Attractor dynamics approach to behavior generation on robots with low-level sensors

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Second order dynamics


idea:

- dynamics not of heading direction, but of turning rate
- target acquisition: define desired turning rate toward target (left vs. right)
- obstacles: turn at desired rate whenever there is impending decision, based on decision left vs. right
dynamical variable

- turning rate omega

- enact by setting new set-point for velocity servo 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

\[
\dot{\omega} = (\alpha + \frac{1}{2} \pi)c_{obs} F_{obs} + \alpha \omega - \gamma \omega^3
\]
obstacle avoidance

\[ \dot{\omega} = (\alpha + \frac{1}{2}\pi)c_{obs} F_{obs} + \alpha \omega - \gamma \omega^3 \]
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

(b) dynamics of turning rate
obstacle avoidance

In presence of obstacle to the right of current heading: tangent bifurcation removes attractor at negative omega, alpha negative, constant negative.
compute constant and alpha from obstacle

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

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

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

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

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

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

- summed to total dynamics

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

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

\[
g_{\text{left}}(\omega) + g_{\text{right}}(\omega)
\]
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
video demonstration
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
chosen were as follows: mutation. After 3,200 trials for each technique, the parameters with Arithmetic cross-over and small random pertubation as the desired behavior. The truncation selection was chosen and they were graded using a desired boxplot that express rithm. The scores were based on the above mentioned metrics then applied an optimization using a score-based genetic algo-

to a qualitatively satisfactory region of parameter space and the structure of the parameter space being sparse. A difficulty of comparisons of different approaches is that parameters and that the parameters not even have the same meaning or the same order of magnitude. Another difficulty is observe that the approaches do not have the same quantity of for systems of coupled dynamical equations. Here, one can of the parameters of the techniques, this being especially true performance and comparability relies heavily on the choice C. Parameter Estimation

capability of the hardware to enact the issued commands. For noisy obstacle data, the stability margin was at a noise level determined by searching for the stability margin of the setup. To tackle this issue, we first hand-tuned all the parameters from them based on the literature.

We ran the trials with small and large noises. Trials with • SAT vs. of the robot diameter, and for the localization of the simulation and the minimum distance to target (M2T). The minimum distance to any obstacle (M2O) throughout the entire trajectories, even in the presence of noise. The Attractor actions and with the lowest variation for the length of the

cm

• ADWD:

K

2=0

m

0

7

mm

29%

• FOAD:

K

2=0

m

0

7

mm

29%

• PFVS:

K

2=0

m

0

7

mm

29%

• CAPF:

K

2=0

m

0

7

mm

29%

1st order 2nd order

[Hernandes, Becker, Jokeit, Schöner, 2014]
implementations

- larger platform for robot soccer (in Portugal)
- autonomous wheel-chair by Pierre Mallet, Marseille