Attractor dynamics approach to behavior generation: vehicle motion Part 2: sub-symbolic approach

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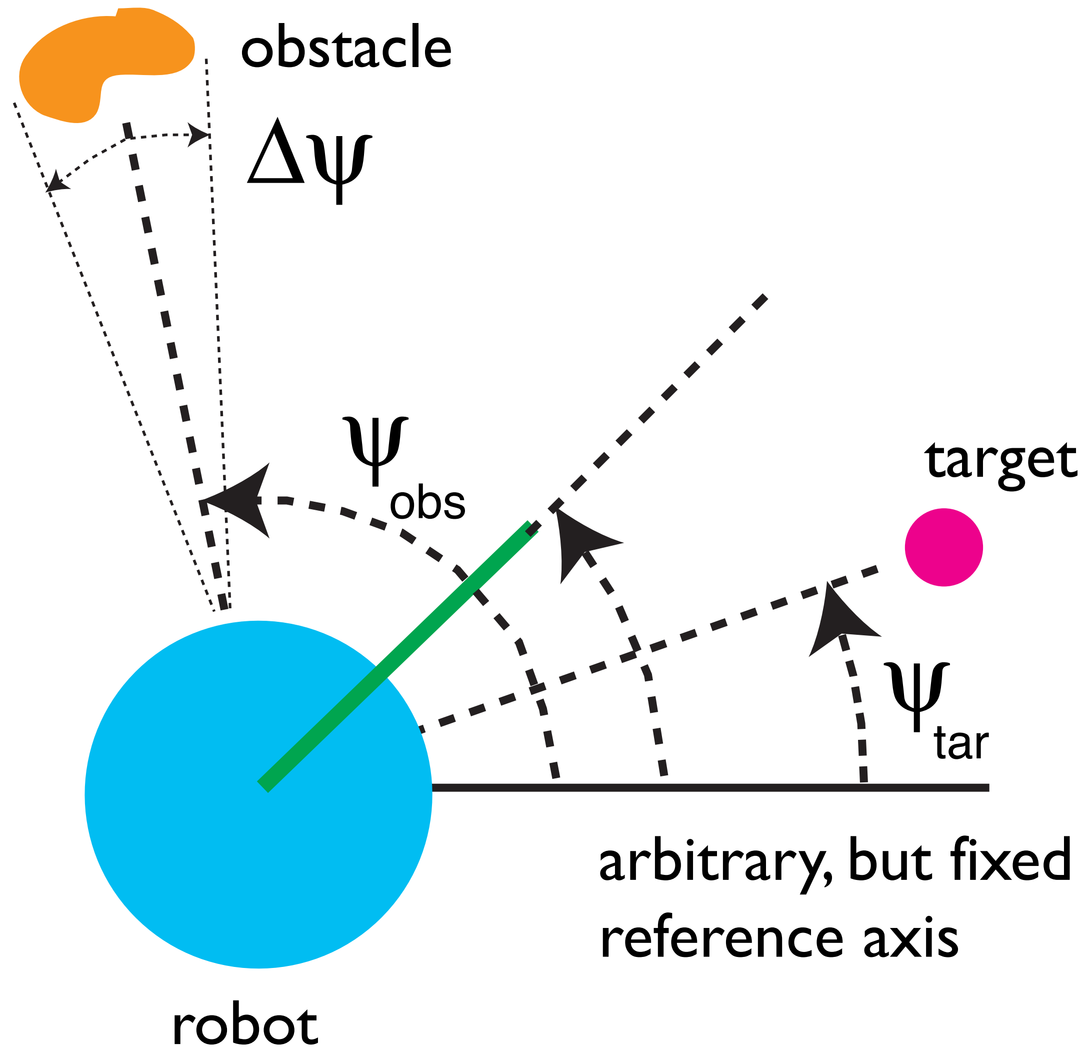
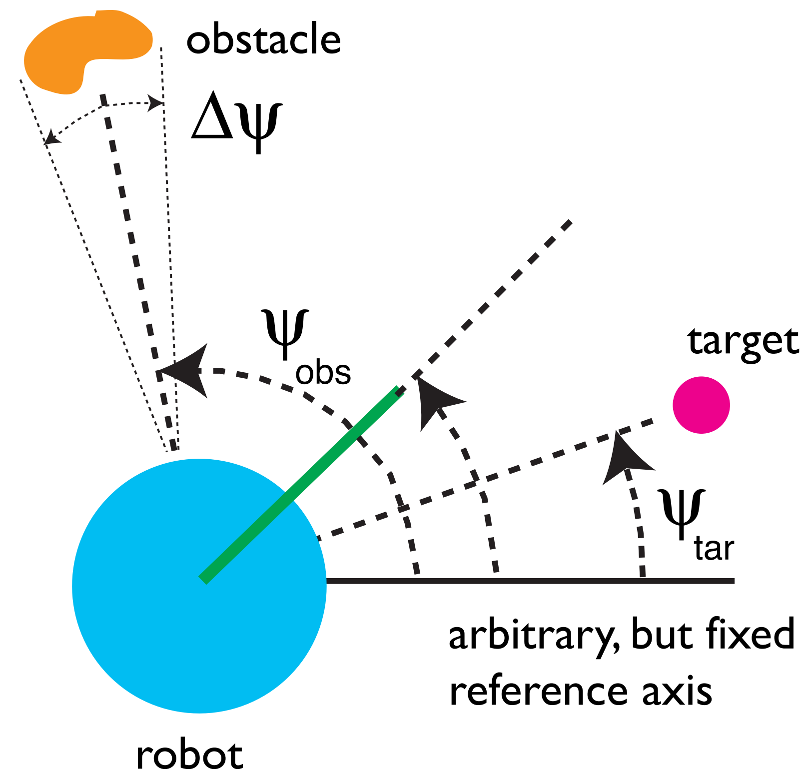
Behavioral dynamics

- constraints: obstacle avoidance and target acquisition



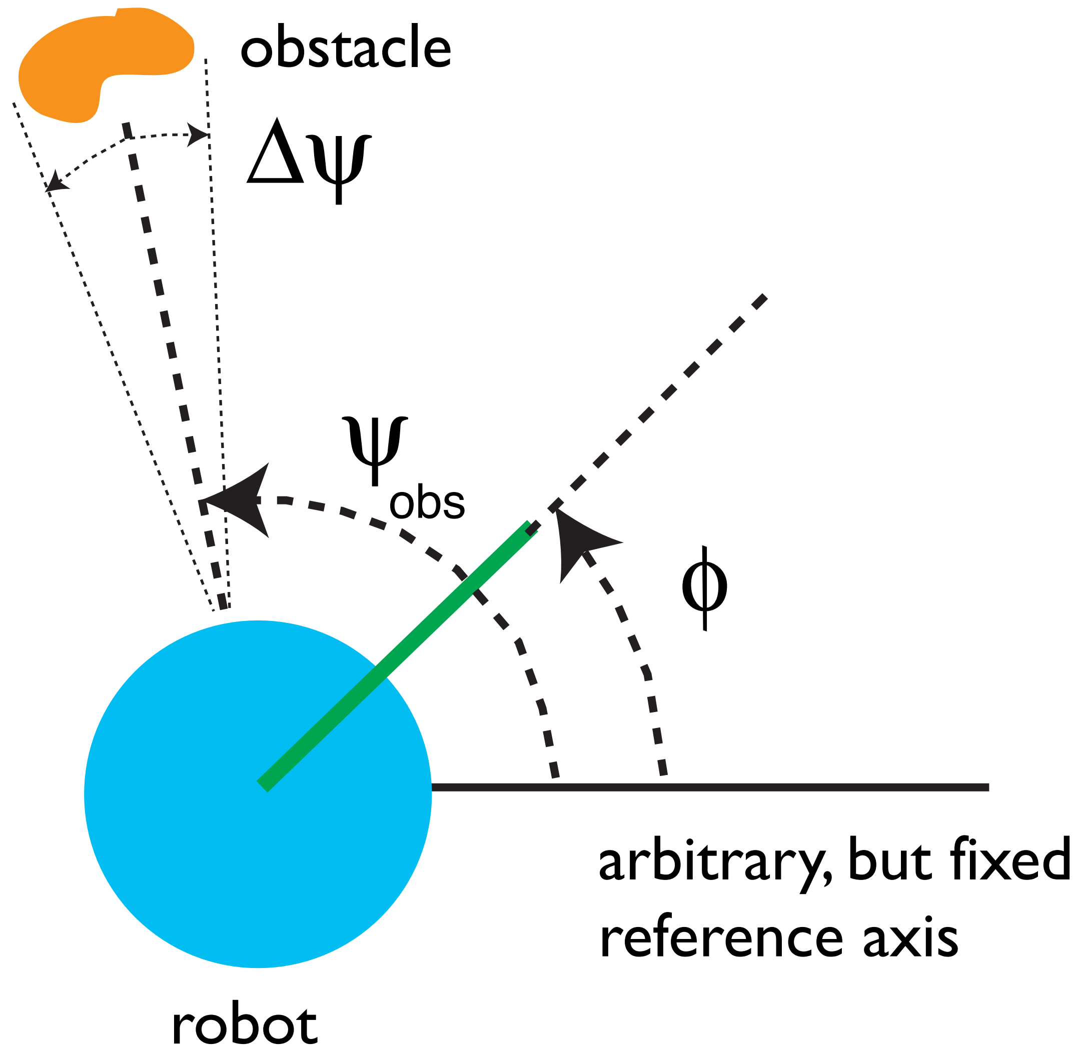
Behavioral dynamics

- so far, we had a "symbolic" approach to behavioral dynamics: the "obstacles" and "targets" were objects, that have identity, are preserved over time…and are represented by contributions to the behavioral dynamics



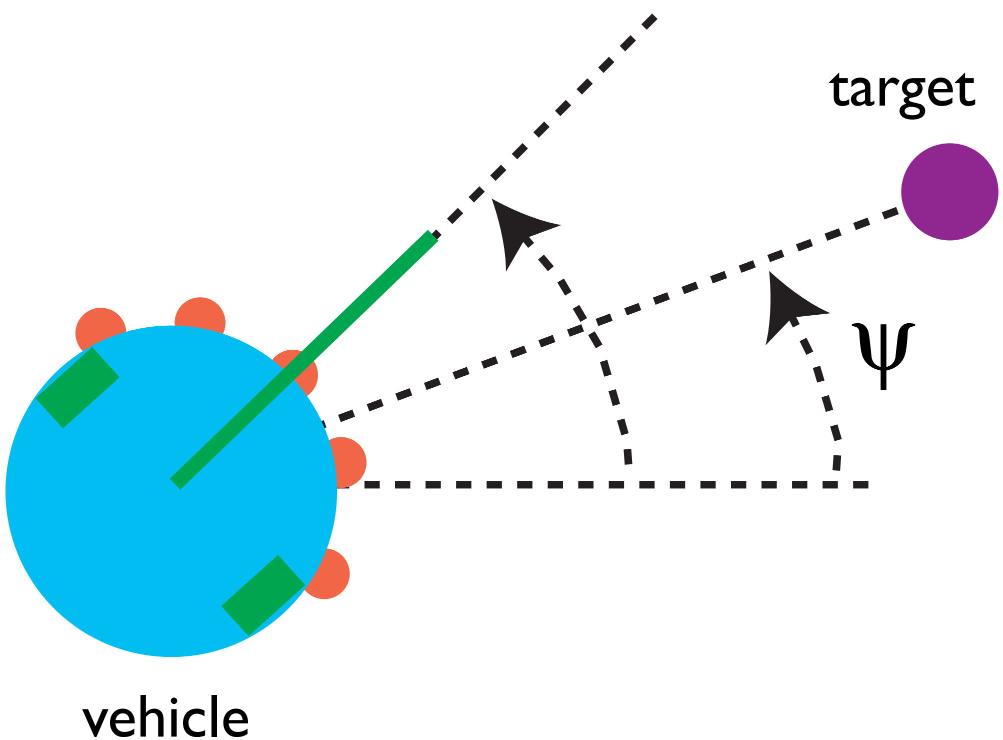
“symbolic” approach

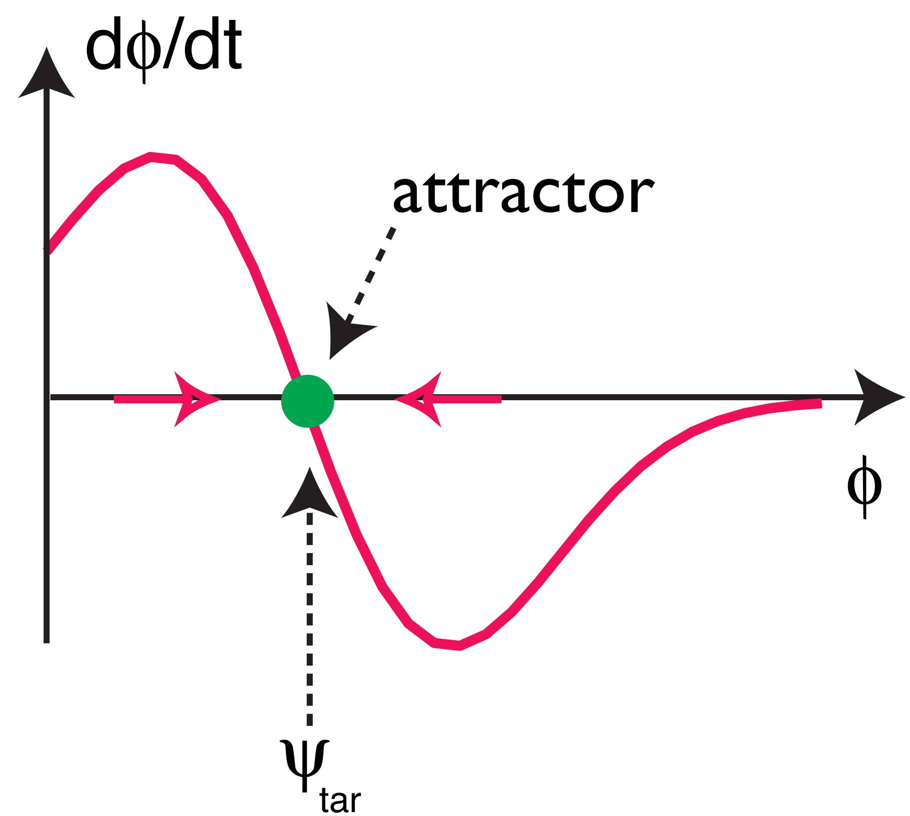
- requires high-level knowledge about objects in the world (“obstacles”, “targets”, etc) and perceptual systems that extract parameters about these.. .
- is that necessary?



Targets….

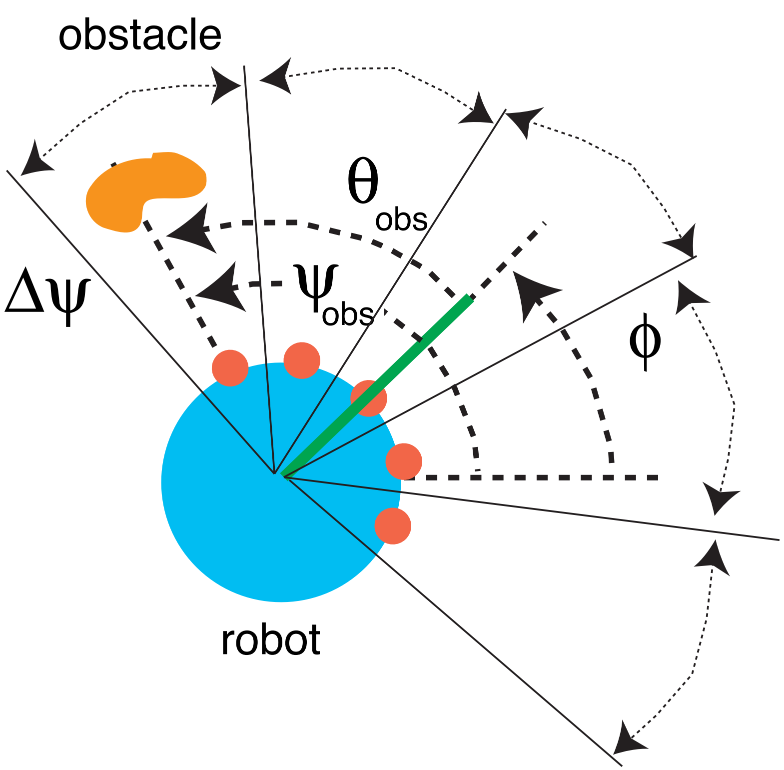
- are segmented… in the foreground
- => neural fields to perform this segmentation from low-level sensory information: Dynamic Field Theory …

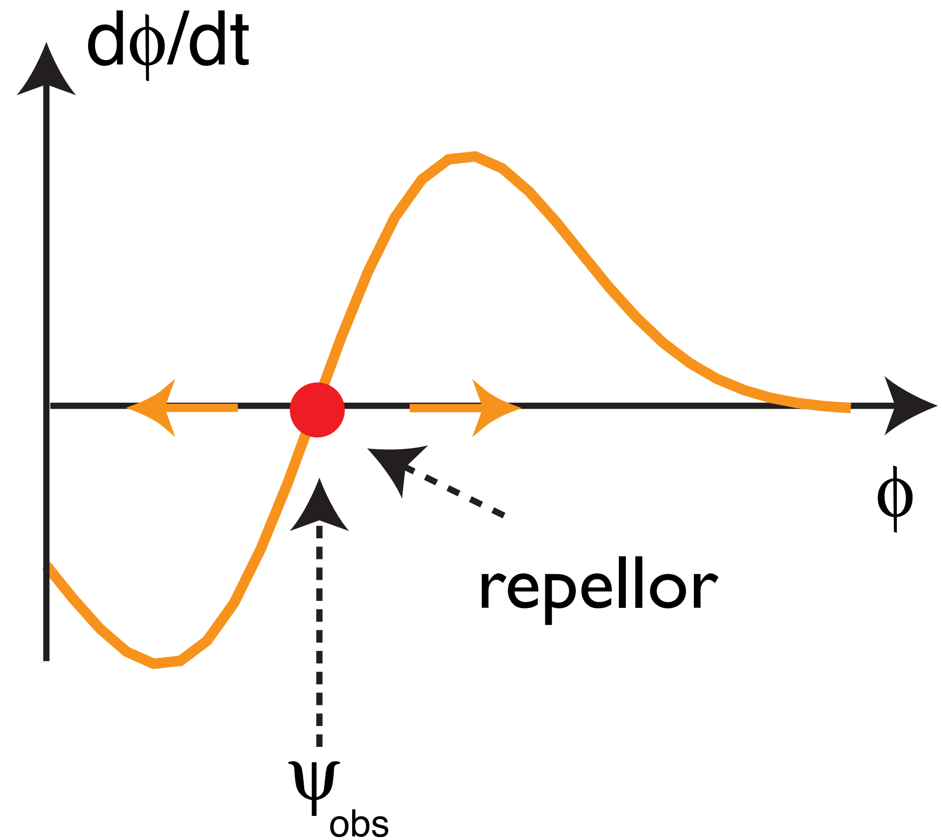




Obstacles ...

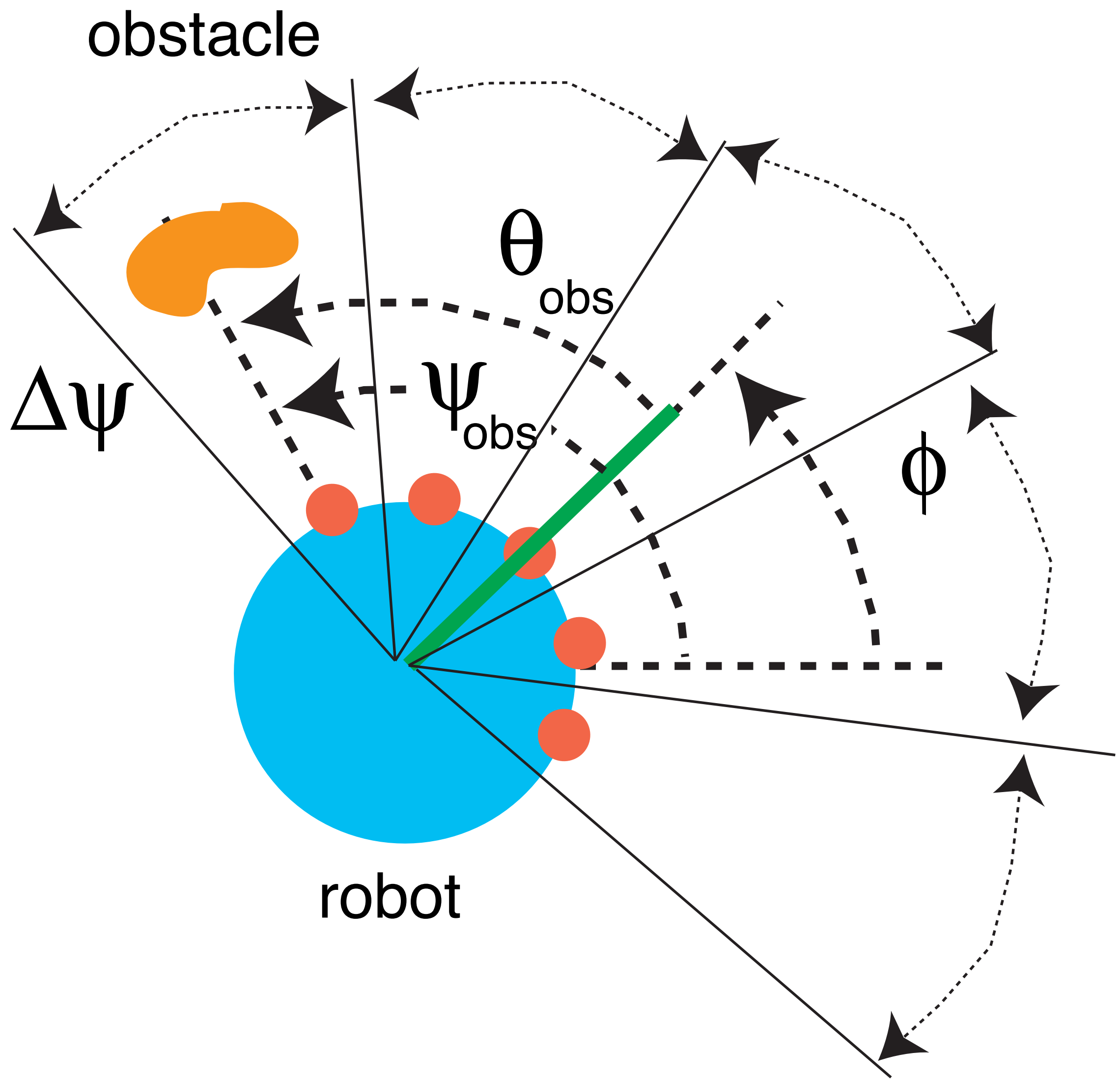
- obstacles need not be segmented ... does not matter if obstacles are one or multiple objects...
- avoidance is about free space...





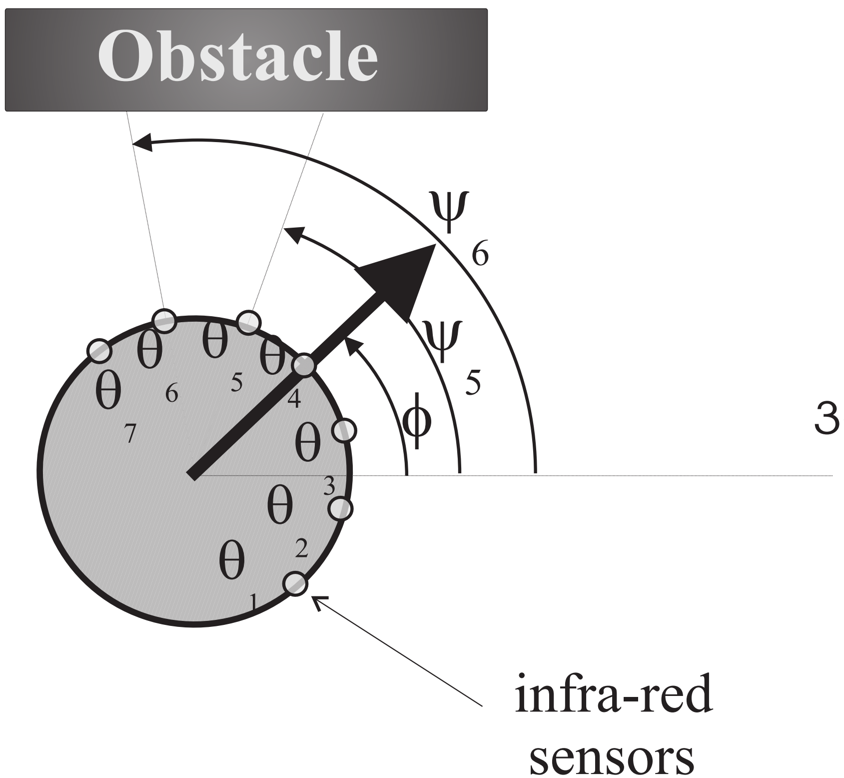
"sub-symbolic" approach

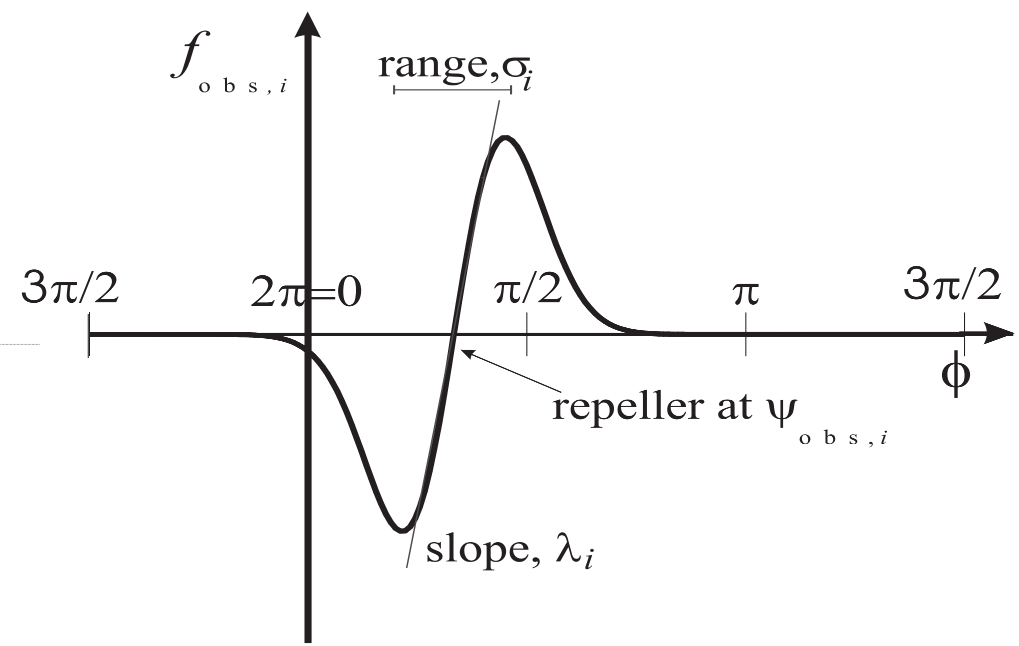
- use low-level sensory information directly, without first detecting, segmenting, and estimating objects



Obstacle avoidance: sub-symbolic

- each sensor mounted at fixed angle θ
- that points in direction ψ=Φ+θ in the world
- erect a repellor at that angle



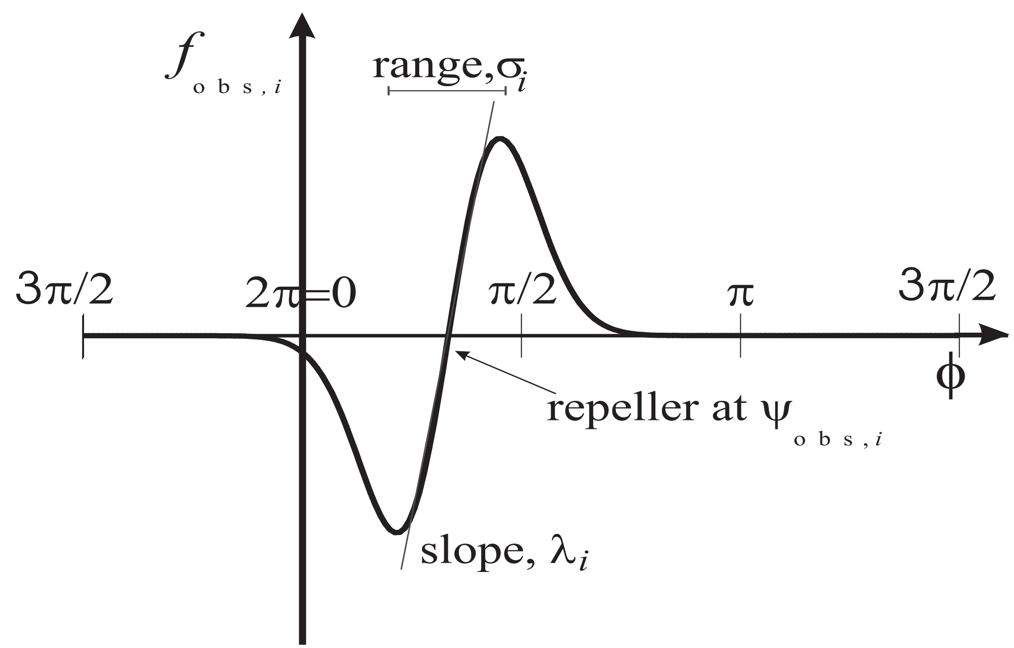


[from: Bicho, Schöner]

Obstacle avoidance: sub-symbolic

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

- Note: only Φ-ψ=-θ shows up, which is constant!
- => force-let does not depend on Φ !



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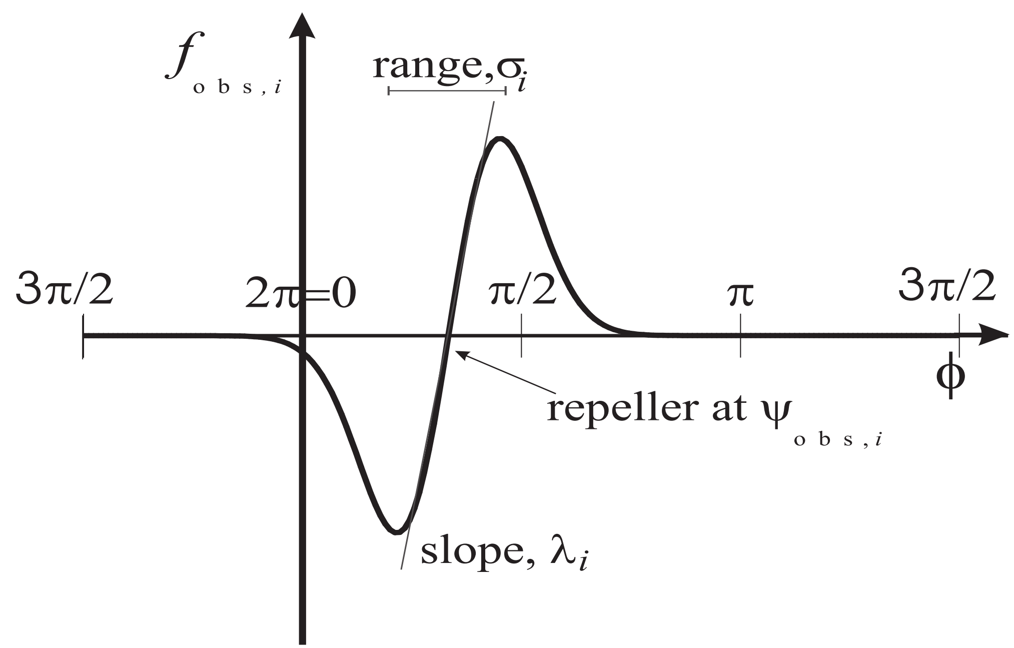
$$\lambda_i = \beta_1 \cdot \exp\left[-\frac{d_i}{\beta_2}\right]$$

- Repulsion strength decreases with distance, d_i
- => only close obstacles matter



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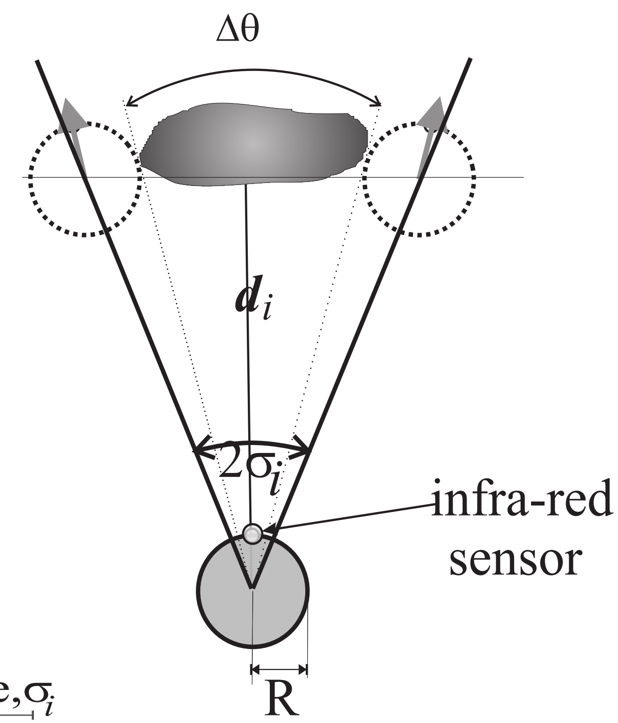
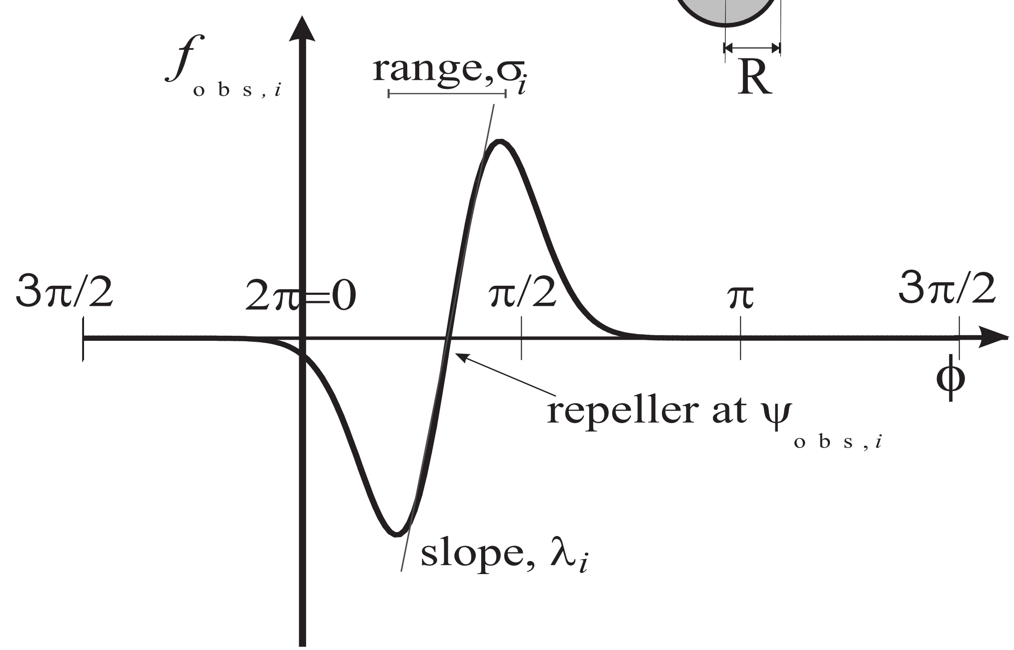
$$f_{\text{obs},i}(\phi) = \lambda_i(\phi - \psi_i)\exp\left[-\frac{(\phi - \psi_i)^2}{2\sigma_i^2}\right]$$

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



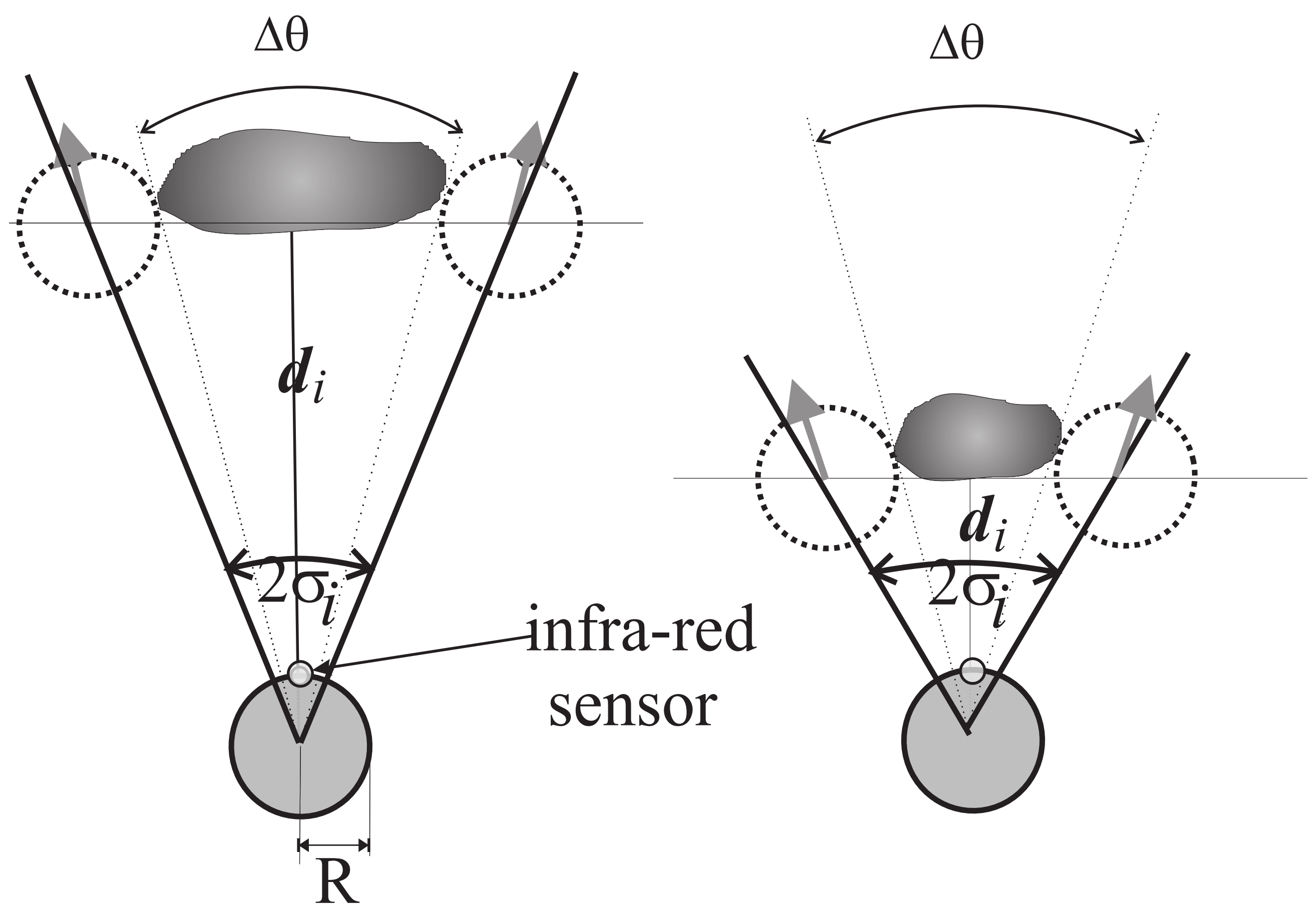


- angular range depends on sensor cone Δθ and size over distance

[from: Bicho, Schöner]

Obstacle avoidance: sub-symbolic

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

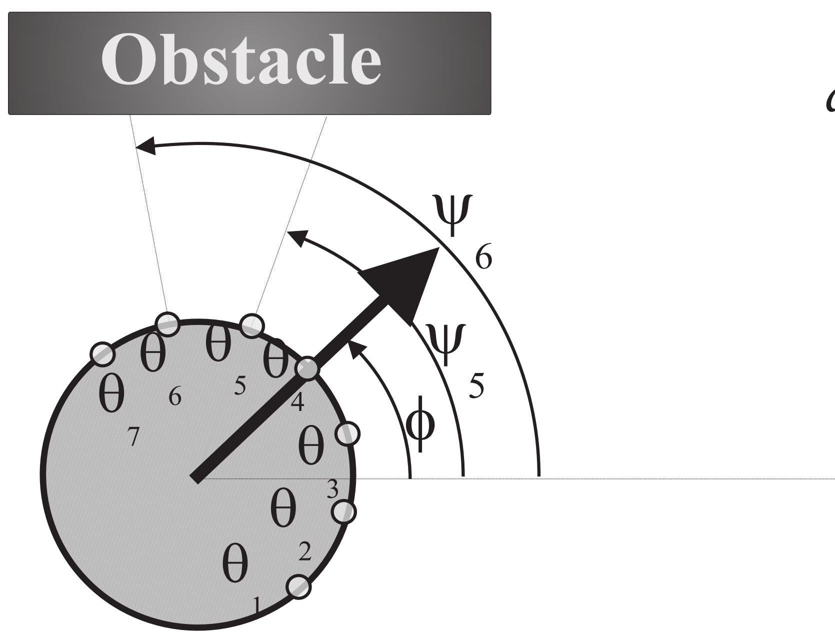


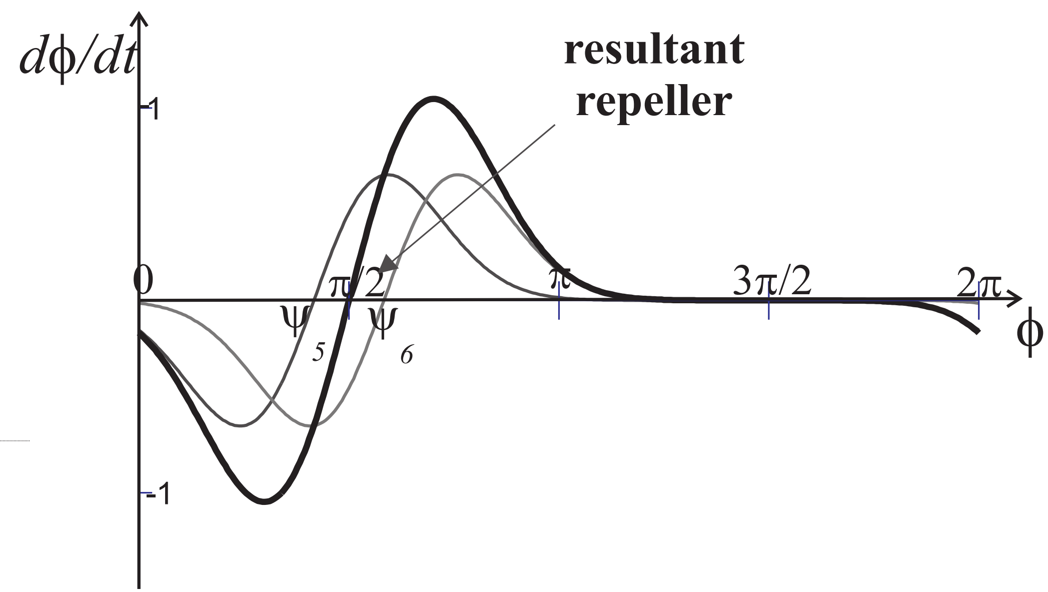
[from: Bicho, Schöner]

Obstacle avoidance: sub-symbolic

- summing contributions from all sensors

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

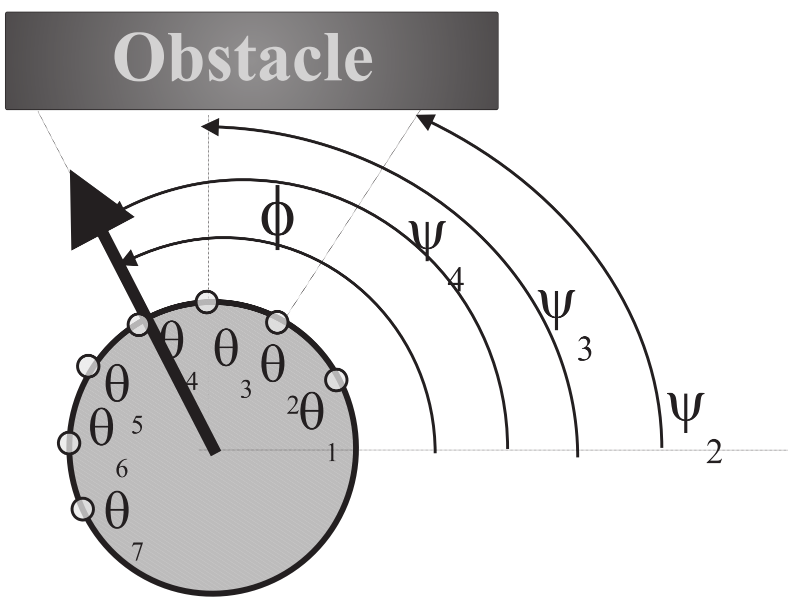


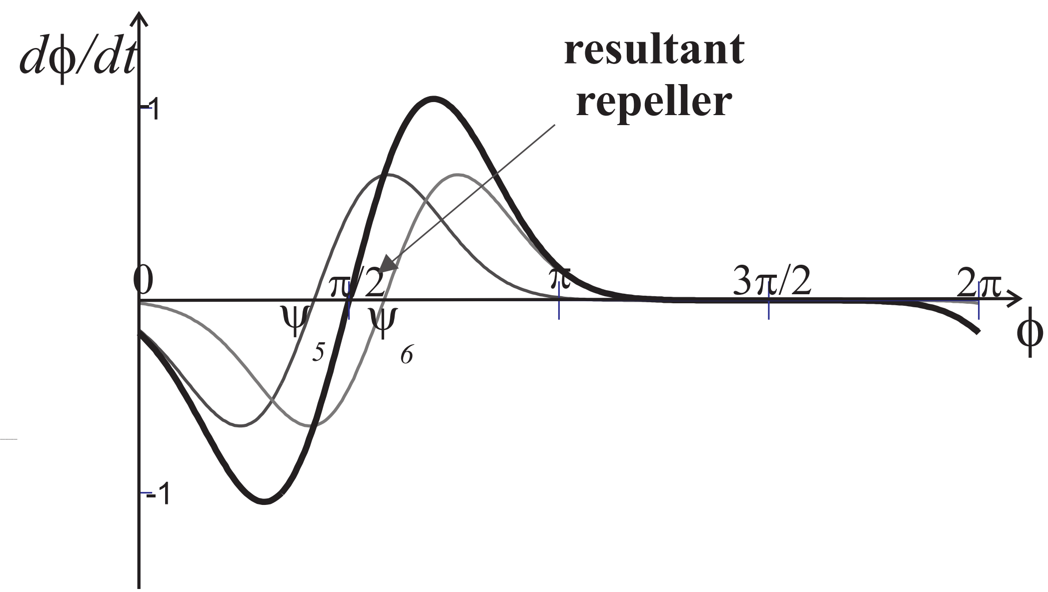


[from: Bicho, Schöner]

Obstacle avoidance: sub-symbolic

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





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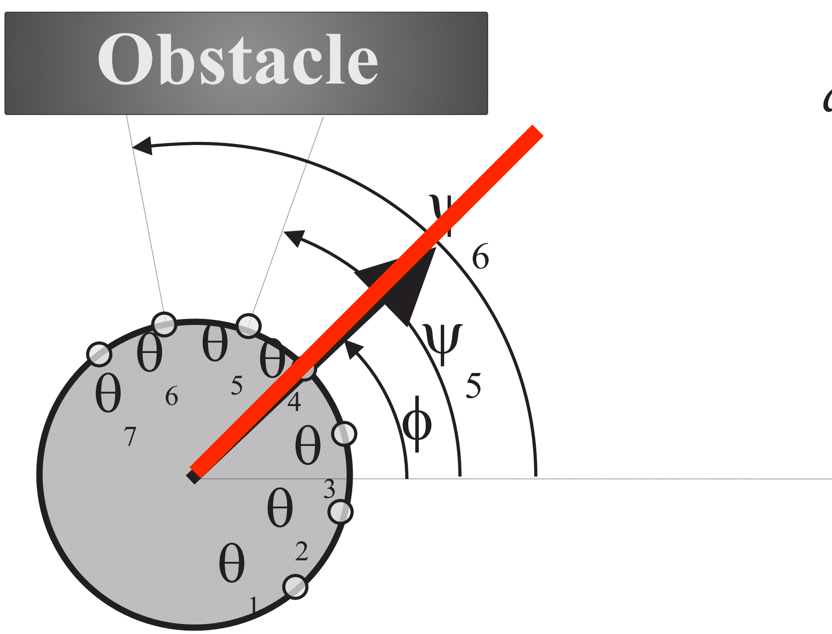

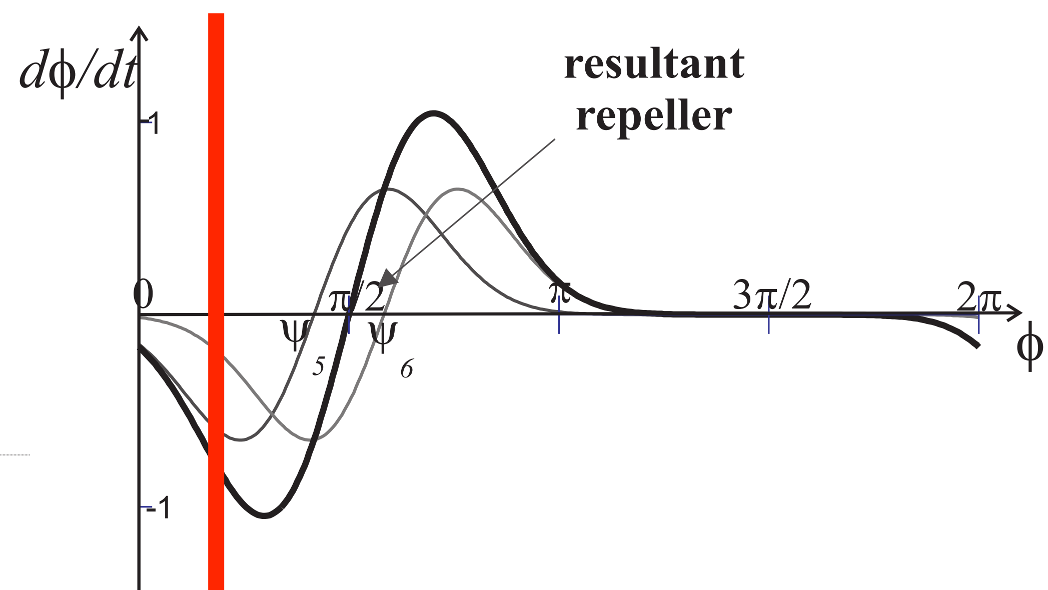

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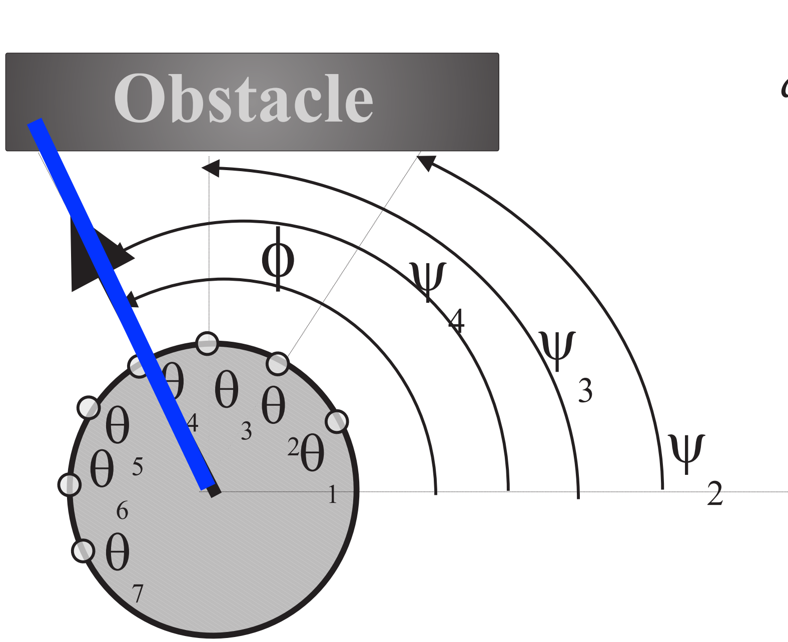

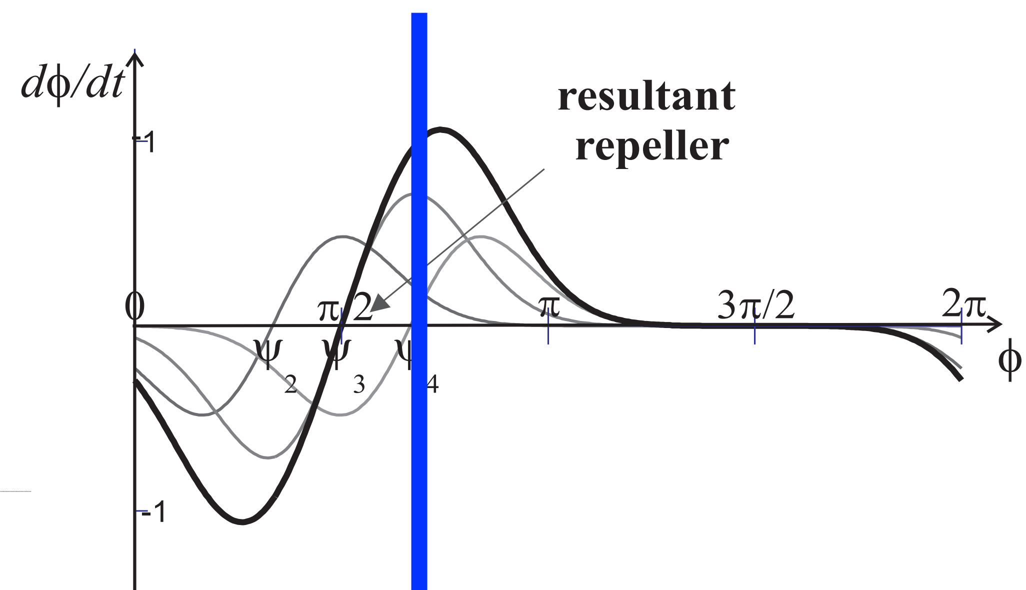

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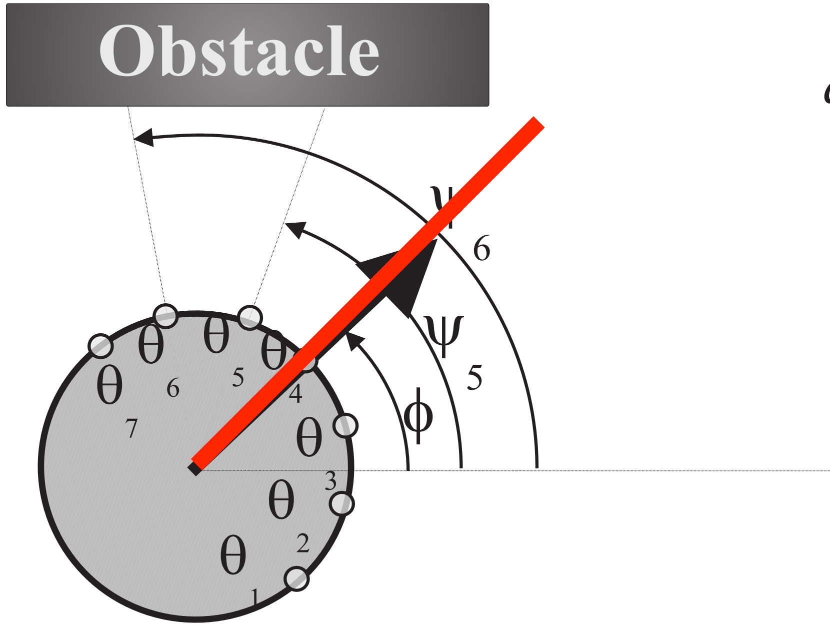
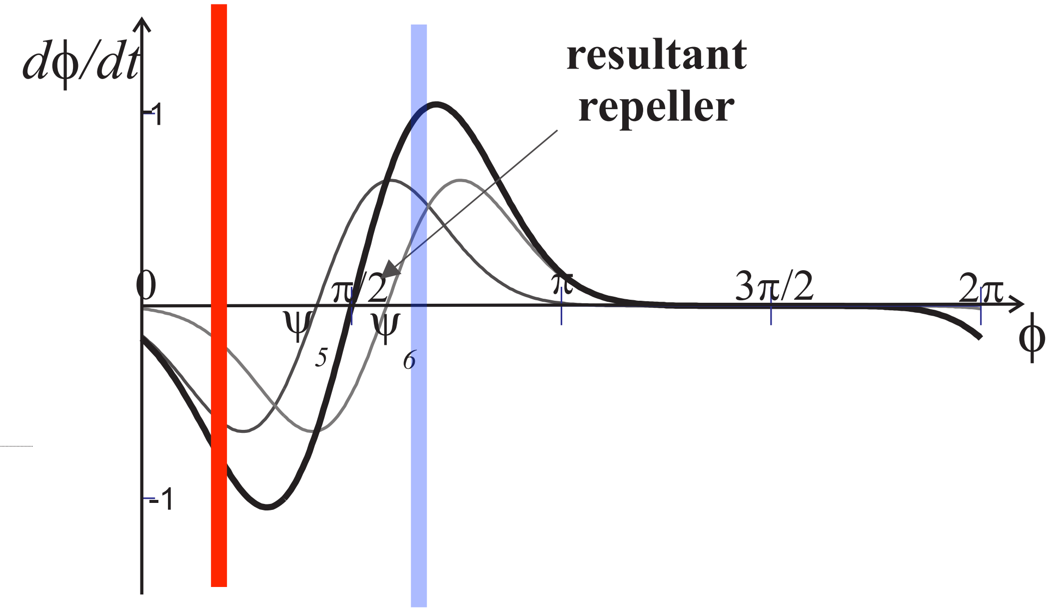
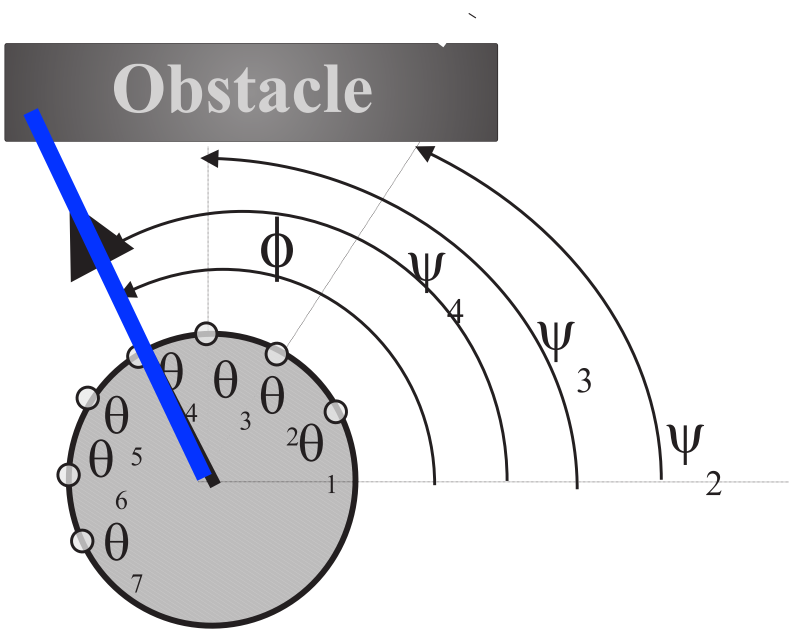
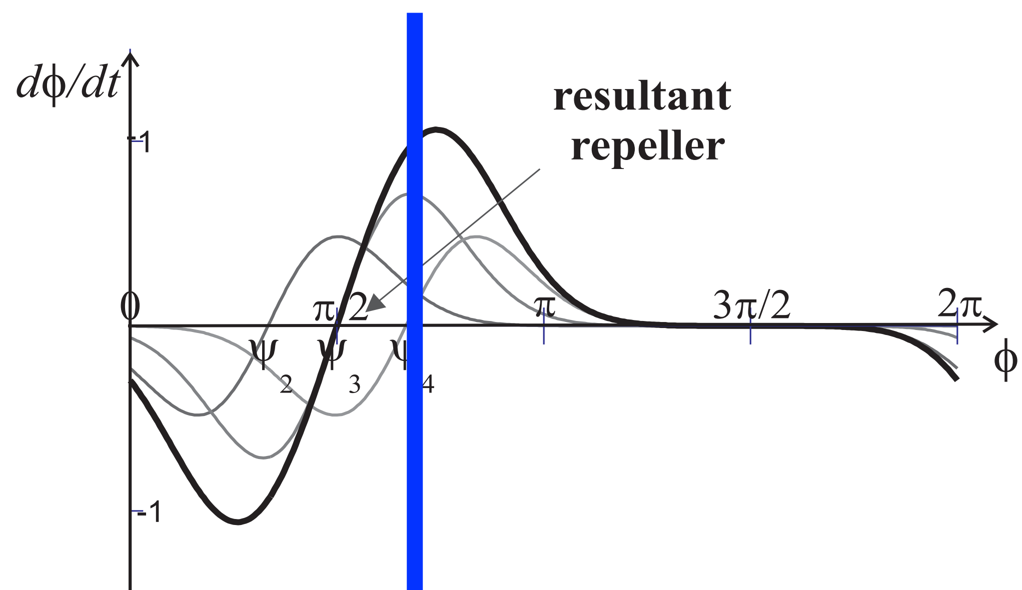








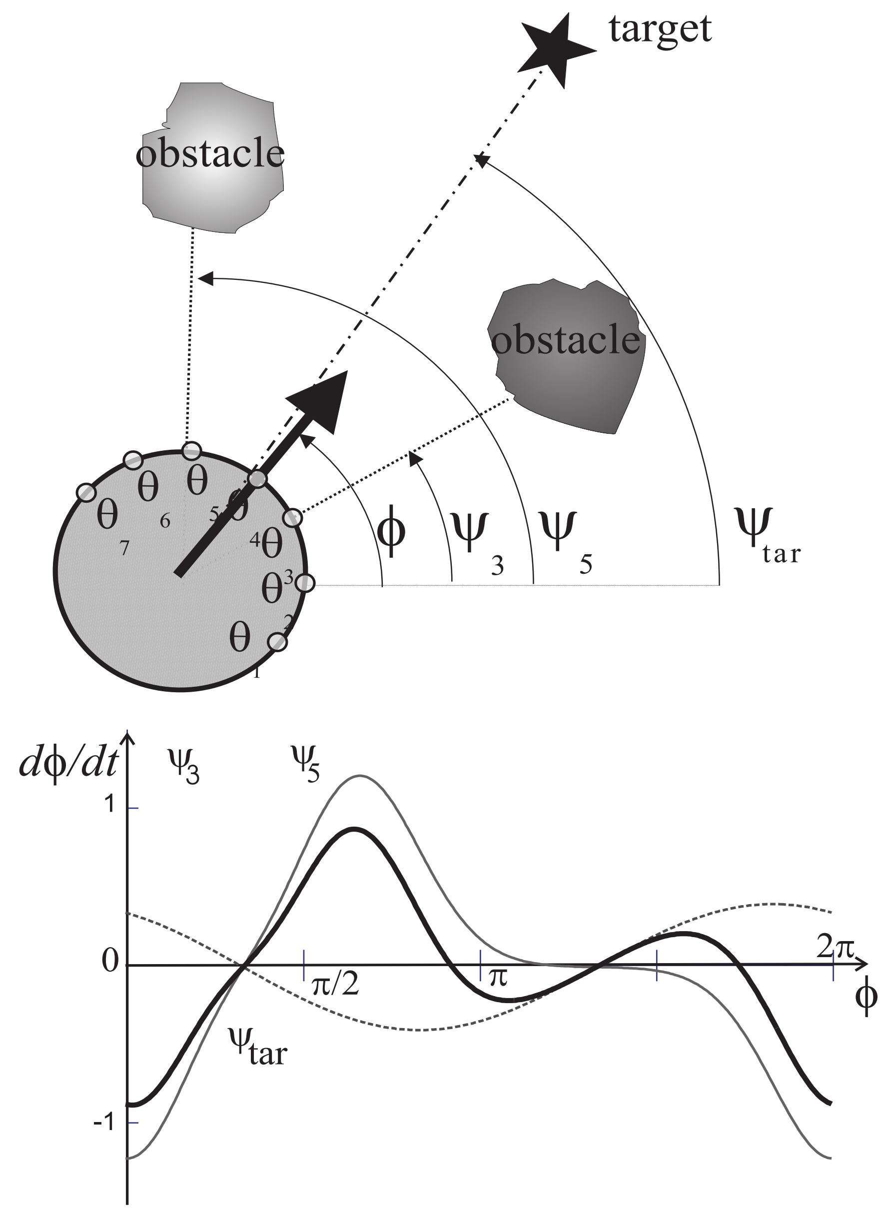
- => dynamics invariant!

[from: Bicho, Schöner]

Behavioral Dynamics

- integrating the two behaviors

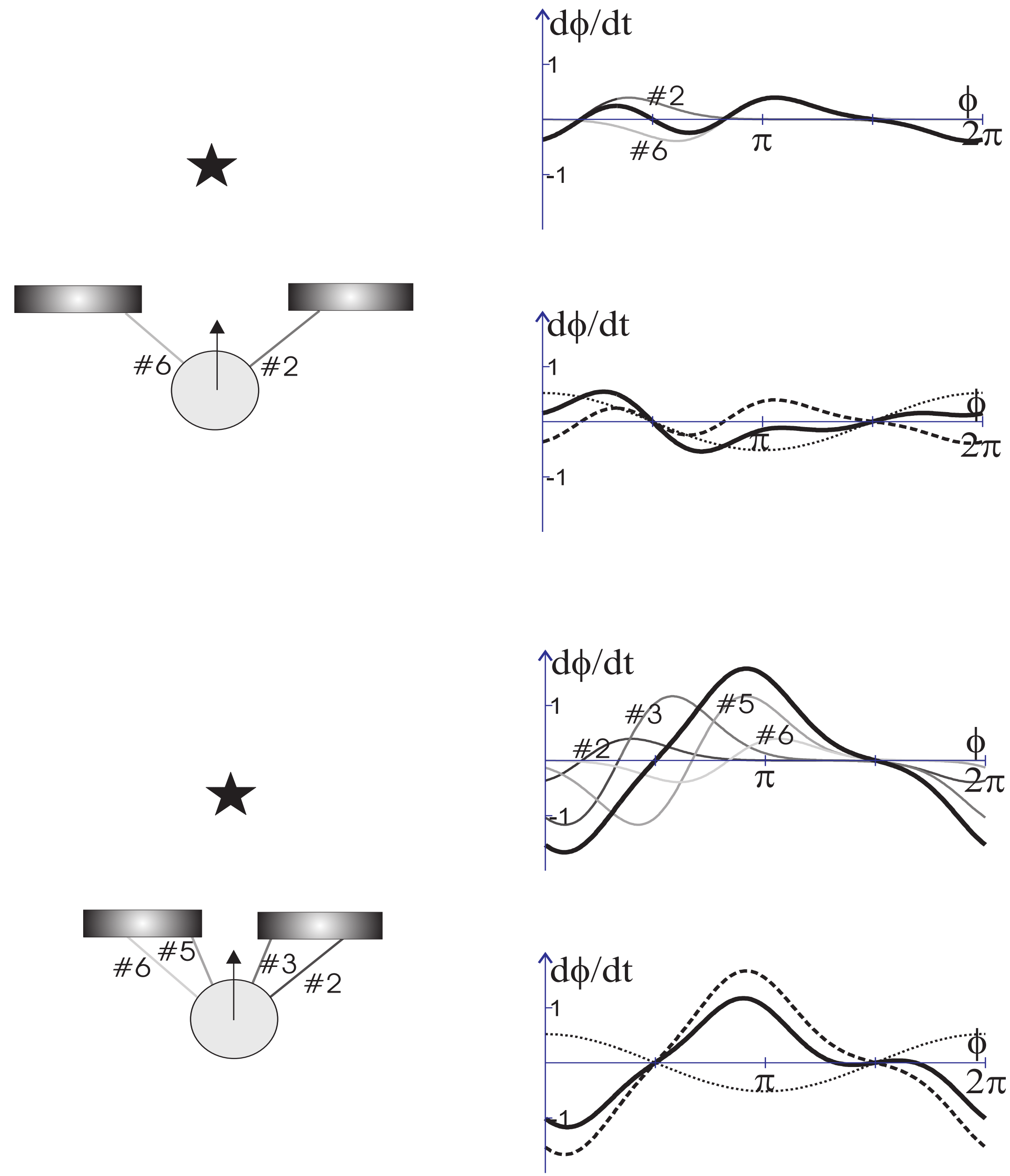
$$\frac{d\phi}{dt} = f_{\mathrm{obs}}(\phi) + f_{\mathrm{tar}}(\phi)$$



[from: Bicho, Schöner]

Bifurcations

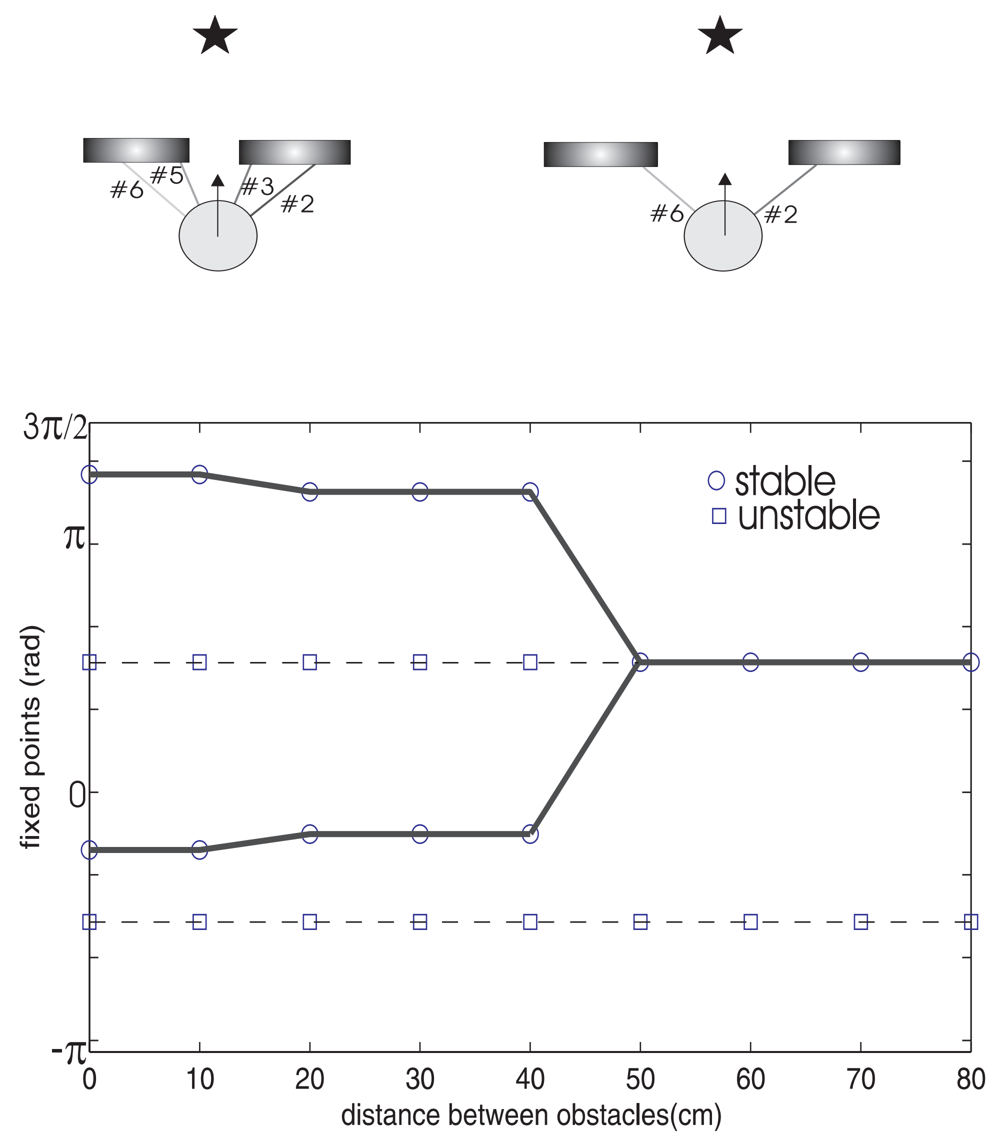
- bifurcation as a function of the size of the opening between obstacles



[from: Bicho, Schöner]

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



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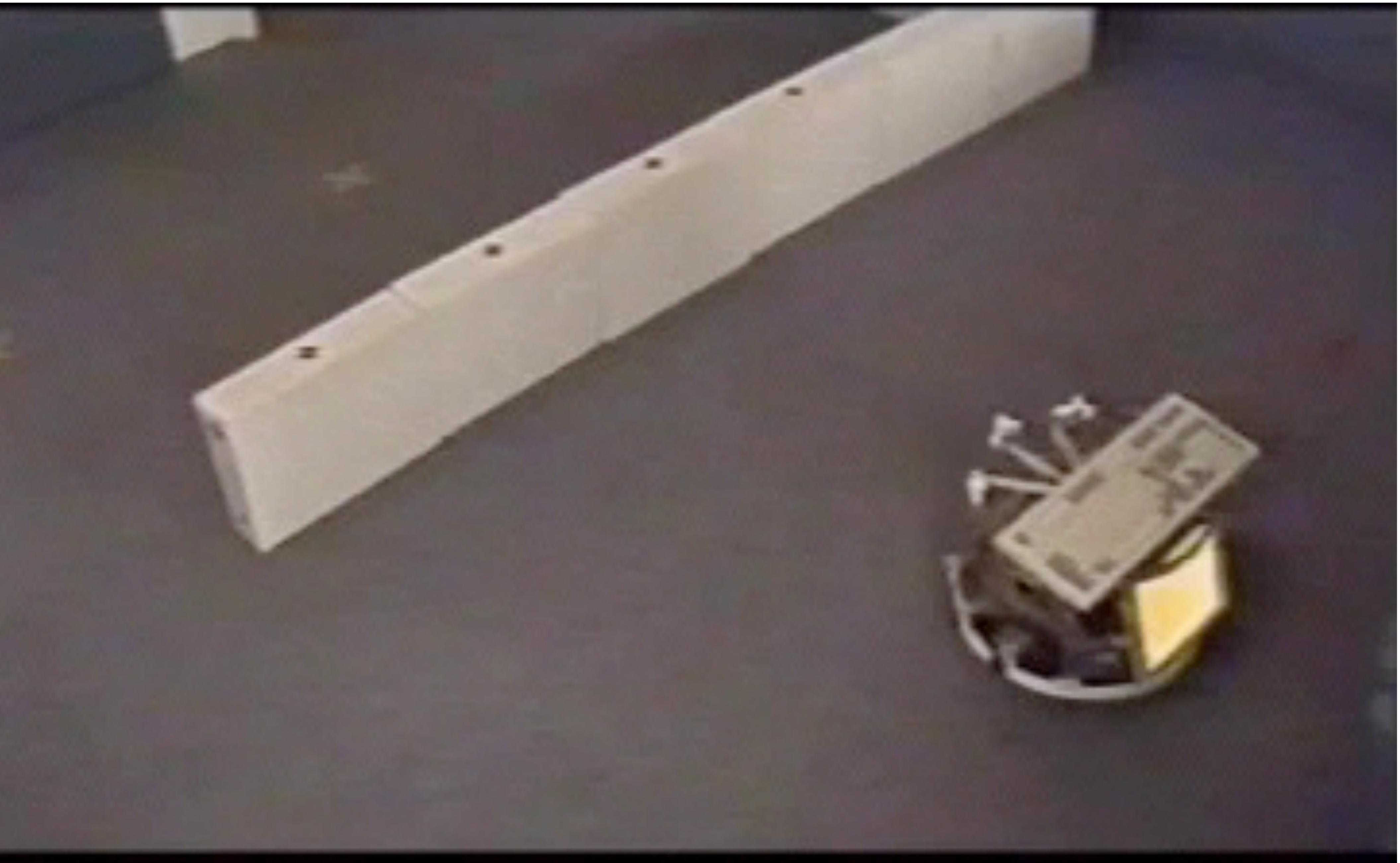
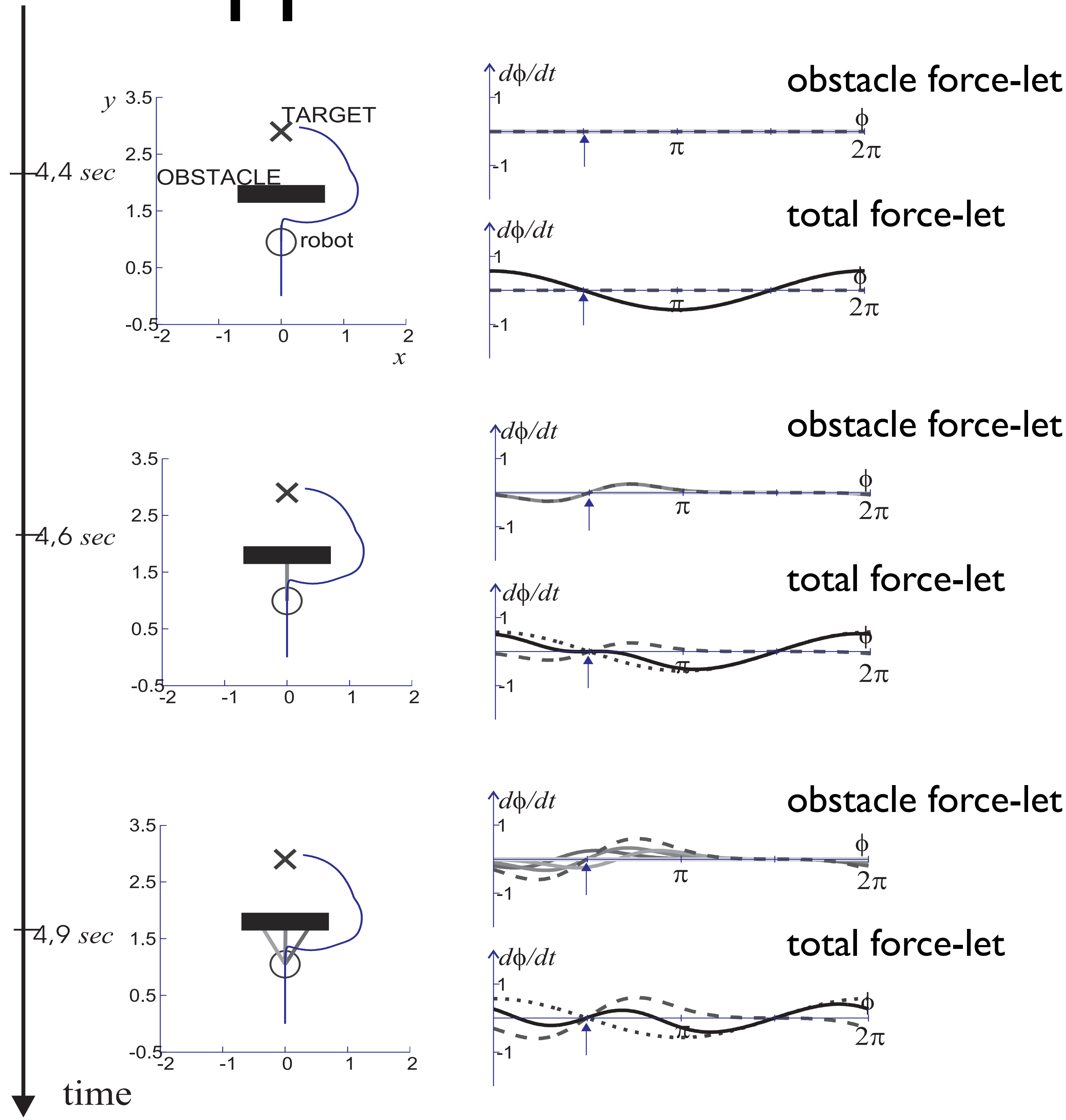


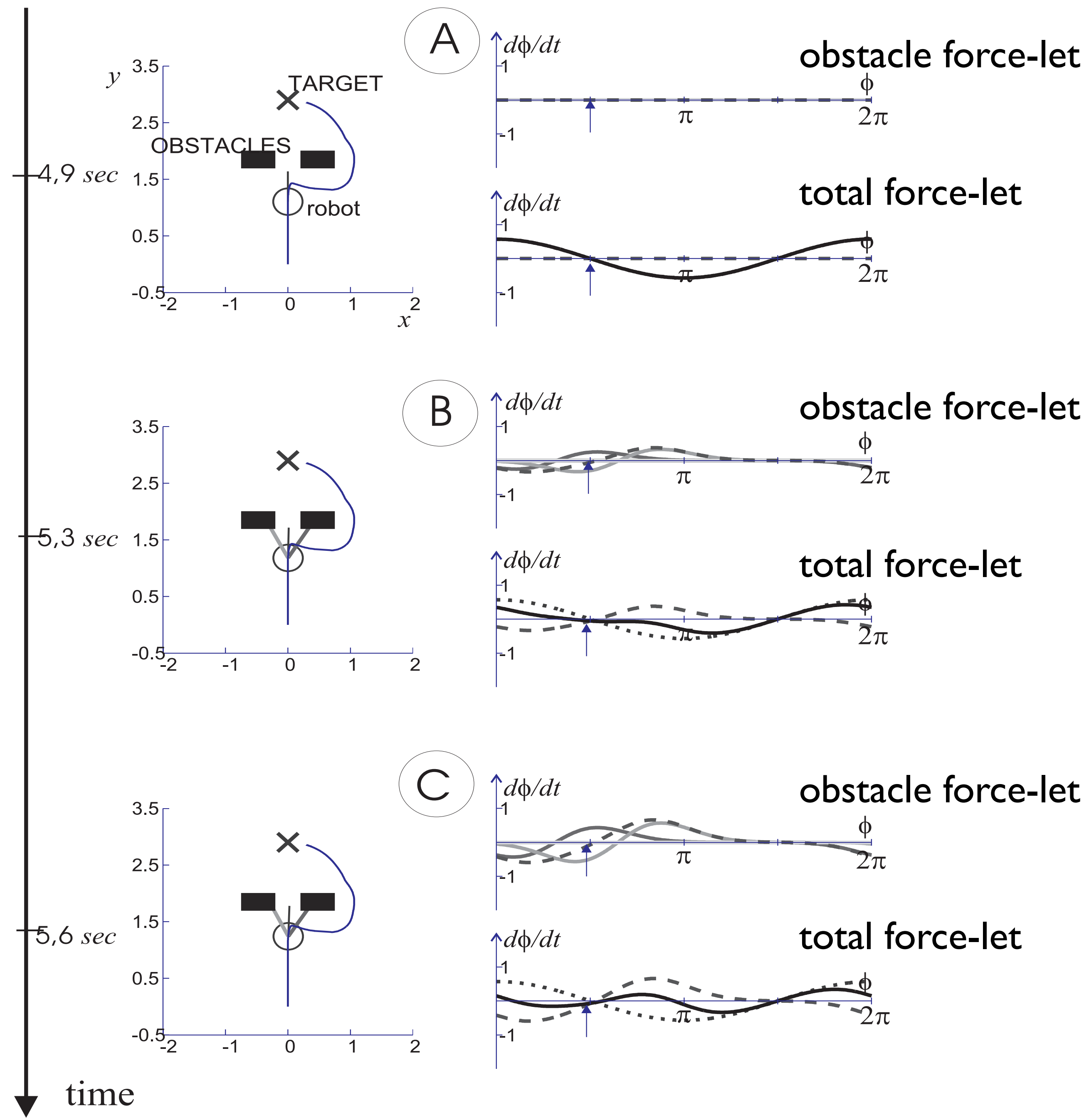
Bifurcation on approach to wall

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



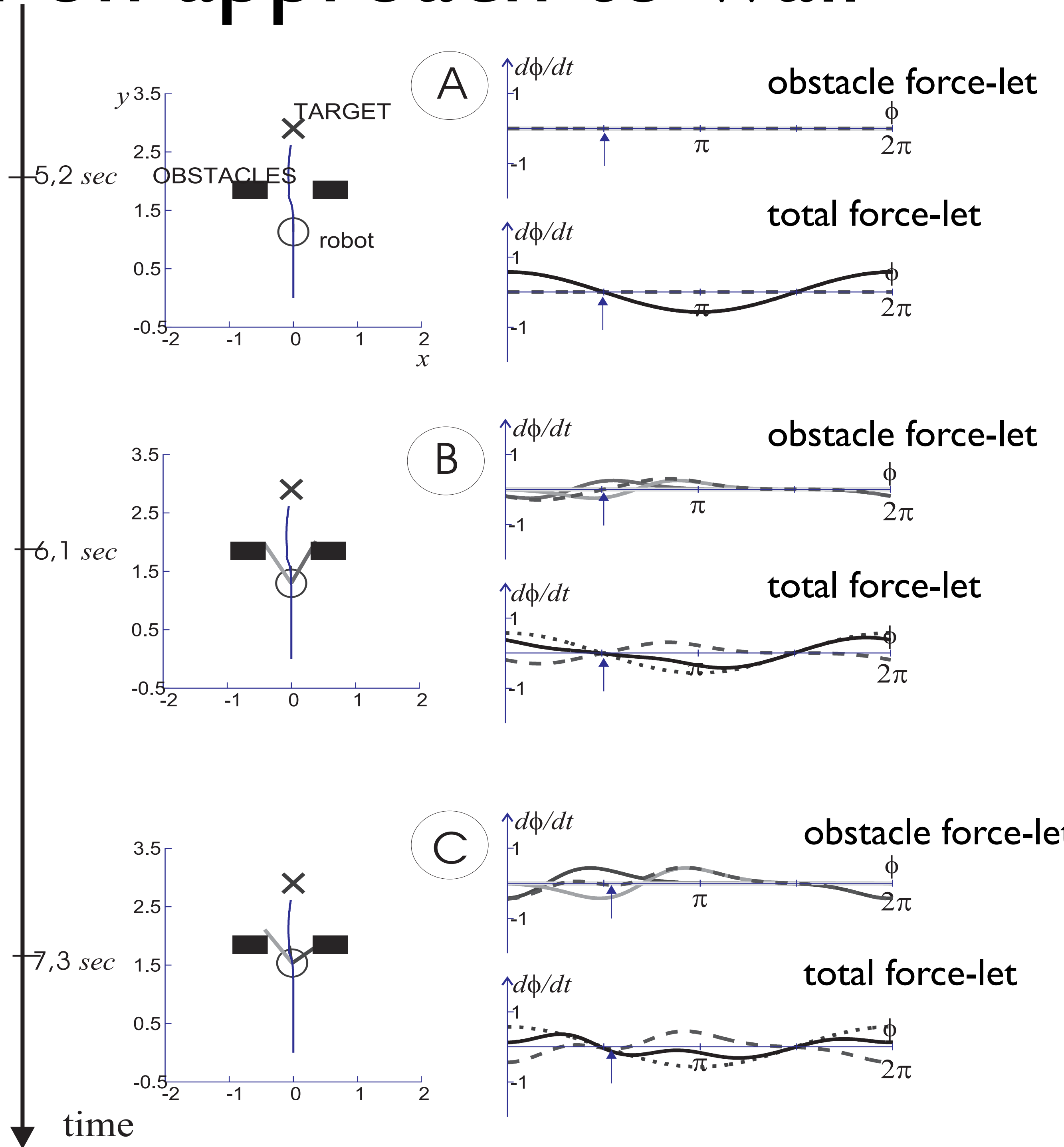
Bifurcation on approach to wall

- same with small opening



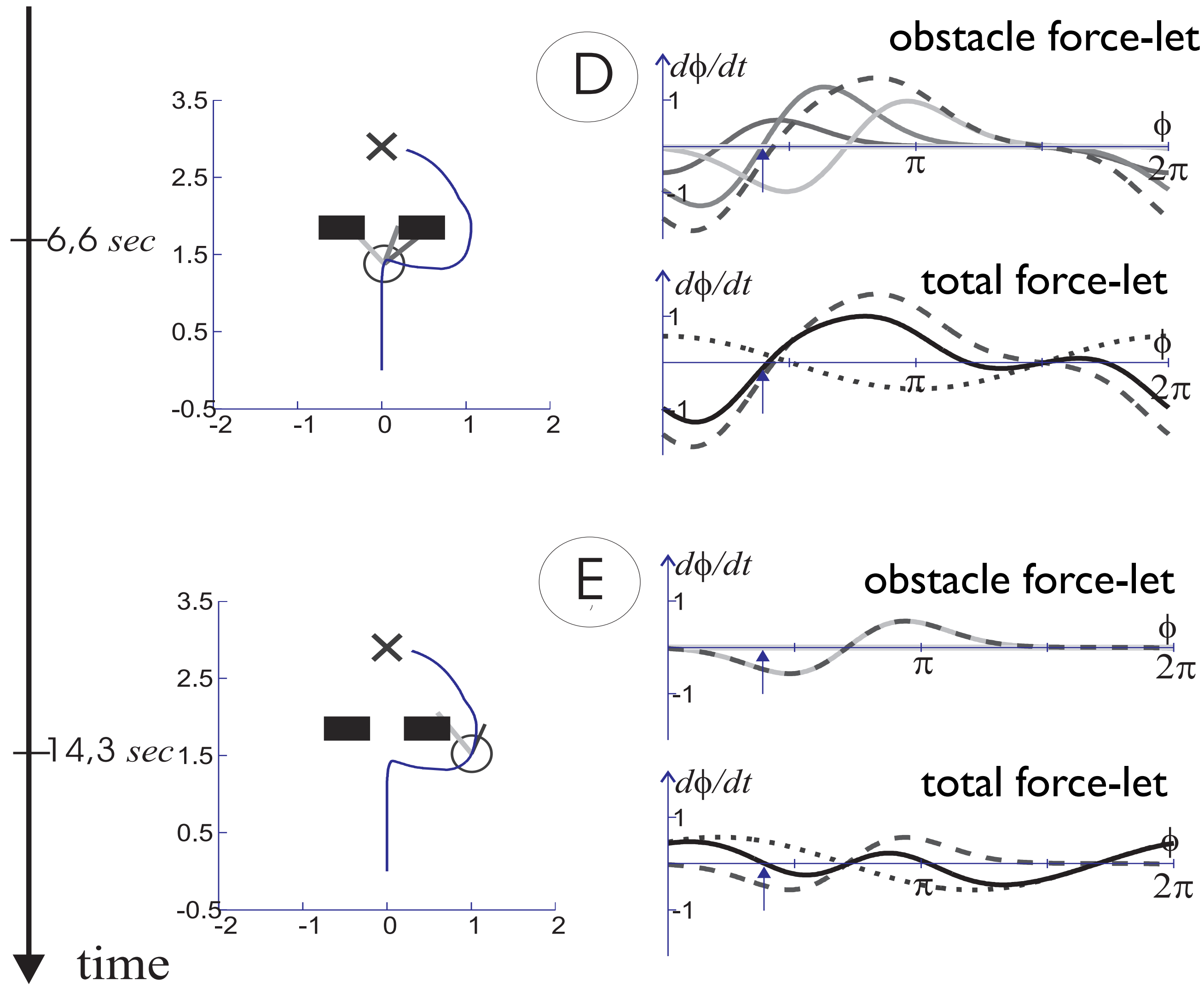
Bifurcation on approach to wall

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



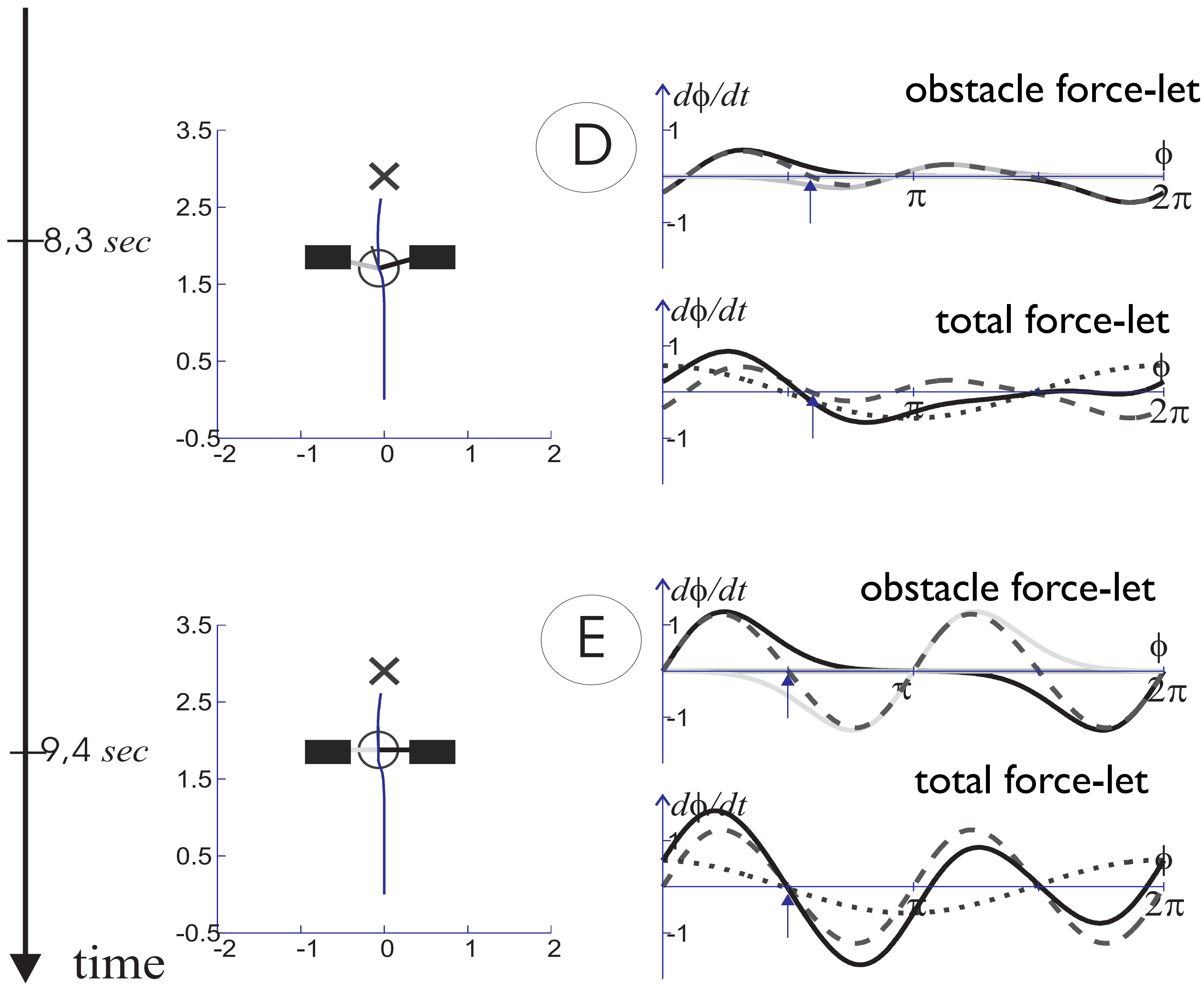
Tracking attractor

- as robot moves around obstacles, tracks the moving attractor

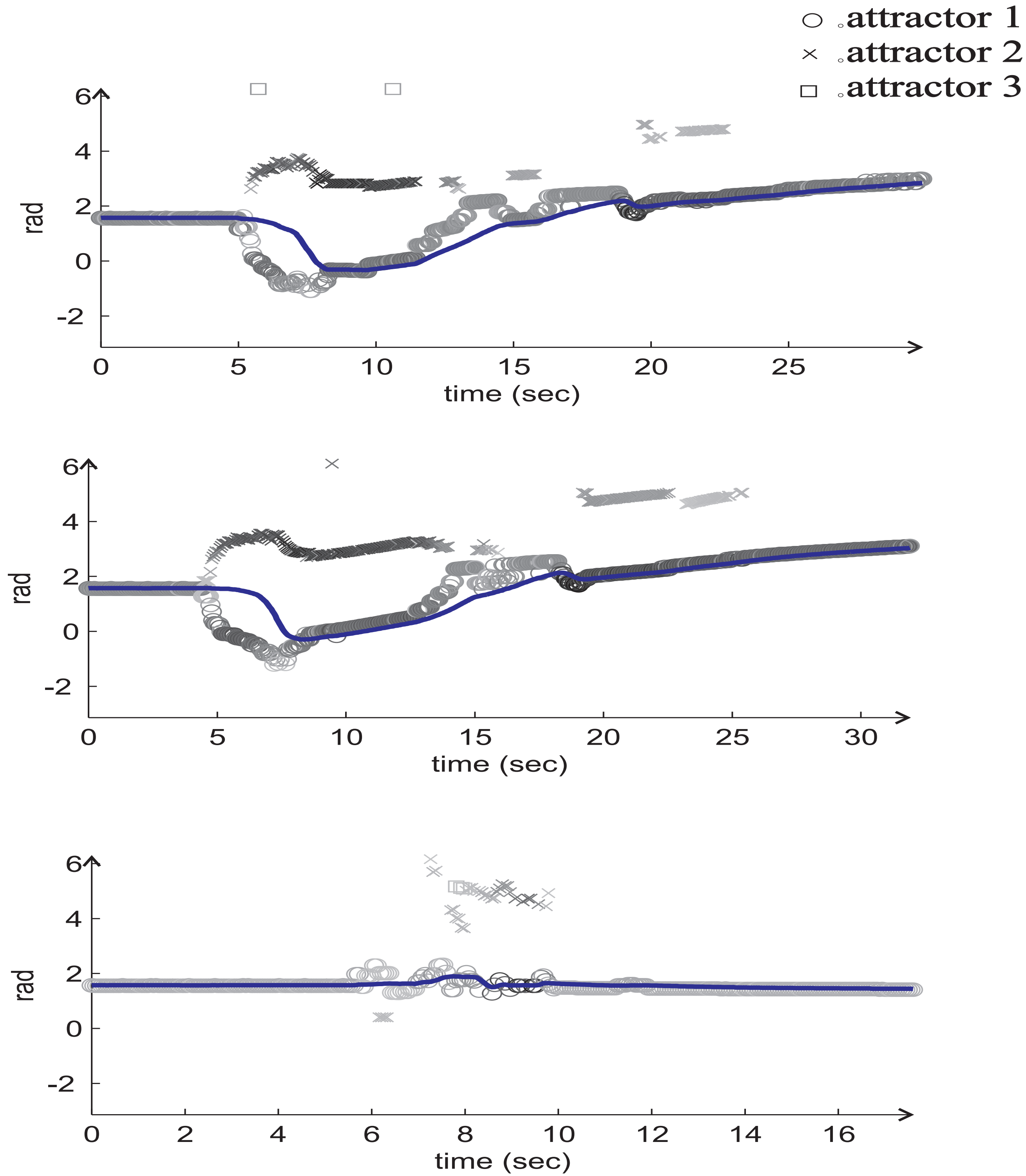


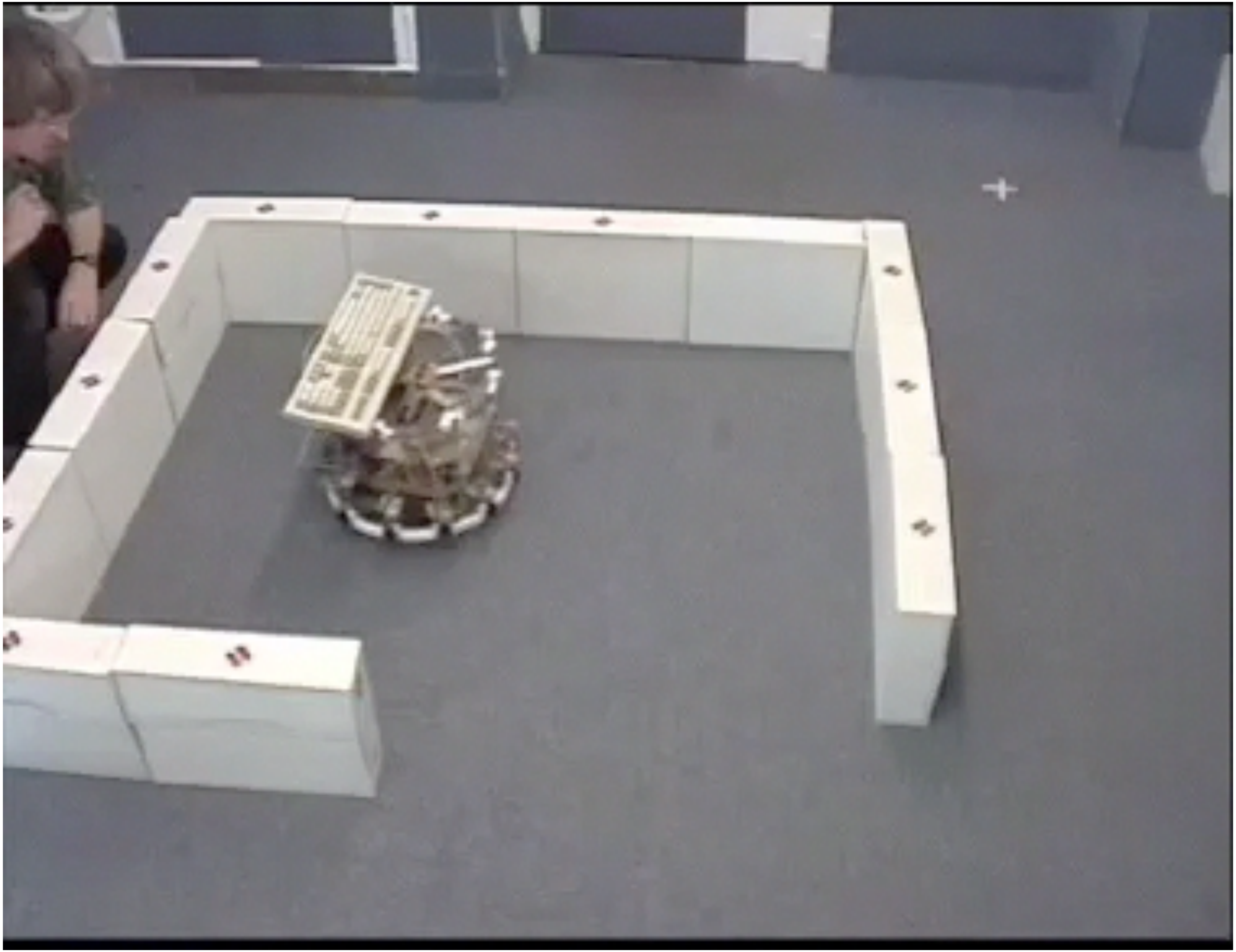
Tracking attractor

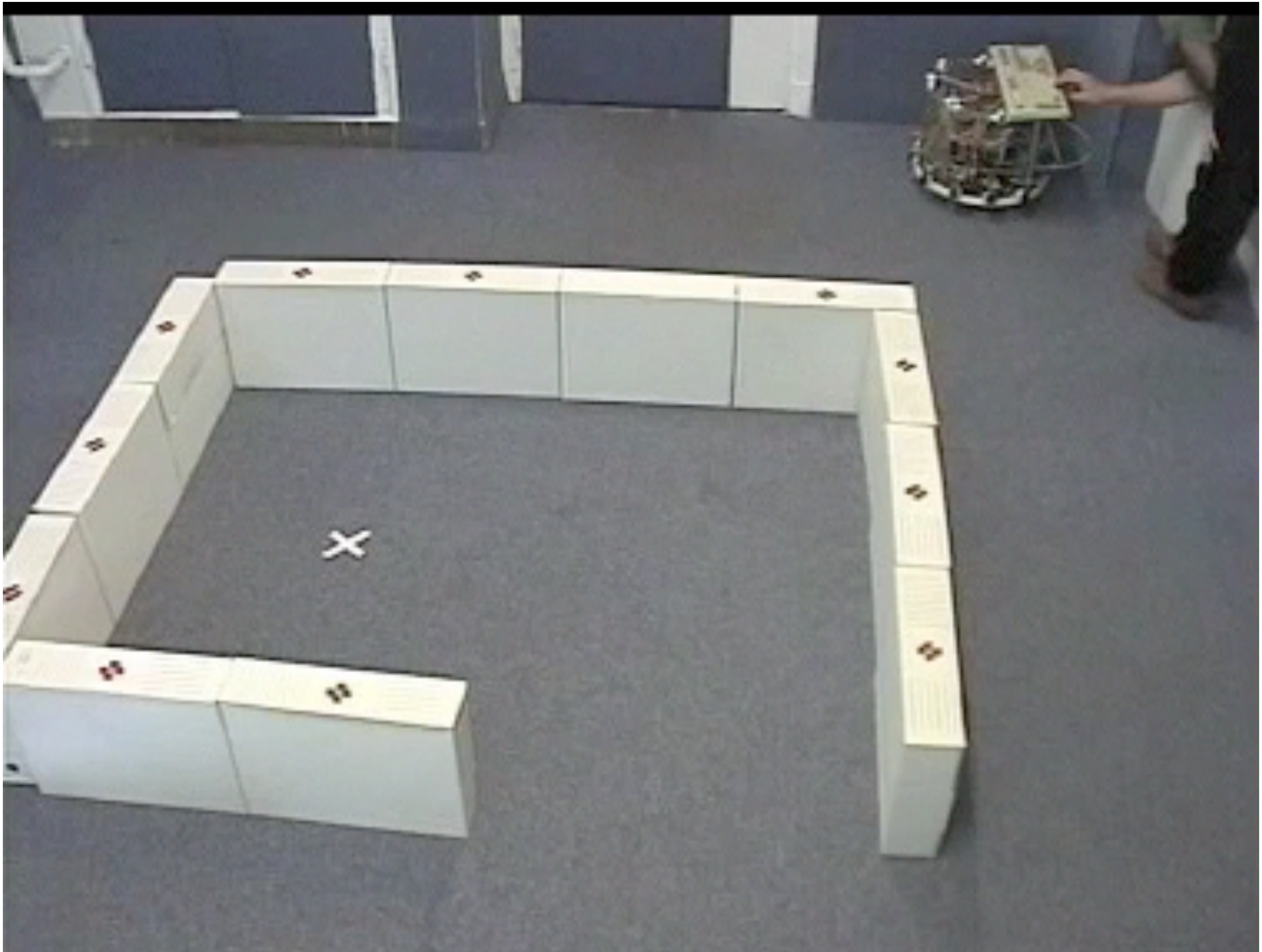
- as robot moves in between obstacles, the dynamics changes but not the attractor



Tracking attractors

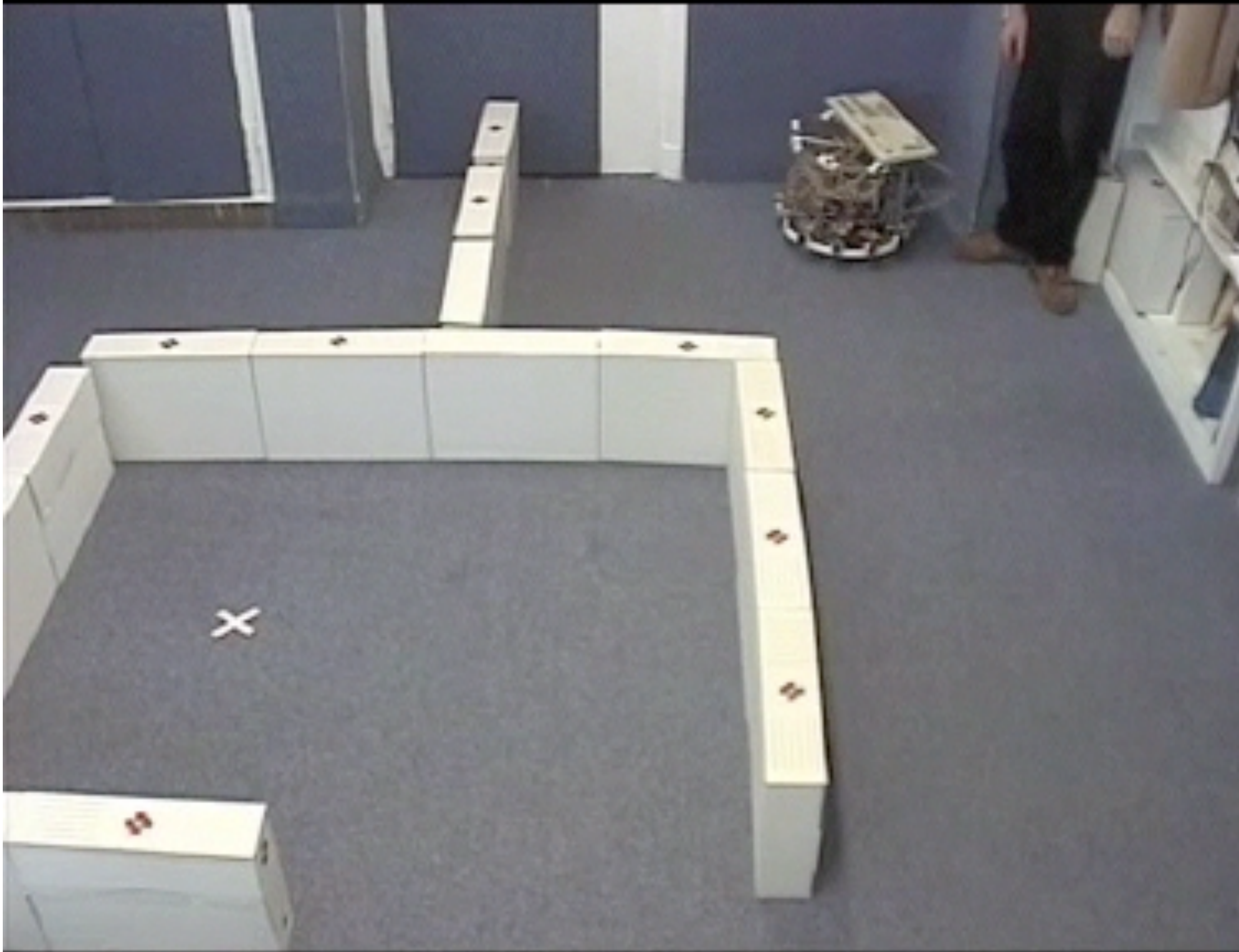






Observation:

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



Observation

- different solutions may emerge depending on the environment…

Other implementations

- autonomous wheel-chair by Pierre Mallet, Marseille

[Pierre Mallet, Marseille]

other implementations

- Estela Bicho’s cooperative robots… => exercises…

Conclusion

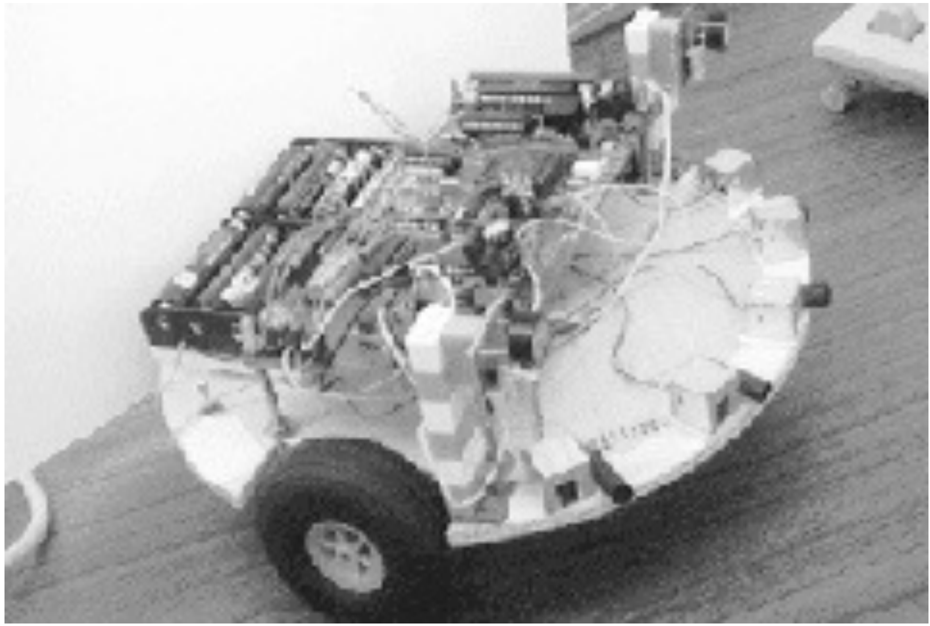
- attractor dynamics works on the basis low-level sensors information
- as long at the force-lets model the sensor-characteristics well enough to create approximate invariance of the dynamics under transformations of the coordinate frames

Second order attractor dynamics

- source: Bicho, Schöner, Robotics and Autonomous Systems 21:23-35 (1997)

Second order dynamics

- idea: go to even lower level sensory-motor systems:
  - a sensor that only knows there is a target or an obstacle on the left vs. on the right…
  - but is not able to estimate the heading of either
  - a motor system that is not calibrated well enough to steer into a given heading direction in the world



behavior variable

- turning rate omega rather than heading direction
- can be ``enacted” by setting set-points for velocity servo controllers of each motor
- target: information about target being to the left, to the right, or ahead, but no calibrated bearing, psi, to target
- obstacle: turning rate
  - to the right when obstacle close and to the left
  - to the left when obstacle close and to the right
  - zero when obstacle far

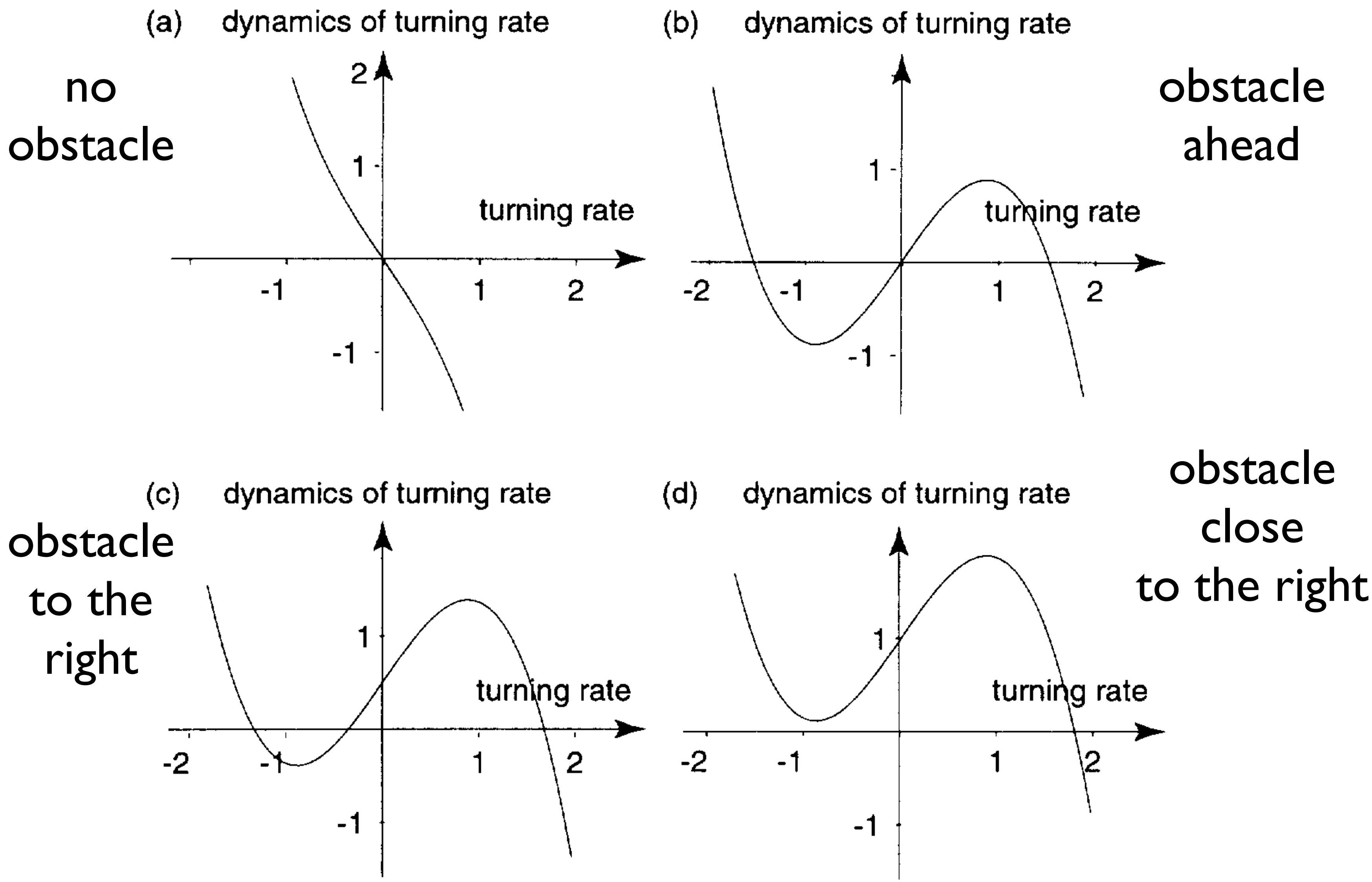
dynamics of turning rate: obstacle avoidance

- pitch-fork normal form (to get left-right symmetry)
- but symmetry potentially broken by additive constant: biases bifurcation toward left or toward right

$$\dot{\omega} = (\alpha + \tfrac{1}{2}\pi) c_{\text{obs}} F_{\text{obs}} + \alpha \omega - \gamma \omega^3$$

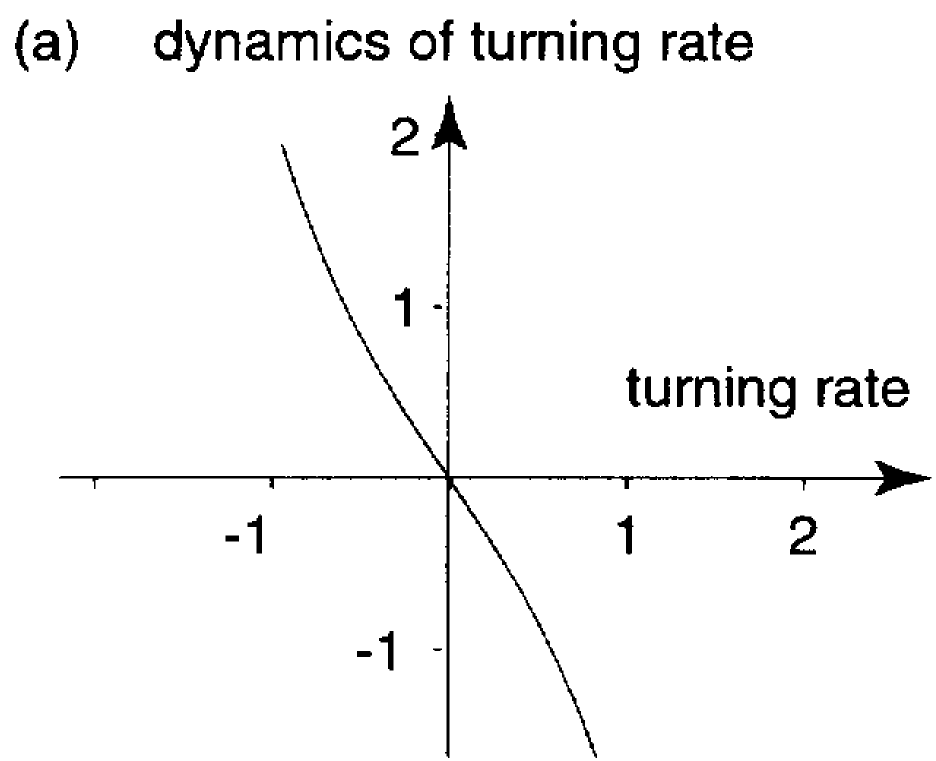
obstacle avoidance

$$\dot{\omega} = (\alpha + \tfrac{1}{2}\pi) c_{\text{obs}} F_{\text{obs}} + \alpha\omega - \gamma\omega^3$$



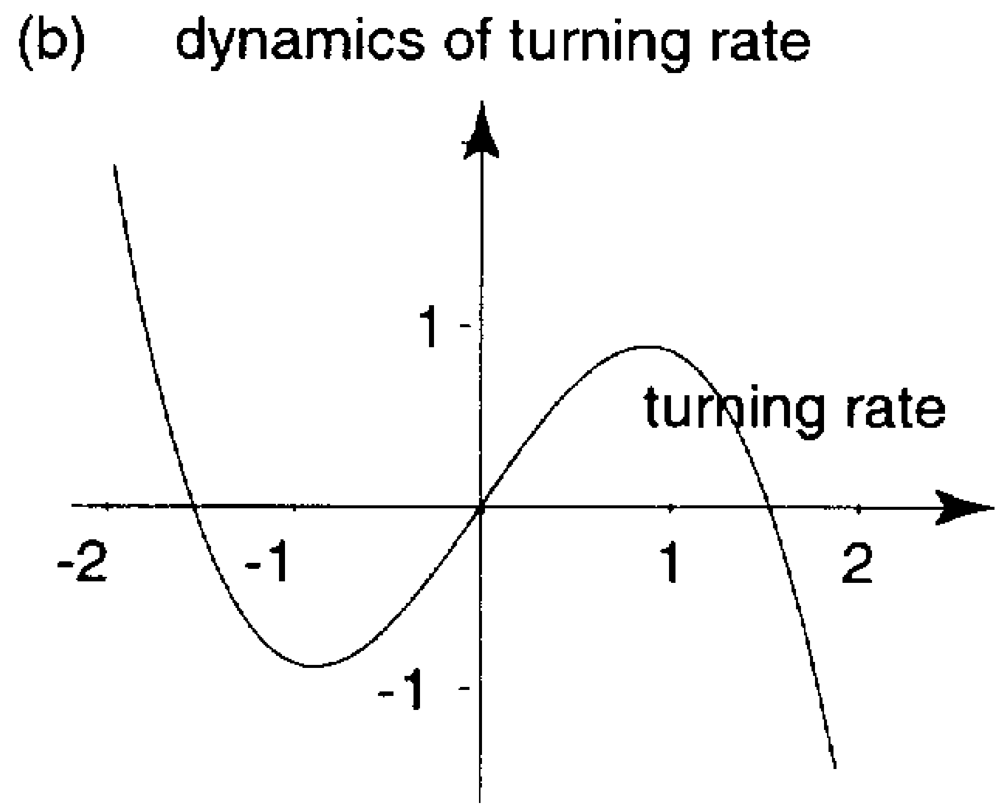
obstacle avoidance

- in absence of obstacle in forward direction (distance large): alpha negative, constant zero



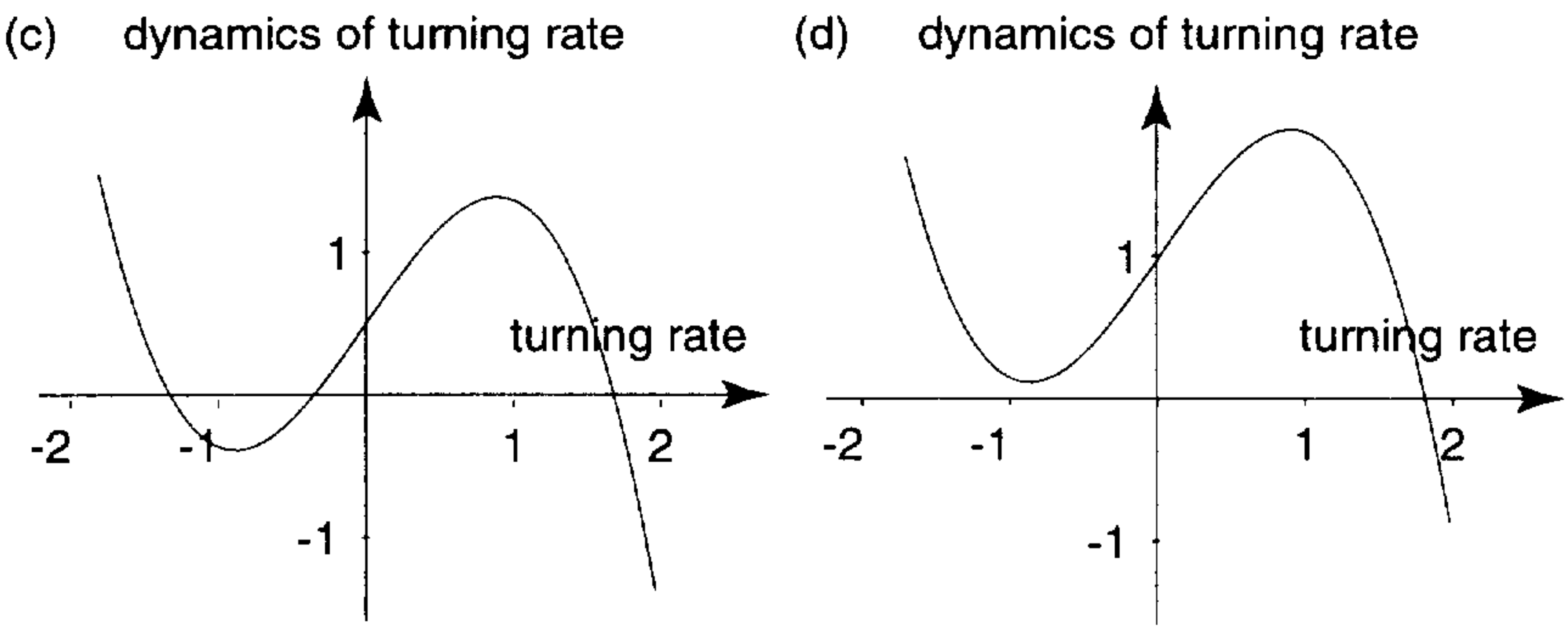
obstacle avoidance

- in presence of obstacle in forward direction, symmetric bifurcation to desired avoidance rotations: alpha positive, constant zero



obstacle avoidance

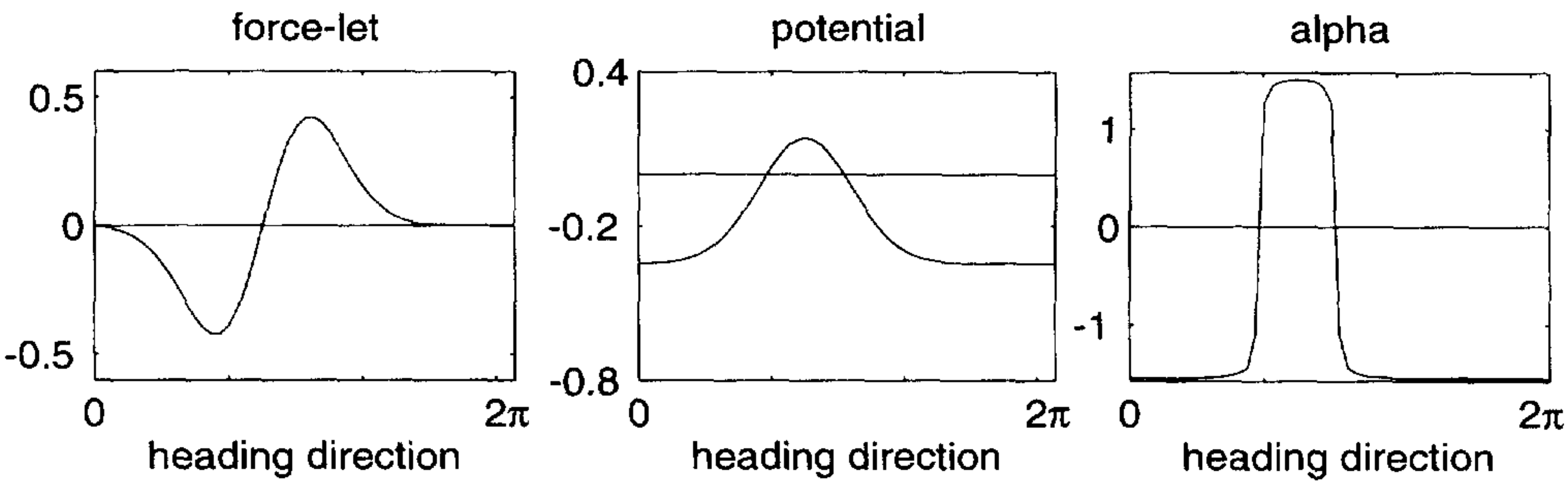
- in presence of obstacle to the right of current heading: tangent bifurcation removes attractor at negative omega, alpha negative, constant negative



mathematical form

- compute constant and alpha from obstacle force lets

$$\dot{\omega} = (\alpha + \tfrac{1}{2}\pi) c_{\text{obs}} F_{\text{obs}} + \alpha\omega - \gamma\omega^3$$



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

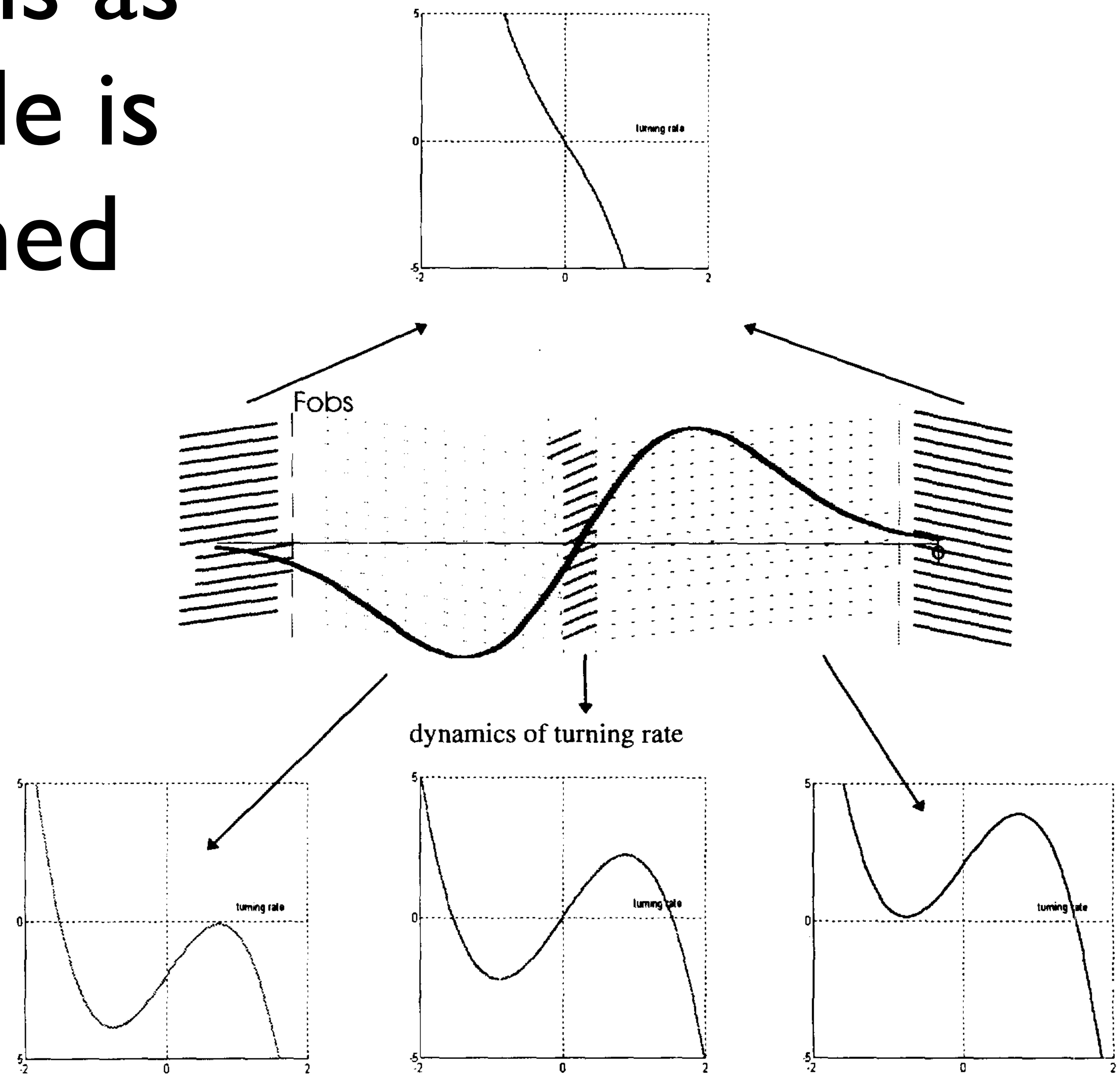
$$\lambda_i = \beta_1 \exp[-d_i/\beta_2]$$

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

$$V = \sum_i \left(\lambda_i \sigma_i^2 \exp\left[-\frac{\theta_i^2}{2\sigma_i^2}\right] - \frac{\lambda_i \sigma_i^2}{\sqrt{e}}\right)$$

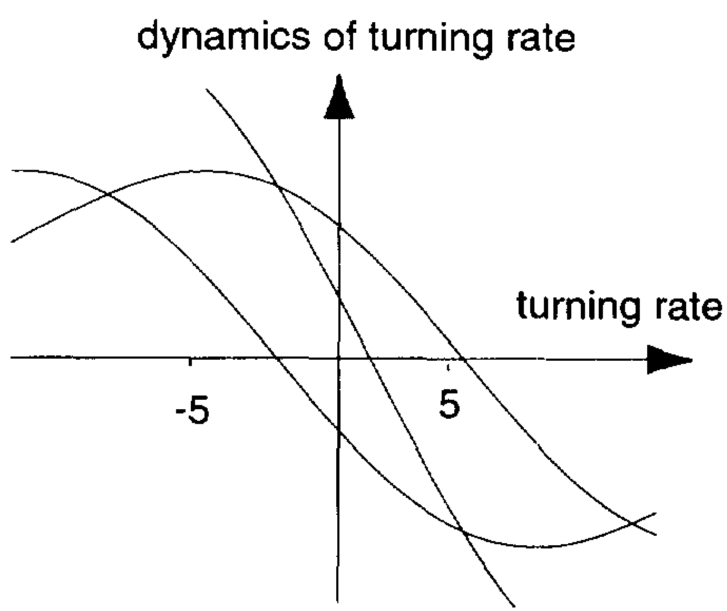
$$\alpha = \arctan[c \quad V]$$

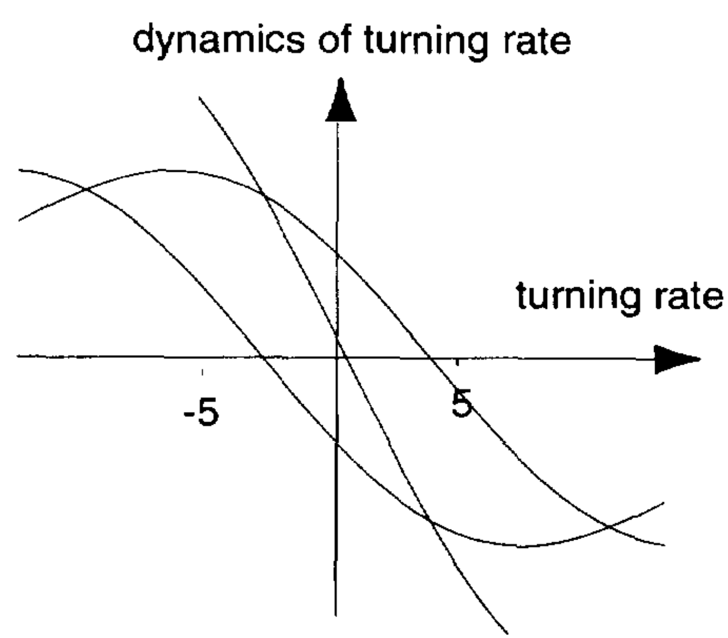
bifurcations as an obstacle is approached



dynamics: target acquisition

- a sensor for a target on the left sets an attractor at positive turning rate, strength graded with intensity
- a sensor for a target on the right sets an attractor at negative turning rate, strength graded with intensity





mathematical formulation

- force-let of each target sensor

$$g_i(\omega) = -\frac{1}{\tau_\omega}(\omega - \omega_i)\exp\left[-2\frac{(\omega - \omega_i)^2}{\Delta\omega^2}\right].$$

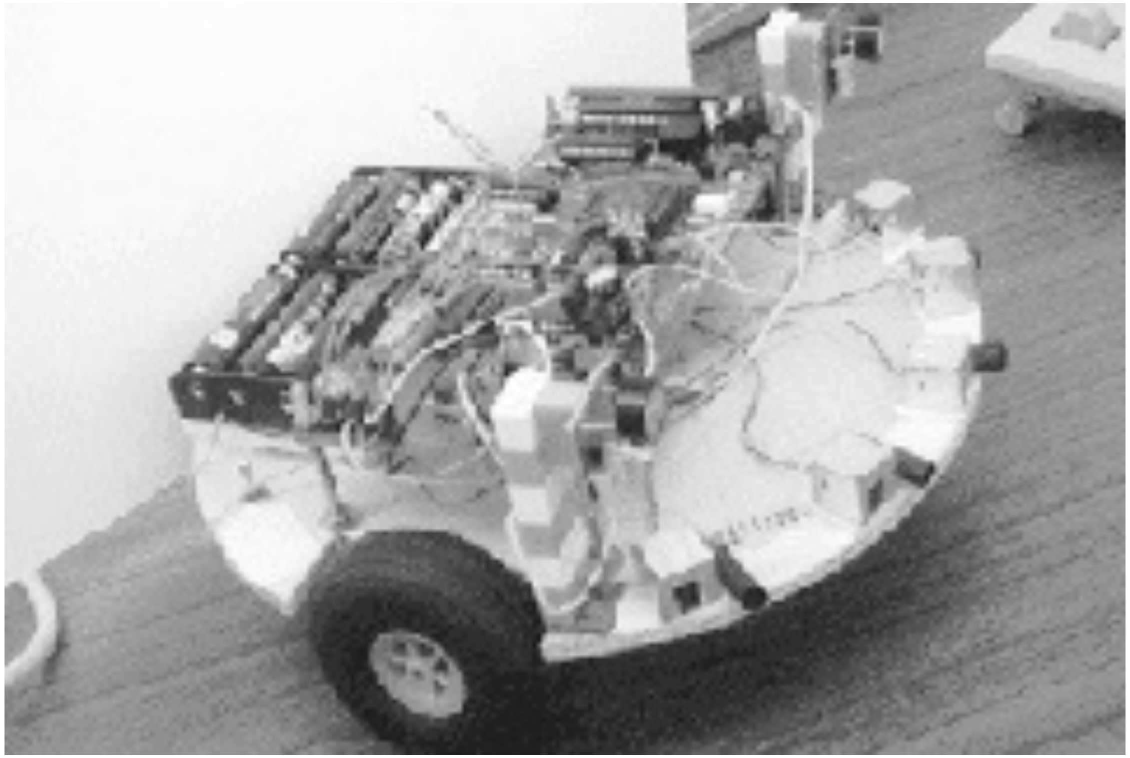
$(i = \text{right or left})$

- summed to total dynamics

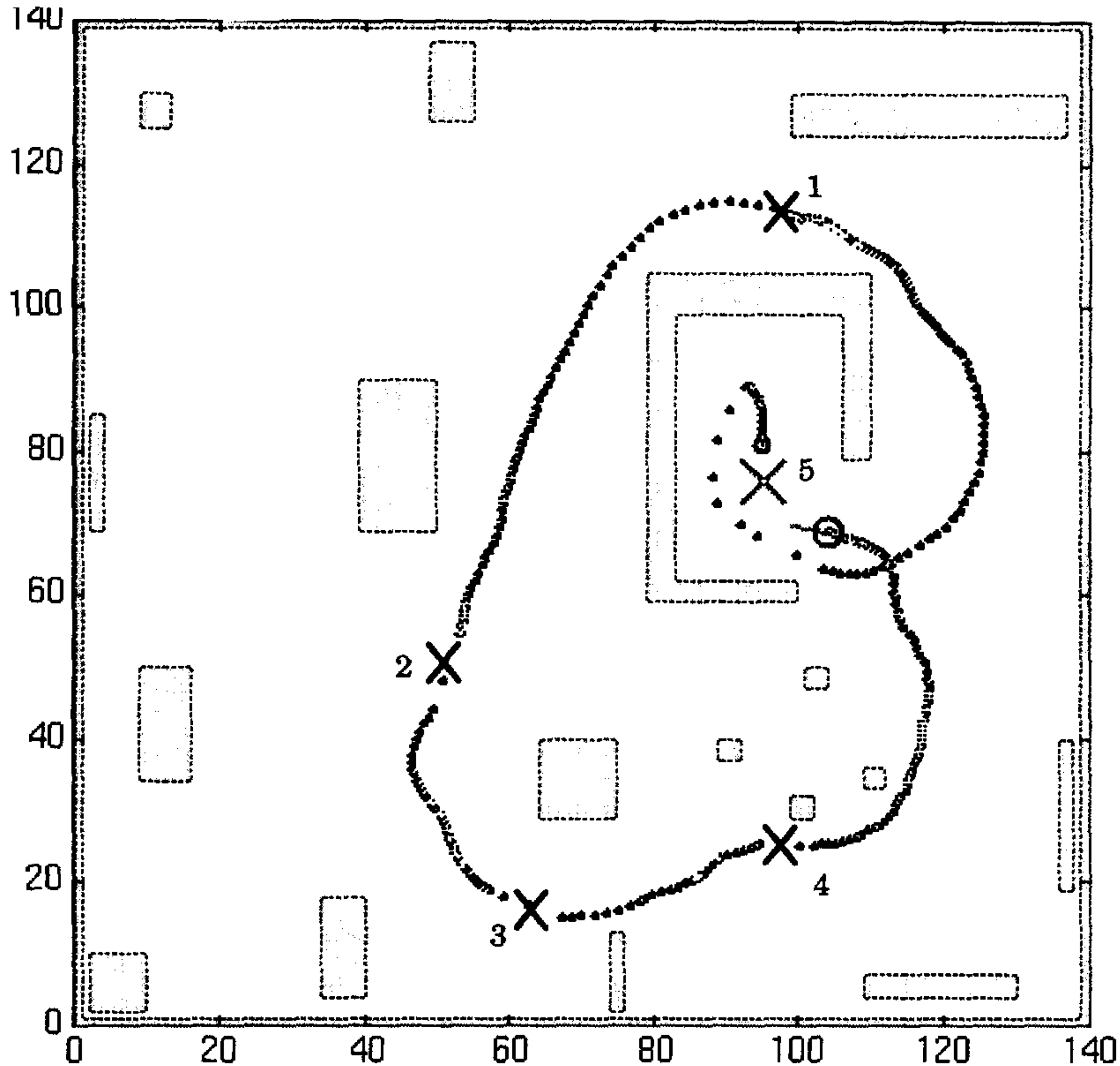
$$g_{\text{left}}(\omega) + g_{\text{right}}(\omega)$$

putting it to work on a simple platform

- Rodinsky!
- circular platform with passive caster wheel
- two (unservoed) motors
- 5 IR sensors
- 2 LDR's
- microcontroller MC68HCA11A0 Motorola (32 K RAM), 8 bit



example trajectories



demonstration

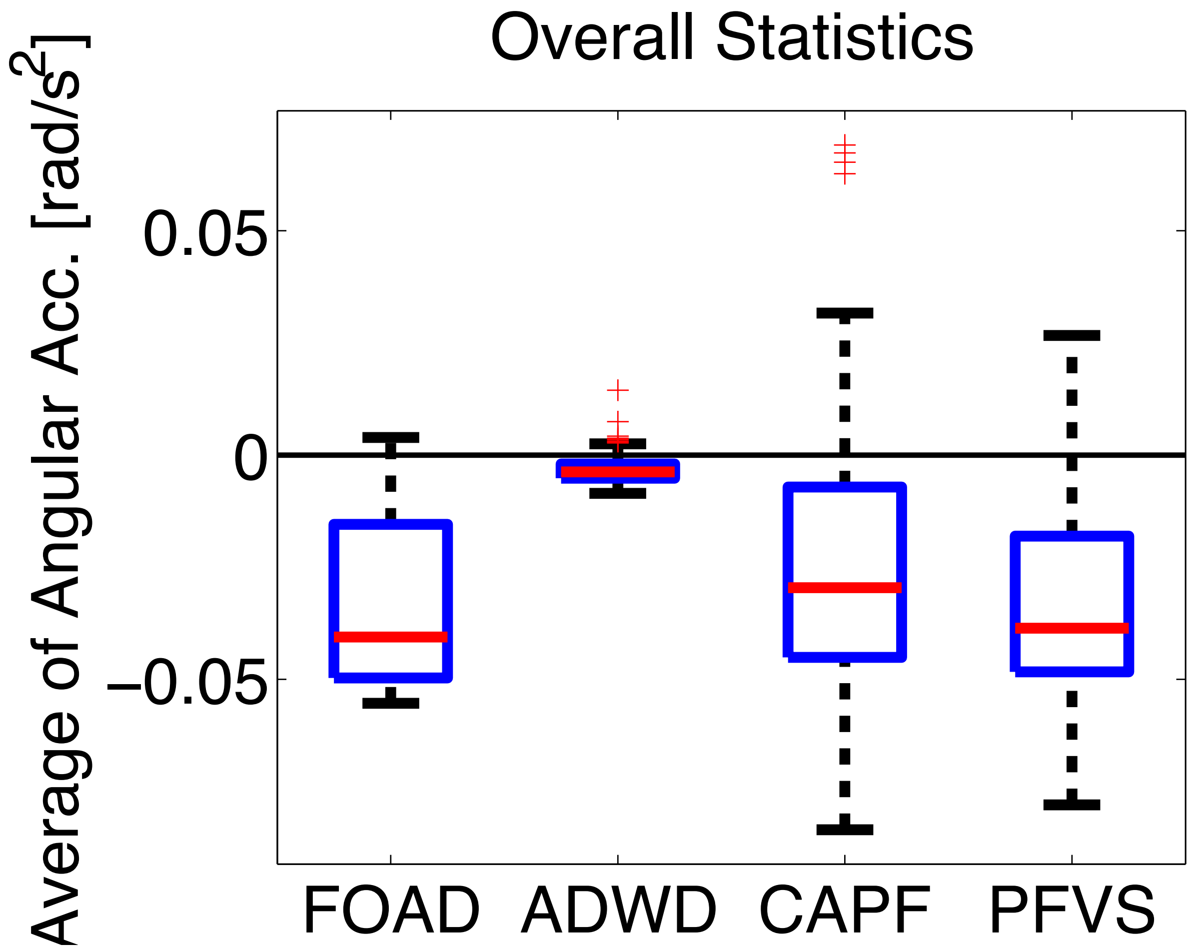
why does it work?

- here the dynamics exists instantaneously while vehicle is heading in a particular direction
- while the vehicle is turning under the influence of the corresponding attractor for turning rate, the dynamics is changing!
- typically undergoing an instability as vehicle's heading turns away from an obstacle…

what is the benefit of using second order dynamics?

- ability to integrate constraints which do not specify a particular heading direction, only turning direction
- ability to impose a desired turning rate => enhances agility in turning
- ability to control the second derivative of heading direction=angular acceleration: enables taking into account vehicle dynamics

quantitative comparison



1st order 2nd order

[Hernandes, Becker, Jokeit, Schöner, 2014]

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