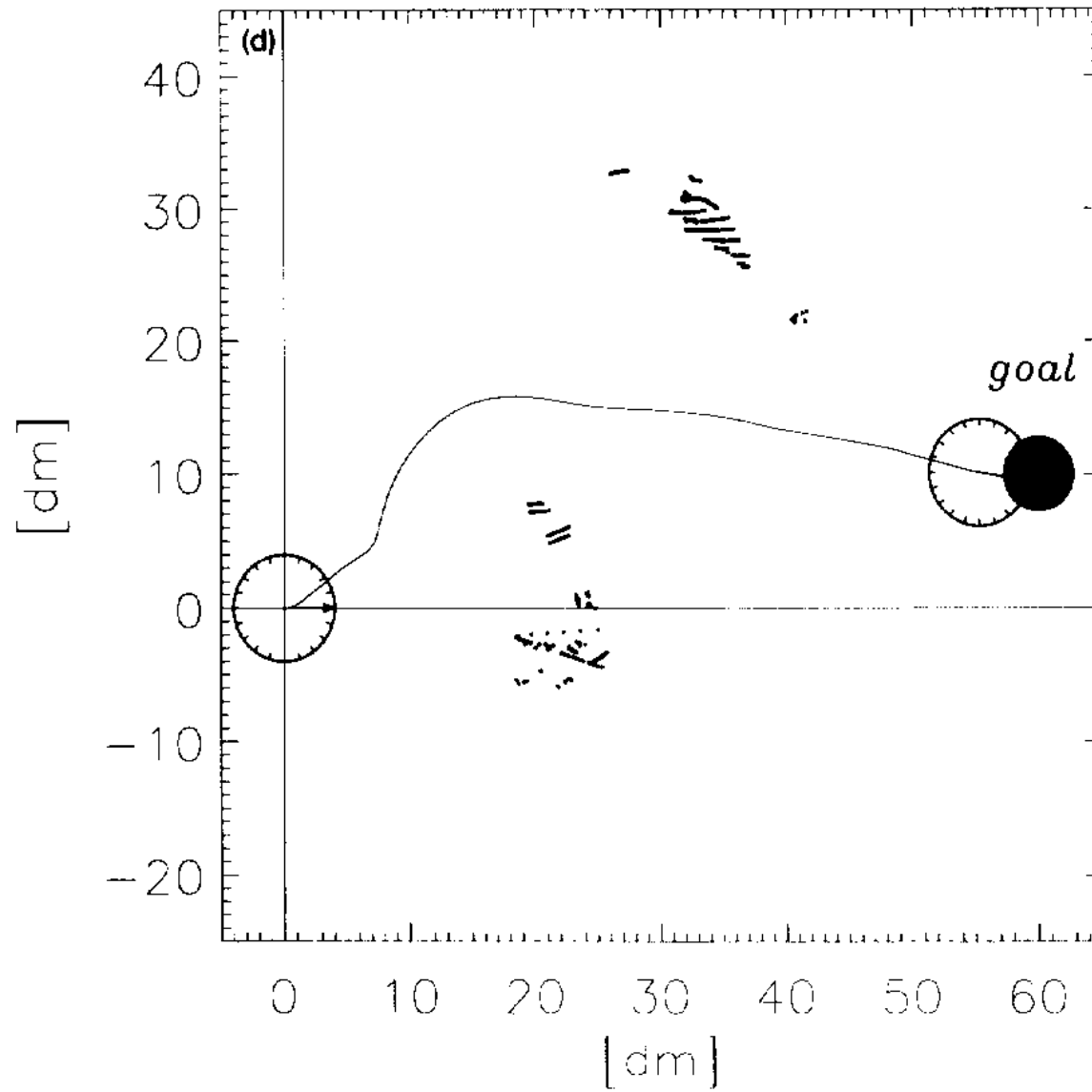
Behavioral dynamics

- But how may complex behavior be generated while “sitting” in an attractor?
- Answer: force-lets depend on sensory information and sensory information changes as the behavior unfolds





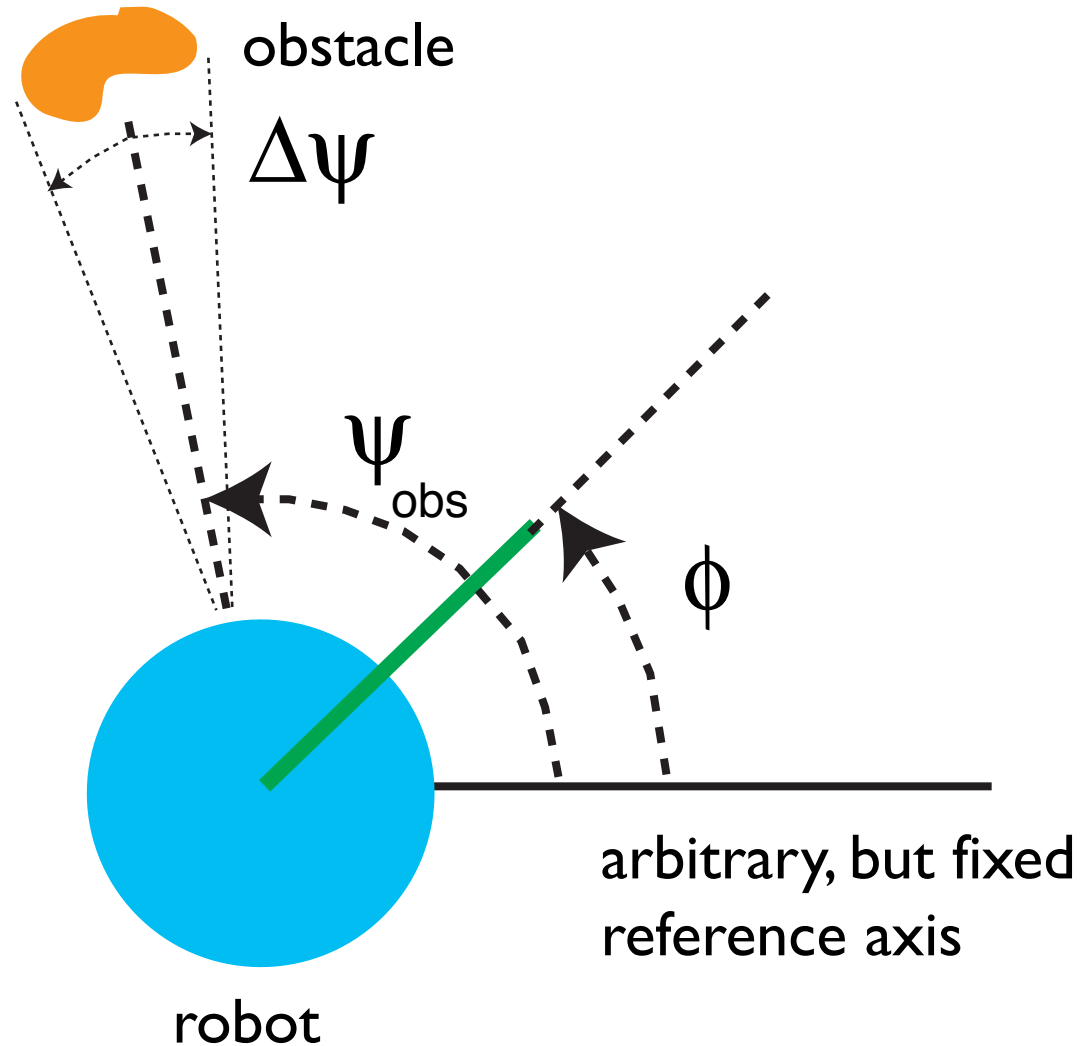
[Schöner, Dose, 1992]



[Schöner, Dose, Engels, 1995]

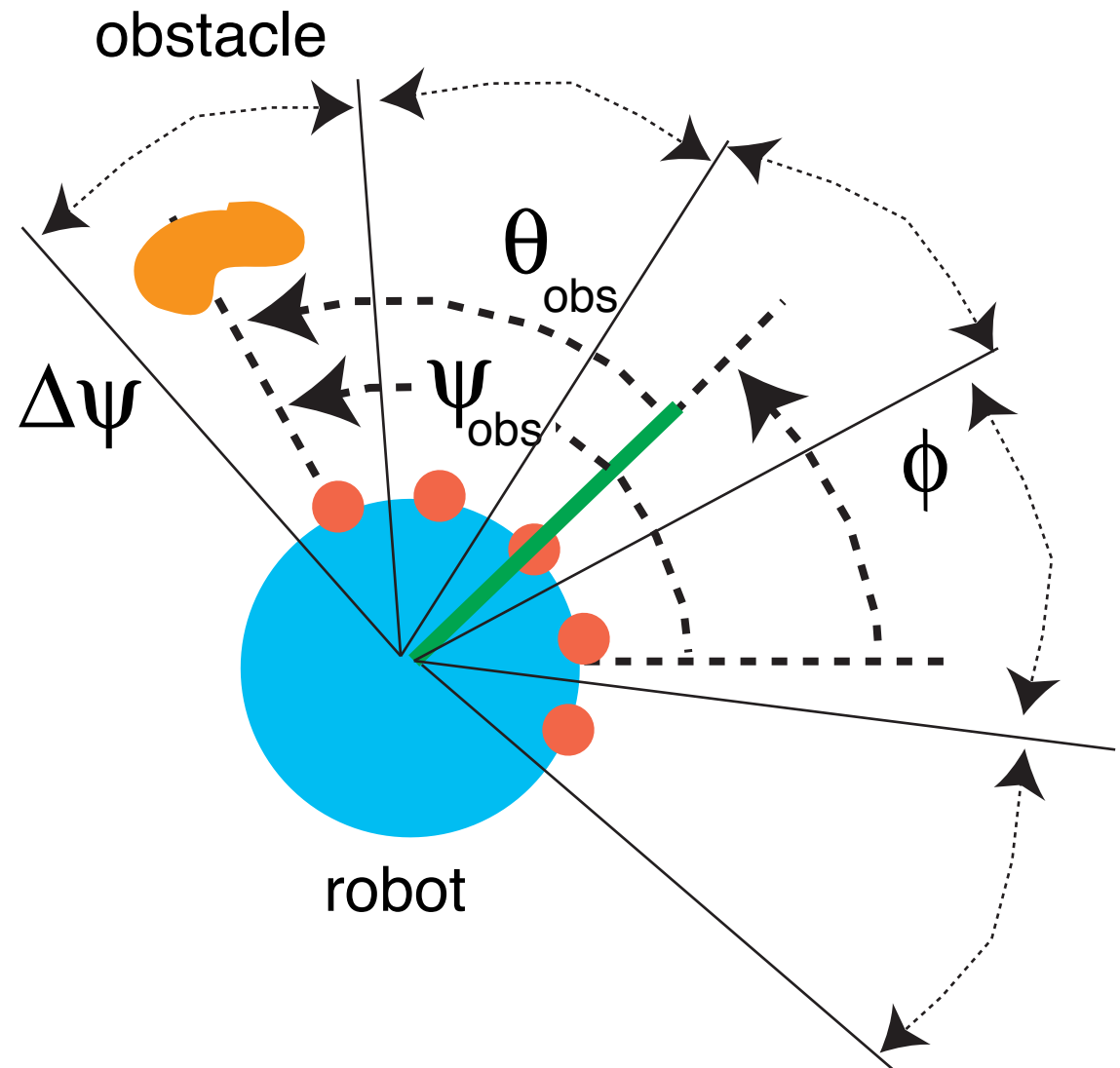
So far: “symbolic” approach

- high-level implementation: knowledge about objects in the world (“obstacles”, “targets”, etc)



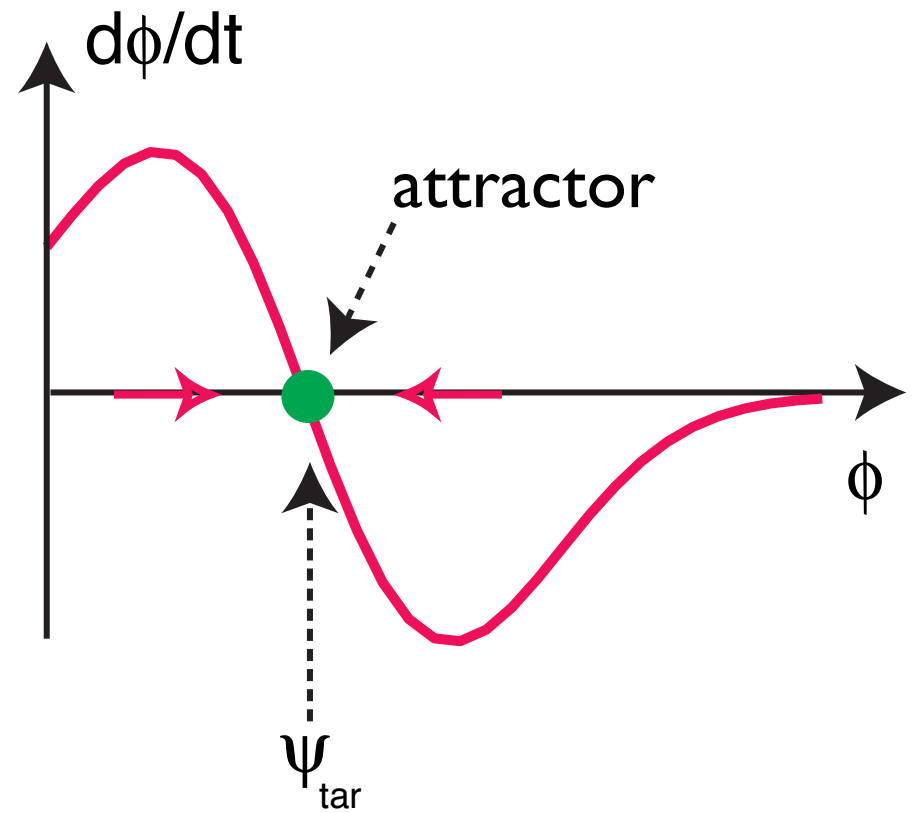
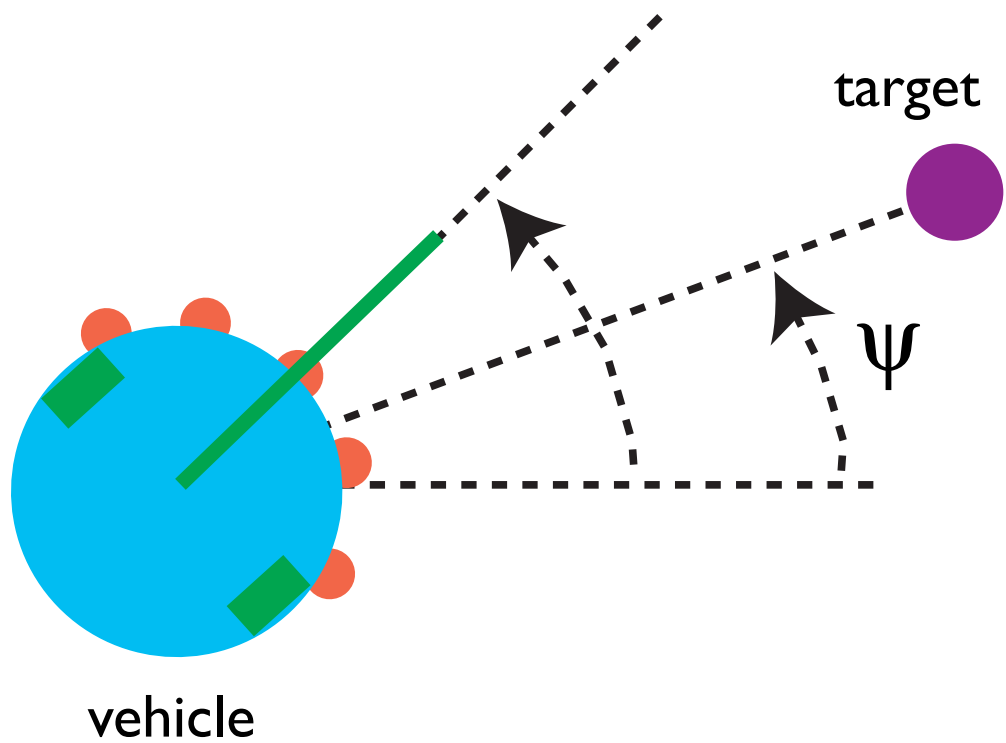
Now: “sub-symbolic” approach

- low-level implementation: use sensory information directly, not via objects



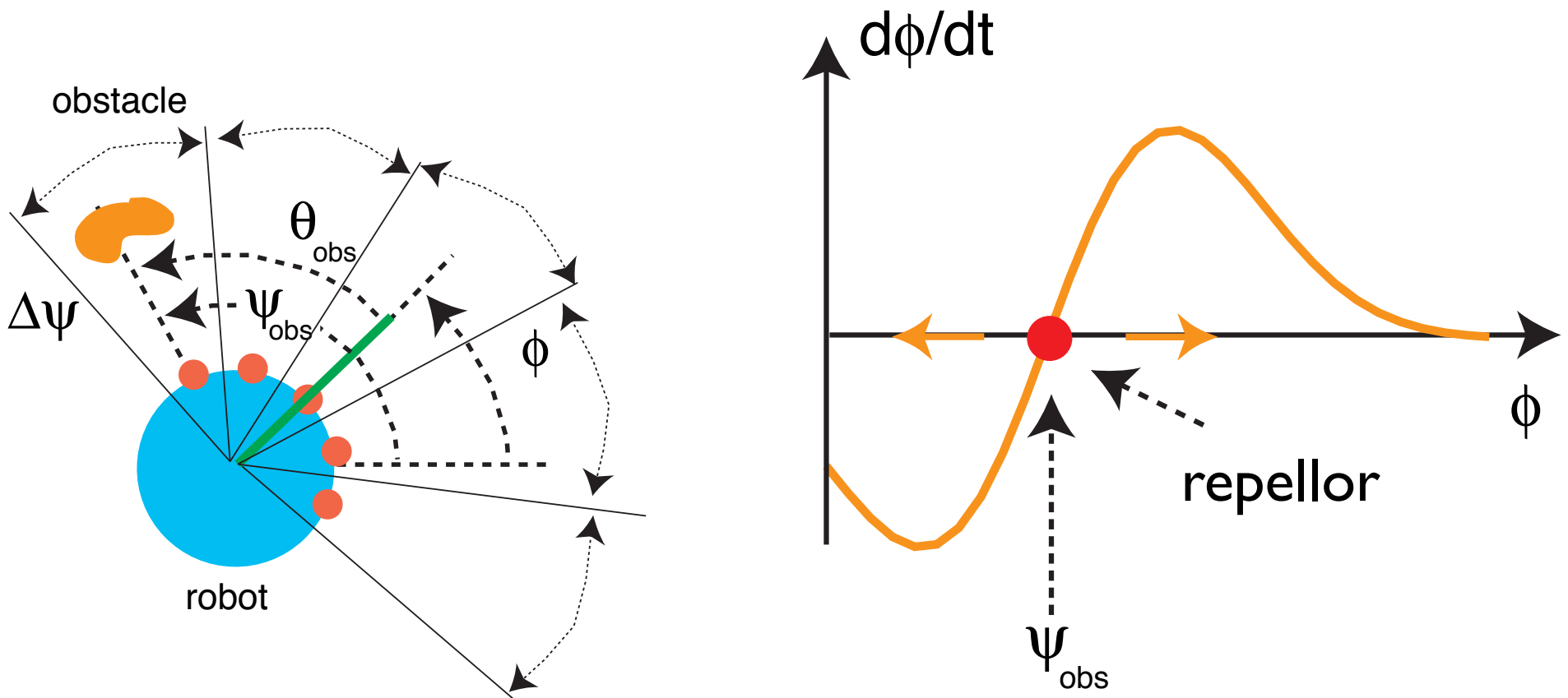
Target acquisition: still symbolic

- targets are segmented... in the foreground
- => need neural fields to perform this segmentation from low-level sensory information: Dynamic Field Theory ...



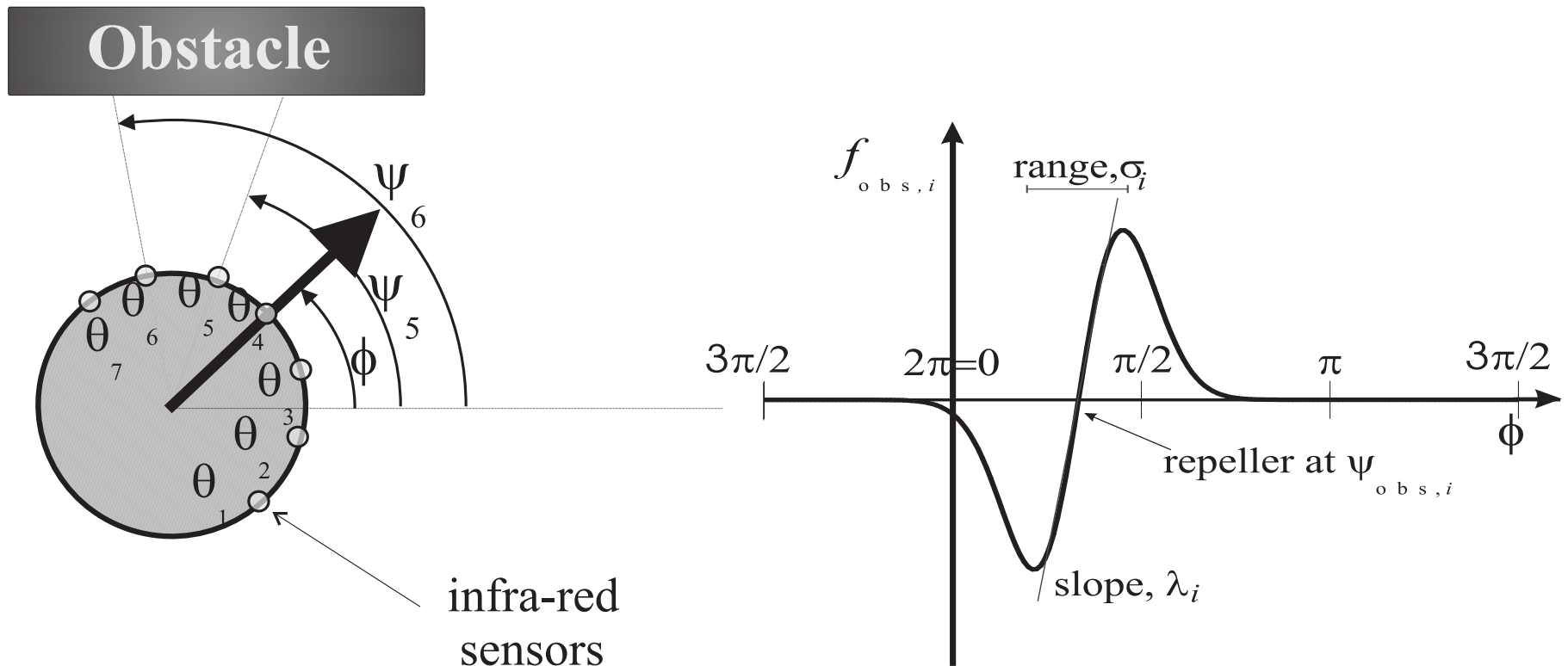
Obstacle avoidance: sub-symbolic

- obstacles need not be segmented
- do not care if obstacles are one or multiple: avoid them anyway...



Obstacle avoidance: sub-symbolic

- each sensor mounted at fixed angle θ
- that points in direction $\psi = \phi + \theta$ in the world
- erect a repeller at that angle

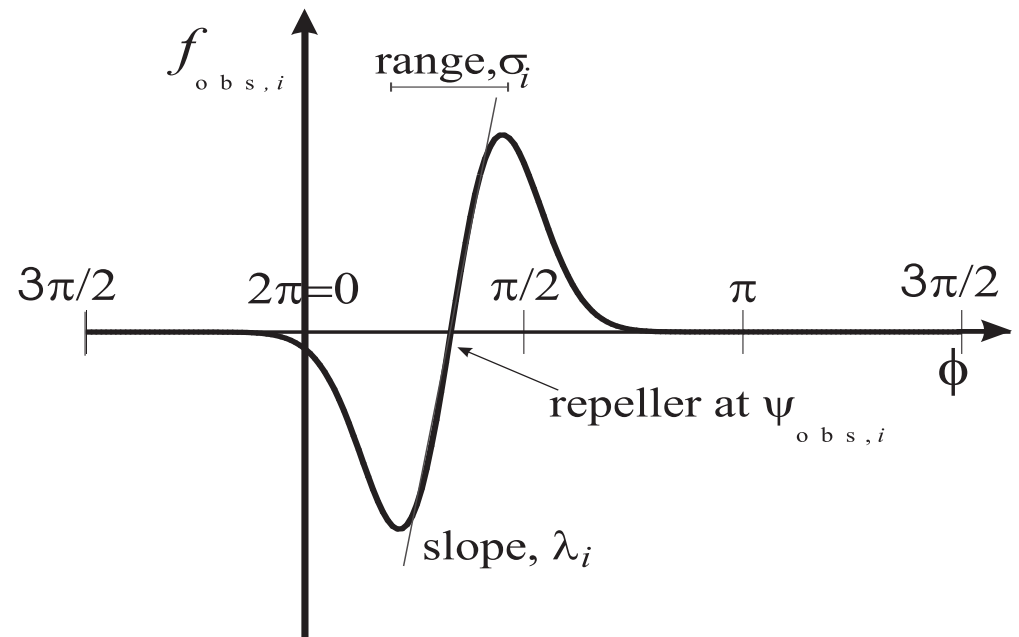


[from: Bicho, Jokeit, Schöner]

Obstacle avoidance: sub-symbolic

$$f_{\text{obs},i}(\phi) = \lambda_i(\phi - \psi_i) \exp \left[-\frac{(\phi - \psi_i)^2}{2\sigma_i^2} \right] \quad i = 1, 2, \dots, 7$$

- Note: only $\phi - \psi = -\theta$ shows up, which is constant!
- \Rightarrow force-let does not depend on ϕ !



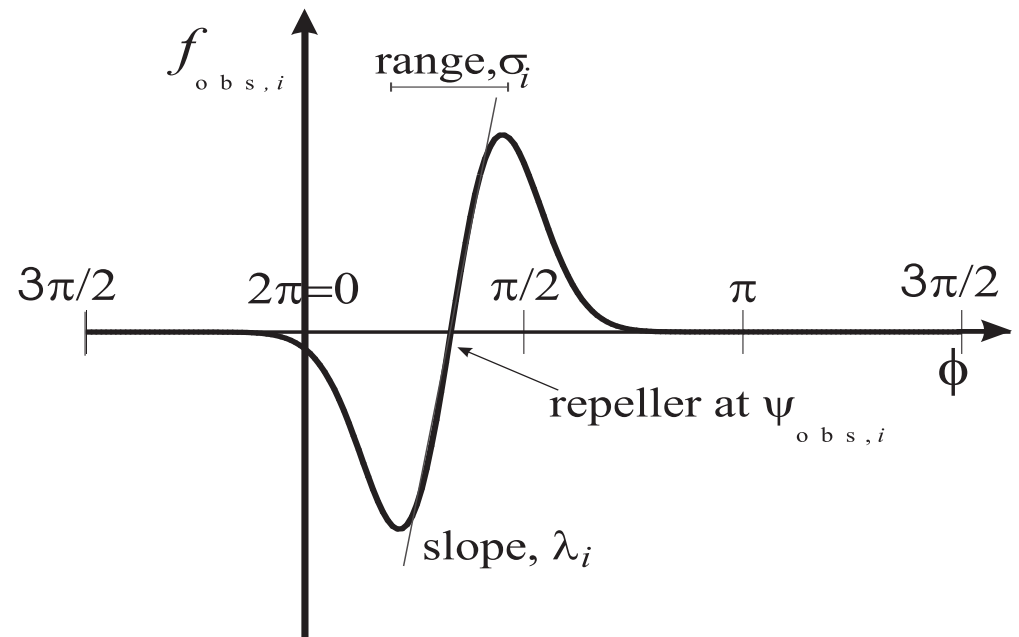
[from: Bicho, Jokeit, Schöner]

Obstacle avoidance: sub-symbolic

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$$\lambda_i = \beta_1 \cdot \exp \left[-\frac{d_i}{\beta_2} \right]$$

- Repulsion strength decreases with distance, d_i
- \Rightarrow only close obstacles matter

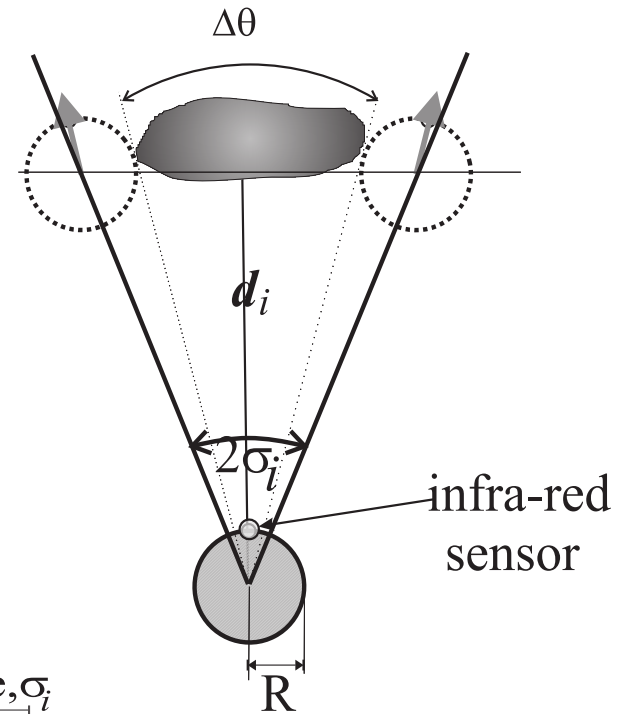


[from: Bicho, Jokeit, Schöner]

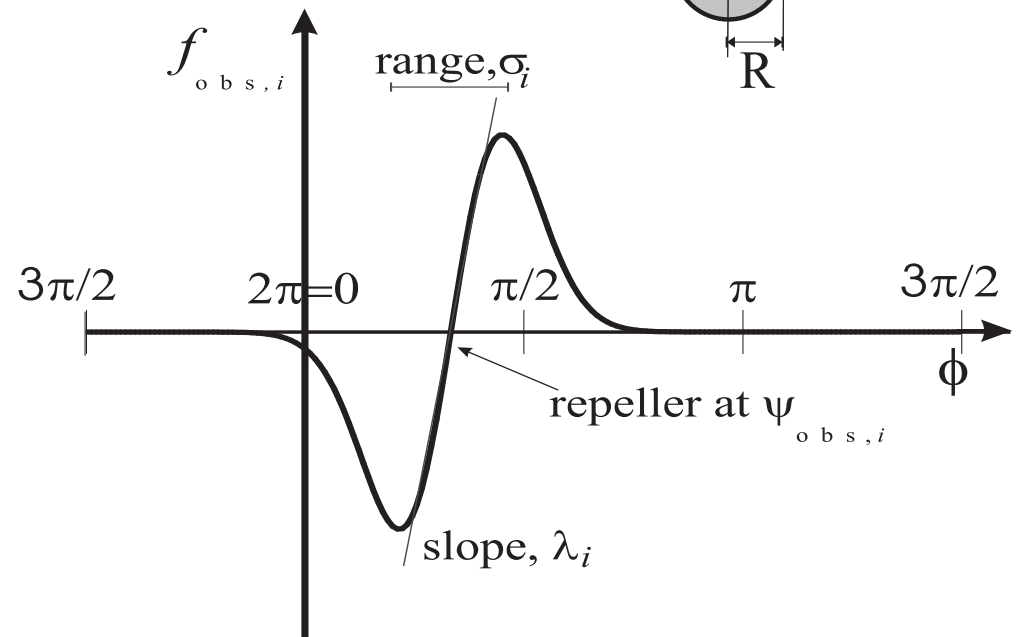
Obstacle avoidance: sub-symbolic

$$f_{\text{obs},i}(\phi) = \lambda_i(\phi - \psi_i) \exp \left[-\frac{(\phi - \psi_i)^2}{2\sigma_i^2} \right]$$

$$\sigma_i = \arctan \left[\tan \left(\frac{\Delta\theta}{2} \right) + \frac{R_{\text{robot}}}{R_{\text{robot}} + d_i} \right].$$



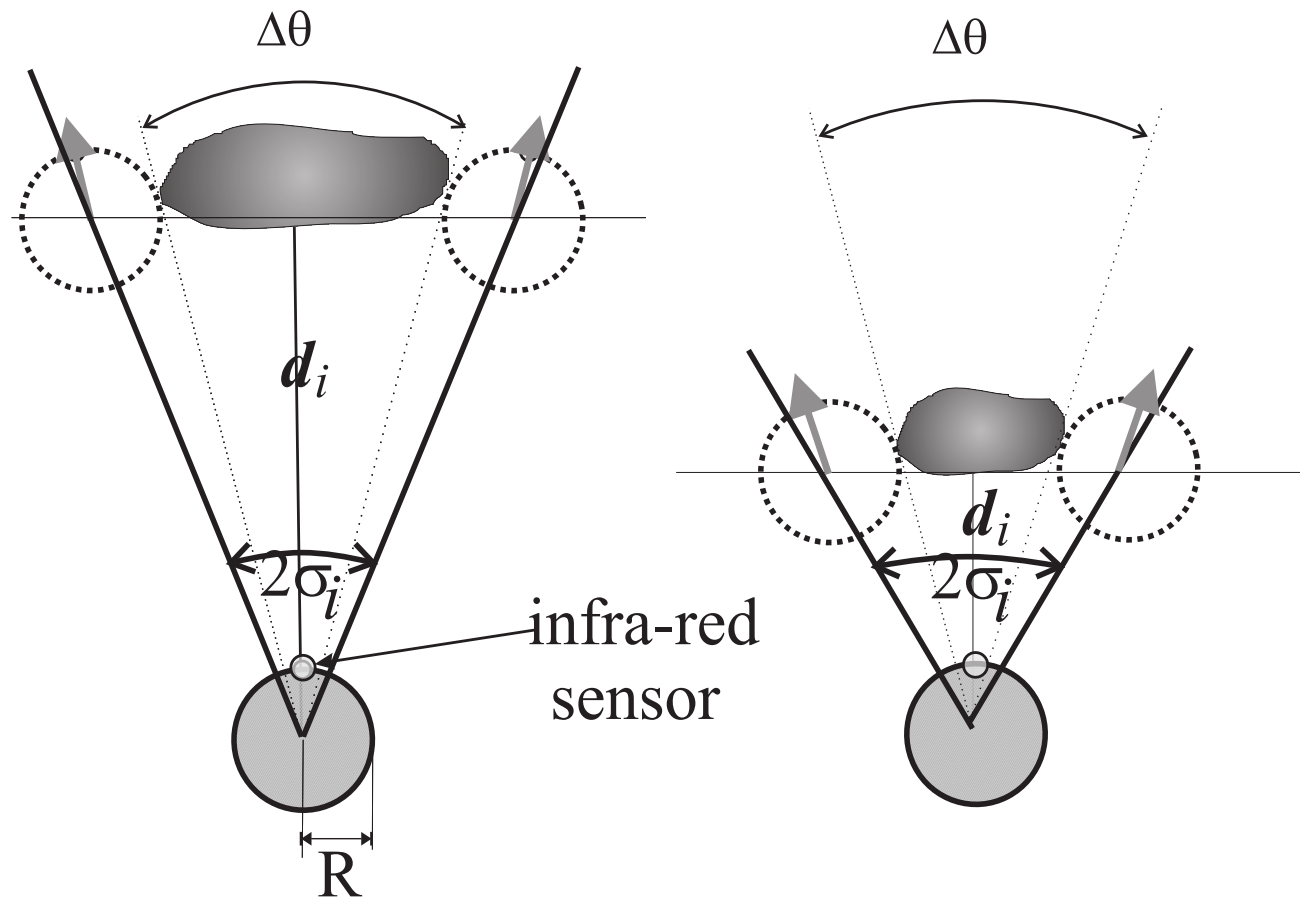
- angular range depends on sensor cone $\Delta\theta$ and size over distance



[from: Bicho, Jokeit, Schöner]

Obstacle avoidance: sub-symbolic

- => as a result, range becomes wider as obstacle moves closer

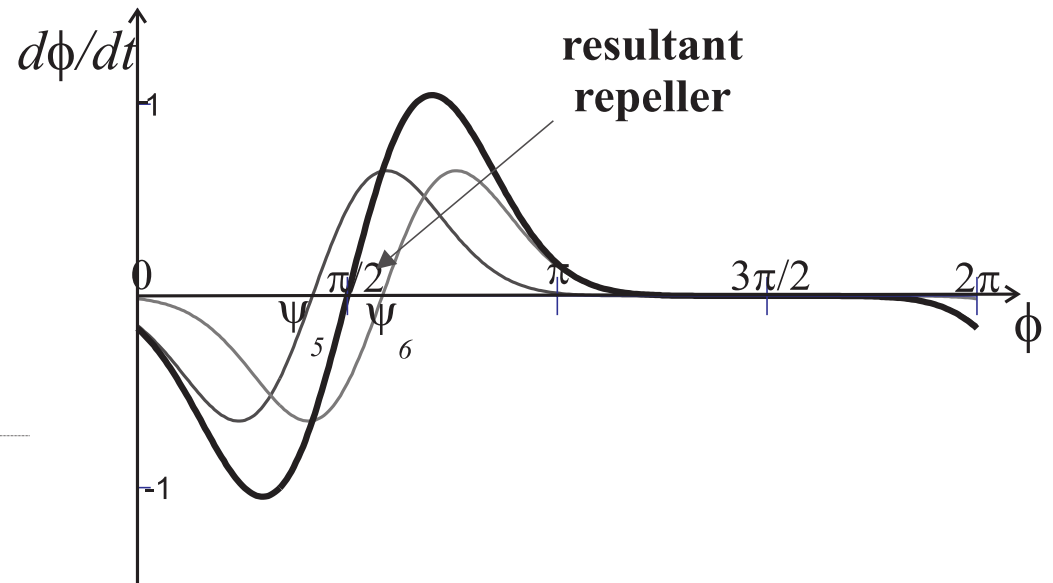
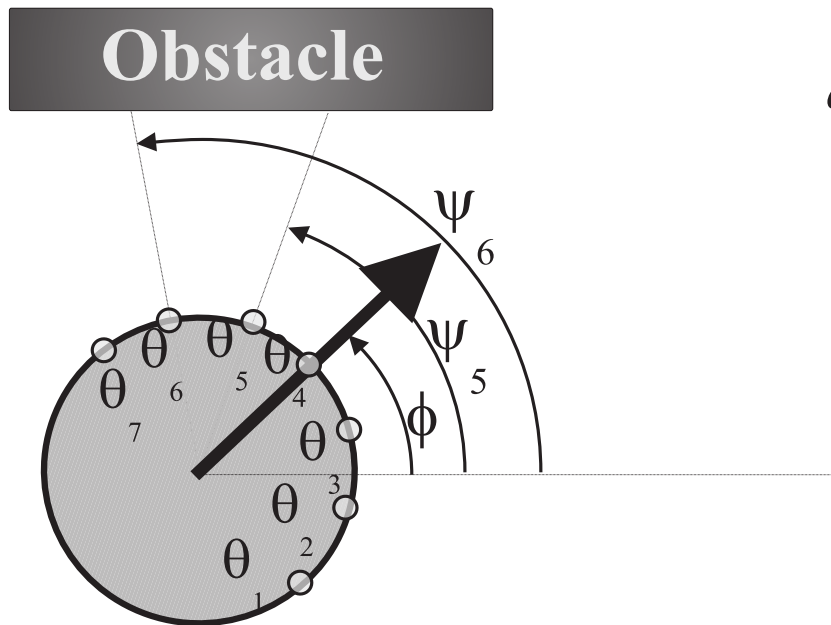


[from: Bicho, Jokeit, Schöner]

Obstacle avoidance: sub-symbolic

- summing contributions from all sensors

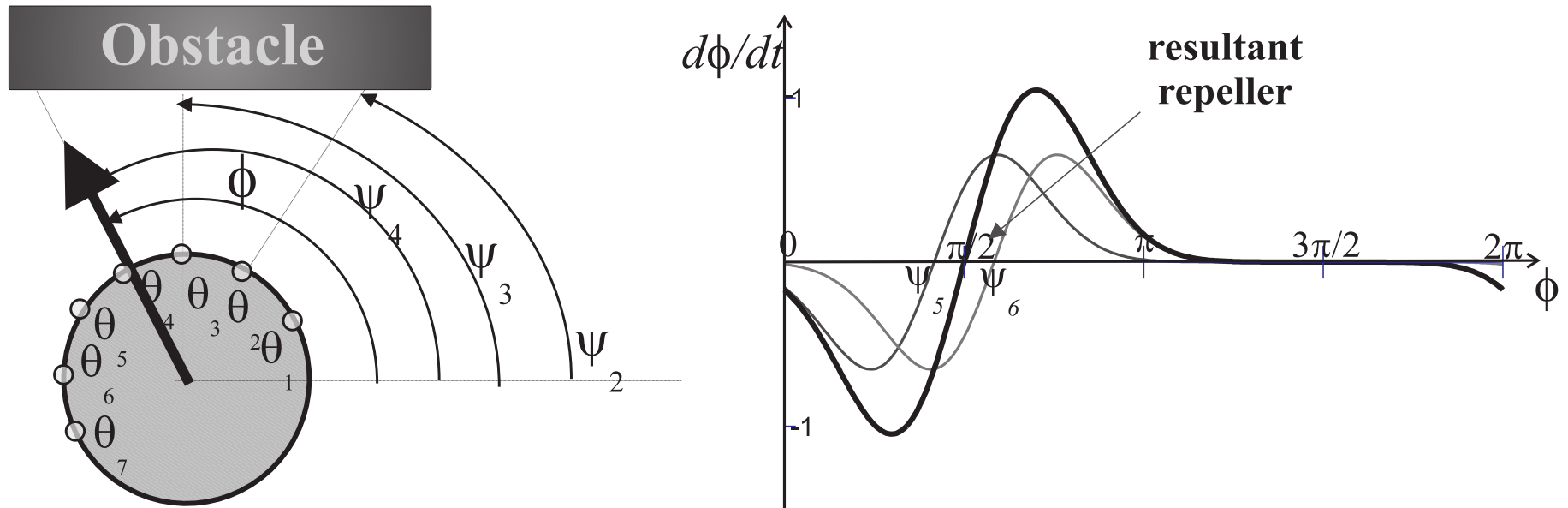
$$\frac{d\phi}{dt} = f_{\text{obs}}(\phi) = \sum_{i=1}^7 f_{\text{obs},i}(\phi)$$



[from: Bicho, Jokeit, Schöner]

Obstacle avoidance: sub-symbolic

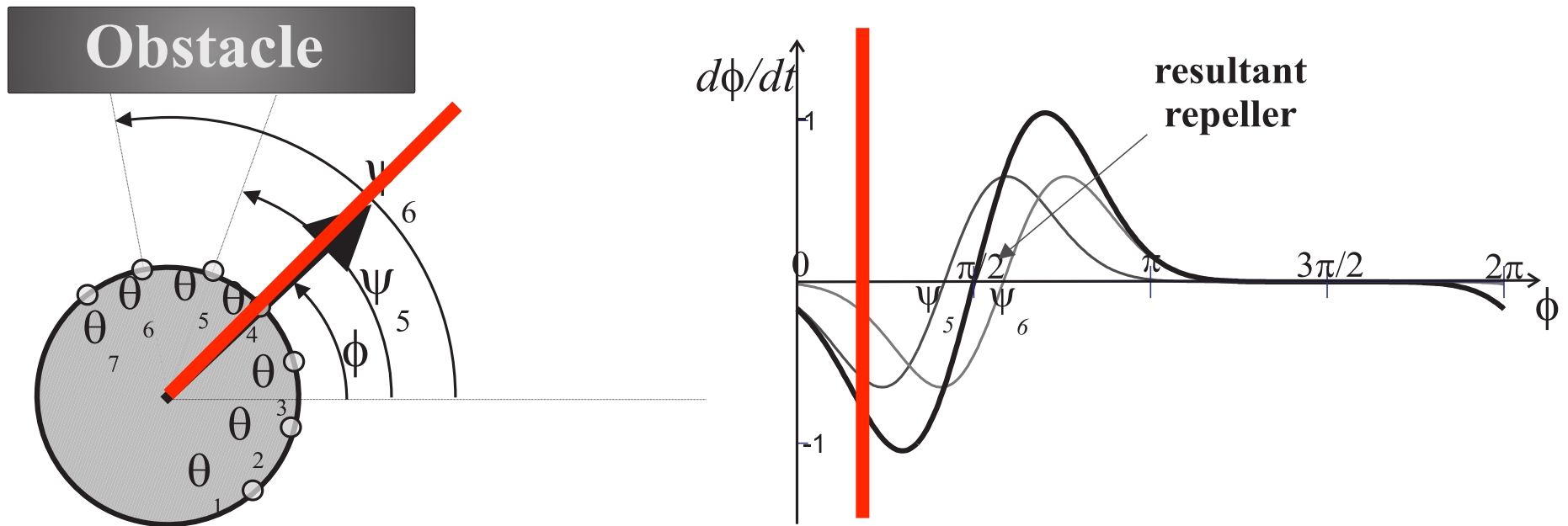
- but why does it work?
- shouldn't there be a problem when heading changes (e.g. from the dynamics itself)?



[from: Bicho, Jokeit, Schöner]

Obstacle avoidance: sub-symbolic

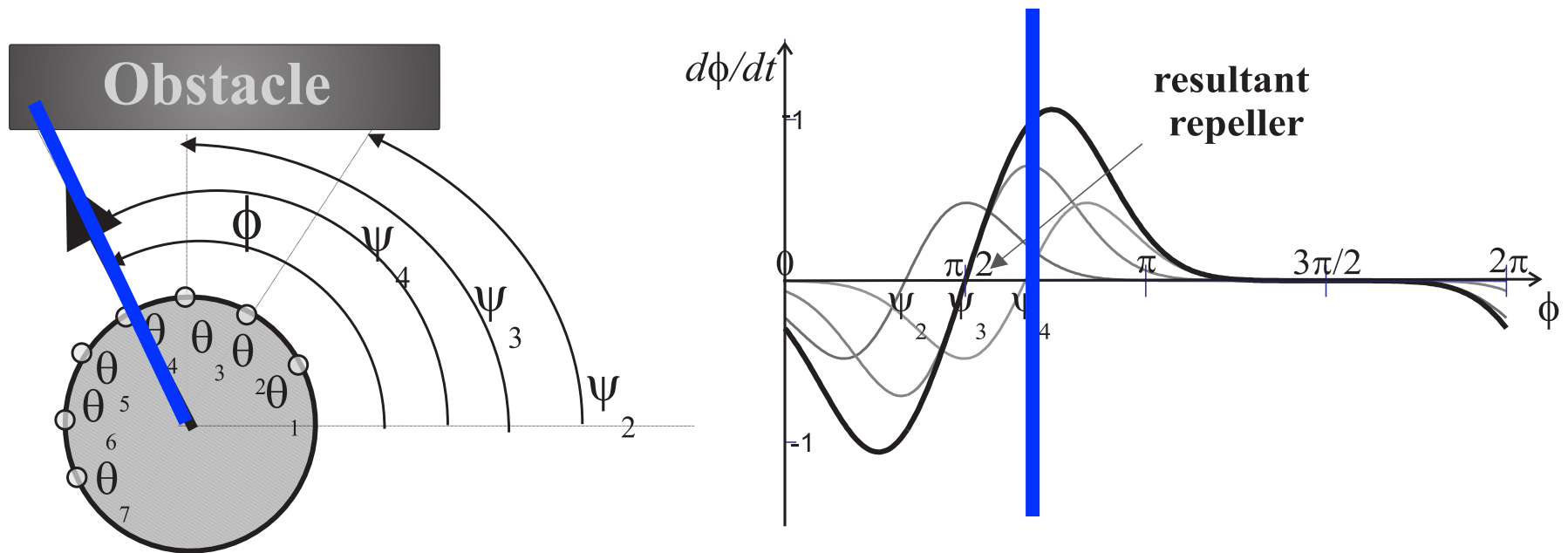
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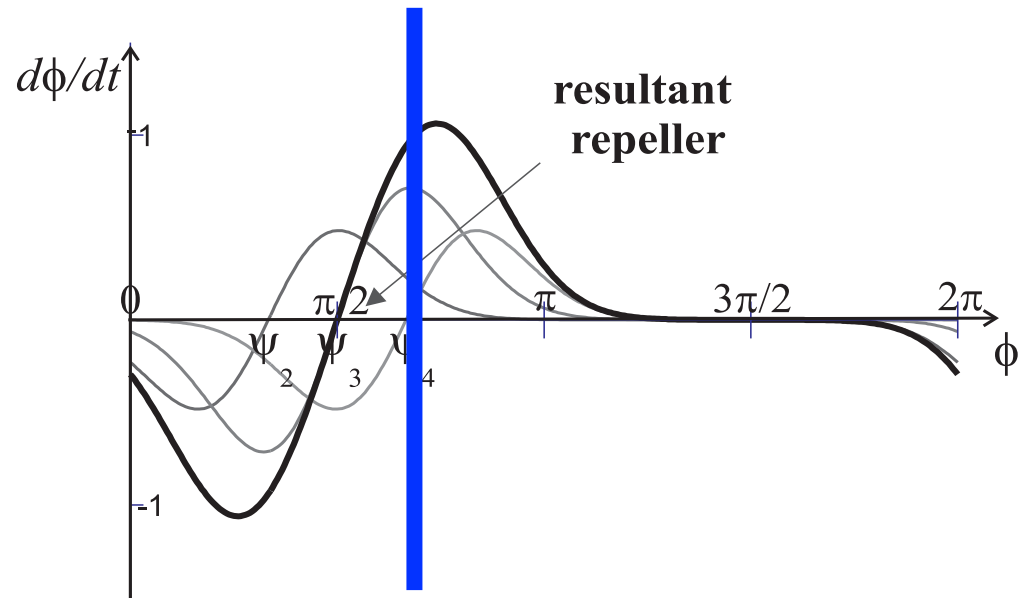
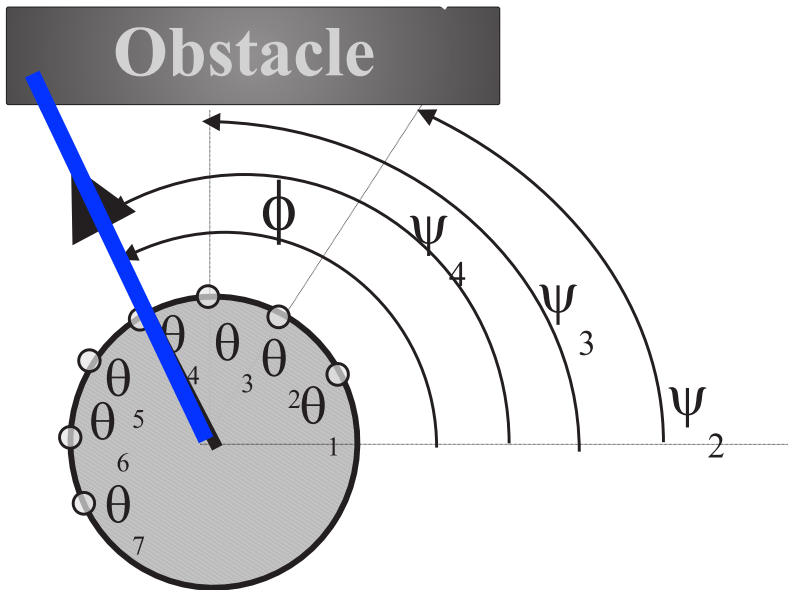
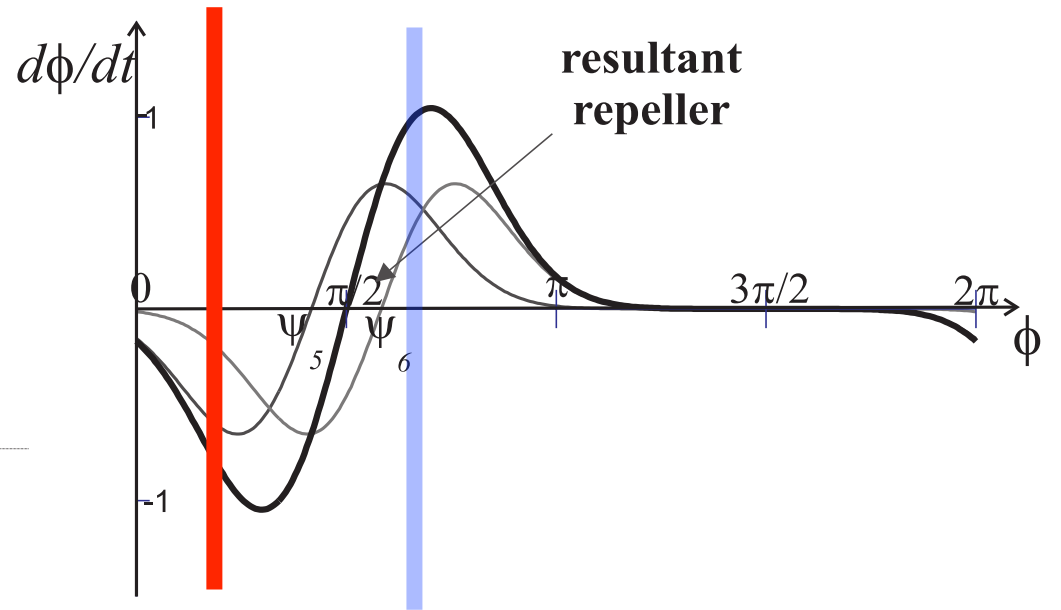
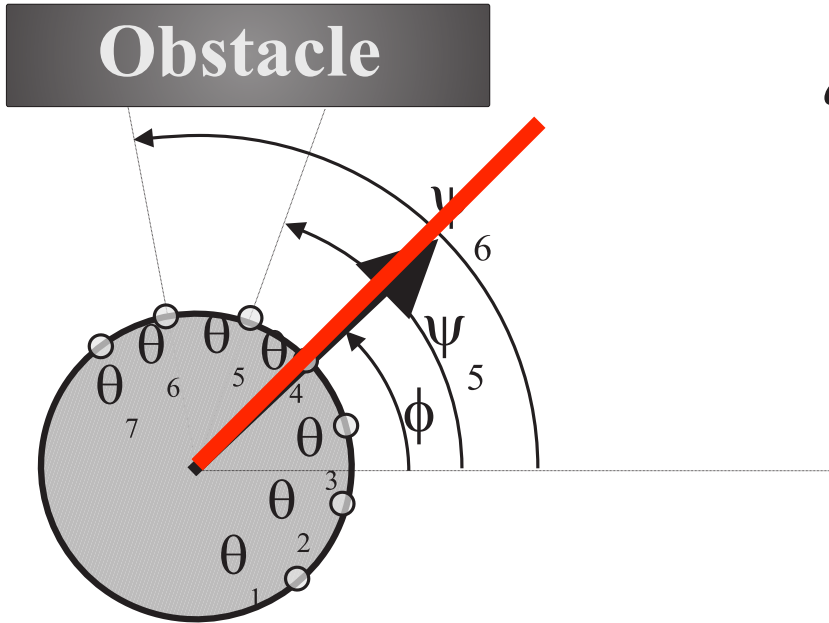
[from: Bicho, Jokeit, Schöner]

Obstacle avoidance: sub-symbolic

- but why does it work?
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[from: Bicho, Jokeit, Schöner]

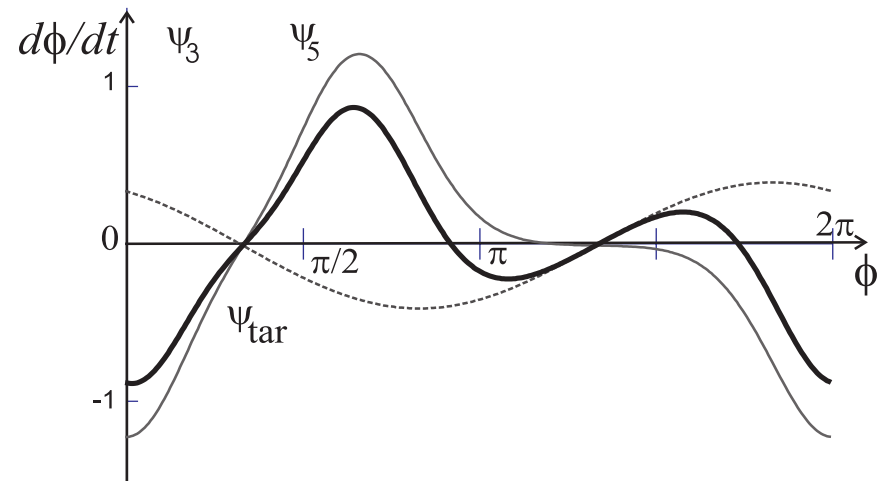
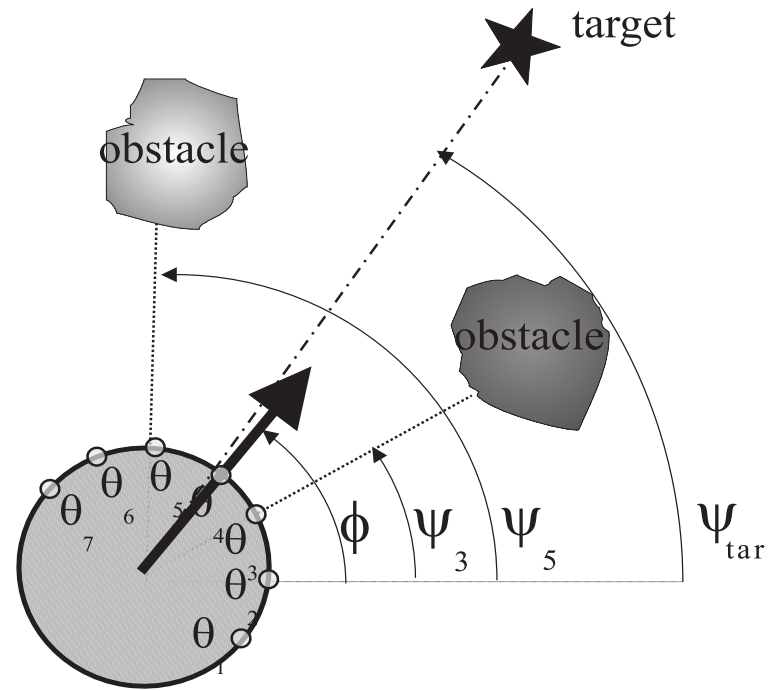


 => dynamics invariant!

Behavioral Dynamics

- integrating the two behaviors

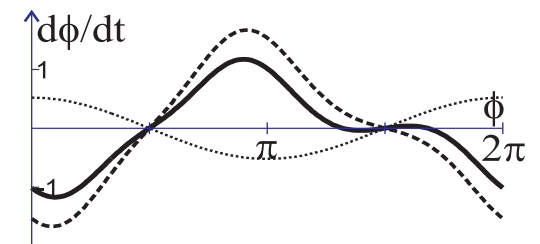
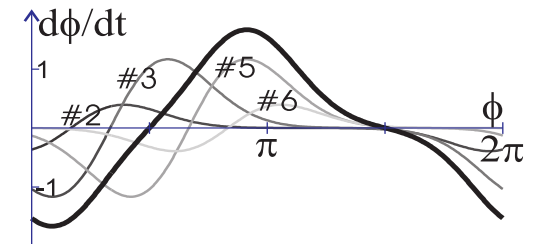
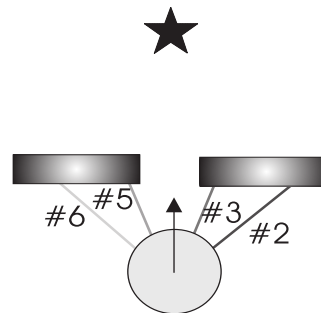
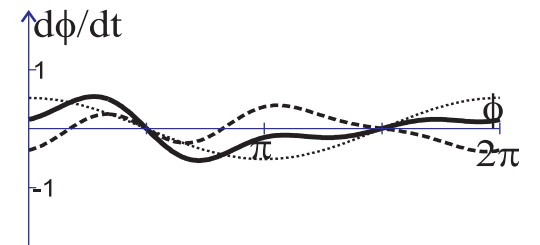
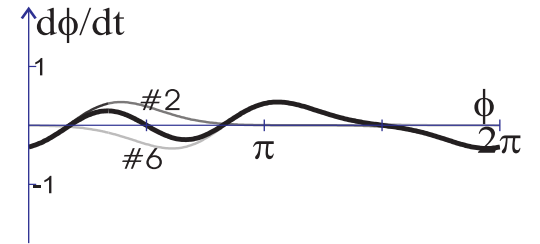
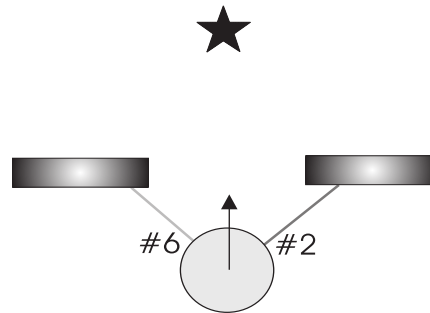
$$\frac{d\phi}{dt} = f_{\text{obs}}(\phi) + f_{\text{tar}}(\phi)$$



[from: Bicho, Jokeit, Schöner]

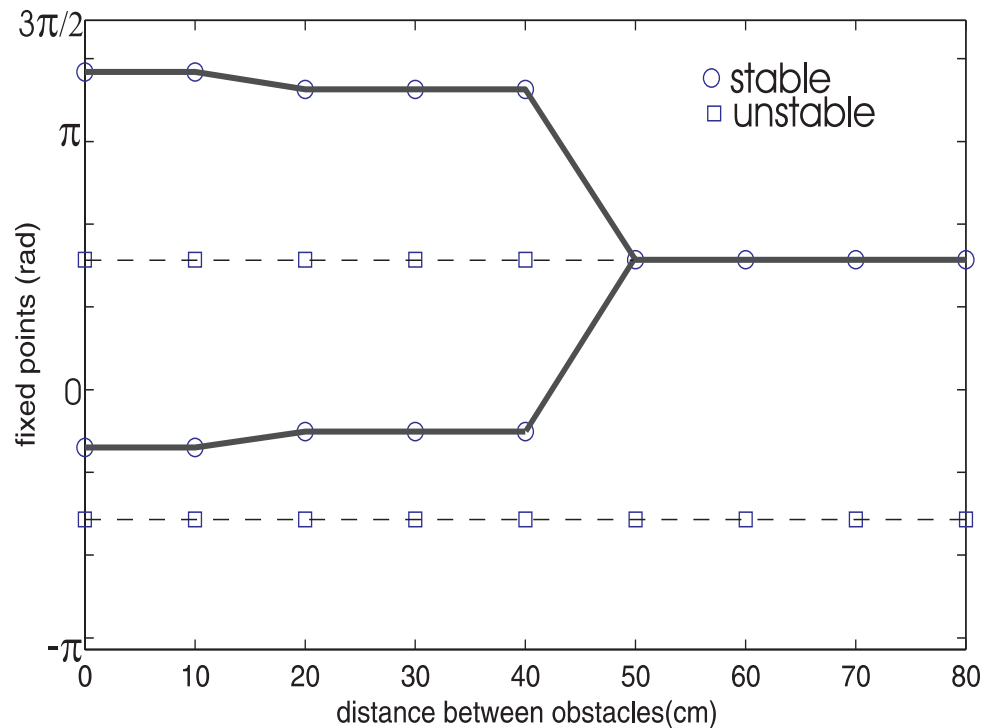
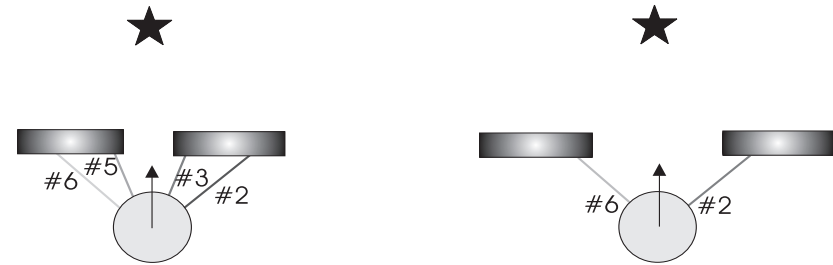
Bifurcations

■ bifurcation as a function of the size of the opening between obstacles

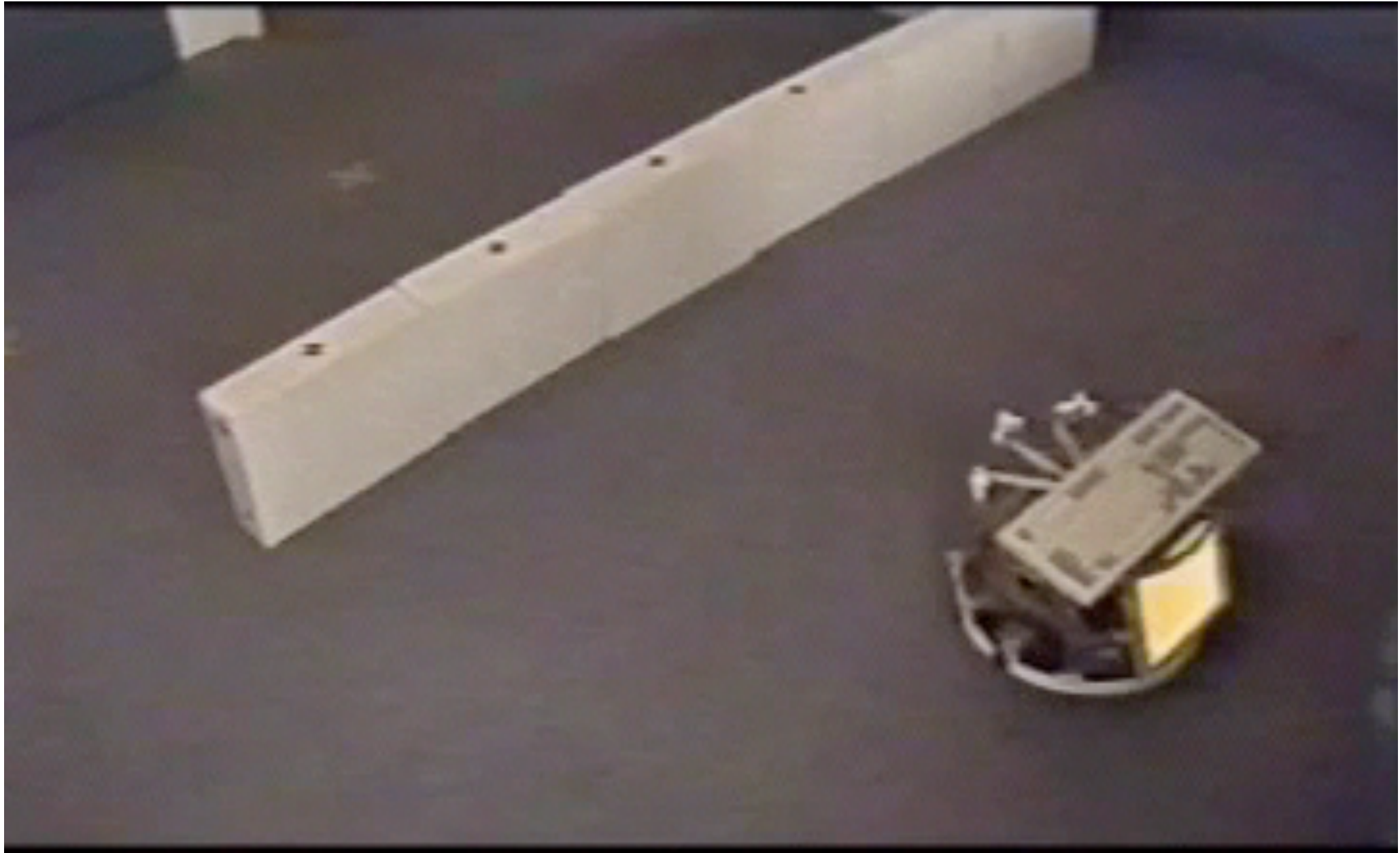


Bifurcations

- bifurcation as a function of the size of the opening between obstacles
- => tune distance dependence of repulsion so that bifurcation occurs at the right opening

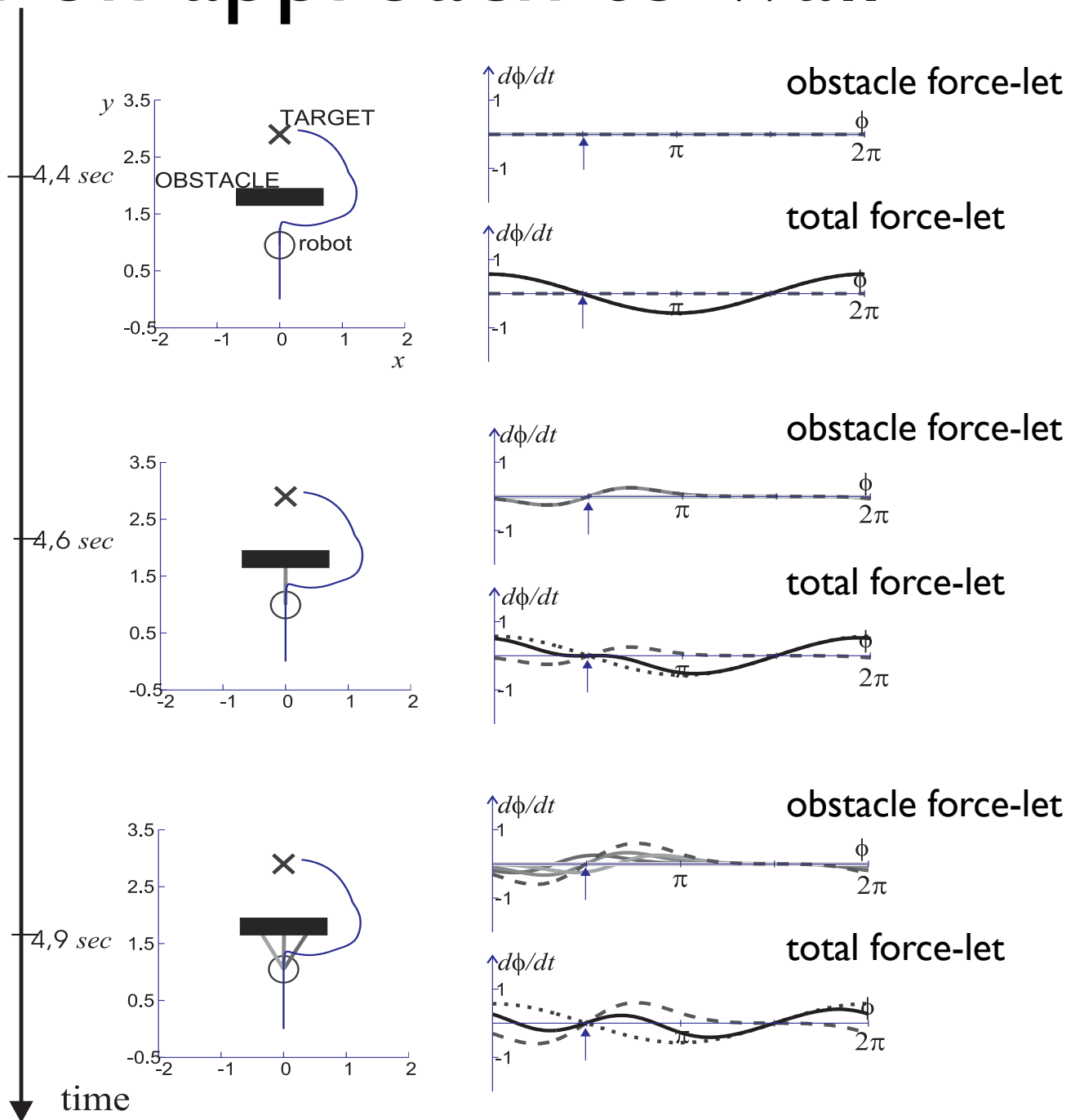


Bifurcations



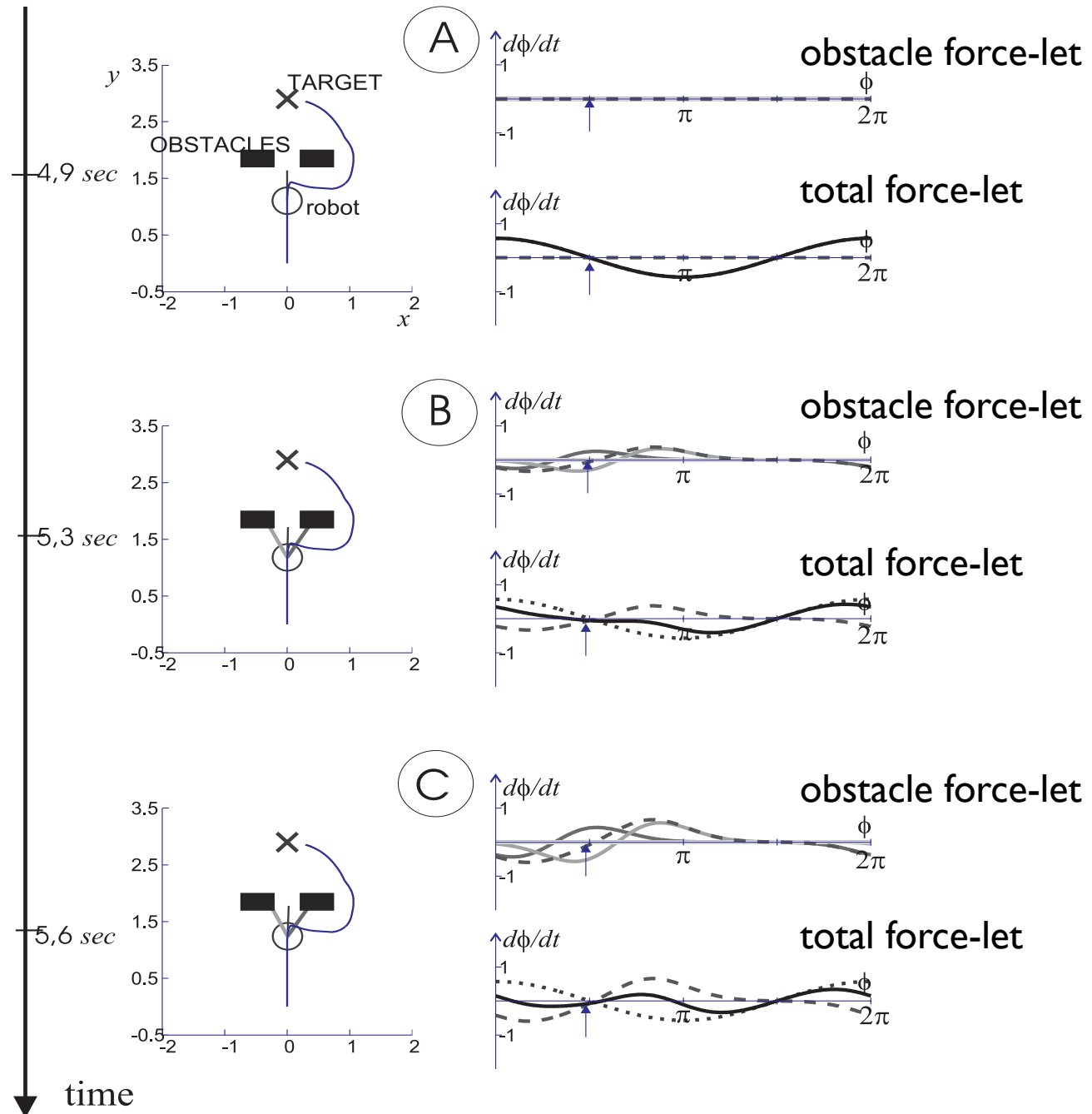
Bifurcation on approach to wall

- initially attractor dominates: weak repulsion
- bifurcation
- then obstacles dominate: strong repulsion and total repulsion



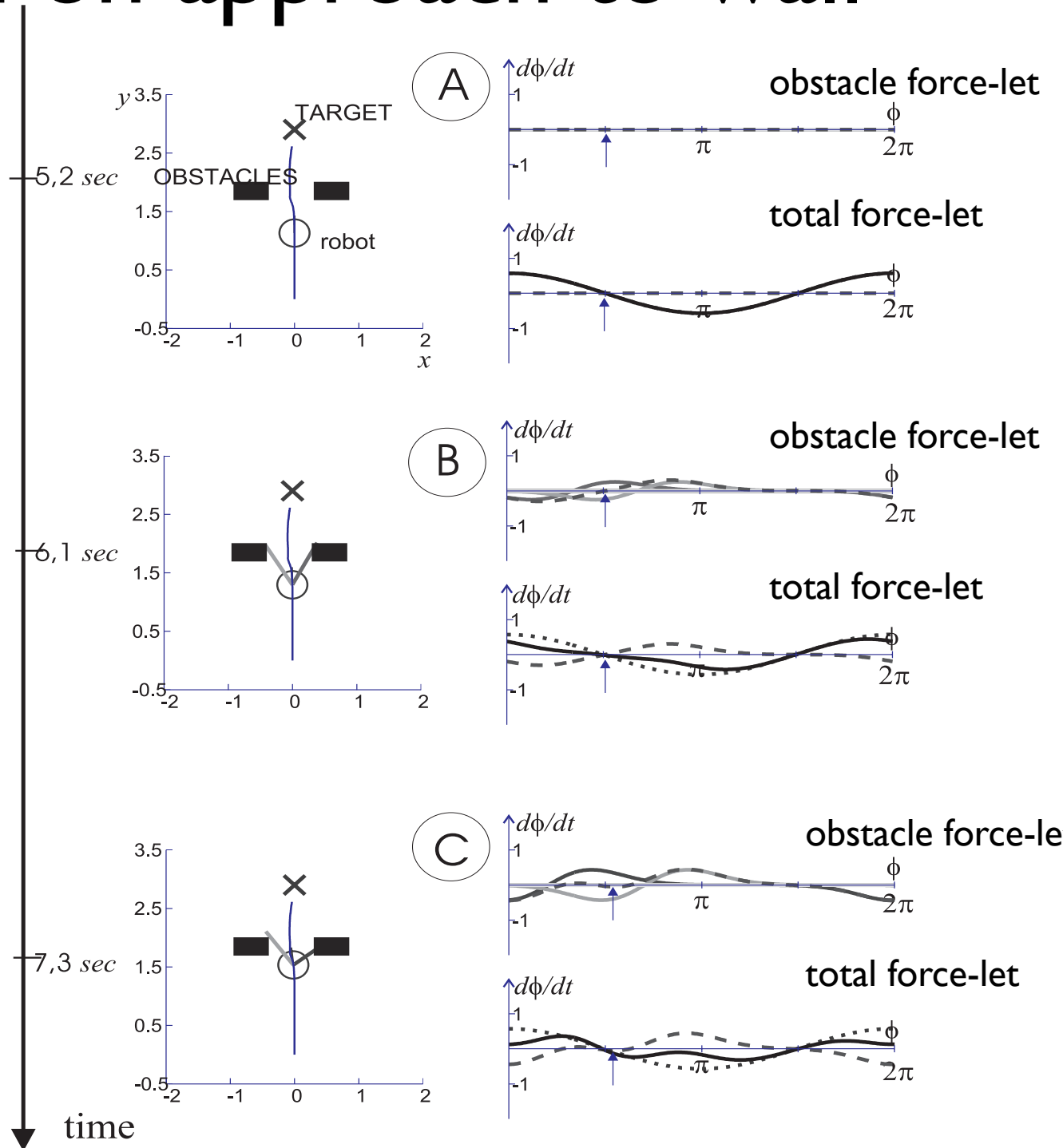
Bifurcation on approach to wall

■ same with small opening



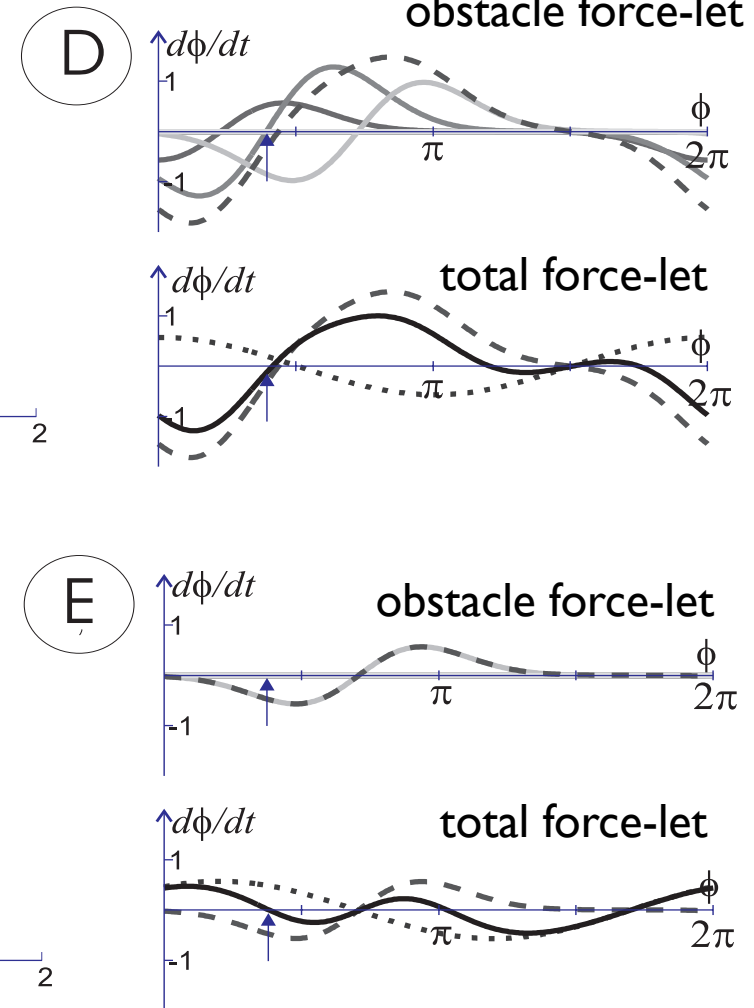
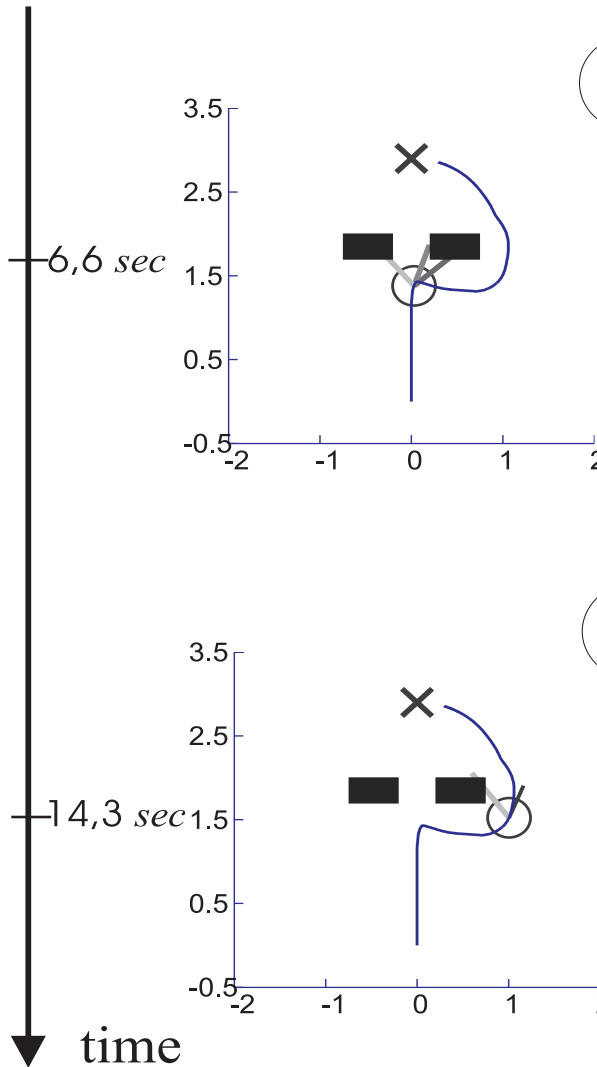
Bifurcation on approach to wall

■ at larger opening:
repulsion
weak all the way
through:
attractor
remains stable



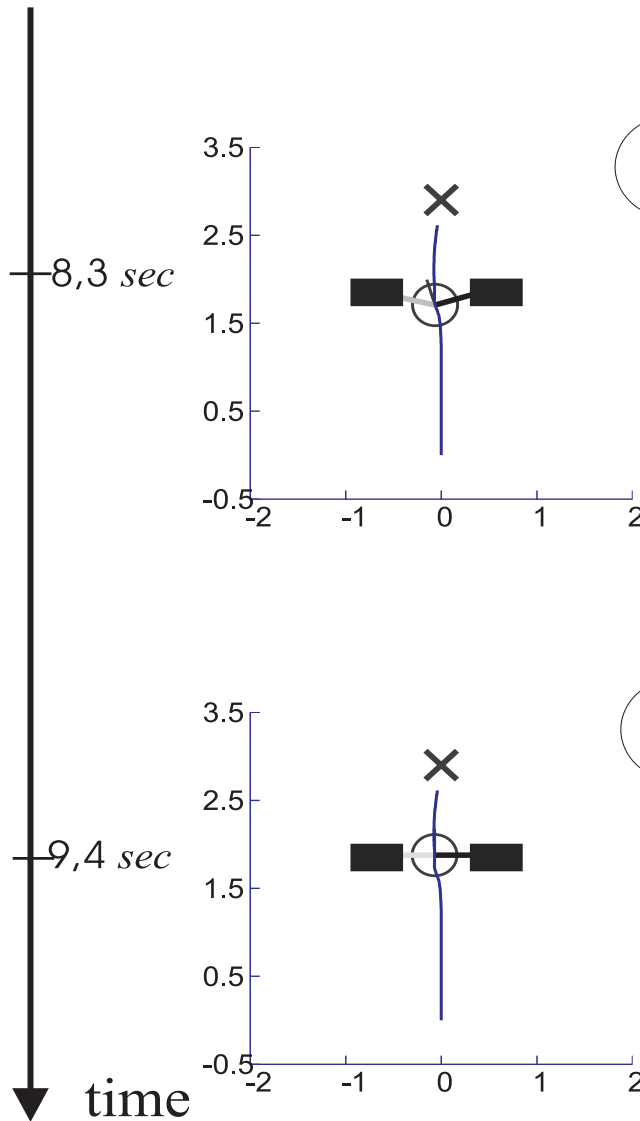
Tracking attractor

■ as robot moves around obstacles, tracks the moving attractor

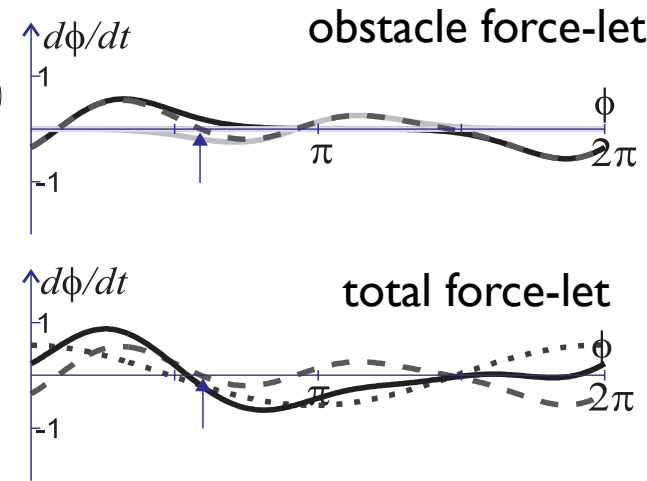


Tracking attractor

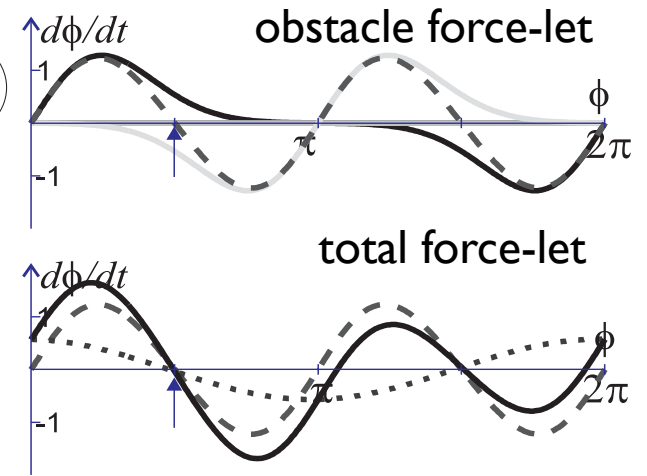
as robot moves in between obstacles, the dynamics changes but not the attractor



D

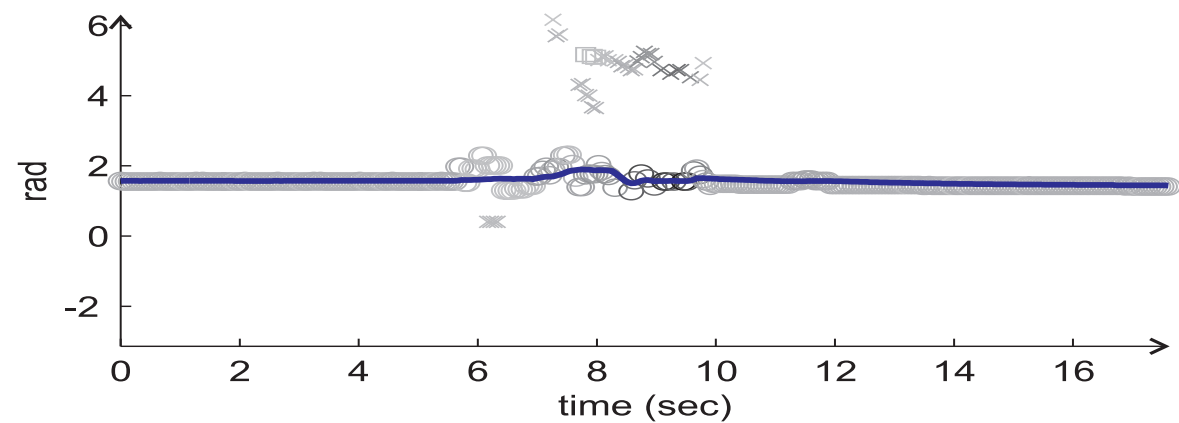
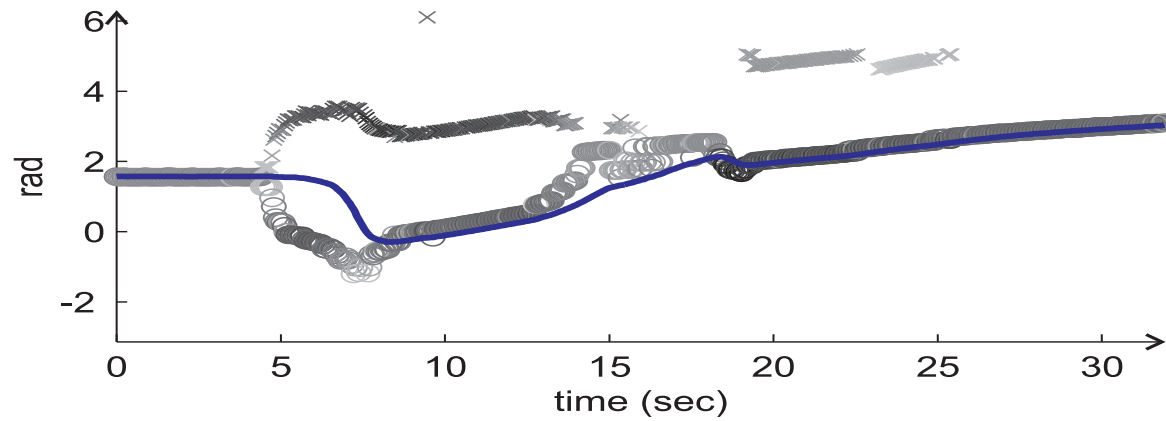
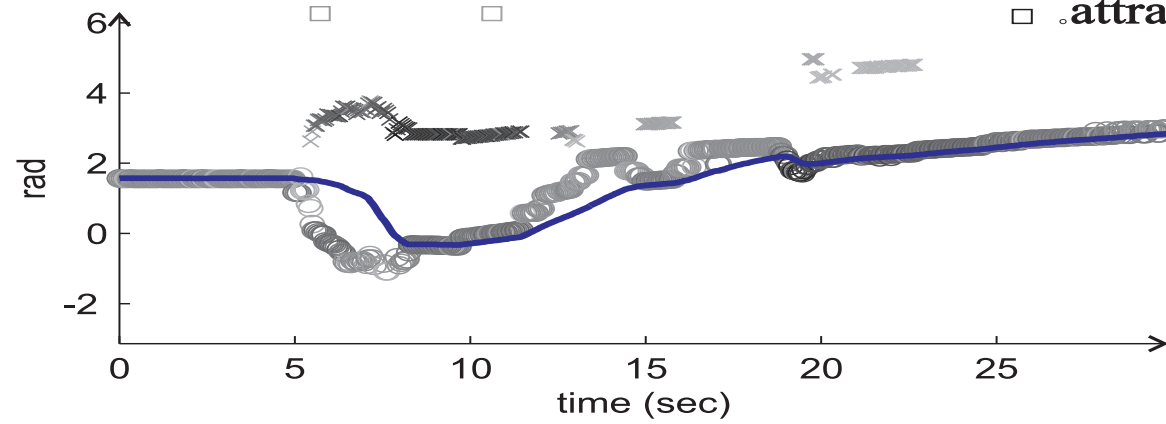


E

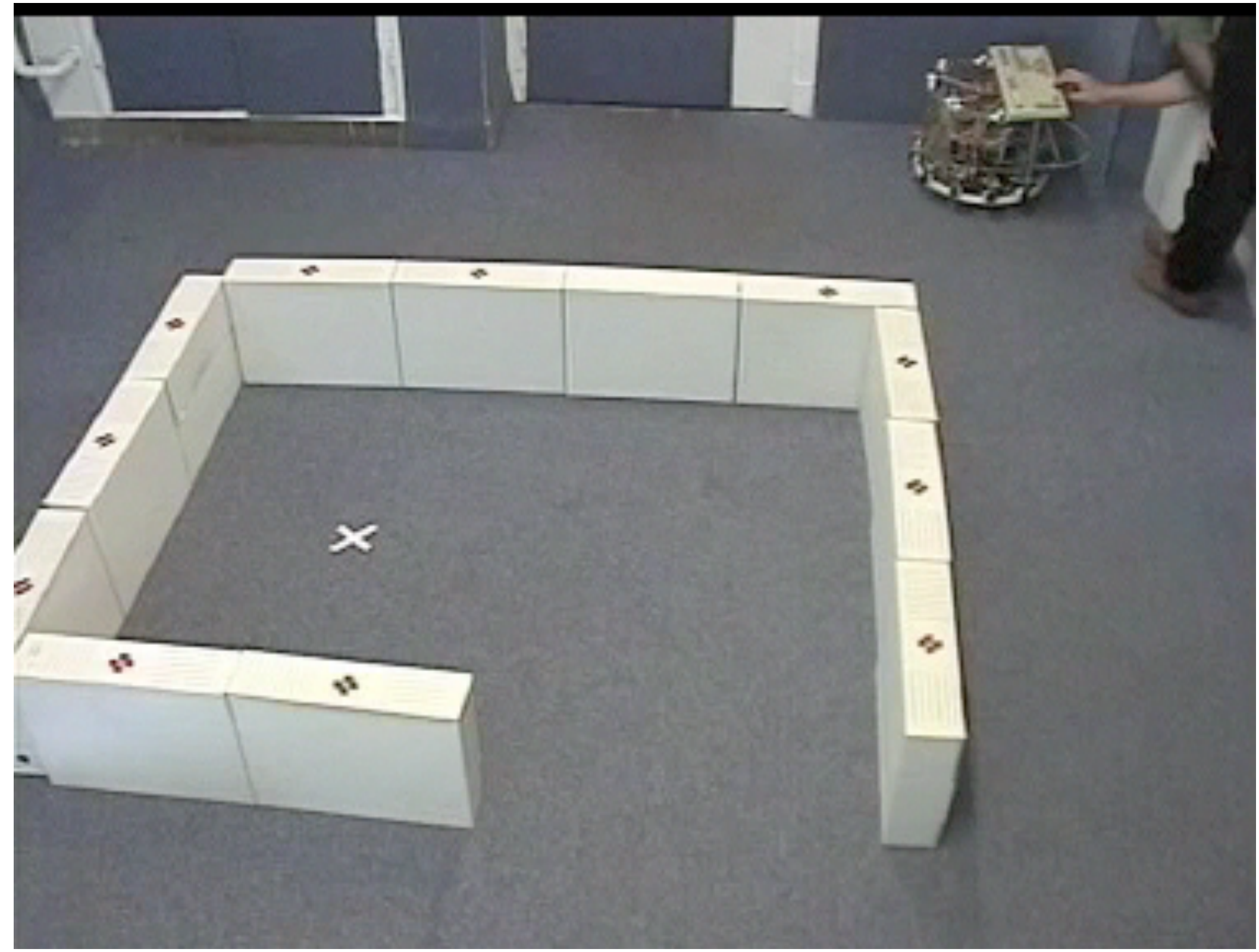


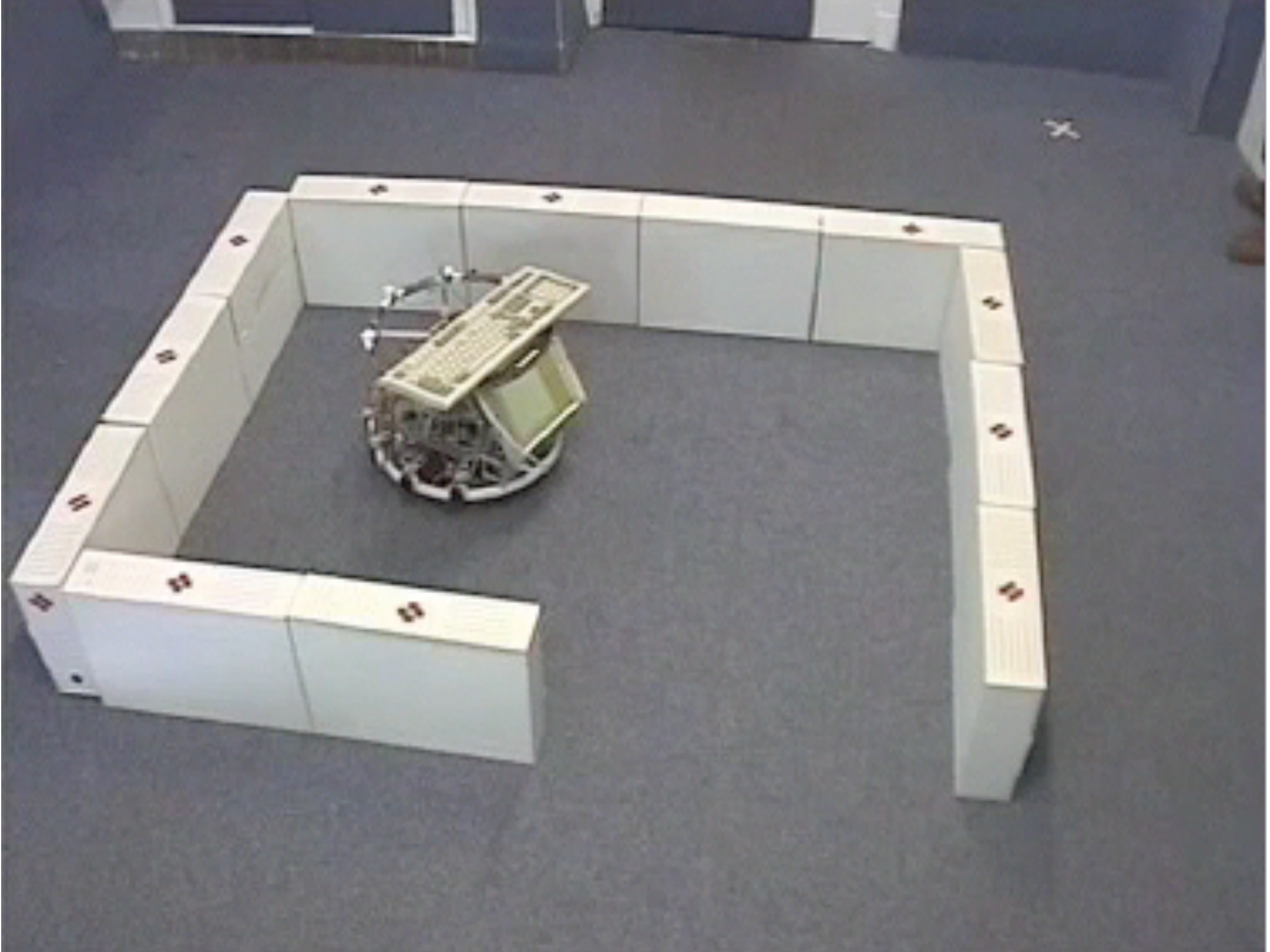
Tracking attractors

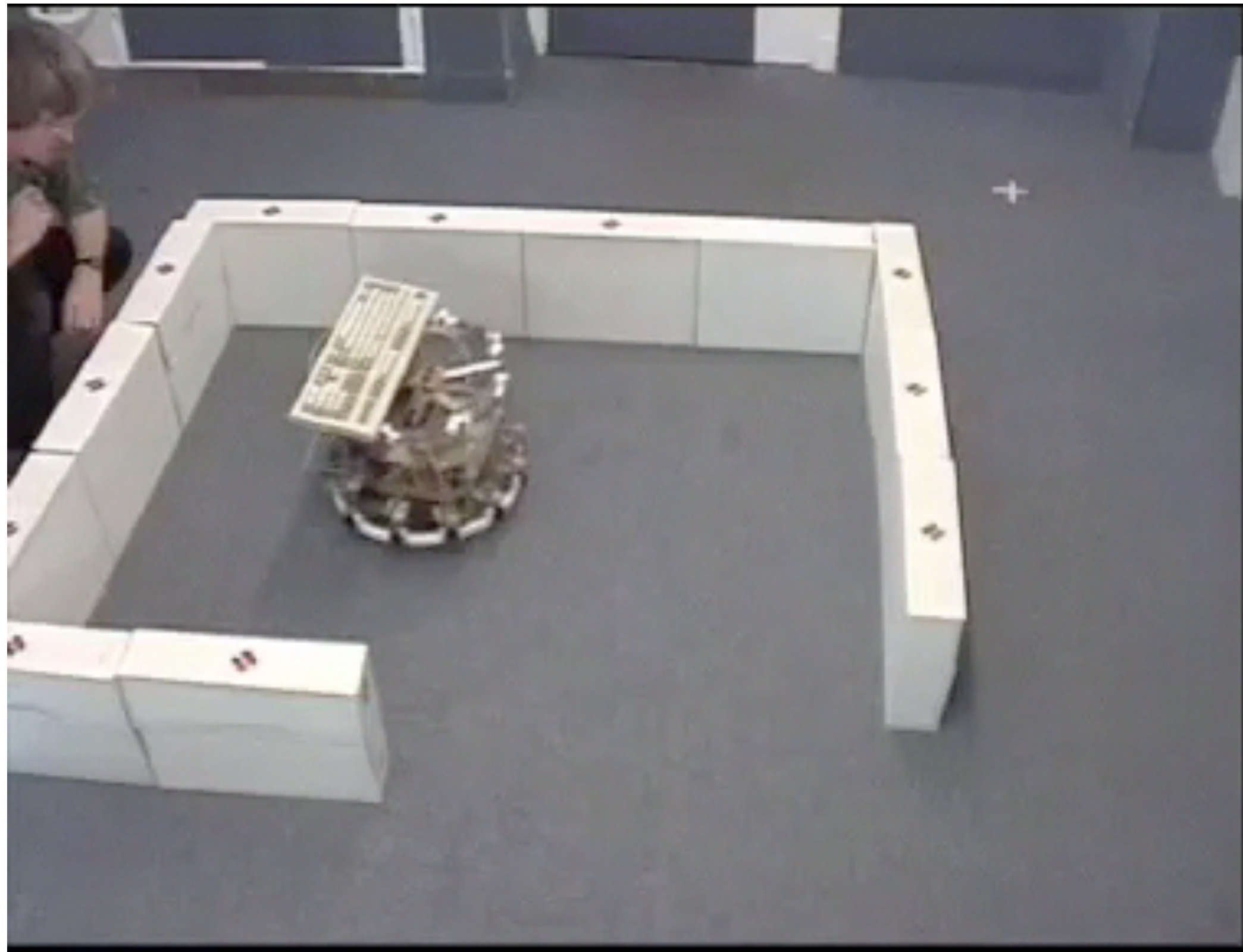
- attractor 1
- × attractor 2
- attractor 3

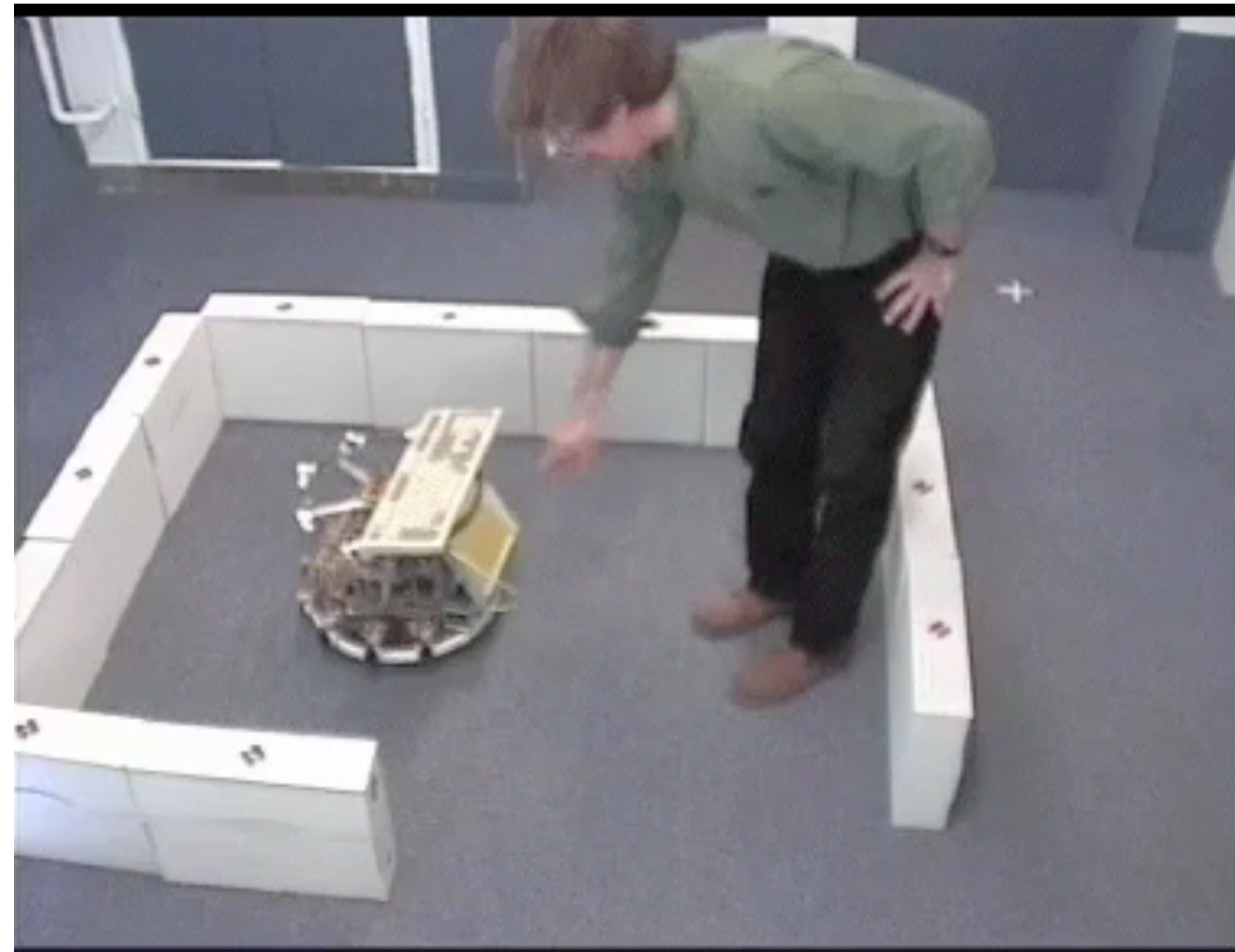












Observation:

- even though the approach is purely local, it does achieve global tasks
- based on the structure of the environment!

Conclusion

- attractor dynamics works on the basis low-level sensors information
- as long as the force-lets model the sensor-characteristics well enough to create approximate invariance of the dynamics under transformations of the coordinate frames

Summary

- behavioral variables
- attractor states for behavior
- attractive force-let: target acquisition
- repulsive force-let: obstacle avoidance
- bistability/bifurcations: decisions
- can be implemented with minimal requirements for perception