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

Source

Intensity

Structured environment

Activation

Intensity

Wheel motion

Activation

Sensory system

Nervous system

Body

Motor system
Emergent behavior: this is a dynamics

- feedforward nervous system
- + closed loop through environment
- => (behavioral) dynamics
Complex environment $\Rightarrow$ complex dynamics

- bistable dynamics for bimodal intensity distribution
- $\Rightarrow$ nonlinear dynamics makes selection decision
“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
vehicle moving in 2D: heading direction

Behavioral variables: example

robot

heading direction

fixed (but irrelevant) world axis
Behavioral variables: example

- constraints:
  obstacle avoidance
  and target acquisition

\[
\Delta \psi
\]

\[
\Psi_{\text{obs}}
\]

\[
\Psi_{\text{tar}}
\]

arbitrary, but fixed
reference axis

robot

obstacle

target
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 constraint: obstacle avoidance

- **Behavioral dynamics: example**

**Obs**

robot

obstacle

arbitrary, but fixed reference axis

\[ Y \]

F

d

\[ \phi \]

repellor

---

**Obs**

\[ \Psi_{\text{obs}} \]

\[ \Delta \psi \]

\[ \Psi \]

\[ d\phi/dt \]

\[ \phi \]

---

**robot**

---

**Obs**

\[ \Psi_{\text{obs}} \]

---
Each contribution is a “force-let” with:
- specified value
- strength
- range

Behavioral dynamics

\[
\frac{d\phi}{dt} \sim \text{strength} \\
\psi_{\text{tar}} \quad \text{specified value}
\]
Behavioral dynamics

- multiple constraints: superpose “force-lets”
- fusion
Behavioral dynamics

- decision making

- vehicle

- target 1

- target 2

\[
\frac{d\phi}{dt}\]

repellor = attractor boundary

individual attractors = resultant attractors => bistable
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

\[ \frac{d\phi}{dt} \]
transition from “constraints not in conflict” to “constraints in conflict” is a bifurcation
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).
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.
2.1 The dynamic approach: stimuli as forces

We briefly present the main concepts of the dynamic approach to the design of autonomous systems in the form of time-invariant systems (see Schöner et al. 1995; or Schöner and Dose 1992). For our purposes, however, this is not a major concern. We exploit the properties of the dynamic mechanism of time-invariant systems.

Sensors contribute forces to the dynamics that are designed from all relevant sources of sensory or internal information. Sensors contribute forces to the dynamics that are designed from all relevant sources of sensory or internal information.

The abstract problem addressed here is reconciling stability and decision-making. For homing a dynamical system maintains an estimate of ego-position relative to the home base to reliably available dead-reckoning information with fluctuating sensory information steers the vehicle through stateless algorithms. Estimating optic flow is computation-intensive with cases in which such specification was possible, at least for behavior generation to handle two elementary problems--obstacle avoidance the resulting problem of ambiguous time-to-contact estimates is addressed by an appropriate design of the motion planning dynamics. The driving speed is adjusted to contact measurements from the optical flows seen by the left and right cameras, together with information about the goal location, are fed into a dynamical system that controls the forward and rotation velocities of the robot. The hysteresis of the dynamics, which manages the heading direction which can occur when fluctuating sensory information does not or only incompletely in view either because of the curvature of the road, or because of an occluding obstacle. The robot is heading towards the home base while avoiding an obstacle. We start from the following boundary conditions:

(a) Flow is determined for two purposes: for obstacle avoidance, time-to-contact estimates are needed in real time. (b) Flow estimation must take place in real time. (c) The behavioral dynamics is erected by contributions of time-to-contact estimates further.

The closed-loop nature of the methods makes it highly appropriate to transform values of these variables into appropriate actions of the robot. Examples of such variables are the current position relative to a home position over a spatial range that is as large as possible. For the latter purpose, we need to estimate flow vectors over large image displacement range that is as large as possible. For the latter purpose, we need to estimate flow vectors over large image displacement range that is as large as possible.

These conditions lead us to compute optic flow on coarsely sampled images using a fast correlational algorithm (Little and Shapiro 1992). For homing this allows the computation of large angles of orientation which can occur when fluctuating sensory information does not or only incompletely in view either because of the curvature of the road, or because of an occluding obstacle. The robot is heading towards the home base while avoiding an obstacle. We start from the following boundary conditions:

(a) Flow is determined for two purposes: for obstacle avoidance, time-to-contact estimates are needed in real time. (b) Flow estimation must take place in real time. (c) The behavioral dynamics is erected by contributions of time-to-contact estimates further.

The closed-loop nature of the methods makes it highly appropriate to transform values of these variables into appropriate actions of the robot. Examples of such variables are the current position relative to a home position over a spatial range that is as large as possible. For the latter purpose, we need to estimate flow vectors over large image displacement range that is as large as possible. For the latter purpose, we need to estimate flow vectors over large image displacement range that is as large as possible.
[Schöner, Dose, Engels, 1995]
So far: “symbolic” approach

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

![Diagram showing a robot with an obstacle and angles labeled with $\Delta\psi$, $\psi_{\text{obs}}$, and $\phi$. The robot's reference axis is arbitrary but fixed.]
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 $\theta$
- that points in direction $\psi = \Phi + \theta$ in the world
- erect a repellor at that angle

[from: Bicho, Jokeit, Schöner]
Obstacle avoidance: sub-symbolic

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

- Note: only \( \Phi - \psi = -\theta \) shows up, which is constant!
- \( \Rightarrow \) force-let does not depend on \( \Phi \)!

[from: Bicho, Jokeit, Schöner]
Obstacle avoidance: sub-symbolic

\[ f_{\text{obs},i}(\phi) = \lambda_i (\phi - \psi_i) \exp \left[ -\frac{(\phi - \psi_i)^2}{2\sigma_i^2} \right] \quad i = 1, 2, \ldots, 7 \]
\[ \lambda_i = \beta_1 \cdot \exp \left[ -\frac{d_i}{\beta_2} \right] \]

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

[from: Bicho, Jokeit, Schöner]
Obstacle avoidance: sub-symbolic

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

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

\[ \text{angular range depends on sensor cone } \Delta \theta \text{ and size over distance} \]

[from: Bicho, Jokeit, Schöner]
Obstacle avoidance: sub-symbolic

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

[Diagram showing obstacle avoidance dynamics with sensor coverage angles and distance values.]

[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

but why does it work?

shouldn’t there be a problem when heading changes (e.g. from the dynamics itself)?

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

shouldn’t there be a problem when heading changes (e.g. from the dynamics itself)?

[from: Bicho, Jokeit, Schöner]
In contrast to higher-level implementations where one obstacle enters this equation, so that the calibration of the external reference frame is a function of distance.

The angular range over which the forcelet exerts its effect is limited based on sensor range and sensitive, and governed by the net contribution is zero. Thus, when no obstacle is within the range of the distance sensor itself, does not matter. The strength of repulsion, which we define as a function:

\[ f(x) = \begin{cases} \frac{\sigma}{x} & \text{if } x < R \\ 0 & \text{if } x \geq R \end{cases} \]

\[ \sigma \] is a decreasing function of the distance, \( \psi \) controls its rate of decay with increasing distance.

On the top: with respect to Figure 5, two virtual obstacles are there.

From this rotation results three virtual obstacles now at directions \( \psi_1, \psi_2, \psi_3 \).

Two repulsive forcelets centered at these directions are there.

On the top: with respect to Figure 6, two virtual obstacles at directions \( \psi_4, \psi_5 \).

In this figure, sensors 5 and 6 specify an external reference frame. In the Figure, sensors 5 and 6 specify an obstacle at direction \( \psi \) and \( \phi \), sensed distances are both \( \pi/12 \) rad.

Distances are 40, 30 and 40 cm respectively. On the top:

Four erected (solid thin lines). The solid bold line shows the resultant repeller.

[from: Bicho, Jokeit, Schöner]
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

Figure 14:

Figure 15:

Graph showing the relationship between distance between obstacles (cm) and fixed points (rad), with stable and unstable points indicated.
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.
Tracking attractors

Figure 19: 20
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