

# Multiagent Coordination in Roombas: From a Neural Network Perspective

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# Section 1

## Problem Motivation

# 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
  - Centralization: full control over all agents
  - Global View: full observations over all scrums
- In this system, the crumb collection can be formulated as an integer programming problem.
- No experiential learning is needed in this case.

# A Slightly Realistic 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 scrums 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 Realistic 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 scrums are available for agents
  - Limited Sharing: a small amount of information is shared between agents
- The difficulty lies in
  - Communication: what information to share for the best performance?
  -
- This can be solved using experiential learning: reinforcement learning or neuroevolution.

## Section 2

# Approaches and Architectures



baseline: random agents, greedy agents

more: neuroevolution, Q Learning

fitness derived from given number of episodes (each episodes with fixed number of actions).



# Section 3

## Experimental Results

# We compared the fitness derived from

## Section 4

# Discussion

# Discussion Time

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

Thanks.