Formation Control using GQ(λ) Reinforcement Learning

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Introduction

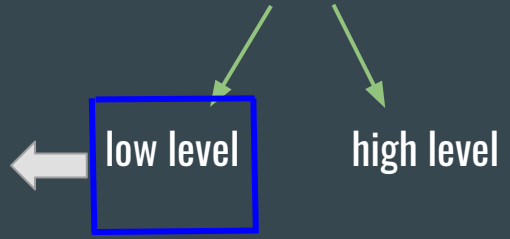
Difficult to implement on low-cost hardware

Problem: Maintaining a specific shape during locomotion.

- Current solutions in the literature are model, potential-field or graph based approaches which yield non-linear control laws.
- Most RL algorithms rely on linear functions which are computationally less complex compared to aforementioned control laws.

Solution: Using RL for Formation Control.

This paper investigates the applicability of the proposed solution on the low level side.



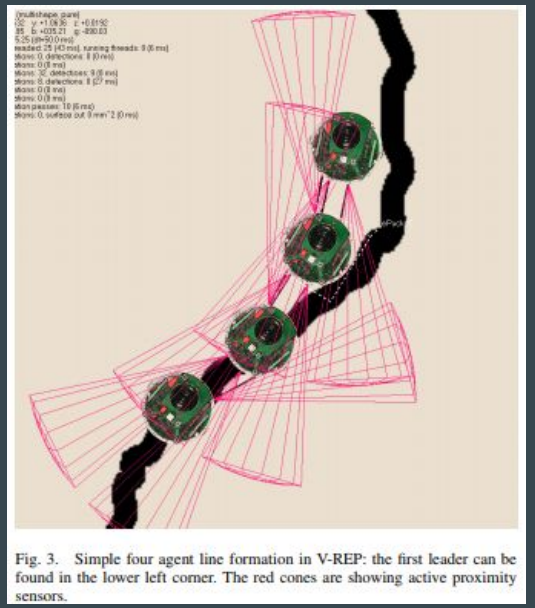


Fig. 3. Simple four agent line formation in V-REP: the first leader can be found in the lower left corner. The red cones are showing active proximity sensors.

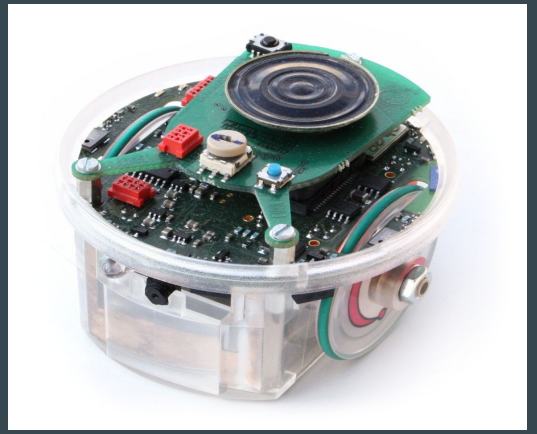
Scenario and Tools

Maximum range approximately 15 cm

Scenario: Simple leader-follower formation which uses proximity sensors as input and motor speeds as actions.

Tools:

- GQ(λ) ➡ state of art reinforcement learning algorithm.
- ε-greedy behavior policy ➡ balances exploration and exploitation.
- E-puck robots ➡ open-source tabletop robots.
- Gumstix Overo COM ➡ Runs embedded Linux and is able to connect to wireless. Used to implement learning algorithms directly on e-puck via Python API.
- V-REP ➡ Open-source robot simulation framework.



ε-greedy GQ(λ) Learning Algorithm

- $\pi : \mathcal{S} \times \mathcal{A} \to [0,1]$; target policy to be learned. Incidently, if π is chosen as the greedy policy with respect to the learned value function, then the algorithm will implement a generalization of the Greedy-GQ algorithm (Maei, Szepesvari, Bhatnagar & Sutton 2010).
- $\gamma : \mathcal{S} \to [0,1]$; termination or discounting function ($\gamma(s) = 1 - \beta(s)$ in GQ paper)
- $r : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$; reward function

Question Functions

- $b : \mathcal{S} \times \mathcal{A} \to [0,1]$; behavior policy
- $I : \mathcal{S} \times \mathcal{A} \to [0,1]$; interest function (can set to 1 for all state-action pairs or indicate selected state-action pairs to be best approximated)
- $\phi : \mathcal{S} \times \mathcal{A} \to \mathbb{R}^n$; feature-vector function
- $\lambda : \mathcal{S} \to [0,1]$; bootstrapping or eligibility-trace decay-rate function

Answer Functions

Recall:

$$\pi(s) = \begin{cases} \text{random action from } \mathcal{A}(s) & \text{if } \xi < \varepsilon \\ \text{argmax}_{a \in \mathcal{A}(s)} Q(s,a) & \text{otherwise,} \end{cases}$$

ε-greedy exploration/exploitation

ε-greedy GQ(λ) Learning Algorithm - Continued

- $\boldsymbol{\theta} \in \mathbb{R}^n$; the learned weights of the linear approximation: $Q^\pi(s,a) = \boldsymbol{\theta}^\top \boldsymbol{\phi}(s,a) = \sum_{i=1}^n \theta_i \phi_i(s,a)$
- $\boldsymbol{w} \in \mathbb{R}^n$; secondary set of learned weights
- $\boldsymbol{e} \in \mathbb{R}^n$; eligibility trace vector

Parameters internal to GQ:

- α; step-size parameter for learning $\boldsymbol{\theta}$
- $\eta \in [0,1]$; relative step-size parameter for learning $\boldsymbol{w}$ $(\alpha\eta)$

Internal Parameters

$$\rho_t = \frac{\pi(S_t, A_t)}{b(S_t, A_t)}, \tag{1}$$

Importance Sampling Ratio

$$\bar{\boldsymbol{\phi}}_t = \sum_{a \in \mathcal{A}} \pi(S_t, a)\boldsymbol{\phi}(S_t, a) \tag{2}$$

Expected Next Feature Vector

ε-greedy GQ(λ) Learning Algorithm - Continued

Goal is to learn this parameter vector.

Full Specification

$$\delta_t = r(S_t, A_t, S_{t+1}) + \gamma(S_{t+1})\boldsymbol{\theta}_t^\top \bar{\boldsymbol{\phi}}_{t+1} - \boldsymbol{\theta}_t^\top \boldsymbol{\phi}(S_t, A_t) \quad (3)$$

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \alpha\left[\delta_t \mathbf{e}_t - \gamma(S_{t+1})(1-\lambda(S_{t+1}))(\mathbf{w}_t^\top \mathbf{e}_t)\bar{\boldsymbol{\phi}}_{t+1}\right] \quad (4)$$

$$\mathbf{w}_{t+1} = \mathbf{w}_t + \alpha\eta[\delta_t \mathbf{e}_t - (\mathbf{w}_t^\top \boldsymbol{\phi}(S_t, A_t))\boldsymbol{\phi}(S_t, A_t)] \quad (5)$$

$$\mathbf{e}_t = I(S_t)\boldsymbol{\phi}(S_t, A_t) + \gamma(S_t)\lambda(S_t)\rho_t \mathbf{e}_{t-1} \quad (6)$$

weight doubling

The main idea of the algorithm is to minimize the projected Bellman error

$$J(\theta) = \|\Pi T^{\pi_\theta} Q_\theta - Q_\theta\|_\mu^2$$

Pseudocode

Initialize $\boldsymbol{\theta}$ arbitrarily and $\mathbf{w} = 0$
Repeat (for each episode):
  Initialize $\mathbf{e} = 0$
  $S \leftarrow$ initial state of episode
  Repeat (for each step of episode):
    $A \leftarrow$ action selected by policy b in state S
    Take action A, observe next state, S'
    $\bar{\boldsymbol{\phi}} \leftarrow 0$
    For all $a \in \mathcal{A}(s)$:
      $\bar{\boldsymbol{\phi}} \leftarrow \bar{\boldsymbol{\phi}} + \pi(S', a)\boldsymbol{\phi}(S', a)$
    $\rho = \frac{\pi(S,A)}{b(S,A)}$
    GQlearn$(\boldsymbol{\phi}(S, A), \bar{\boldsymbol{\phi}}, \lambda(S'), \gamma(S'), r(S, A, S'), \rho, I(S))$
    $S \leftarrow S'$
  until S' is terminal

GQLearn$(\boldsymbol{\phi}, \bar{\boldsymbol{\phi}}, \lambda, \gamma, R, \rho, I)$
  $\delta \leftarrow R + \gamma\boldsymbol{\theta}^\top \bar{\boldsymbol{\phi}} - \boldsymbol{\theta}^\top \boldsymbol{\phi}$
  $\mathbf{e} \leftarrow \rho\mathbf{e} + I\boldsymbol{\phi}$
  $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha(\delta\mathbf{e} - \gamma(1-\lambda)(\mathbf{w}^\top \mathbf{e})\bar{\boldsymbol{\phi}})$
  $\mathbf{w} \leftarrow \mathbf{w} + \alpha\eta(\delta\mathbf{e} - (\mathbf{w}^\top \boldsymbol{\phi})\boldsymbol{\phi})$
  $\mathbf{e} \leftarrow \gamma\lambda\mathbf{e}$

Design of State and Action Space

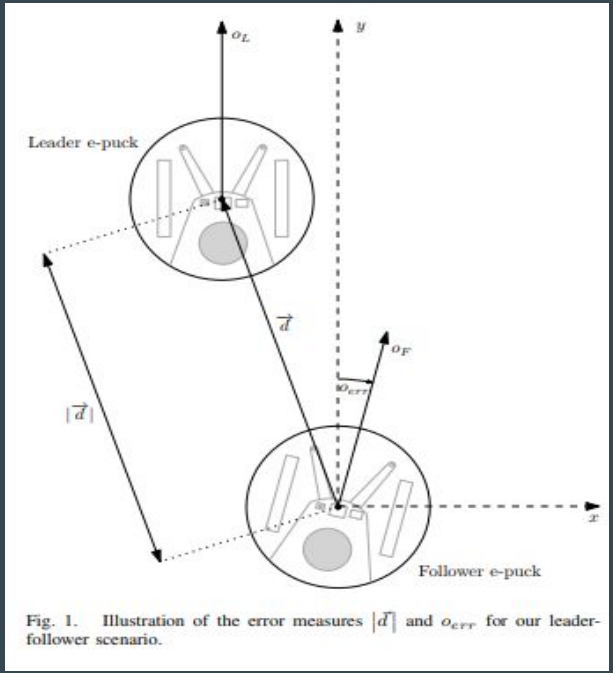


Fig. 1. Illustration of the error measures $|\vec{d}|$ and o_{err} for our leader-follower scenario.

Since there are two motors in each robot, action space is directly 2-dimensional which represents motor speeds. It is tile coded [linear uniform] as 7x7 for discretization.

State space is determined to be 2-dimensional as well:
1) Deviation from optimal distance*, i.e. distance err
2) Angular error.

*optimal distance: middle between the maximum and minimum allowed distance

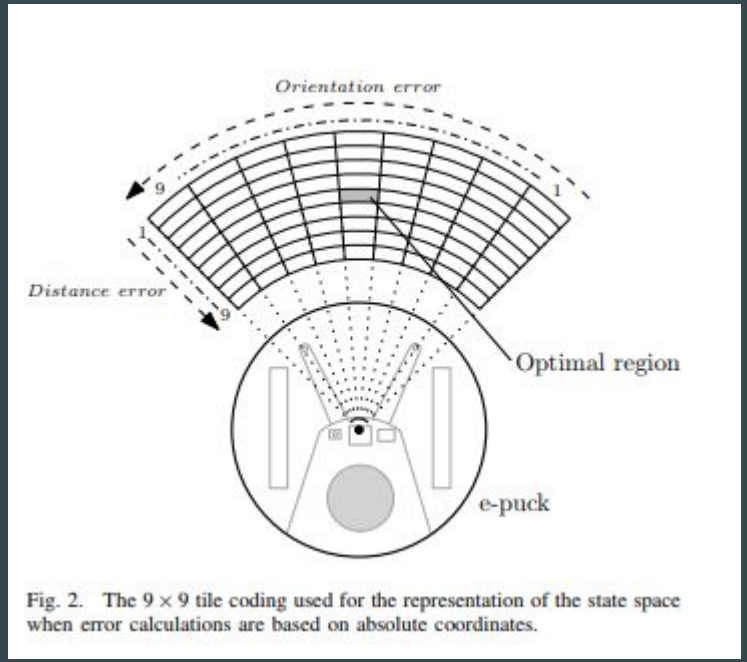


Fig. 2. The 9×9 tile coding used for the representation of the state space when error calculations are based on absolute coordinates.

State space is tile coded [logarithmic] too, as 9x9 for discretization.

Experiments & Results

Simulation

Leader: Simple statistical line follower. Moves arbitrarily.

- Up to 4 followers. Line-like formation. Try to learn the robot directly in front of them.
- Finding: Robots start to stabilize their behavior from first follower towards end of the line formation.

In 74% of all cases, the leader was detected in the dark red area right to optimal region. Additionally, the leader stayed within the orange/red 3x3 area in 98.7% of the time. Logaritmic tiling is used to have rarely visited states distinguishable.

Shift to the right side in the distribution is caused by the overall path which is a closed circular loop.

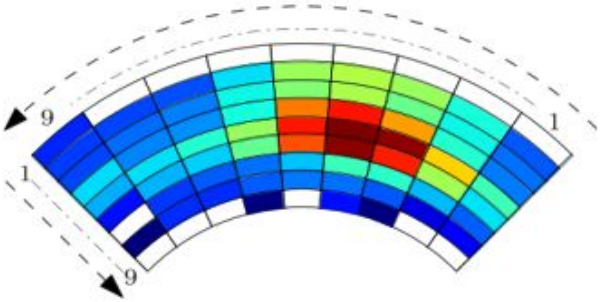


Fig. 4. Distribution of visited states at around 1.3 million steps. In 74% of all cases, the leader was detected in the dark red area right to our optimal region. It stayed within the orange/red 3×3 area on the right side of the optimal region in 98.7% of the time. To make the rarely visited states discernible, a logarithmic scale is used: red and orange values are in the range of 30%–1%, green values are at around 0.1%, and blue values are another magnitude below that. The non-colored states were never visited in this experiment.

Experiments & Results - Continued

Real World

Overero COM instead of a Standart PC is used for whole training.

- Computational bottlenecks are introduced.
- Tiling is reduced from 9x9, 7x7 to 5x5 and 3x3 respectively for state and action values.
- Environmental lighting may heavily distort the sensor readings.
- Tradeoff between smoothness & learning efficiency vs. insurance of followers can keep up with the leader in limited time.

Cure: Transferability of learned parameters from simulation.

✔ Despite all sensor and computational issues, learning algorithm showed that it is able to learn the right parameters for following the leader, i.e. keeping the formation valid.

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! Nonetheless, stabilization take much more time than the simulation.

Conclusion

- ε-greedy GQ(λ) can be used to have robots learn to keep a line-like formation.
- Required learning parameters can be adapted from a simulation (through transfer of value function estimation).
- “Natural” behavior is obtained through smoothed variant of the leader’s path which would intuitively increase the acceptance of the robot’s behavior by non-experts.