Multiagent Coordination in Roombas: From a Neural Network Perspective

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Structure of the Roomba Environment

- Objects:
  - Agent: dynamic dirt collectors (Black Disks)
  - Scrumb: static dirt to clean (Blue Dots)
  - Wall: static boundary of the world
  - Chair/Desk: static decorations as hidden obstacles

  Roomba pictures
- Objectives:
  - collect as many scrumbs as possible
  - make as few collision as possible

A Ideal Case

- The most ideal case is to set up a system with
  - Centrailization: full control over all agents
  - Global View: full observations over all scrumbs
- In this system, the crumb collection can be formulated as an integer programming problem.
- No experiential learning is needed in this case.

A Slightly Realisitc Case

- Relax the "Centralization" assumption and yield a decentralized system with
  - Autonomy: all agents should decide on its own
  - Global View: full observations over all scrumbs are still available for all agents
- We need
  - Local policy optimizers that approximates the globally optimal policies
  - Collision-free or collision-tolerant protocol between agents

A More Realisitc Case

- Relax the "Global View" assumption, but allow limited information sharing between agents. These yield a system with
  - Autonomy: all agents should decide on its own
  - Local View: only local observation of scrumbs are available for agents
  - Limited Sharing: a small amount of information is shared between agents
- We are going to solve the maximum crumbs collection problem using experiential learning.

Challenges and Difficulties

- Communication:
  - what information to share?
  - how to share it for the best performance?
- Learning Mechanism: What learning policy makes the learning simplest and fastest?
  - Enforced SubPopulation (ESP).
  - Opportunistic Cooperative Learning (OCL).
- Sensors:

Approaches

baseline: random agents, greedy agents
more: neuroevolution, Q Learning
fitness derived from given number of episodes (each episodes with fixed number of actions).

Results

Conclusions

Future Work

Discussion Time

- Any questions or suggestions?
  sert pictures
- Or email us at
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Acknowledgement

Thanks.