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

- Robot, obstacle, and target with reference axes

-arbitrary, but fixed reference axis
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?
“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…

\[ Y_{\text{obs}} \]

\[ Q_{\text{obs}} \]

\[ F \]

\[ \Delta \psi \]

\[ \theta_{\text{obs}} \]

\[ \psi_{\text{obs}} \]

\[ \phi \]

\[ d\phi/dt \]

repellor
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

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

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

- 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)?

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The contributions from all seven sensors are summed: with increasing distance. This is illustrated in Figure 5.

Thus, the angular range over which a forcelet acts decreases by half the vehicle's width, where the constant $\beta$ controls its rate of decay with increasing distance. The net contribution is zero.

The constant $\sigma_2$ into this equation, so that the calibration of the external refer-
ence frame (the current value of $\Delta \theta$, is a decreasing function of the distance, $\text{distance}$).

The robot turned left inexemplarily illustrate that the summed obsta-
cle contributions depend little on the current orientation of the robot.

In the situation depicted in Figure 6, two virtual obstacles are under.

An-
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

Demonstration of decision making by the path planning dynamics:
- The robot is placed at a distance 20 cm from the obstacles and facing them. The target lies behind the obstacles. The two pictures in the left column illustrate two situations: In the first (top of this column) the separation between the two obstacles is larger than the robot's size, while in the second (bottom of the column) the separation between the two obstacles is smaller than the robot's size.

To illustrate how the dynamics changes from one form to the other, the distance between the obstacles was changed stepwise (solid bold line). When the separation between the two obstacles is sufficiently far from each other, the vehicle may pass between or go around them to both the left or to the right. Here, decision making means a change in the number of attractors as sensory information changes. In the bottom panel, the robot again faces two obstacles, but this time they are positioned too close together for the robot to pass in between. In this situation four obstructions, modeled as four virtual obstacles, are detected, two corresponding to the obstacle on the left, the other two to the obstacle on the right. The repulsive forcelets from these four virtual obstacles attract towards a direction in-between the obstacles, the overpass between the obstacles. Because the target contribution is quite unperturbed by the obstacle avoidance forcelets, it attracts towards a direction in-between the obstacles, leading to a single repellor at the mean of the four directions in which the virtual obstacles lie. Behaviorally, the two obstacles opening down to 0 cm illustrates how such a bifurcation can come about. In this case the corresponding obstacle contributions overlap little and can be thus said to be linearly independent. The superposed obstacle avoidance dynamics has repellors corresponding to each obstacle respectively and an attractor in between which allows the robot to pass between or go around them.

Conversely, given a fixed initial heading direction, a small change in the target heading direction creates differences in the size of the two basins of attraction, that is, near initial heading directions lead to left-ward avoidance paths. Near the boundary between left-ward and right-ward avoidance paths, initial heading directions to the right of that direction lead to left-ward avoidance paths, initial heading directions slightly to the left of the angle in which the obstacle lies lead to right-ward avoidance paths. Note that there are two constraint the overall dynamics has a repellor at that direction. Attractors corresponding to turning either left or right. This leads to paths that turns away. Therefore, heading changes are bifurcations of the overall dynamical system. At a critical distance between the two obstacles, a small change in environmental or sensory conditions may lead to one scenario or the other. The presence of two obstacles, as shown in Figure 14, demonstrates how such a bifurcation can come about. In this case the corresponding obstacle contributions overlap little and can be thus said to be linearly independent.
Bifurcations

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

- \( \Rightarrow \) Tune distance dependence of repulsion so that bifurcation occurs at the right opening

![Graph showing bifurcations and distance dependence.](image-url)
Bifurcation on approach to wall

- Initially, an attractor dominates: weak repulsion
- Bifurcation
- Then obstacles dominate: strong repulsion and total repulsion
Bifurcation on approach to wall

- same with small opening

- Figure 16: cont.
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!
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