Vehicle motion planning and control: Survey of approaches

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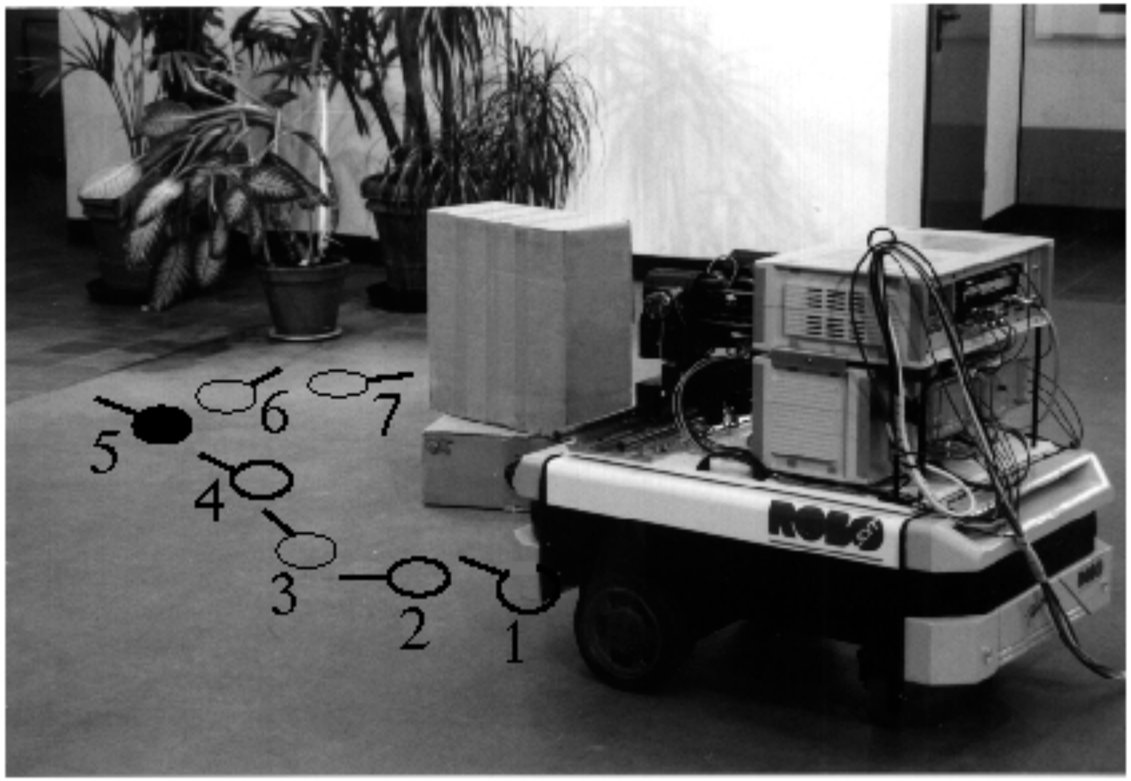
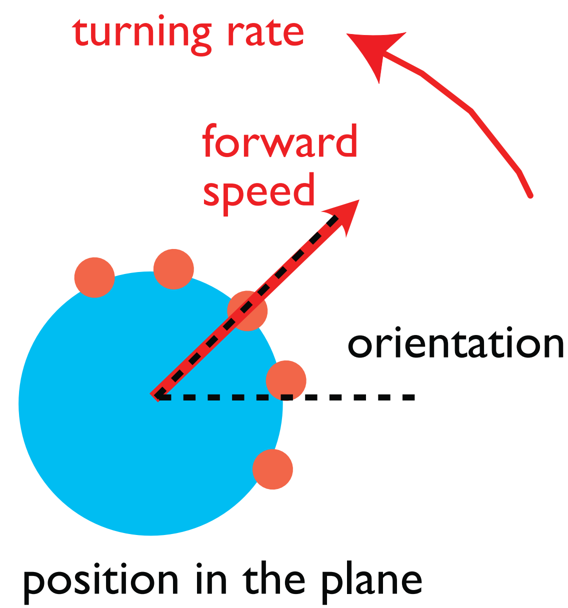
The problem

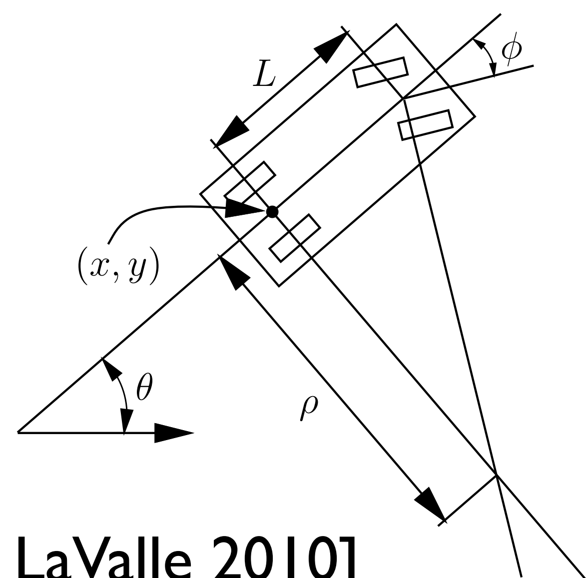
- move about in a 2D world, which is occupied by objects/stuff
- constraints
  - reach targets
  - avoid collisions
  - via points
  - orientations



Non-holonomic constraints

- Vehicles have typically non-holonomic constraints
  - fewer variables can be varied freely (e.g. velocities chosen) than variables that describe the physical state
  - state depends on the history of movement





[from LaValle 2010]

What is needed to autonomously move in an environment?

- sense something about the environment
- know about the environment
- plan movement in the environment that is collision-free
- control vehicle to achieve planned movement
- estimate what vehicle actually did

Concepts for planning

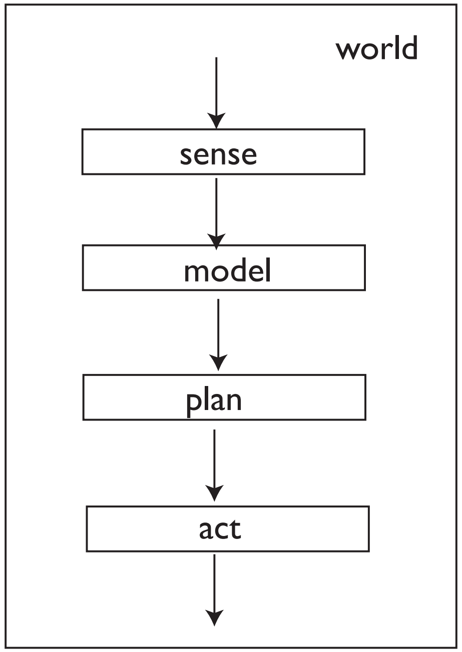
- local vs. global
  - planning based on information only about the local environment of the robot
  - vs. based on global map information about the environment
- reactive vs. planning
  - motion planning "on the fly" in response to sensory inputs
  - vs. motion planning for an entire action from initial to goal state

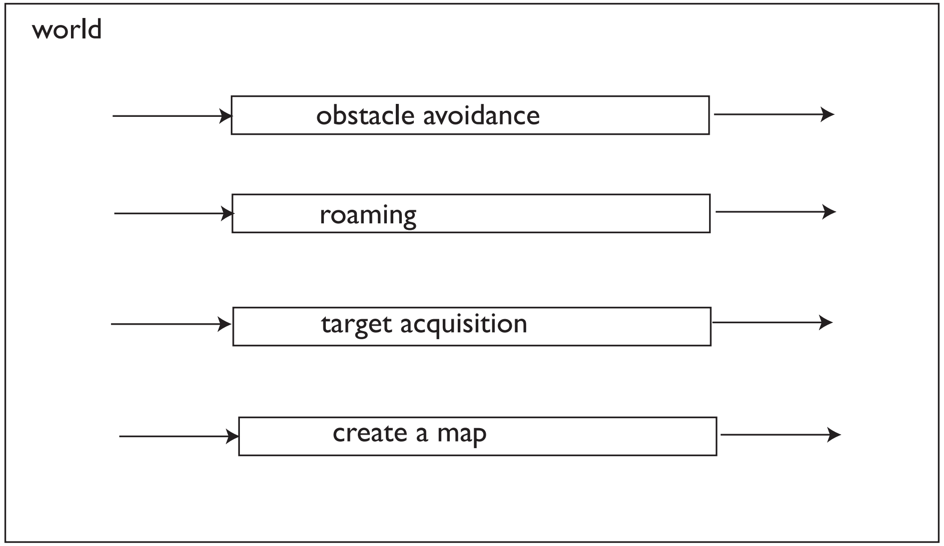
Concepts for planning

- exact vs. heuristic
  - exact: guarantee that a path that fulfills the constraints is found when one exists
  - vs. generate a plan based on ad hoc approach that is likely to fulfill constraints
- continuous vs. discrete:
  - continuous state space variables
  - vs. grid state spaces, graph state spaces

Concepts for planning

- sense-plan-act vs behavior-based
  - based on world representation that informs all planning
  - vs. based on low-level sensory information that is specific to each individual behavior, planning emerges from how behaviors interact



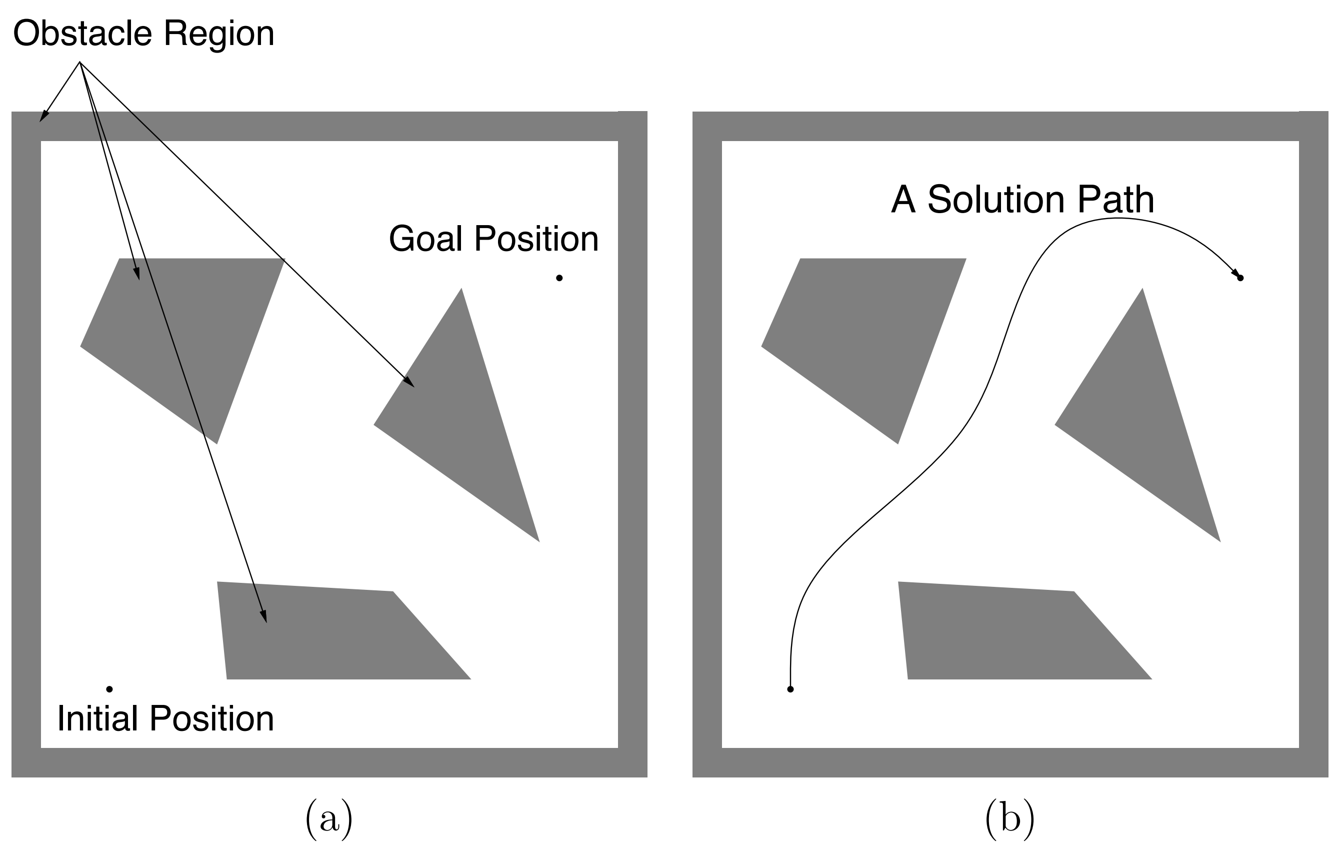


Approaches to vehicle path planning

- classical planning approaches
- potential field approach
- Borenstein & Koren
- (dynamic window approach)

Classical global path planning

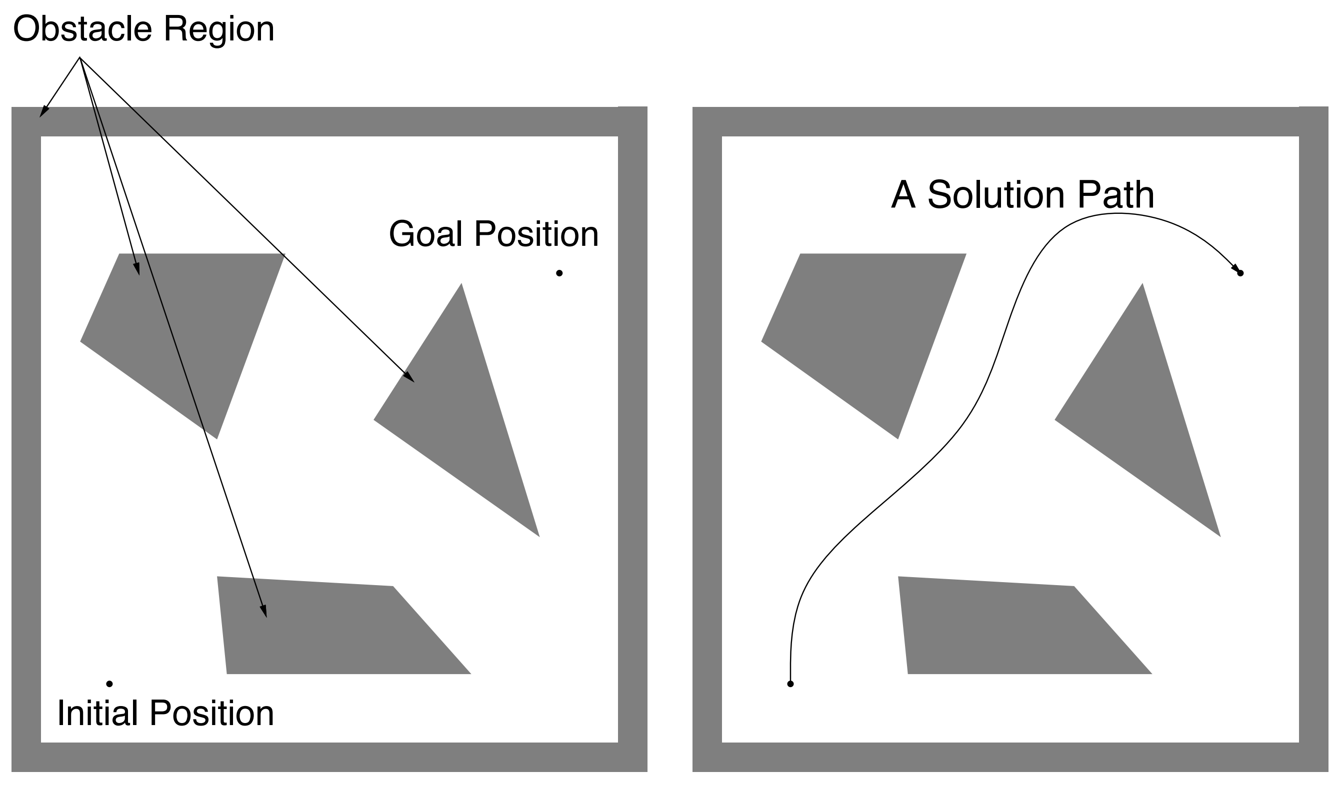
- standard reference: Latombe: Robot motion planning, 1991
- very good general review: LaValle: Planning algorithms, 2006, 2010



[LaValle, 2006]

Classical global path planning

- mathematical theories of constraint satisfaction and decision theory
- searching spaces, sampling approaches



(a) (b)

[LaValle, 2006]

Classical local path planning

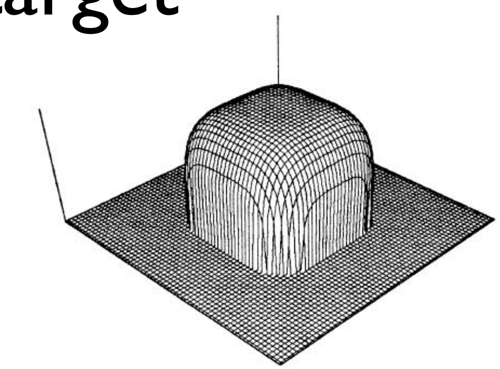
- reference: Cox, Wilfong: Autonomous Robot Vehicles, 1990
- based on a known world (e.g., represented as a polygonial model of surfaces)
- taking into account a kinematic model of the vehicle
- add smoothness constraints

Potential field approach

- invented by Khatib, 1986 (similar earlier formulation: Neville Hogan's impedance control)
- the trajectory of a manipulator or robot vehicle is generated by moving in a potential field to a minimum
- the manipulator 3D end-position or vehicle 2D position is updated by descending within that potential field
- obstacles are modeled as hills of potential field; target states are valleys/minima of the potential field

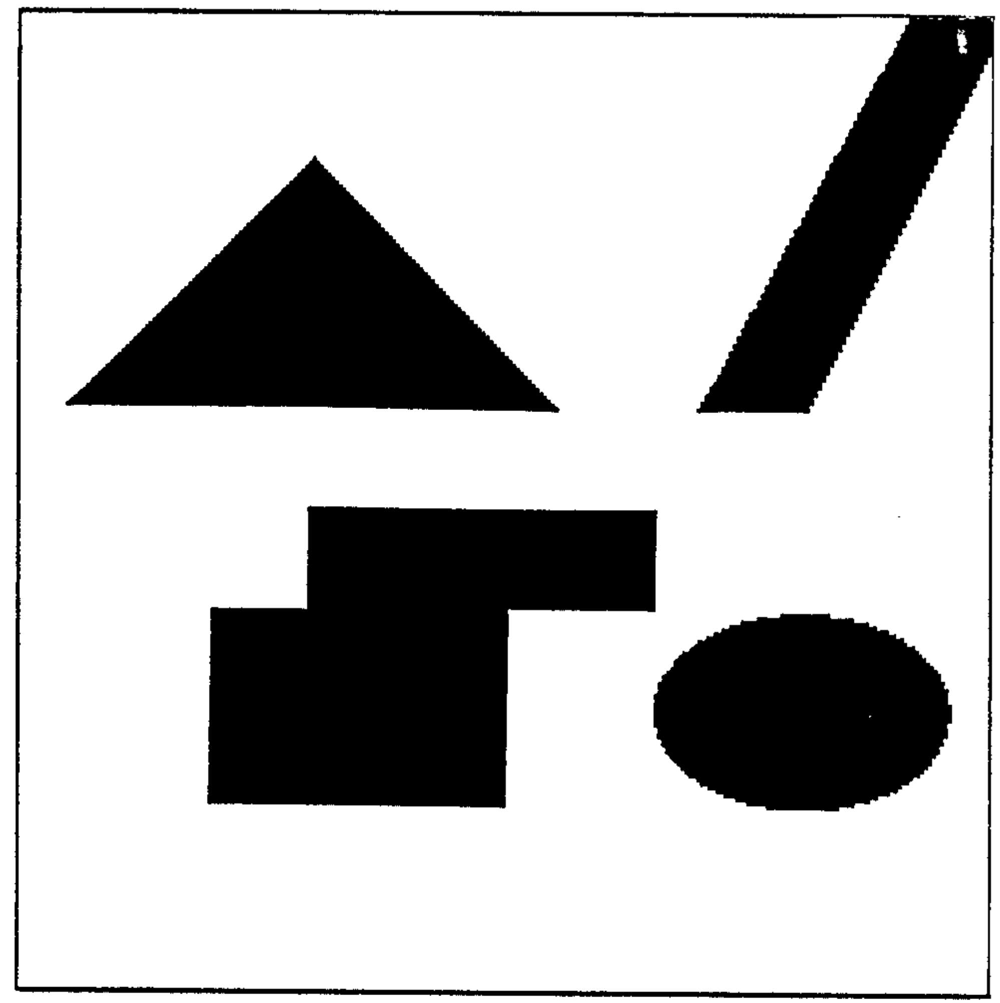
Potential field approach as a heuristic planning approach

- need a mathematical representation of target and obstacle configuration
- make potential minimum at target
- make potential maximum at obstacles
- compute downhill gradient descent for path generation



Potential field approach

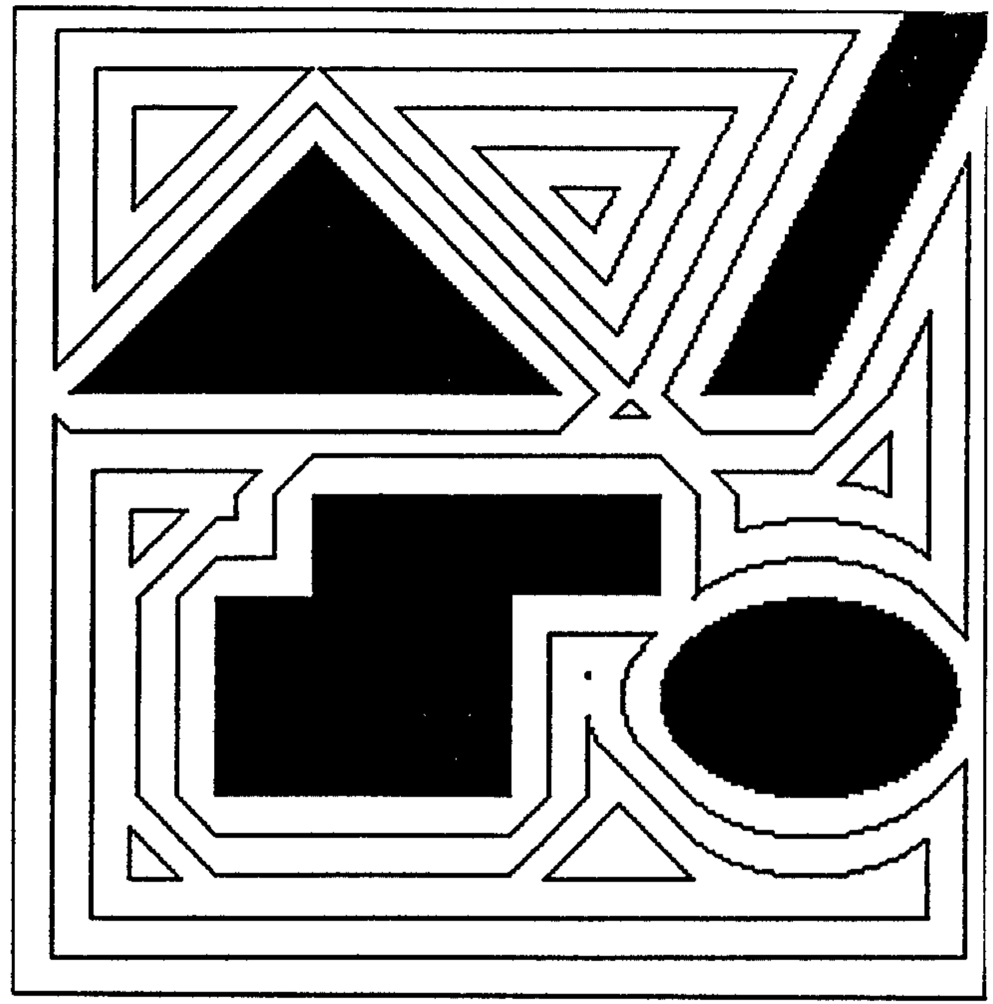
- obstacle configuration



[Barranquand, Langlois, Latombe, 1989]

Potential field approach

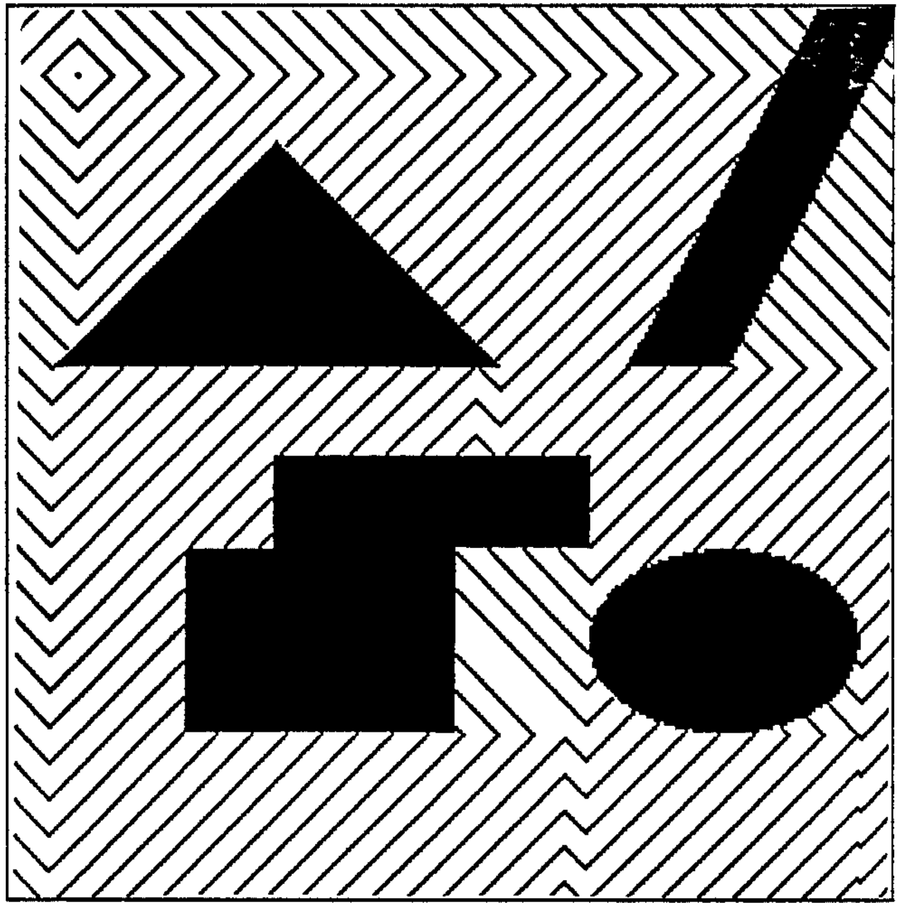
- contours of associated obstacle potential field



[Barranquand, Langlois, Latombe, 1989]

Potential field approach

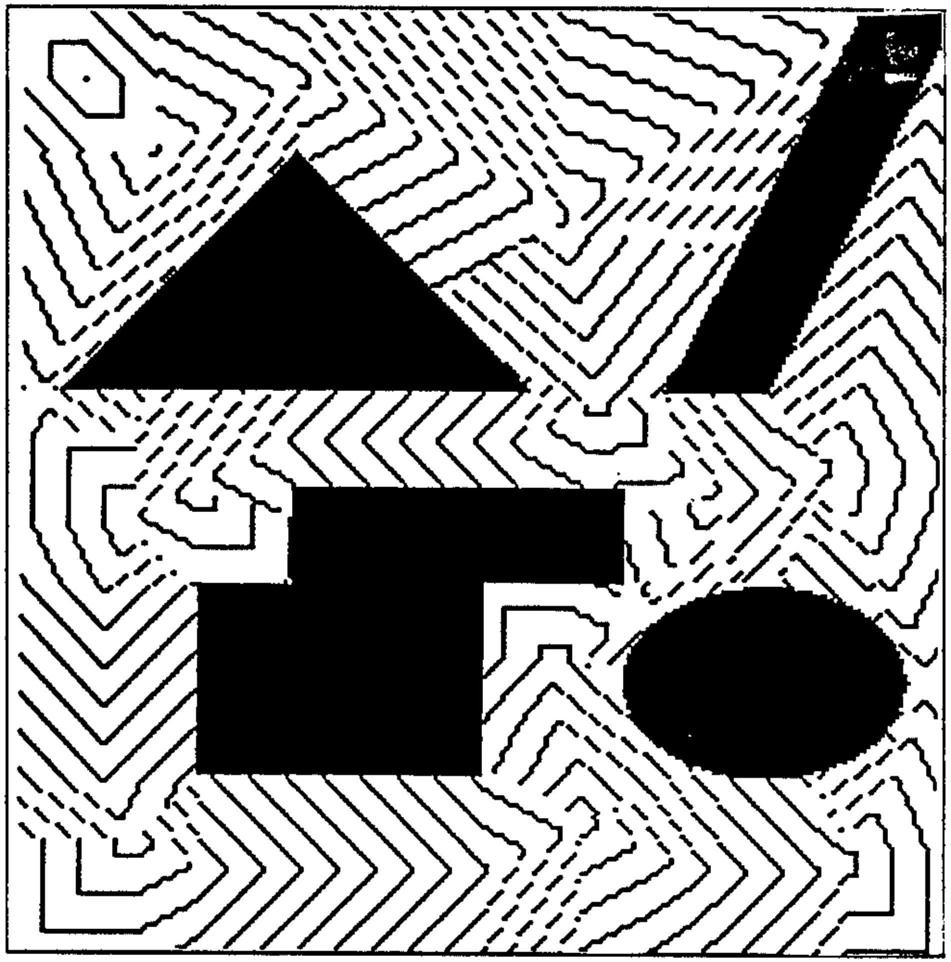
- contours of target potential field



[Barranquand, Langlois, Latombe, 1989]

Potential field approach

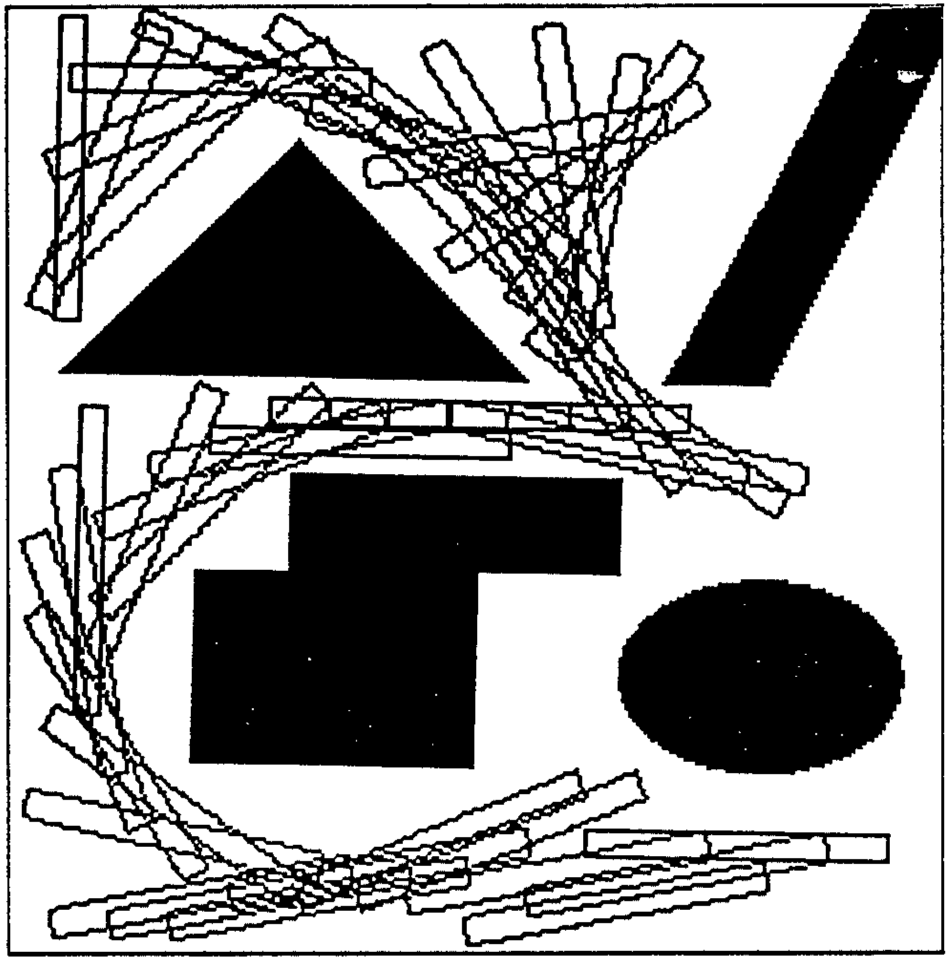
- contours of improved target potential field (by adding bubbles around obstacles)



[Barranquand, Langlois, Latombe, 1989]

Potential field approach

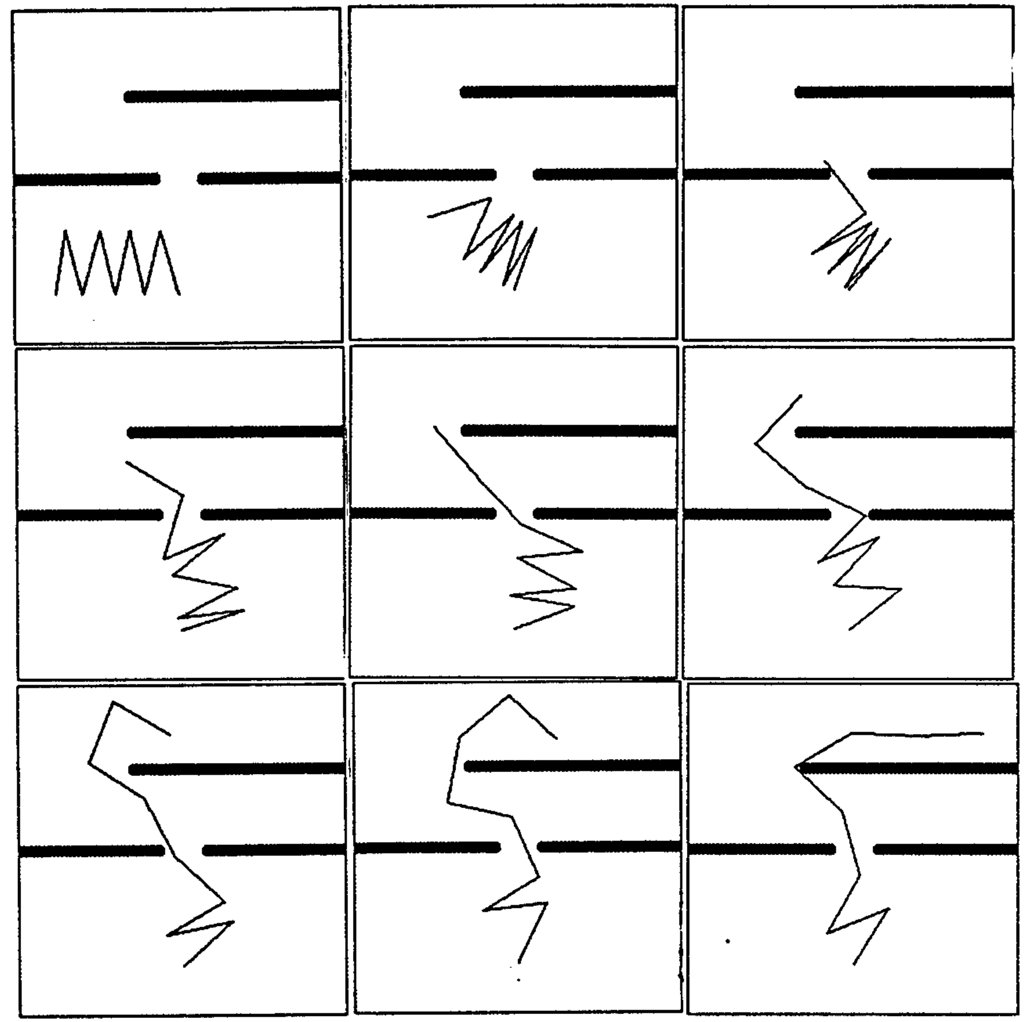
- adding all contributions leads to solution: gradient descent for vehicle



[Barranquand, Langlois, Latombe, 1989]

Potential field approach

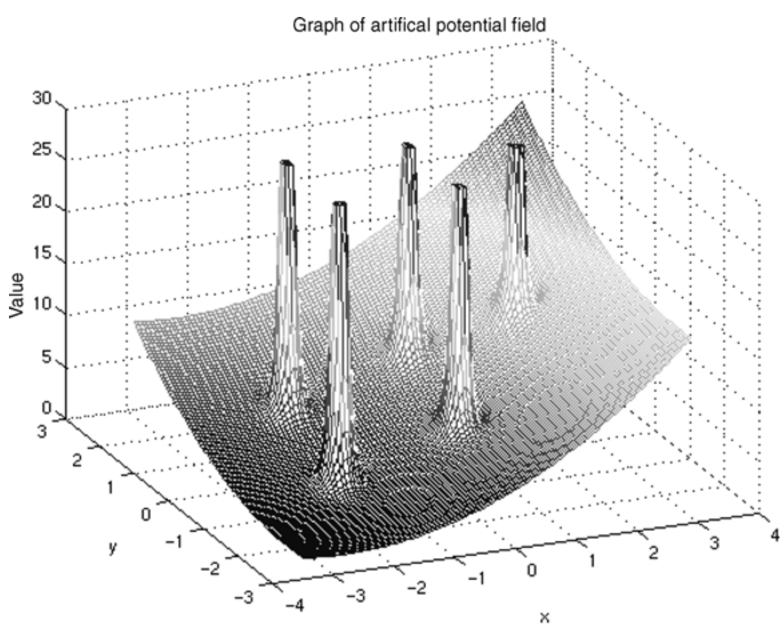
- generalization to higher-dimensional configuration spaces



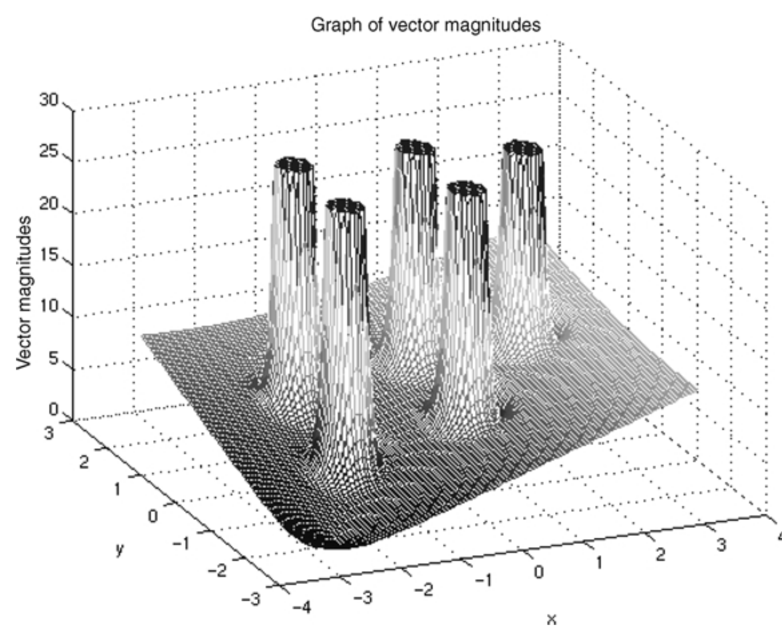
[Barranquand, Langlois, Latombe, 1989]

Comparison to human behavior

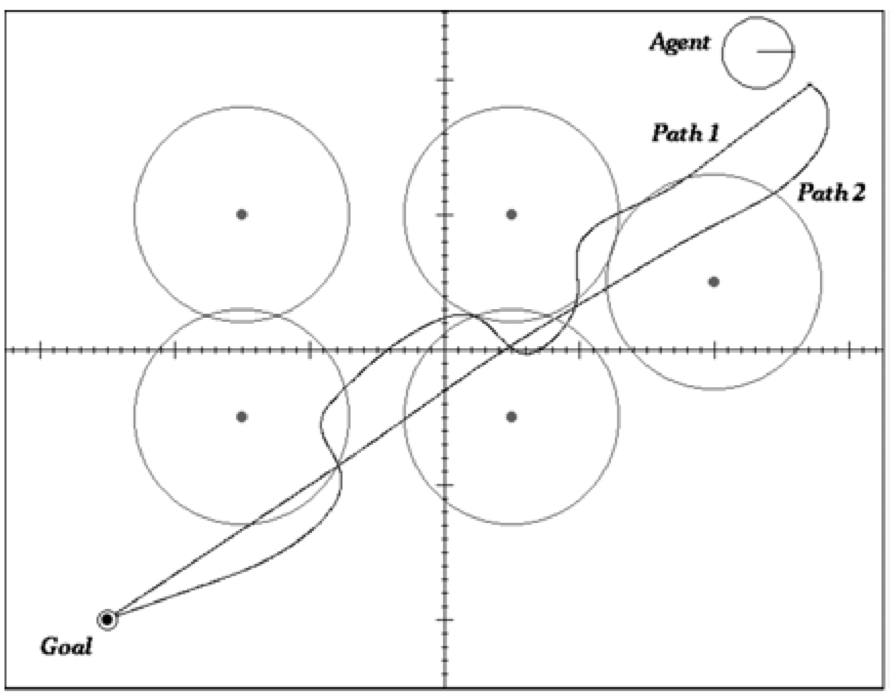
- Fajen/Warren compared the fit of a potential field approach to the fit of the attractor dynamics approach of human locomotion data

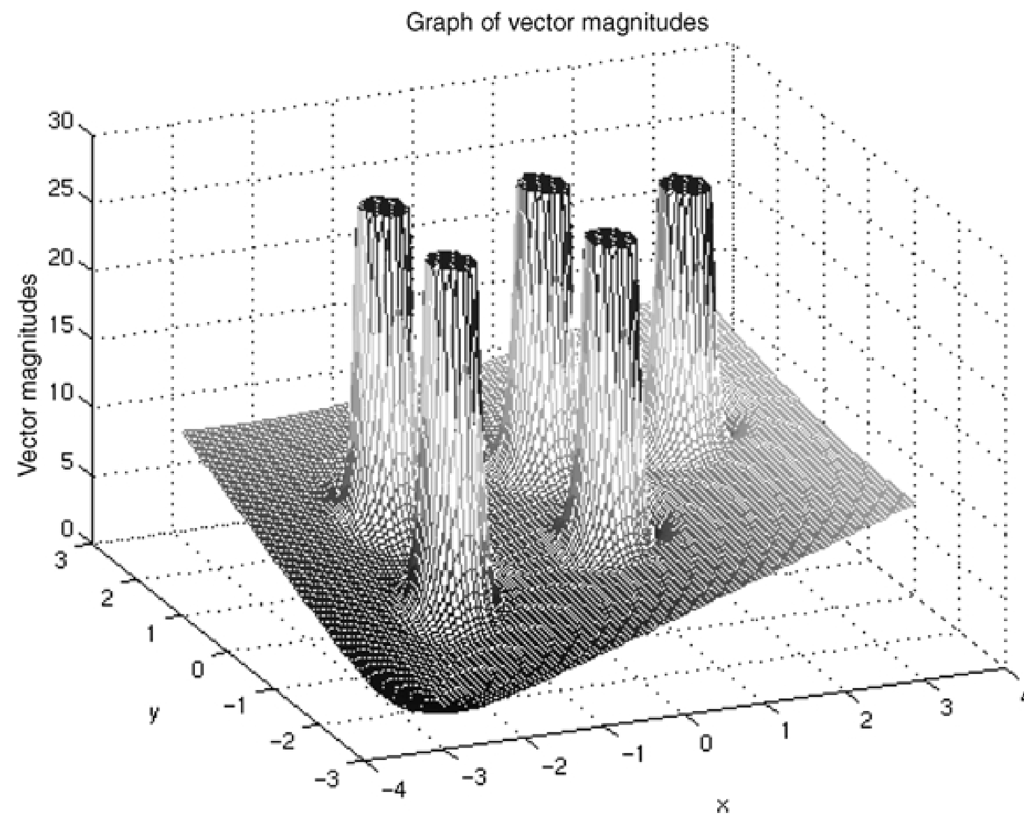


(a)

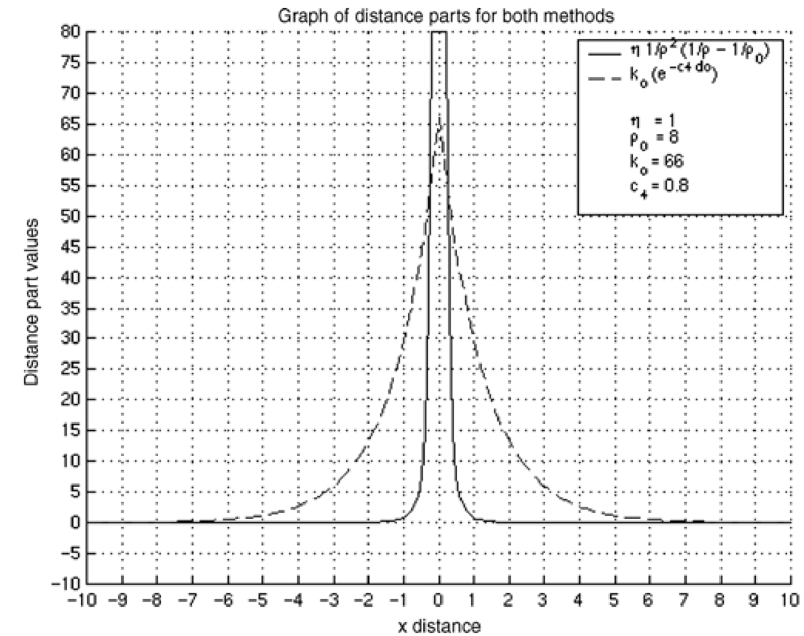


Comparison to human behavior

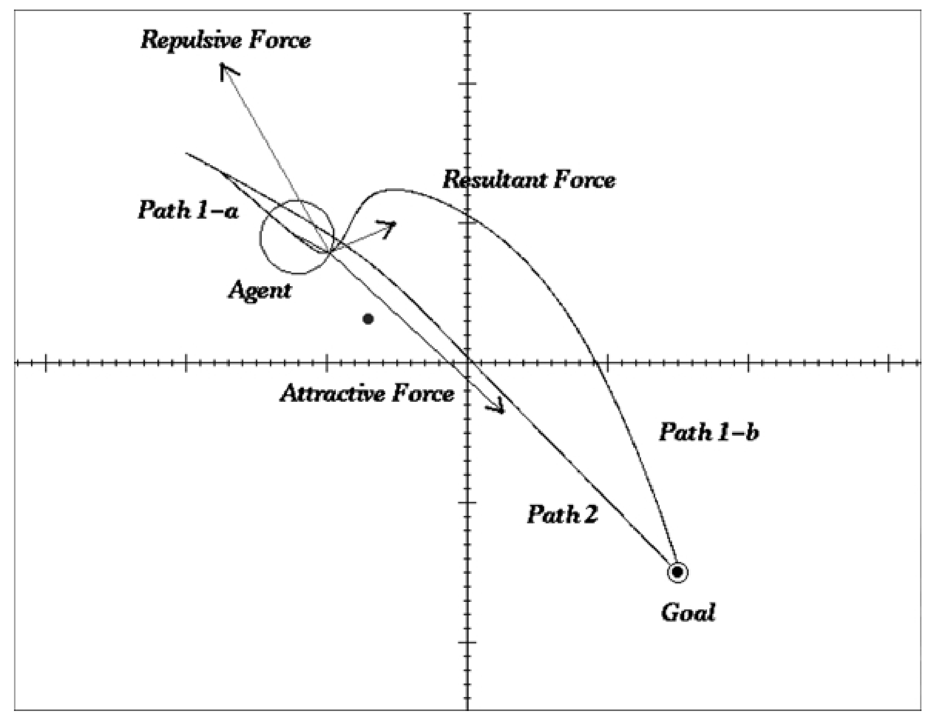




comparison potential field vs. attractor dynamics



(a)

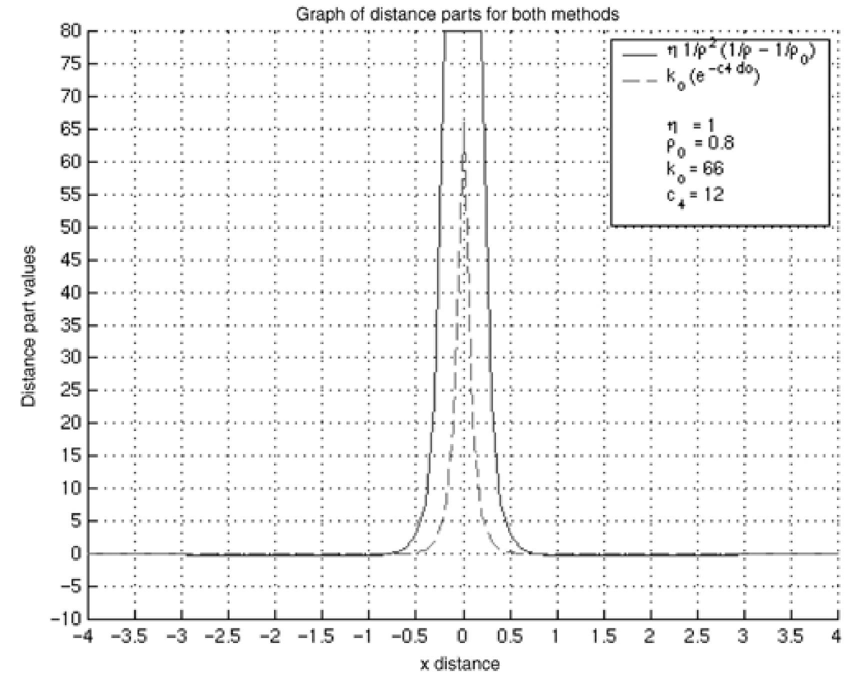


(b)

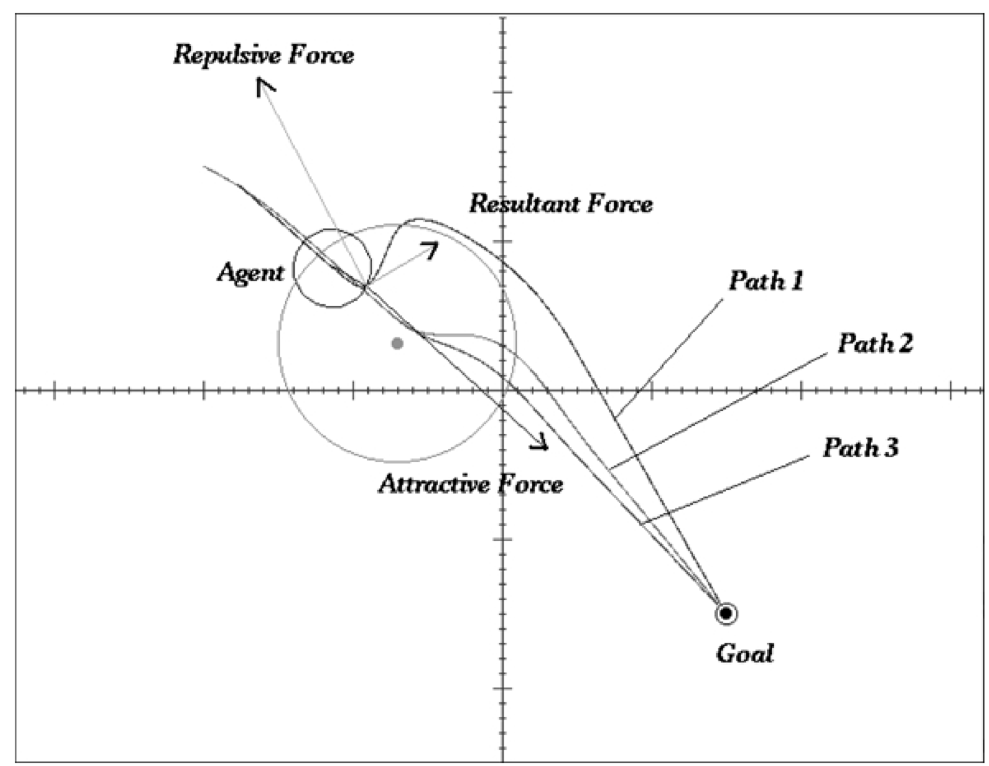
- potential sharper than distance dependence of repellor

comparison potential field vs. attractor dynamics

- potential softer than distance dependence of repellor

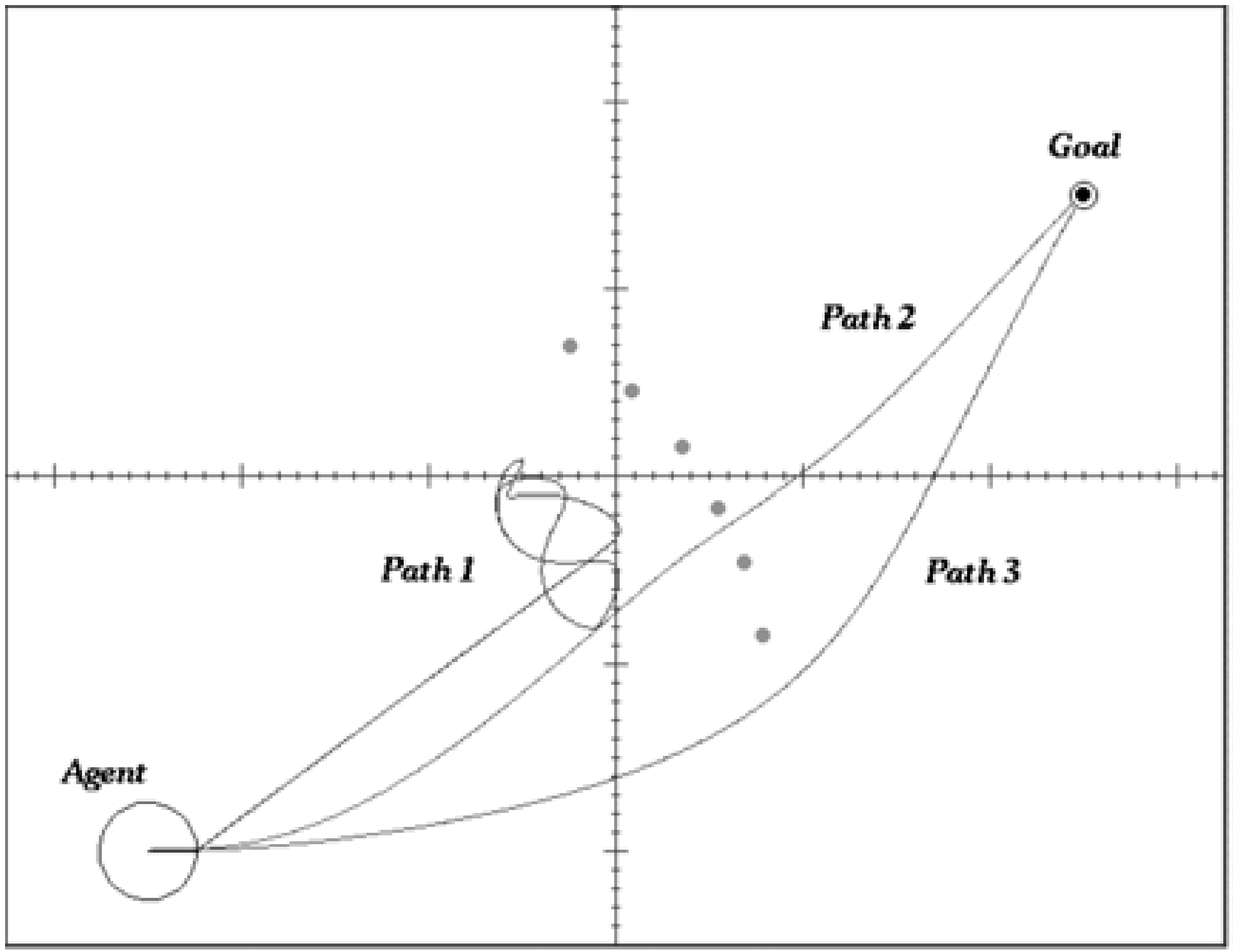


(a)



(b)

spurious attractors in potential field approach



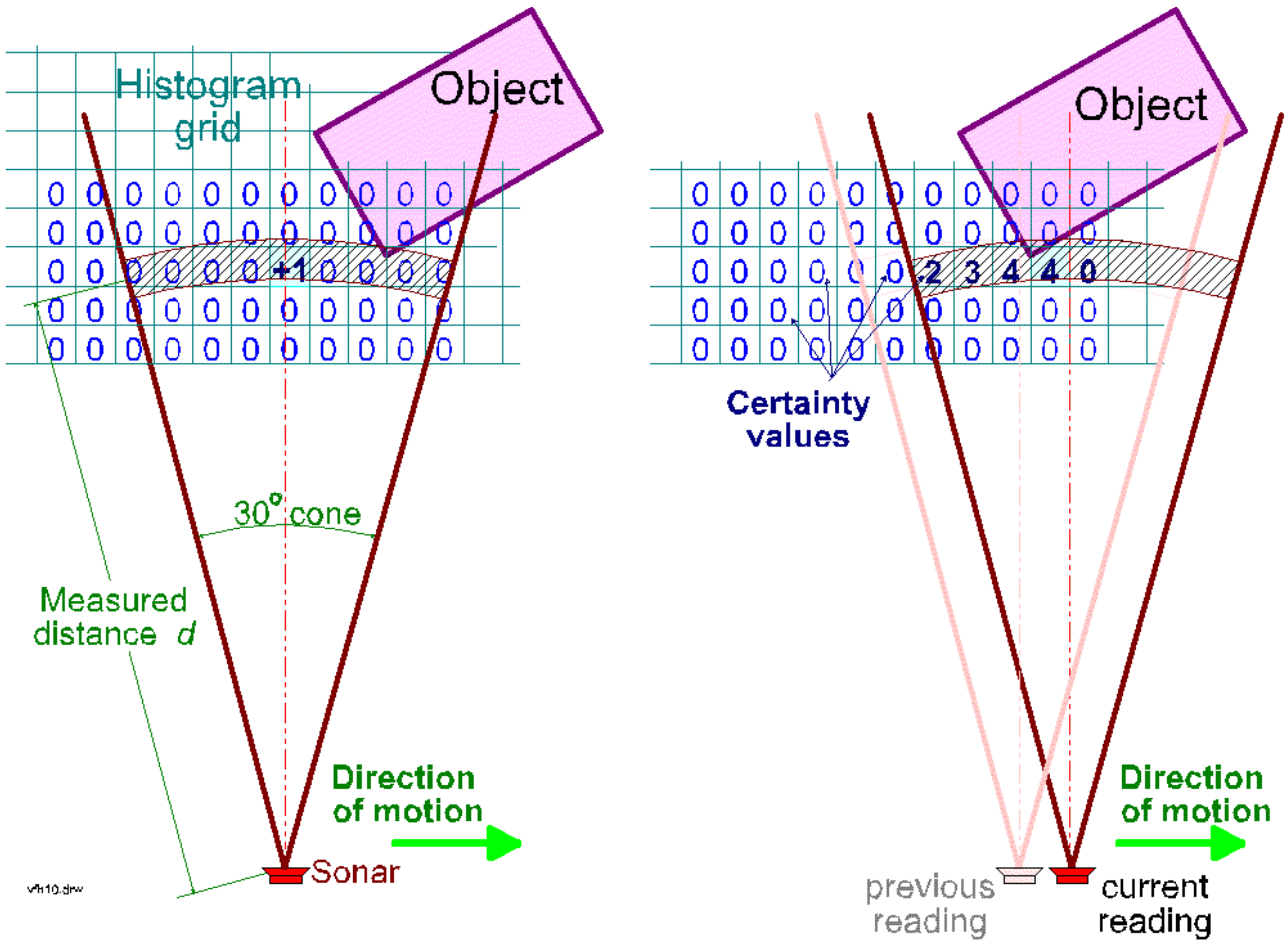
Potential fields: limitations

- spurious attractors and constraint violations
- solution: making potential field approach exact and global: navigation functions
- potential computed such that it only has the right maxima and minimal
- but: computational cost
- but: requires global information

Virtual force field: Borenstein & Koren

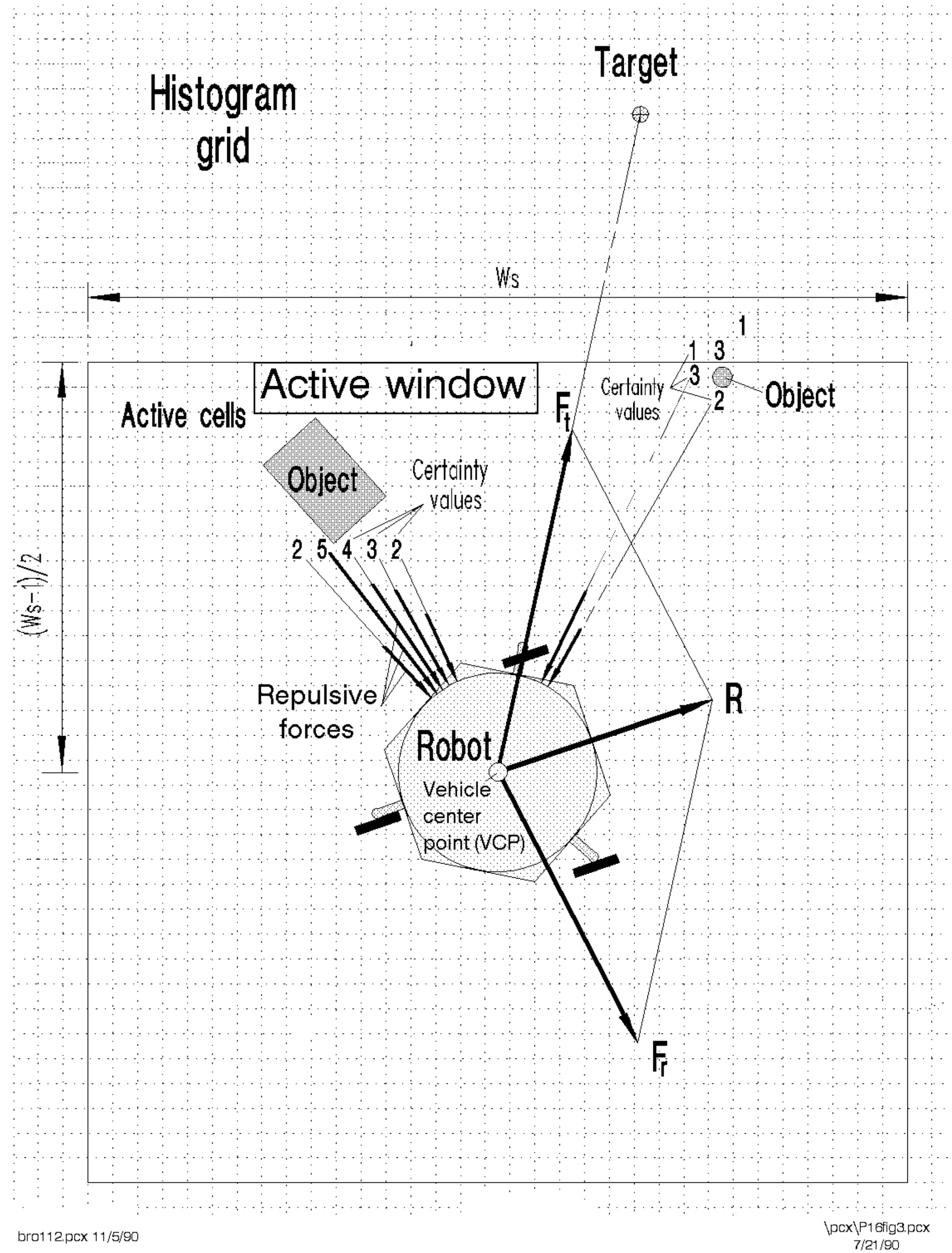
- ultra-sound histograms: the virtual force field concept
- vector-field histogram concept: polar histogram (heading direction!); height (strength) depends on both certainty and distance
- threshold: determine free sectors
- select free direction closest to target

Virtual force field: Borenstein & Koren



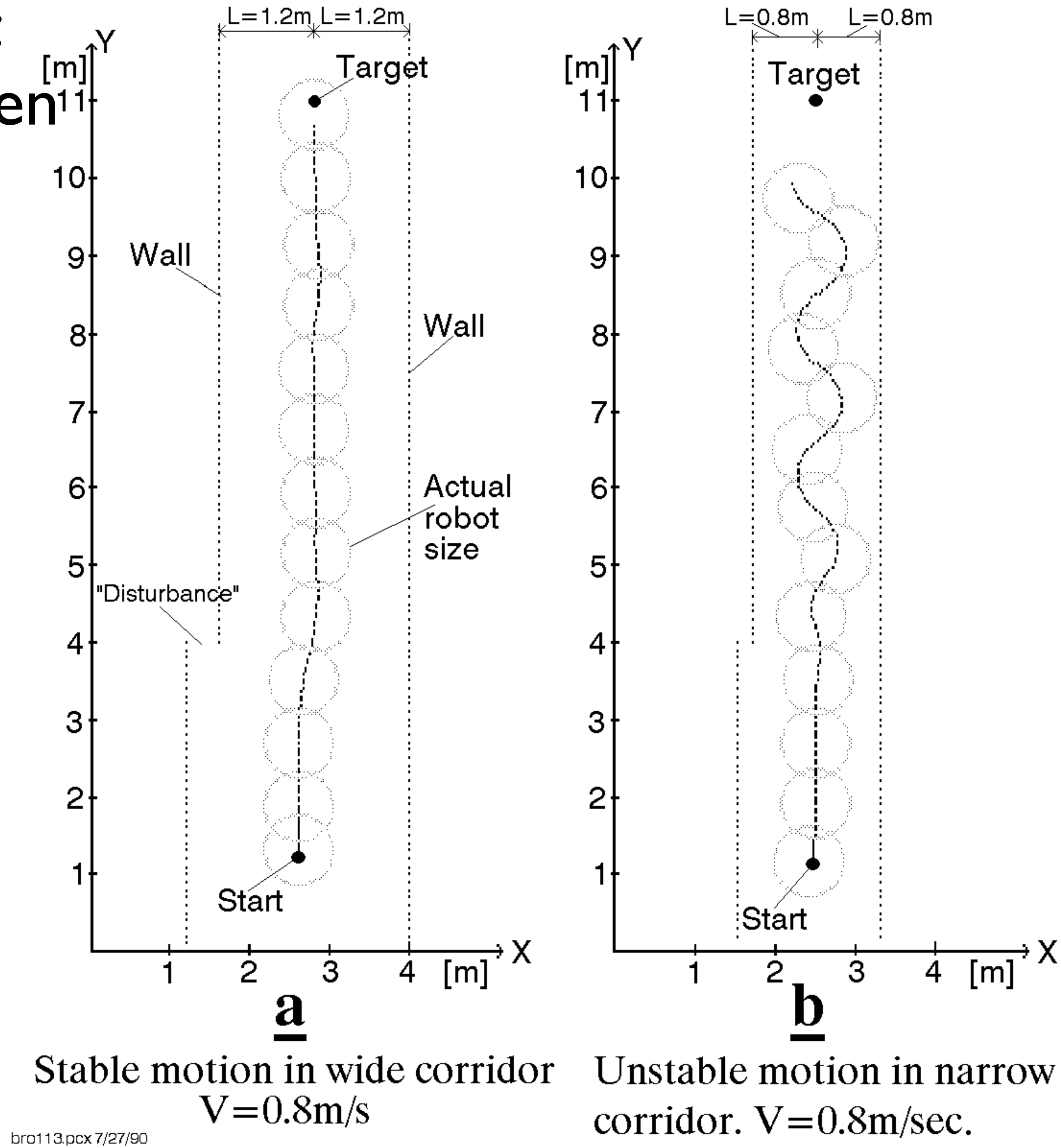
Virtual force field: Borenstein & Koren

- vector toward target
- active window around robot
- use histogram within active window to compute vectors pointing away from obstacle
- vector summing
- ~dynamic approach!



Virtual force field: Borenstein & Koren

- Problem: oscillations in narrow passages

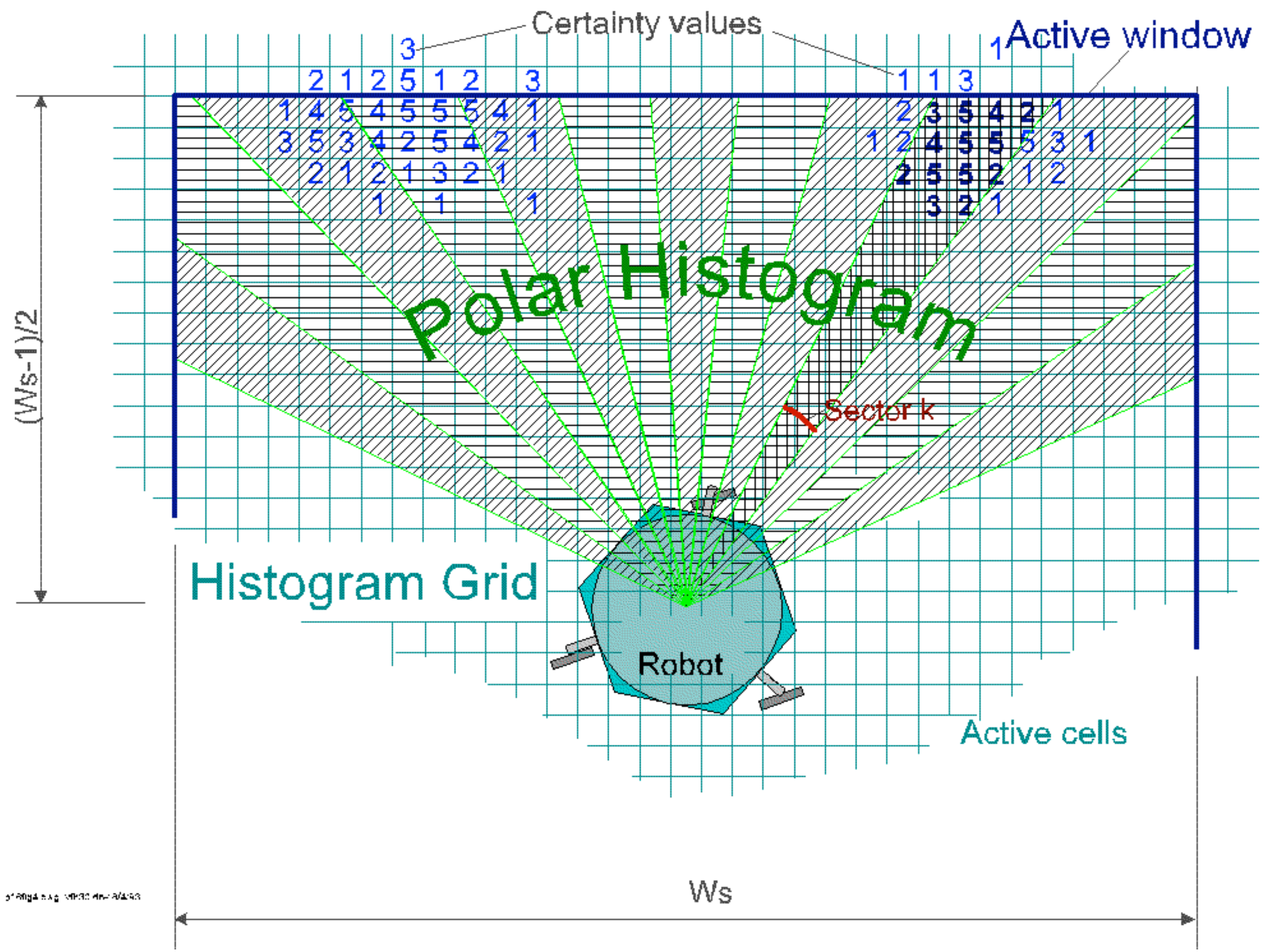


Stable motion in wide corridor V=0.8m/s

Unstable motion in narrow corridor. V=0.8m/sec.

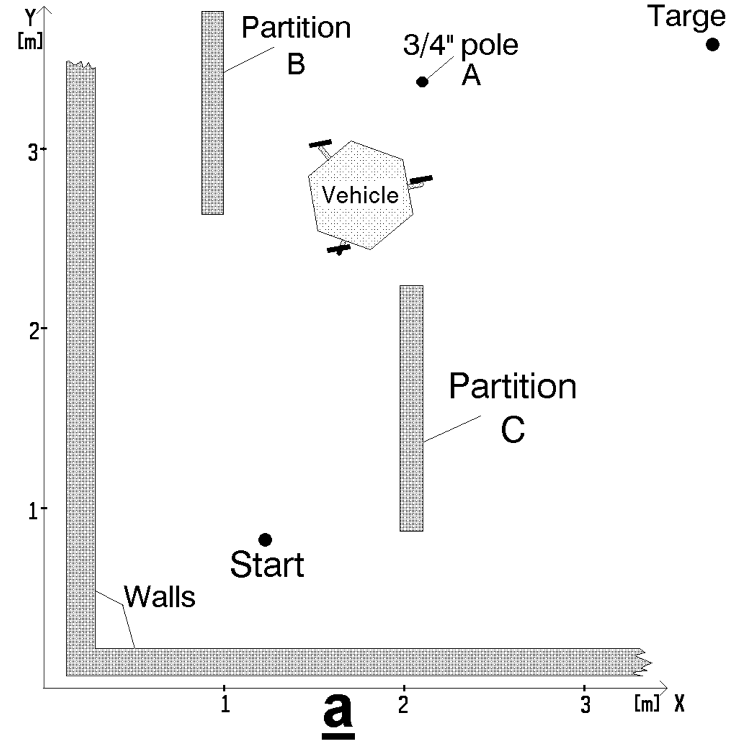
Vector field histogram: Borenstein & Koren

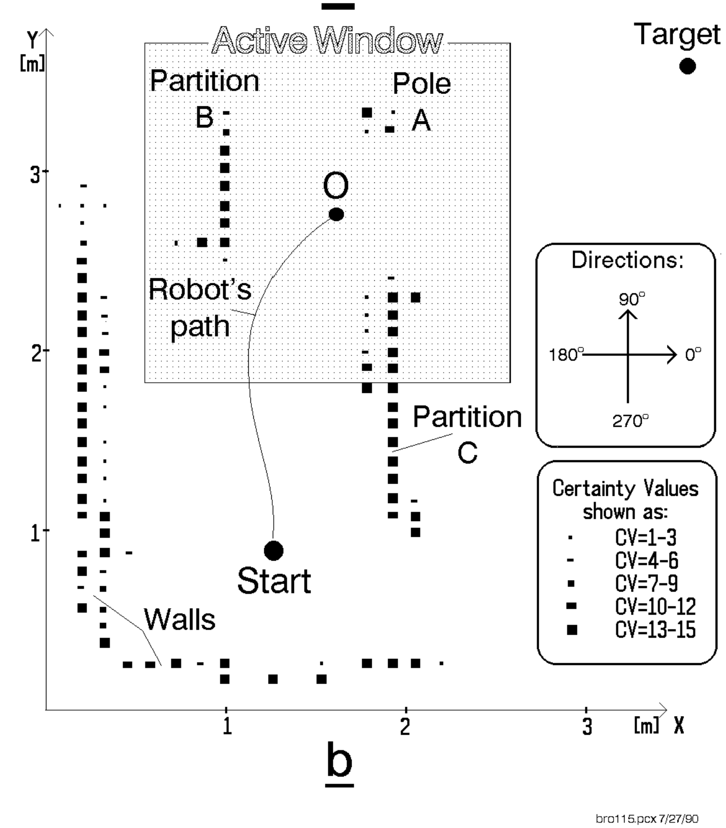
- transform active window in world grid into polar histogram



Vector field histogram: Borenstein & Koren

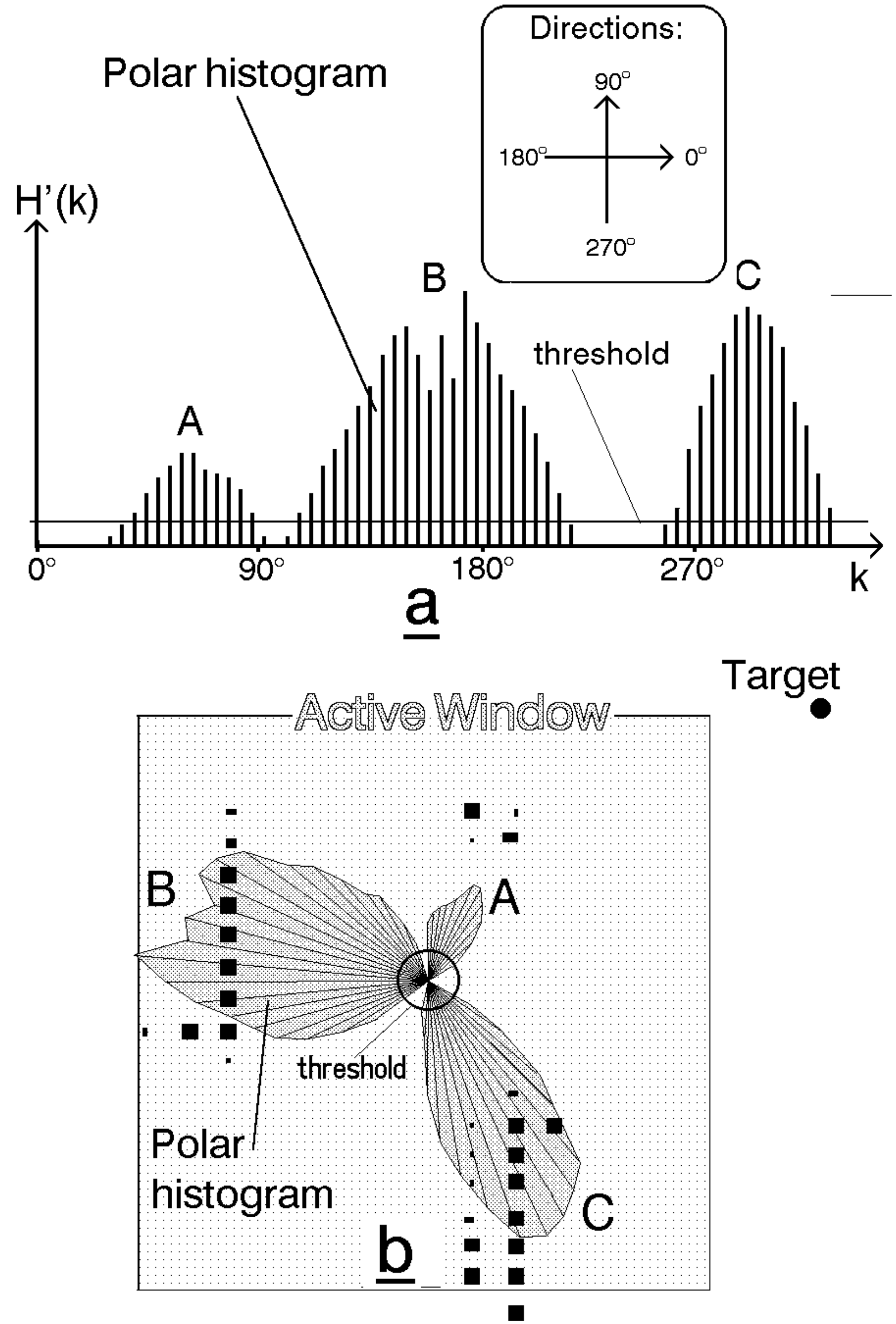
- lab set-up





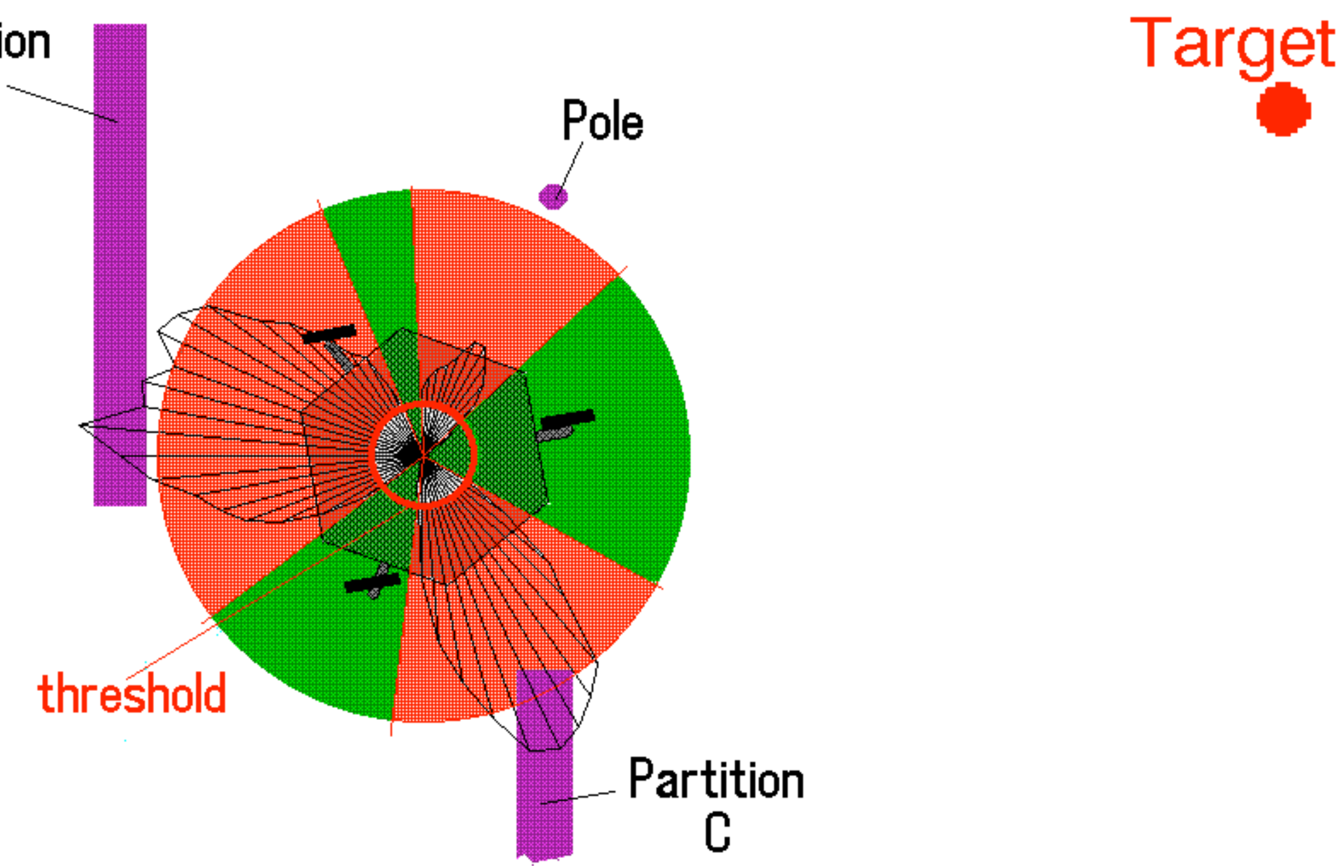
Vector field histogram: Borenstein & Koren

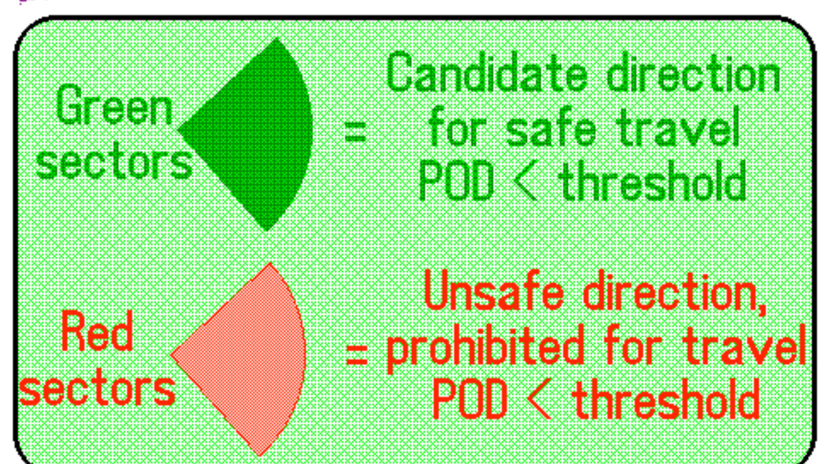
- local polar histogram provides "free" directions



Vector field histogram: Borenstein & Koren

- Select safe direction algorithmical

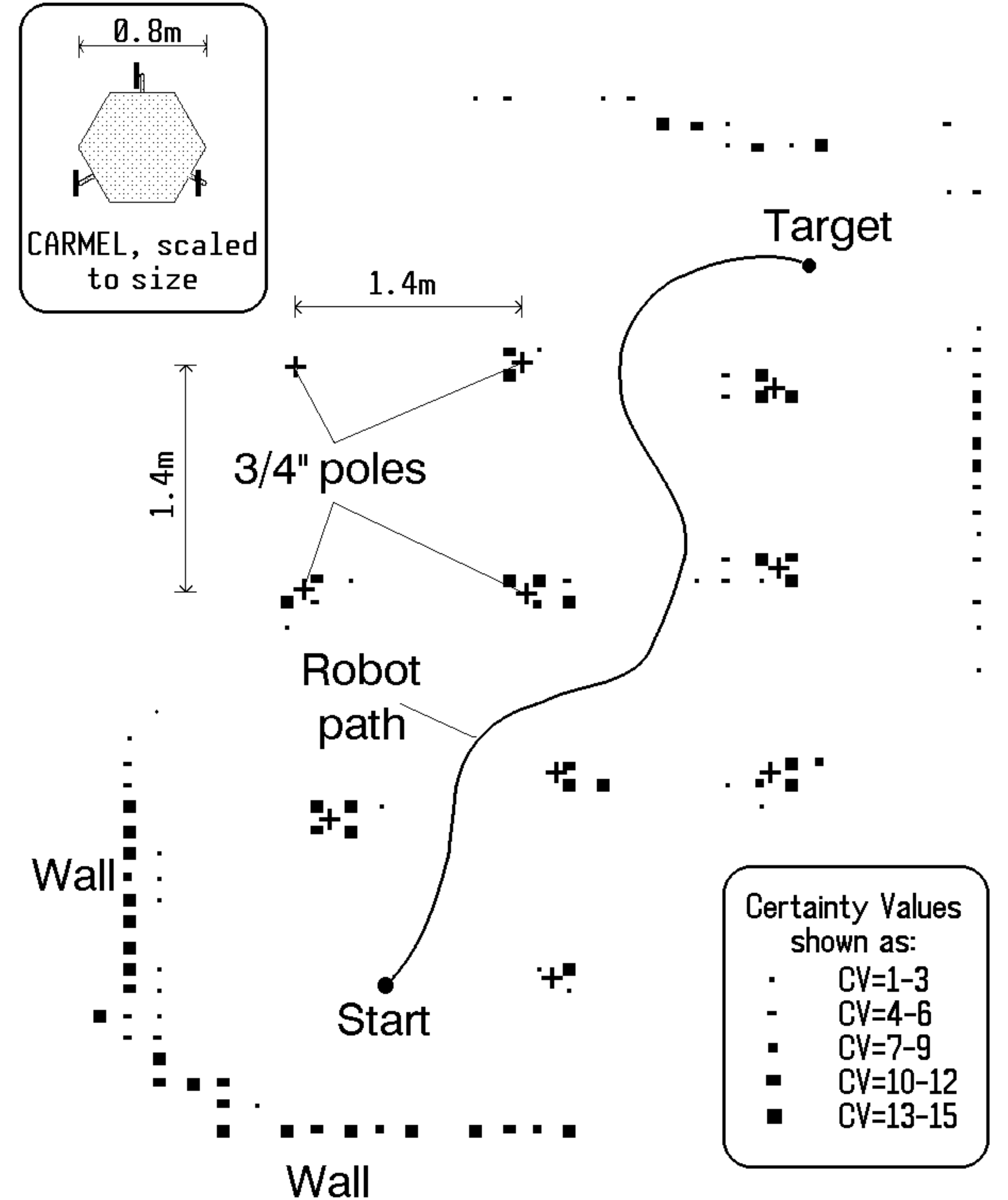




Finding candidate directions for safe travel

Vector field histogram: Borenstein & Koren

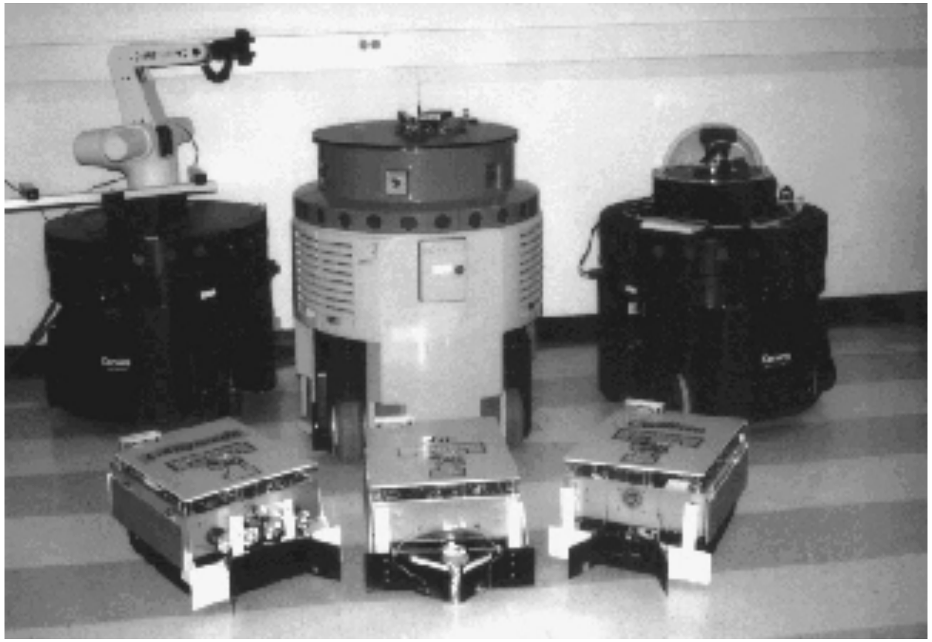
- works



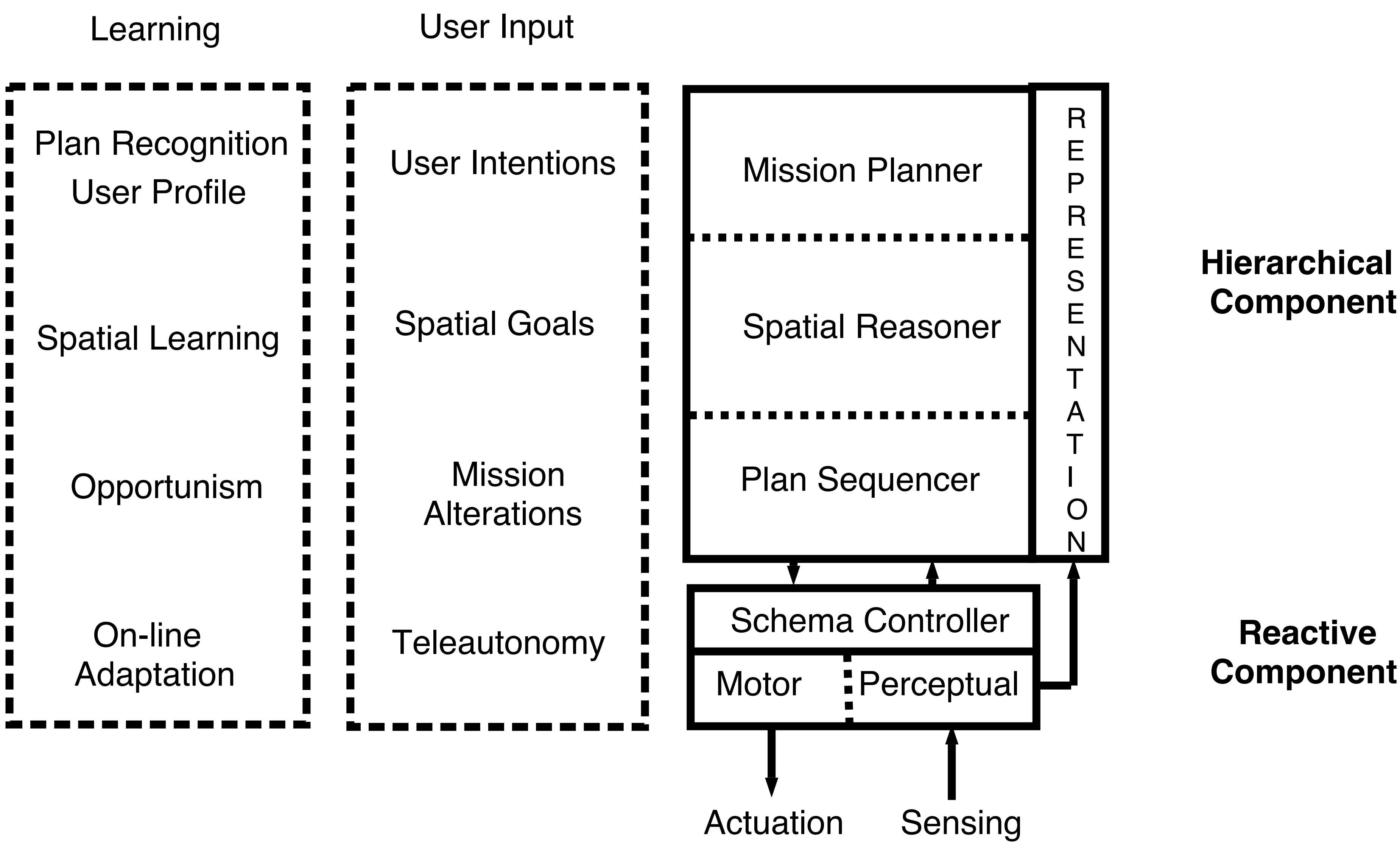
Potential fields as reactive planners

- use potential field to plan locally based on low-level sensory information (reactive)
- different "behaviors" generated by different vector-fields ("schema", slight generalization of potential fields)
- organize the different behaviors in an architecture

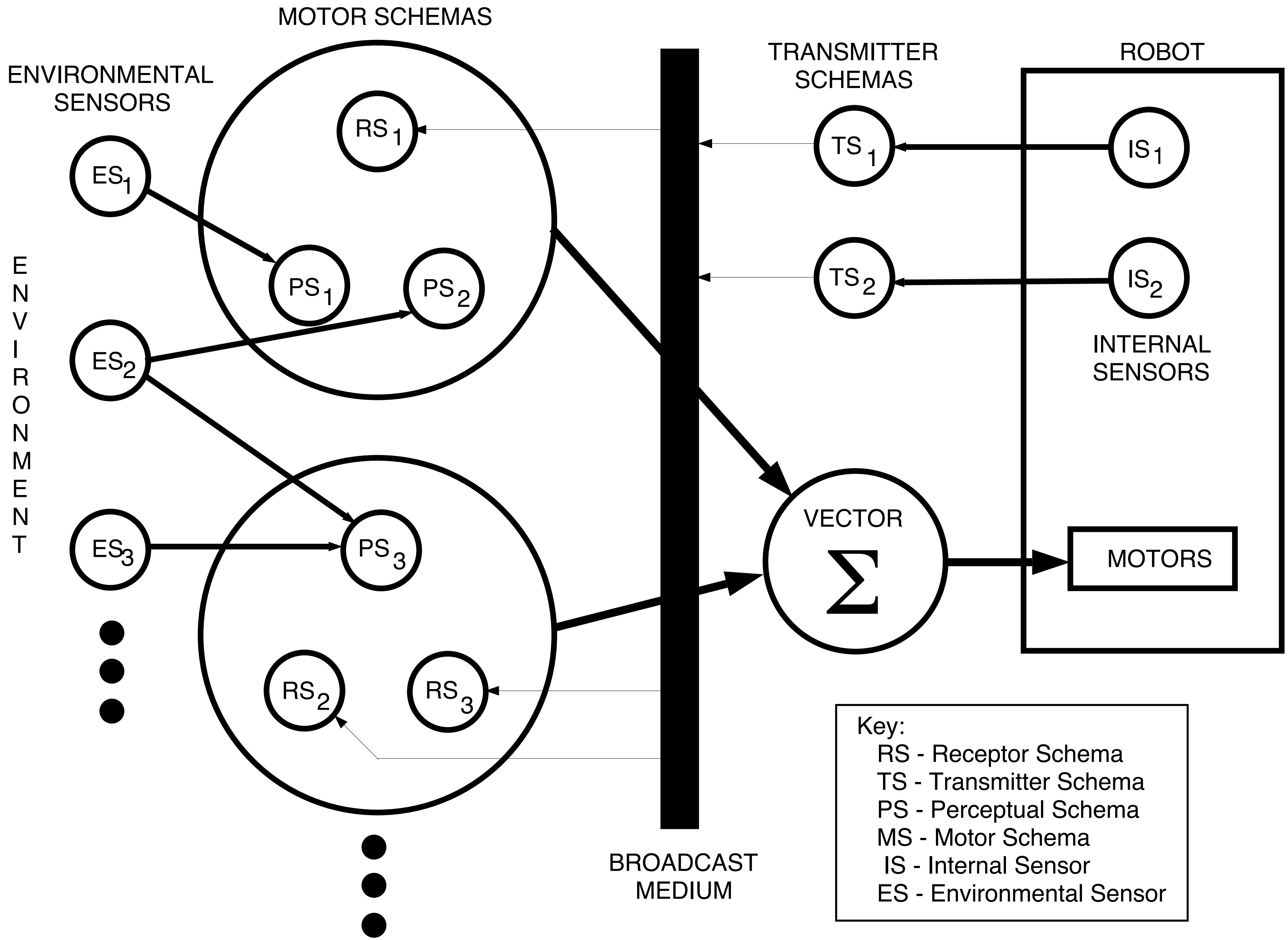
[Arkin, Blach: AuRA 1997]



Architecture



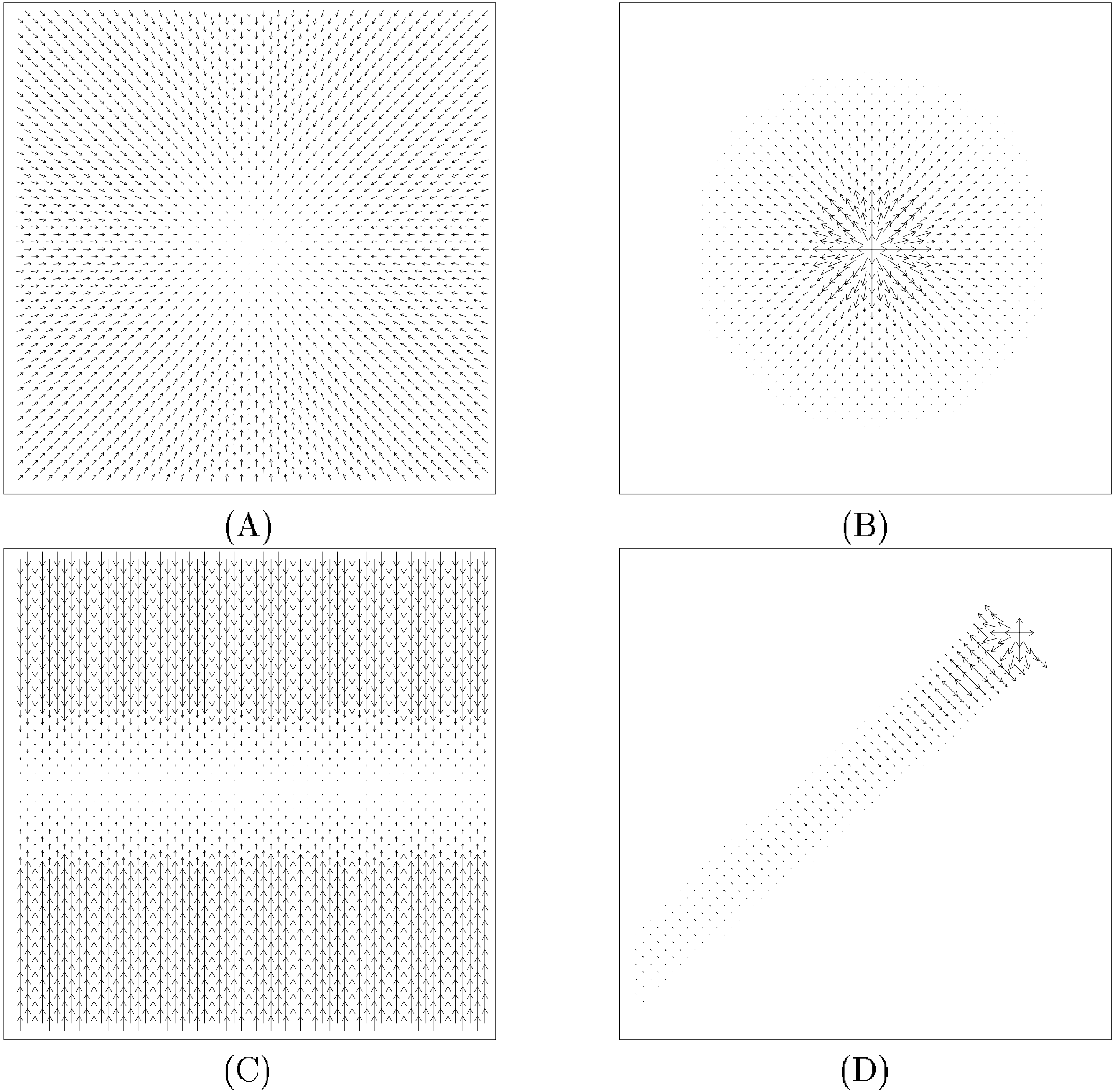
The reactive component



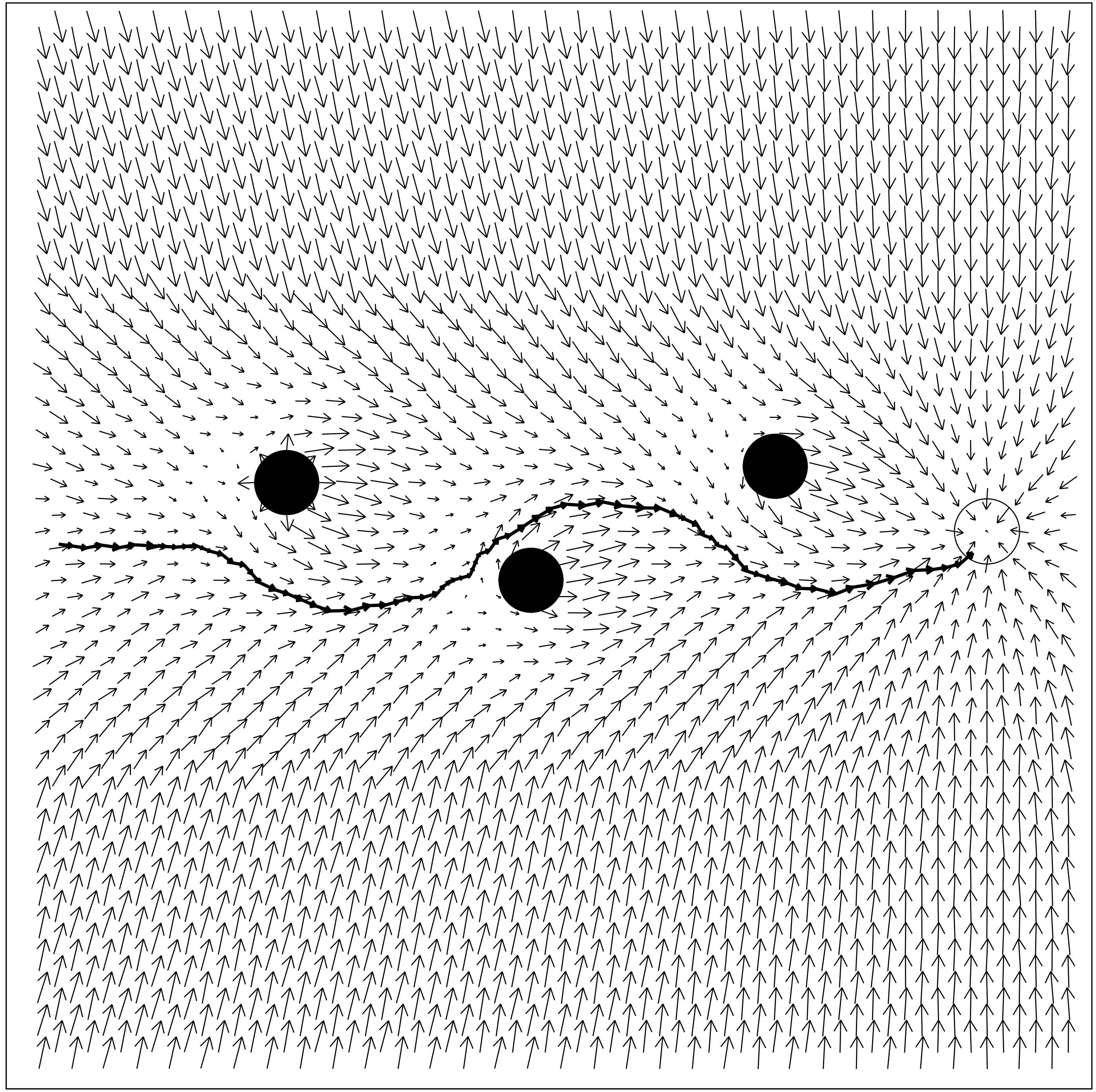
Motor schemata

- **Move-ahead**: move in a particular compass direction.
- **Move-to-goal** (both ballistic and guarded): move towards a discrete stimulus.
- **Stay-on-path**: move towards the center of a discernible pathway, e.g., a hall or road.
- **Avoid-static-obstacle**: move away from non-threatening obstacles.
- **Dodge**: sidestep approaching ballistic objects.
- **Escape**: Evade intelligent predators.
- **Noise**: move in a random direction for a fixed amount of time. (persistence)
- **Avoid-past**: move away from recently visited areas.
- **Probe**: move towards an open area.
- **Dock**: move in a spiral trajectory towards a particular surface.
- **Teleautonomy** - introduce a human operator at the same level as other behaviors.

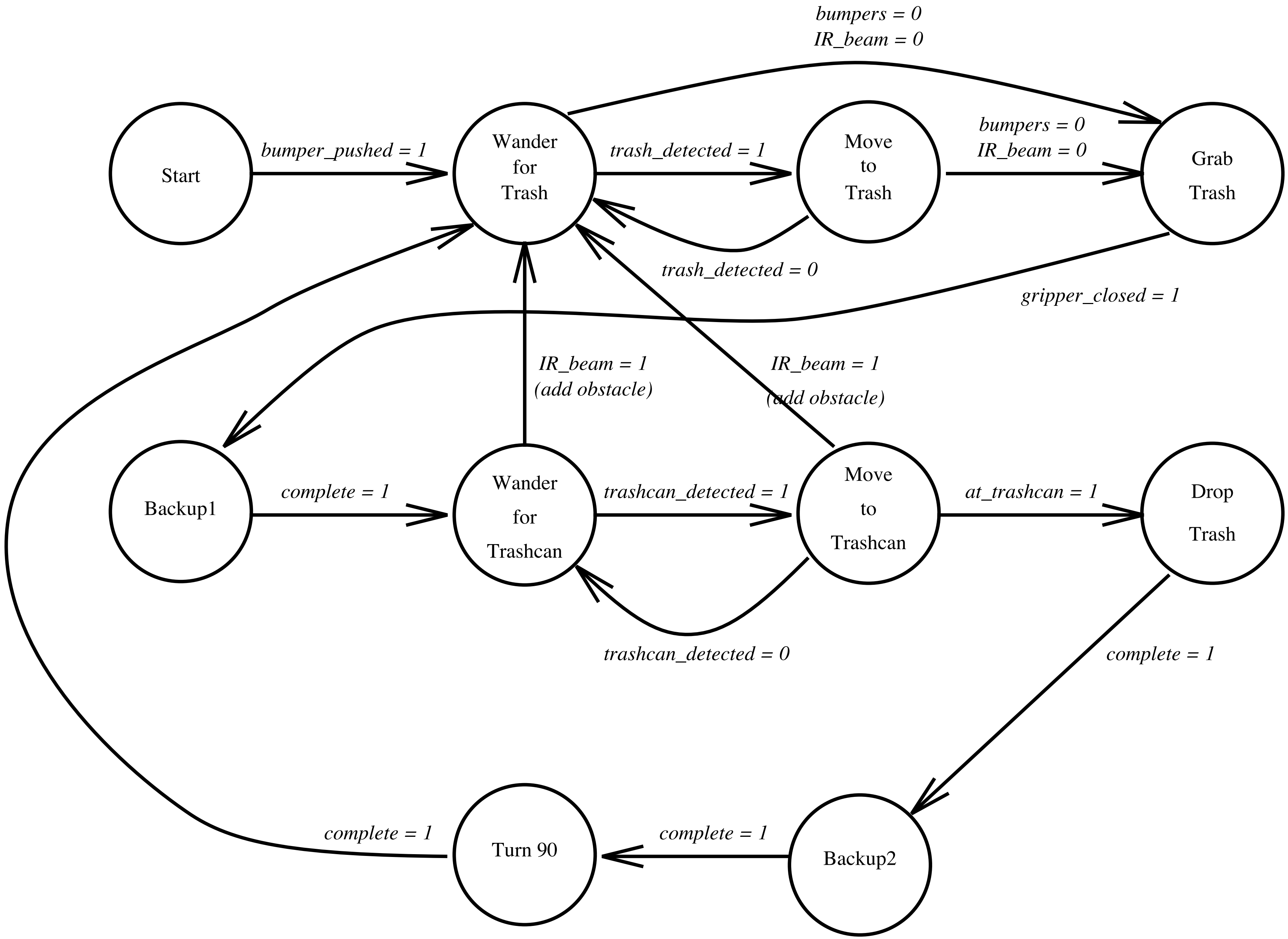
Vector-fields for different behaviors (schemata)



Superposing potential fields to combine behaviors

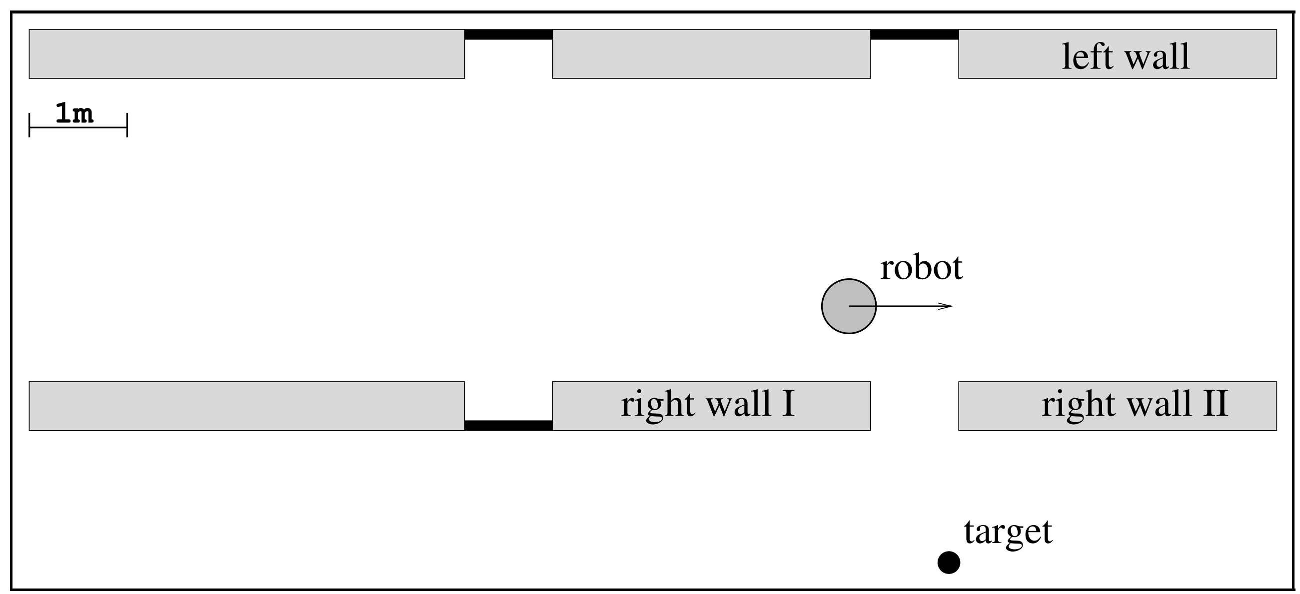


Behavior-based sequence planner



Dynamic window approach

- take dynamic constraints of vehicle into account (maximal decelerations/accelerations)… to drive fast



[Fox, Burghard, Thrun, 1996]

Dynamic window approach

- discretize motor control space: linear and angular velocity
- => search space: circular trajectories of v, omega

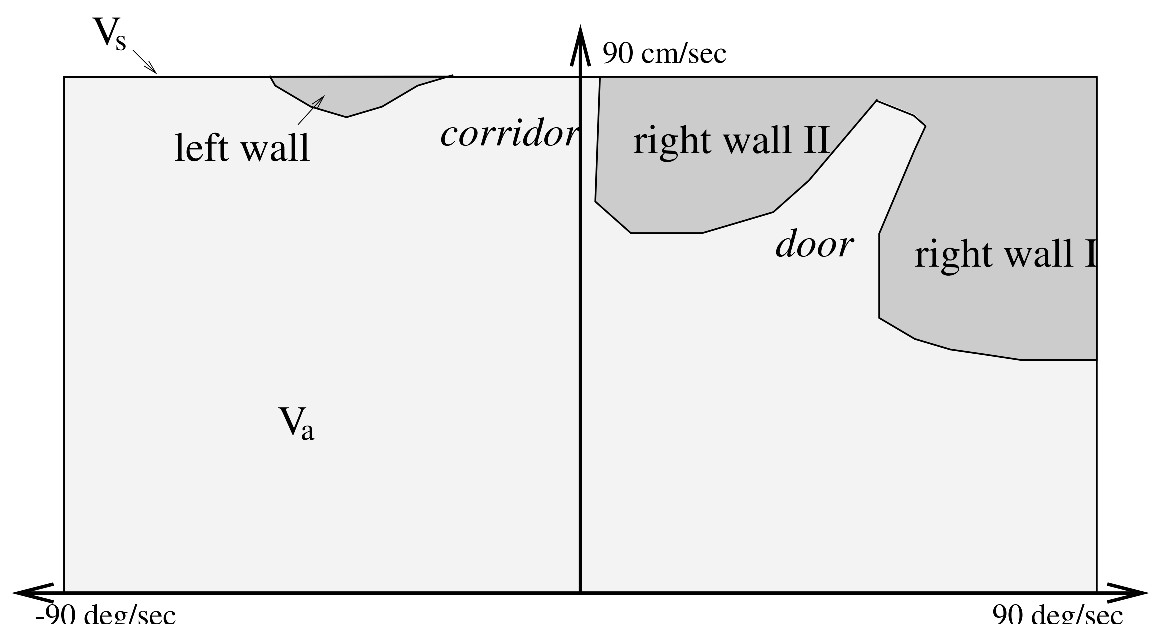


Figure 4. Velocity space

Dynamic window approach

1. **Search space:** The search space of the possible velocities is reduced in three steps:
   (a) **Circular trajectories:** The dynamic window approach considers only circular trajectories (curvatures) uniquely determined by pairs (v, ω) of translational and rotational velocities. This results in a two-dimensional velocity search space.
   (b) **Admissible velocities:** The restriction to admissible velocities ensures that only safe trajectories are considered. A pair (v, ω) is considered admissible, if the robot is able to stop before it reaches the closest obstacle on the corresponding curvature.
   (c) **Dynamic window:** The dynamic window restricts the admissible velocities to those that can be reached within a short time interval given the limited accelerations of the robot.

Dynamic window approach

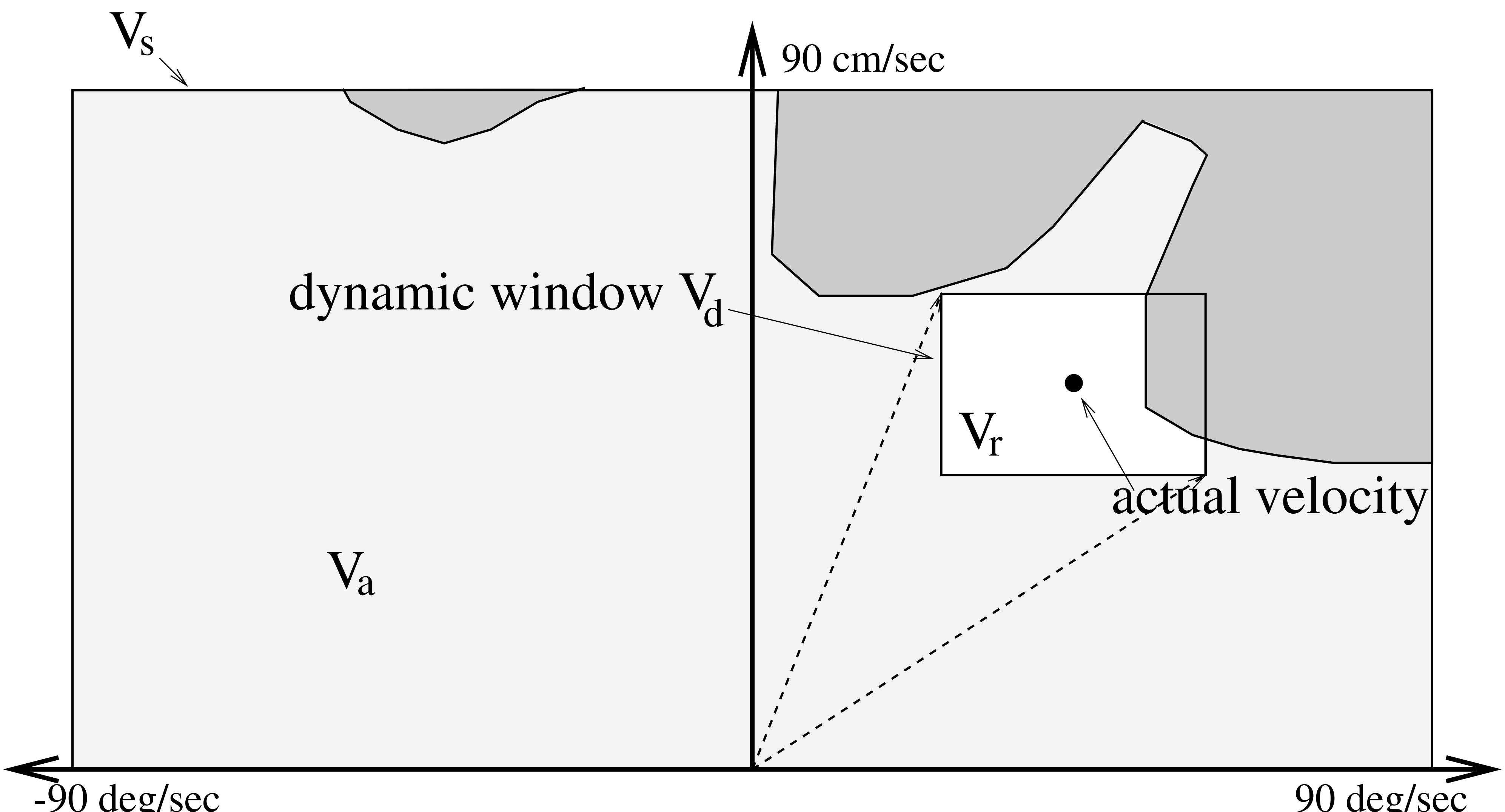


Figure 5. Dynamic window

Dynamic window approach

2. **Optimization:** The objective function

$$G(v, \omega) = \sigma(\alpha \cdot \text{heading}(v, \omega) + \beta \cdot \text{dist}(v, \omega) + \gamma \cdot \text{vel}(v, \omega)) \tag{13}$$

is maximized. With respect to the current position and orientation of the robot this function trades off the following aspects:

(a) **Target heading:** *heading* is a measure of progress towards the goal location. It is maximal if the robot moves directly towards the target.

(b) **Clearance:** *dist* is the distance to the closest obstacle on the trajectory. The smaller the distance to an obstacle the higher is the robot's desire to move around it.

(c) **Velocity:** *vel* is the forward velocity of the robot and supports fast movements.

The function σ smoothes the weighted sum of the three components and results in more side-clearance from obstacles.

Dynamic window approach

- target cost function

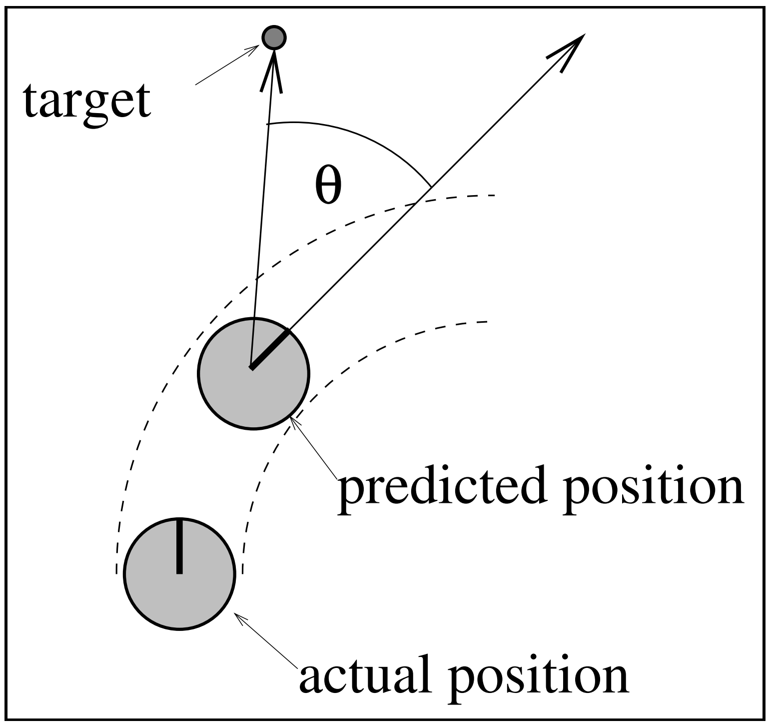


Figure 6. Angle θ to the target

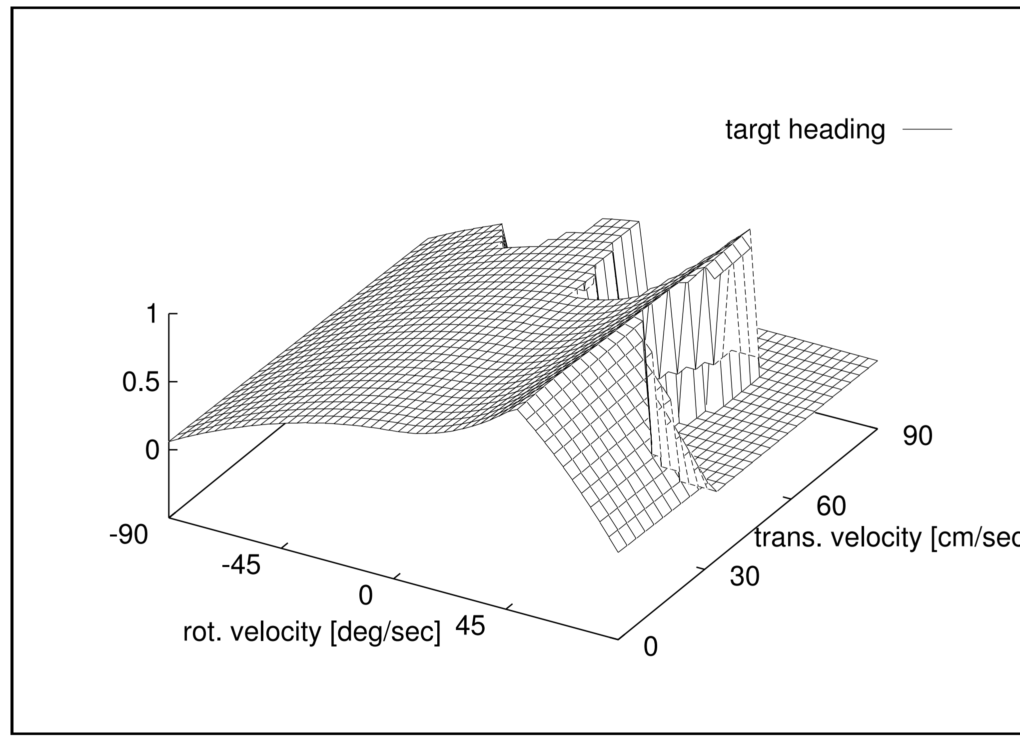


Figure 7. Evaluation of the target heading

Dynamic window approach

- clearance cost function

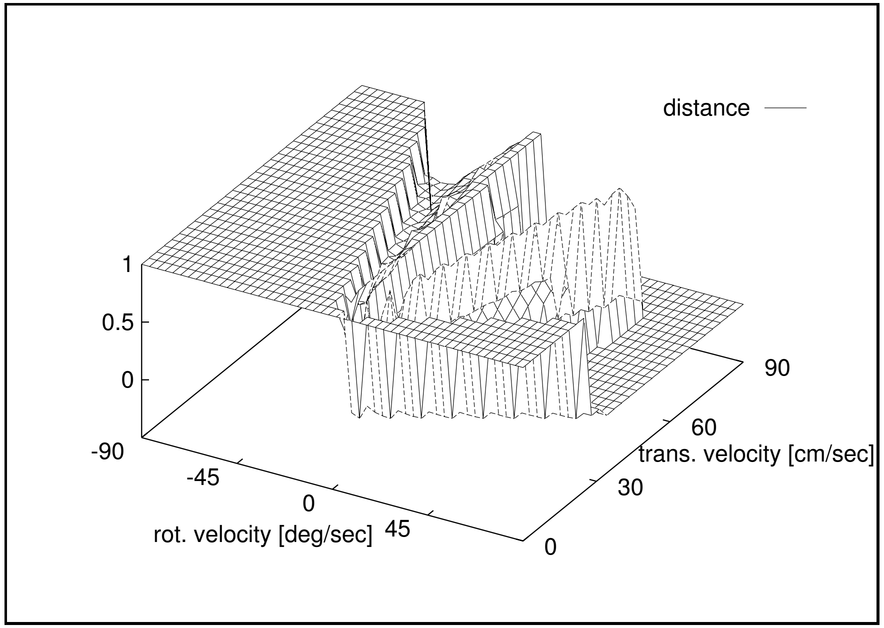


Figure 8. Evaluation of the distances

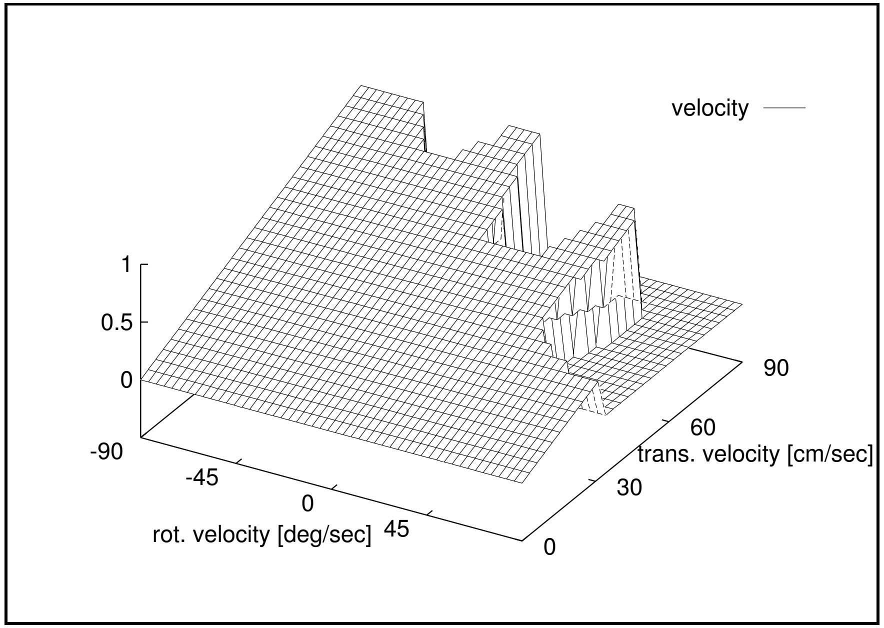


Figure 9. Evaluation of the velocities

Dynamic window approach

- smoothing the cost functions

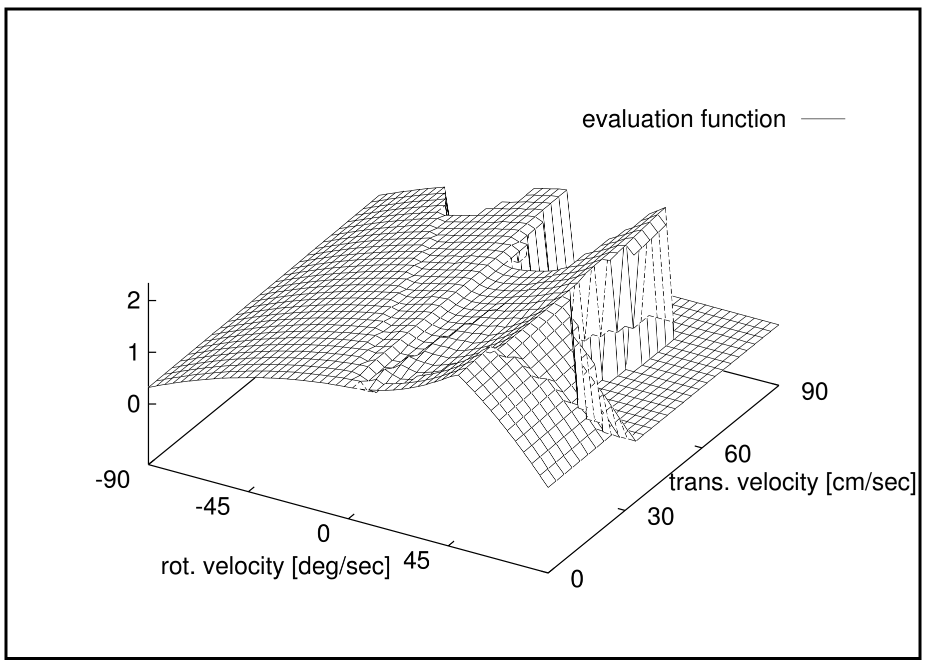


Figure 10. Combined evaluation function

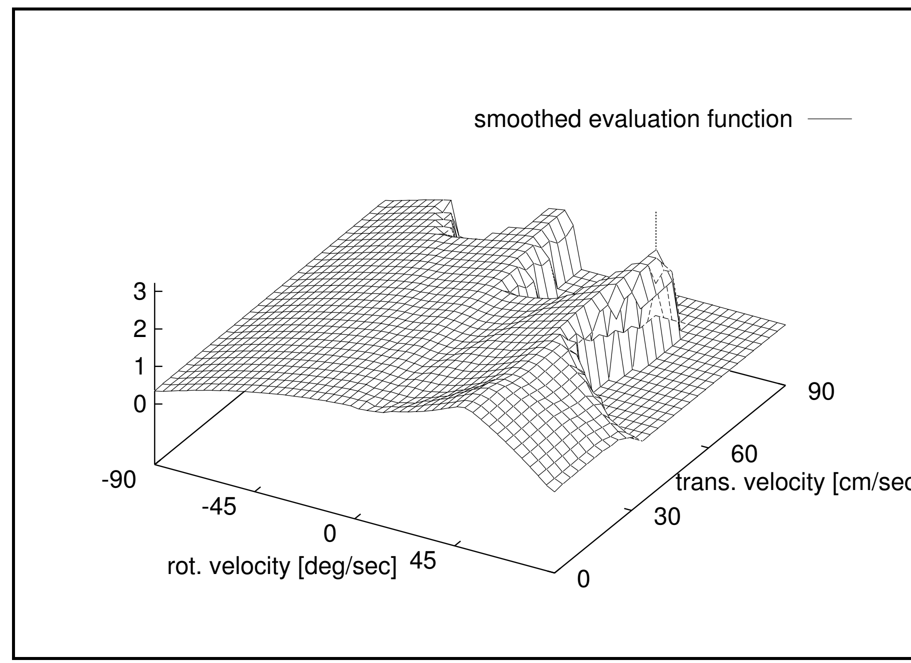


Figure 11. Objective function

Dynamic window approach

- two samples of actual velocities

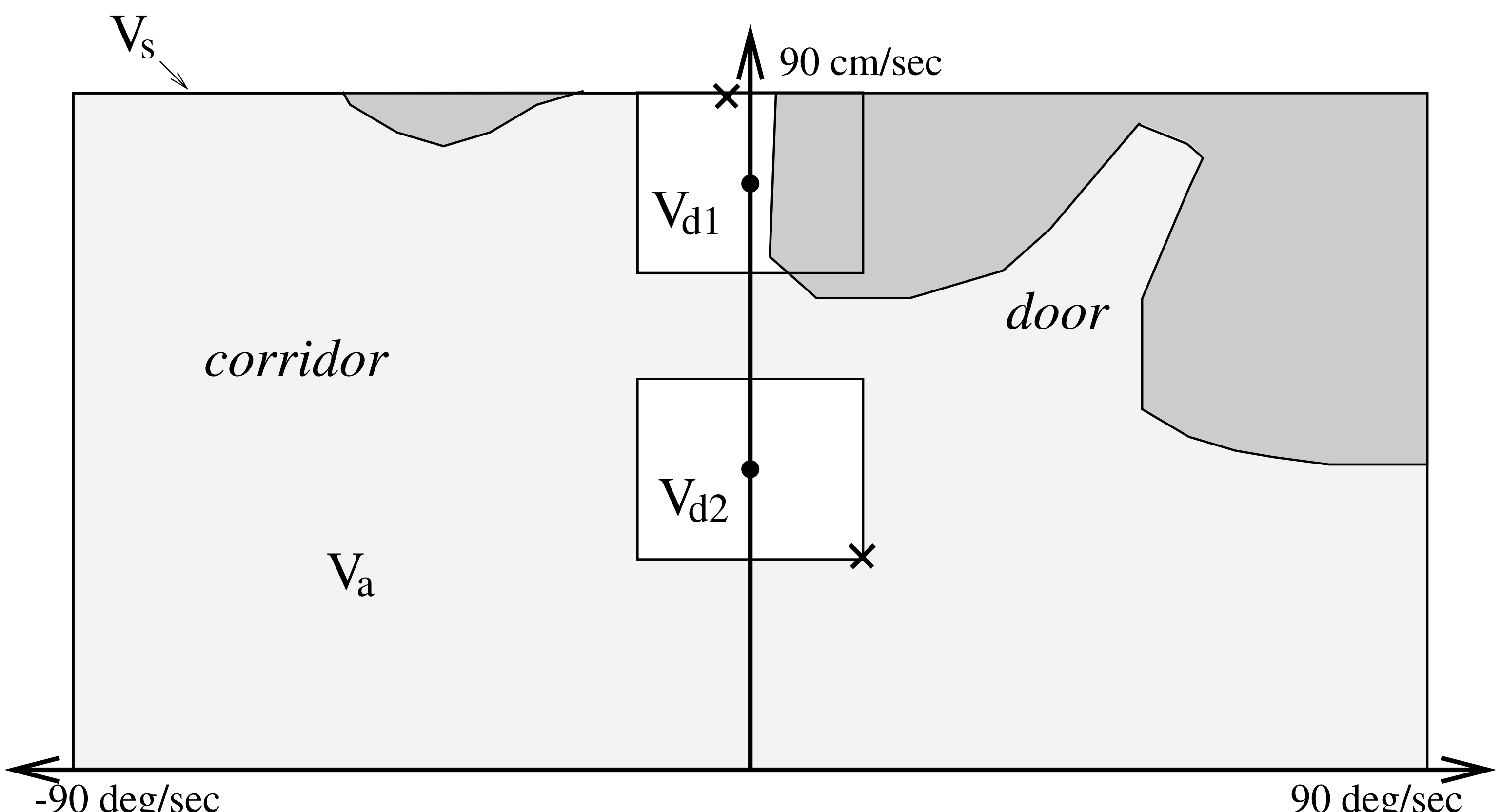


Figure 12. Velocity space

Dynamic window approach

- cost function for the action velocities

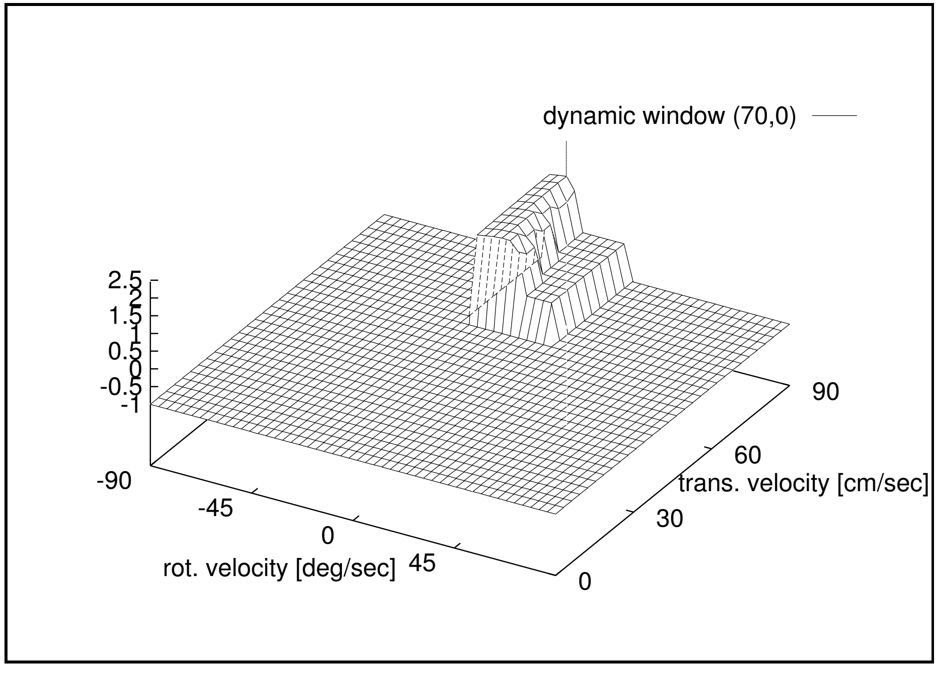


Figure 13. Objective function for actual velocity (75,0)

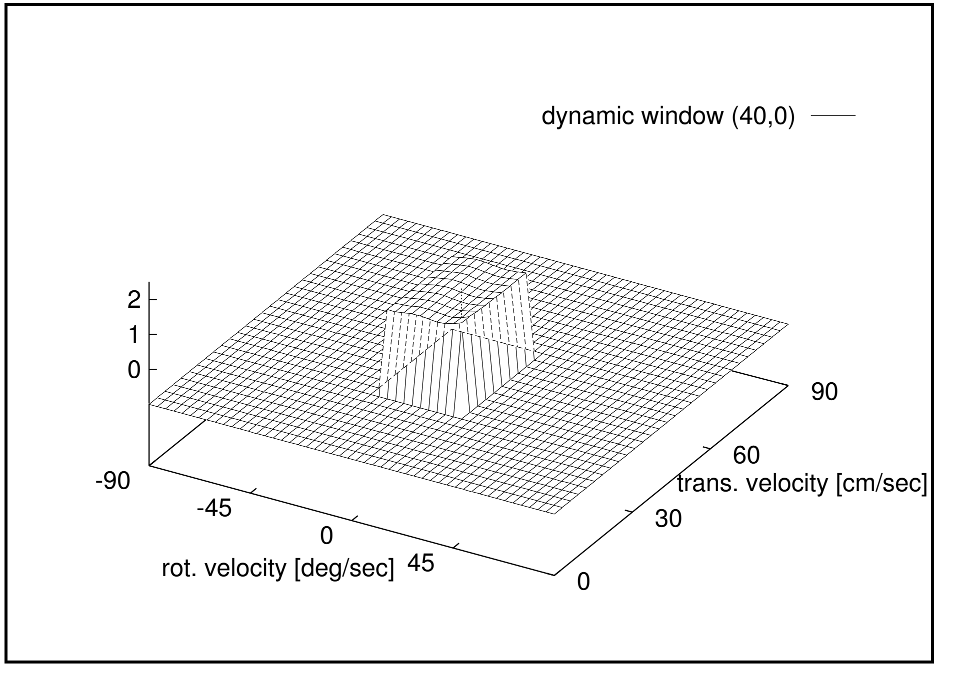


Figure 14. Objective function for actual velocity (40,0)

Dynamic window approach

- example RHINO
- used Borenstein Koren approach to smooth and accumulate sonar distance data

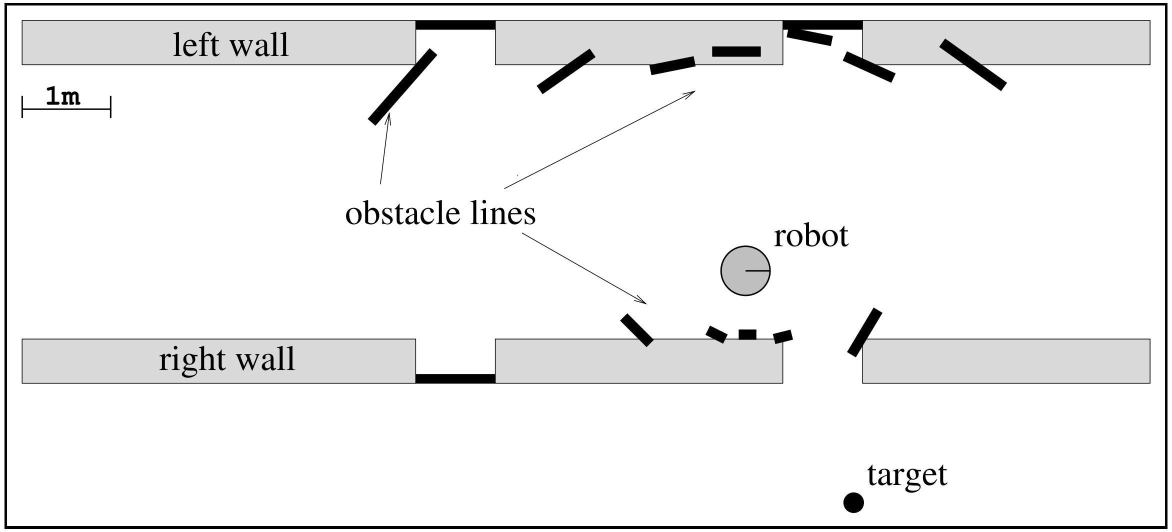


Figure 18. Example environment with obstacle lines and target point

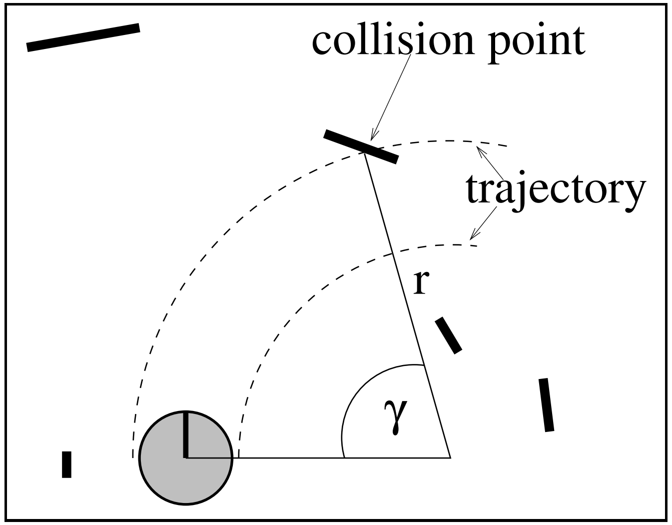


Figure 19. Determination of the distance

Dynamic window approach

- data

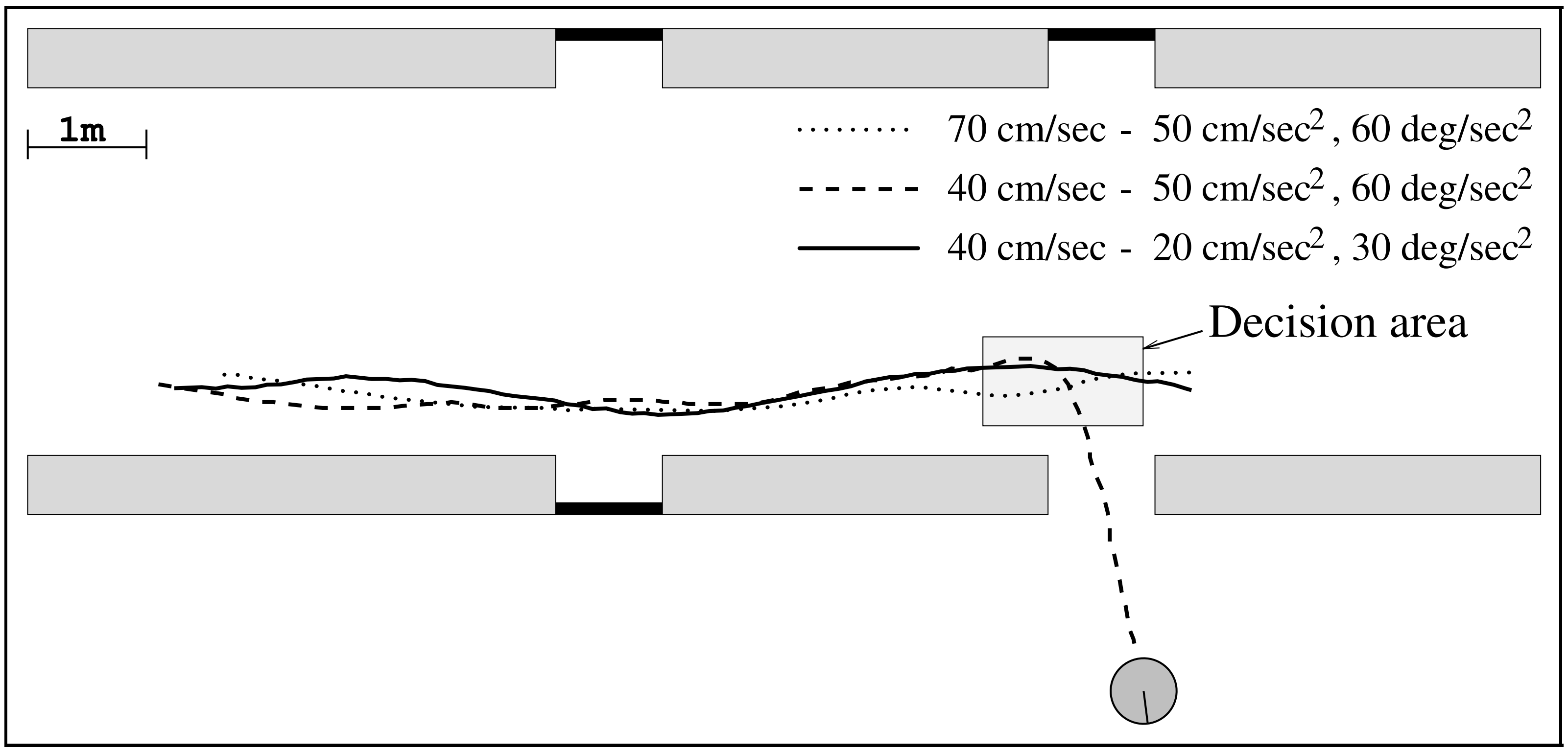


Figure 20. Trajectories chosen for different dynamic parameters

Dynamic window approach

- data

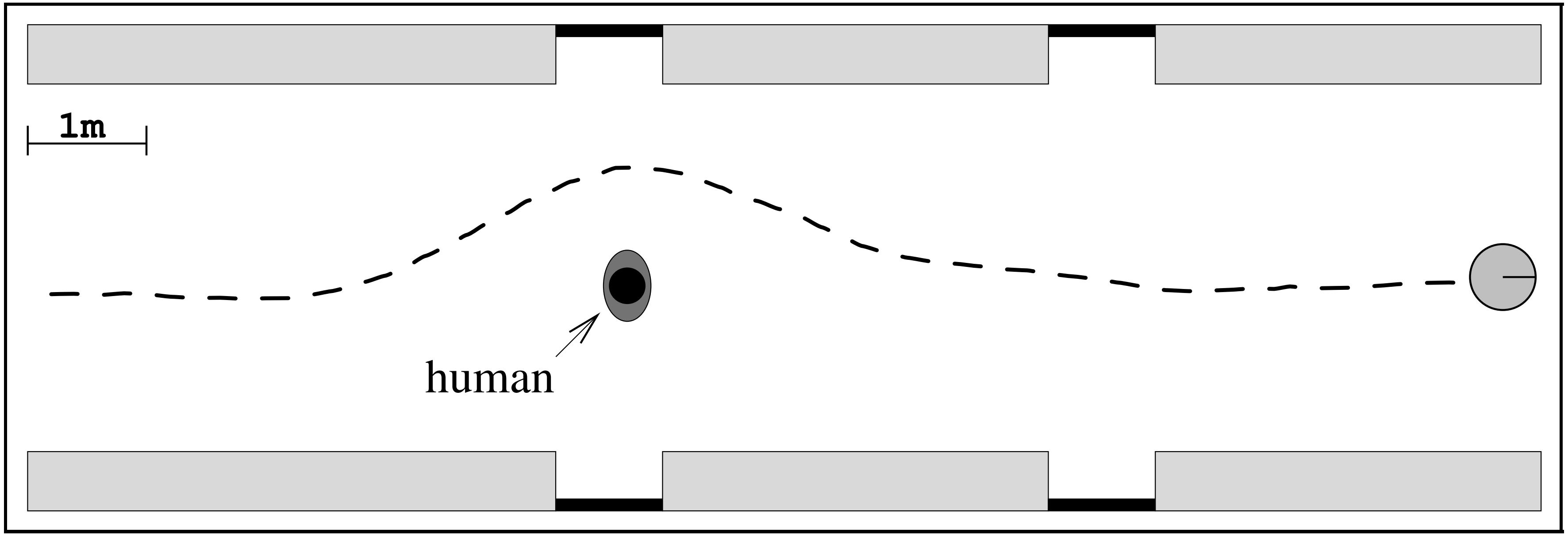


Figure 21. Trajectory through corridor

Dynamic window approach

- data

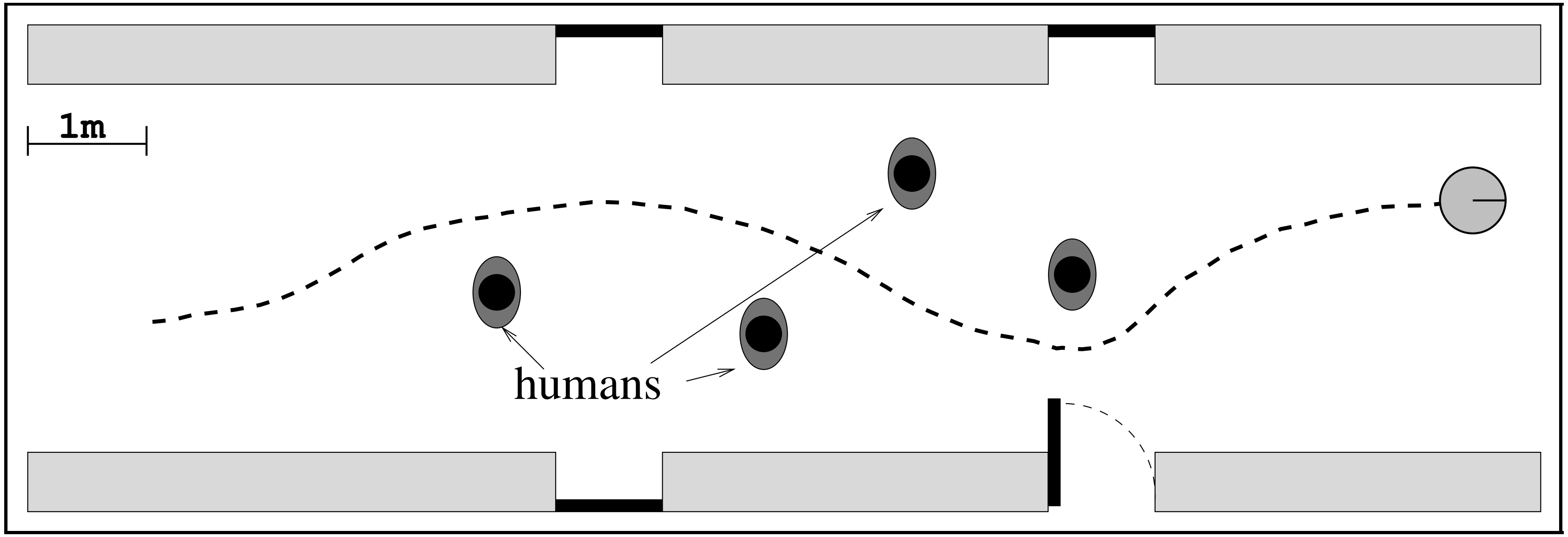


Figure 22. Trajectory through cluttered corridor

Summary

- powerful approaches exist for motion planning
- the best/exact approaches make strong demands on world representations and computation
- heuristic "reactive" approaches are state of the art (often combined in hybrid architectures with deliberative planning)
- the attractor dynamics approach is competitive as a reactive approach

Outlook

- deliberative planning…
  - moving beyond the vehicle navigation problem
  - planning sequences of actions to achieve goals
  - searching spaces, often represented as graphs
  - … a huge field…