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ICRA 2015 Workshop

Bio-inspired algorithms for distributed control of small teams of low-cost aquatic robots

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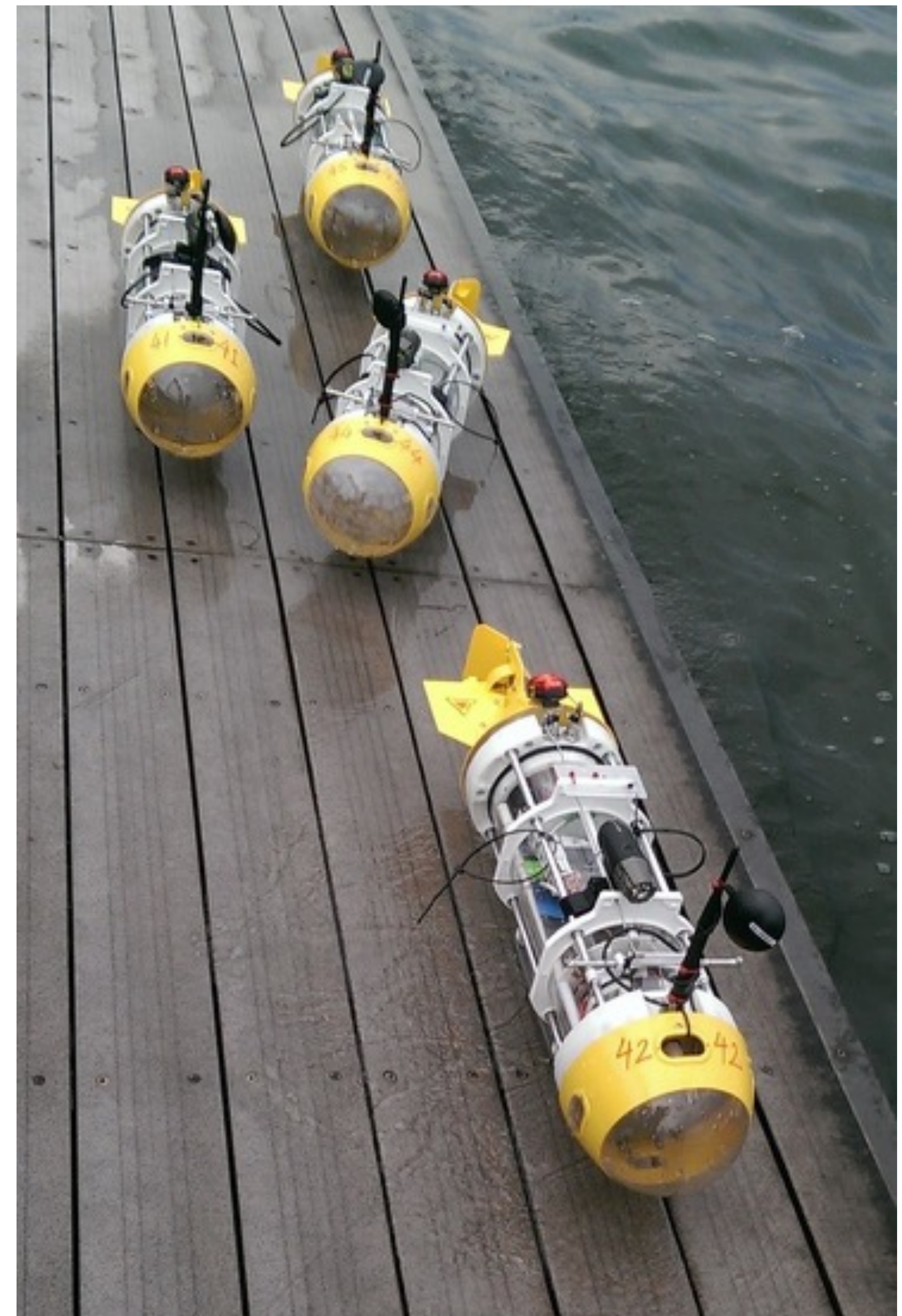
Context

Persistent Autonomy for Aquatic Robots

- Desired properties:
  - Endurance: long
  - Robustness: high
  - Cost: low

Persistent Autonomy for Aquatic Robots



- Desired properties:
  - Endurance: long
  - Robustness: high
  - Cost: low

- Multi-robot systems with:

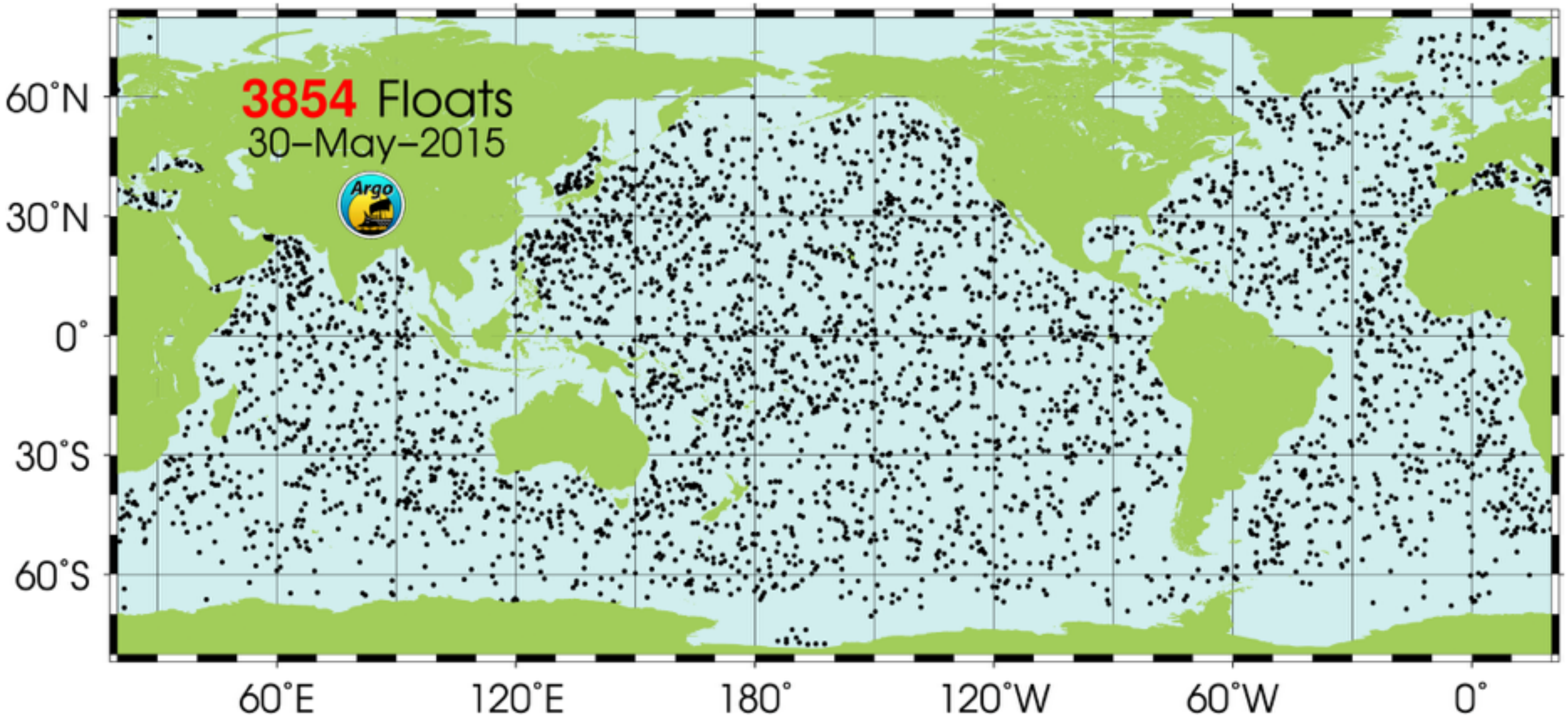
  simple individuals

  minimal sensors

  minimal/implicit communication

Argo Floats

Low cost, long endurance, robust – but very little control



Motivational Example

Motivational Example

- The larvae of nearly all coral reef fish develop at sea for weeks to months before settling back to reefs as juveniles.
- Although larvae have the potential to disperse great distances, a substantial portion recruit back to their natal reefs.
- Larvae are not passively dispersed but develop a high level of swimming competence.
- Recruits respond actively to reef sounds.

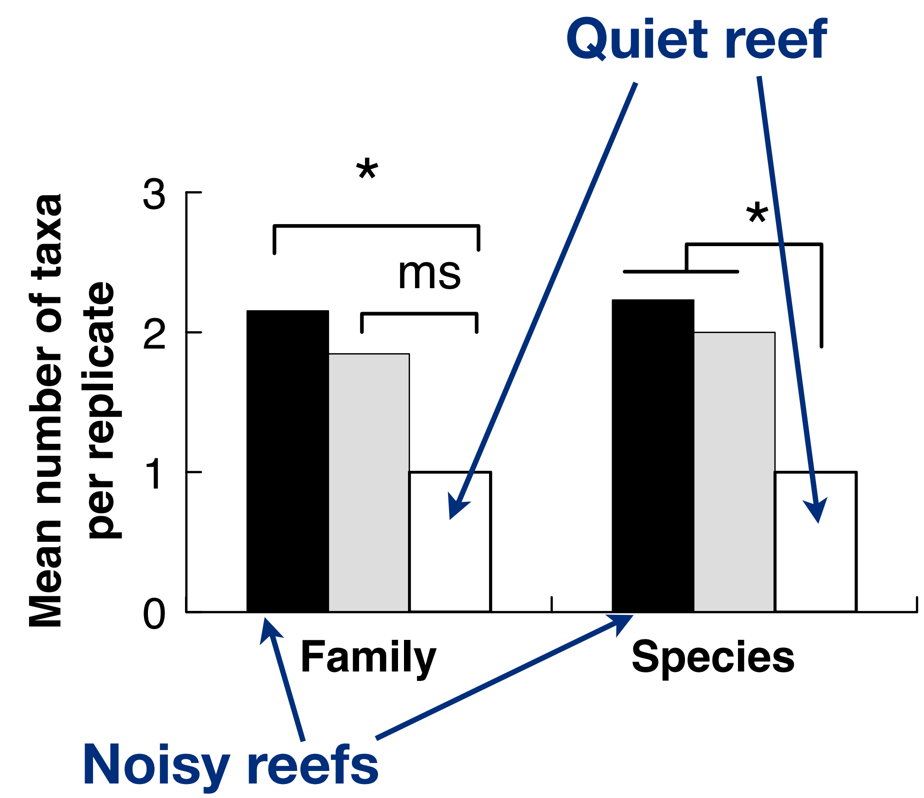


Figure reproduced from [1]

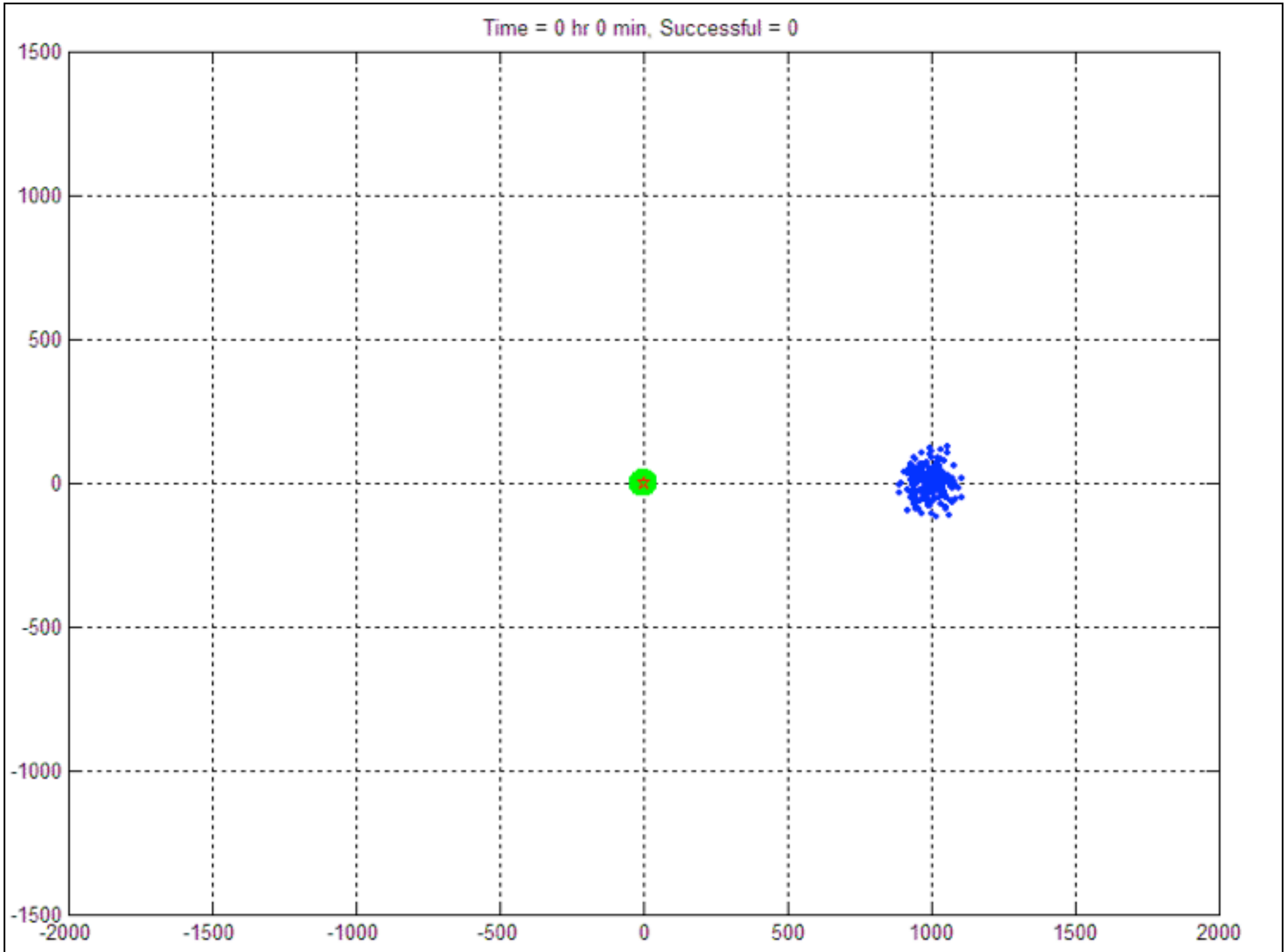
[1] S. D. Simpson, M. Meekan, J. Montgomery, R. McCauley, and A. Jeffs. Homeward sound. *Science*, 308(5719):221, 2005.

Simulation #1: Basic Model

- Fish larvae start at 1 km from the reef.
- The larvae can estimate intensity changes of sound from the reef to within 1 dB.
- Each larva swims for 15 minutes in a random direction. Then:
  - If the intensity of sound increases, it keeps swimming in that direction.
  - If the intensity of sound decreases, it randomly changes direction with a bias towards the opposite direction.
  - If the intensity of sound does not change, it randomly turns by about 90 degrees.

[2] J. R. Potter and M. A. Chitre. Do fish fry use emergent behaviour in schools to find coral reefs by sound? In *AGU Ocean Sciences Meeting*, Honolulu, Hawaii, February 2006.

Simulation #1: Sample Run



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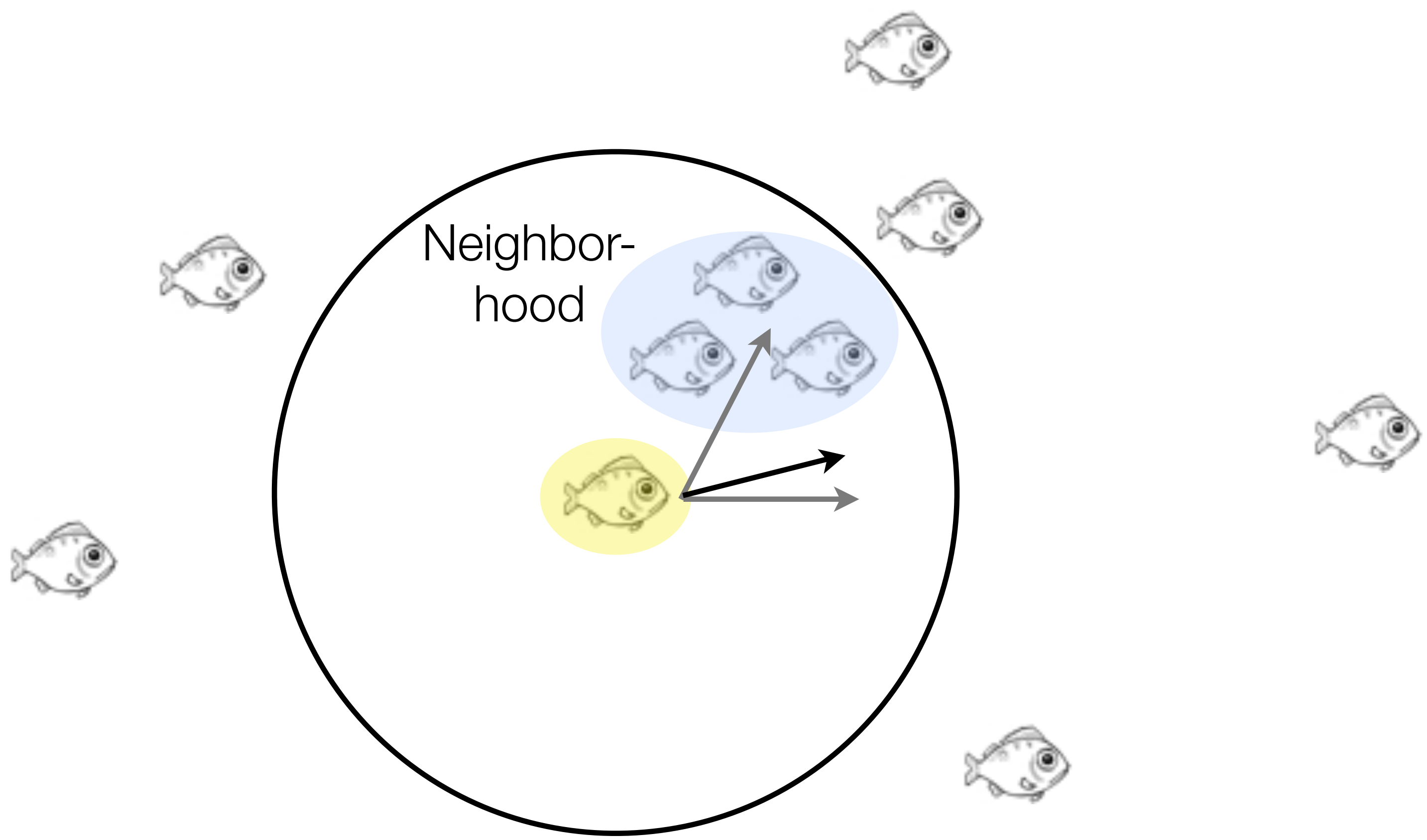
Simulation #2: Schooling Model

- Same as simulation #1 model.
- Additionally, larvae have a small bias to move towards the centroid of the neighbors that they can see.



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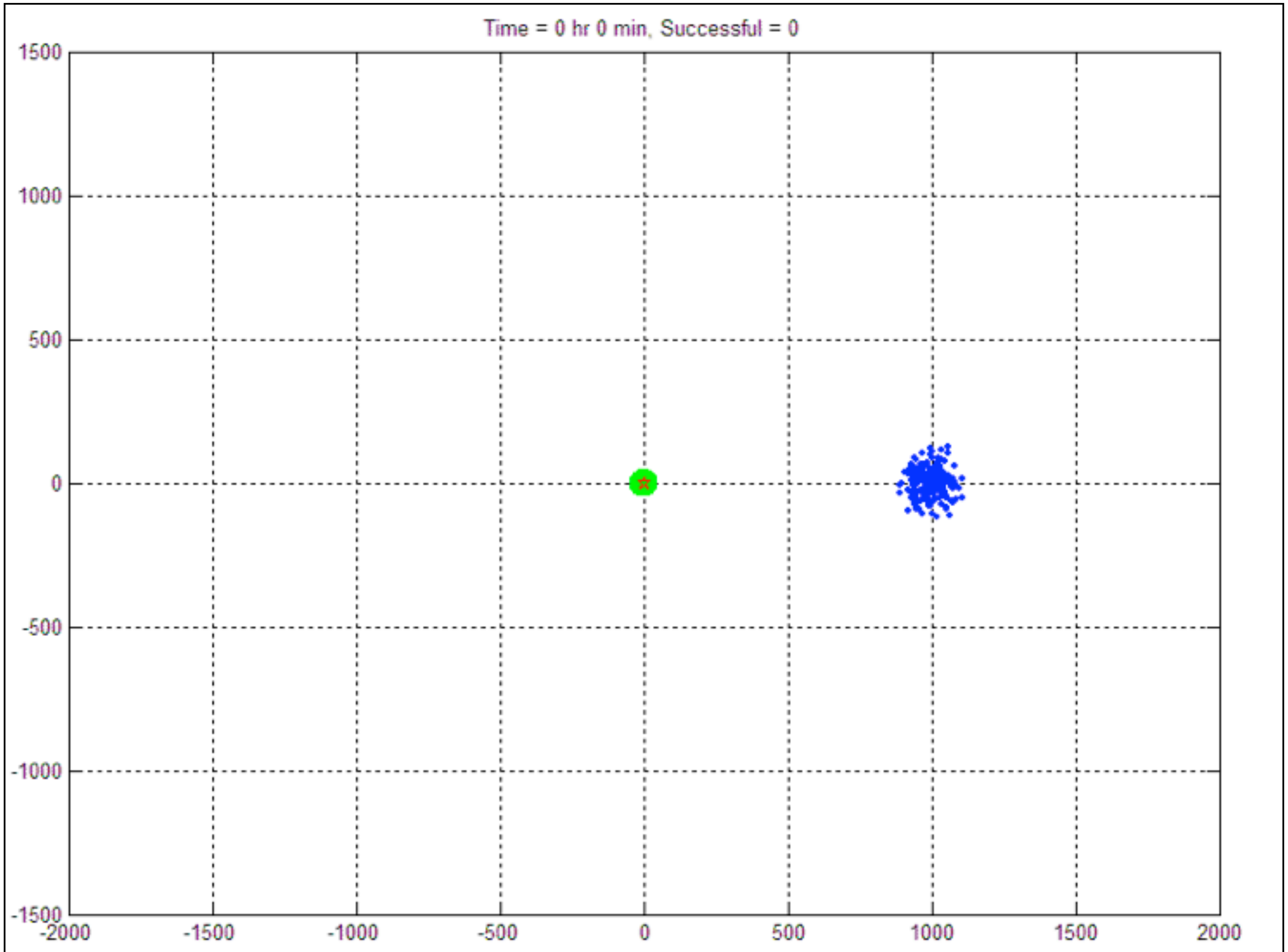
Simulation #2: Sample Run



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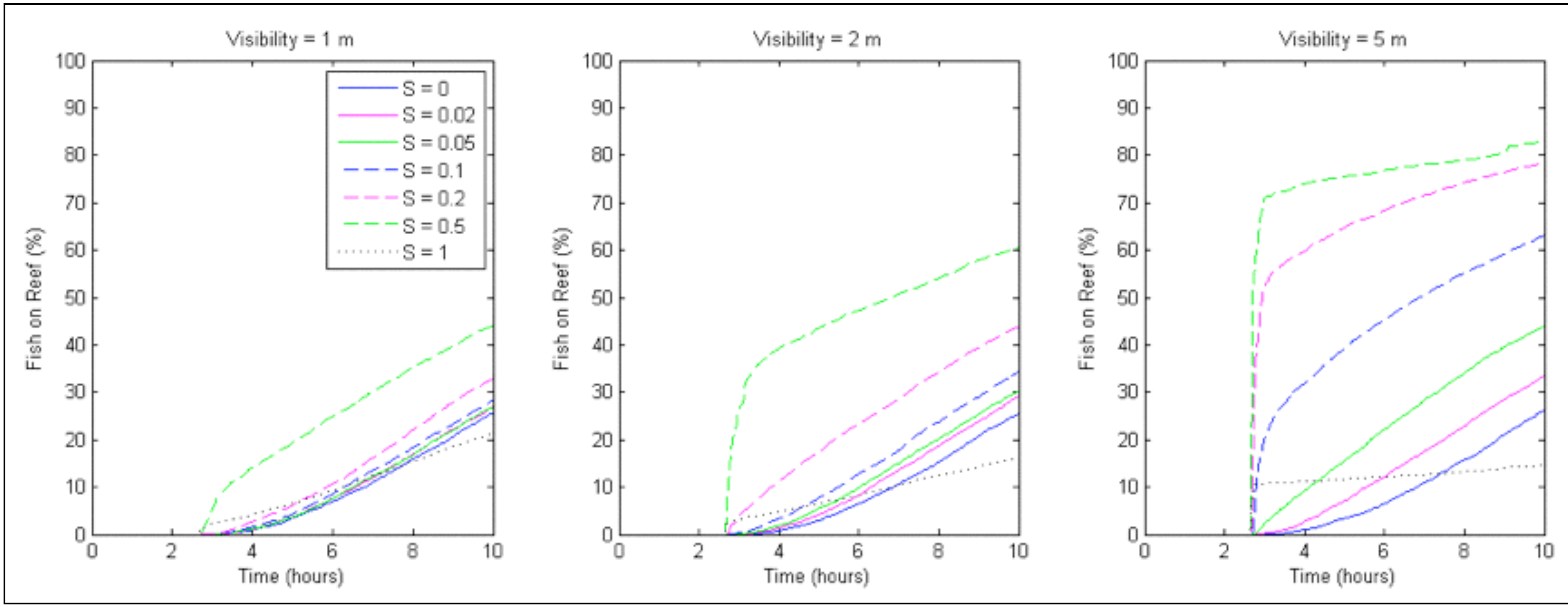
Simulation Results



Key Takeaways

1. The team "knows" more than each of the individual in the team.
2. A bunch of noisy sensors may be sufficient, if the sensors can cooperate.
3. Communication is key in a team; but it can be implicit and very limited.
4. Apparently sophisticated team behavior can result from simple individual behaviors.

Problem Statement

Key Research Question

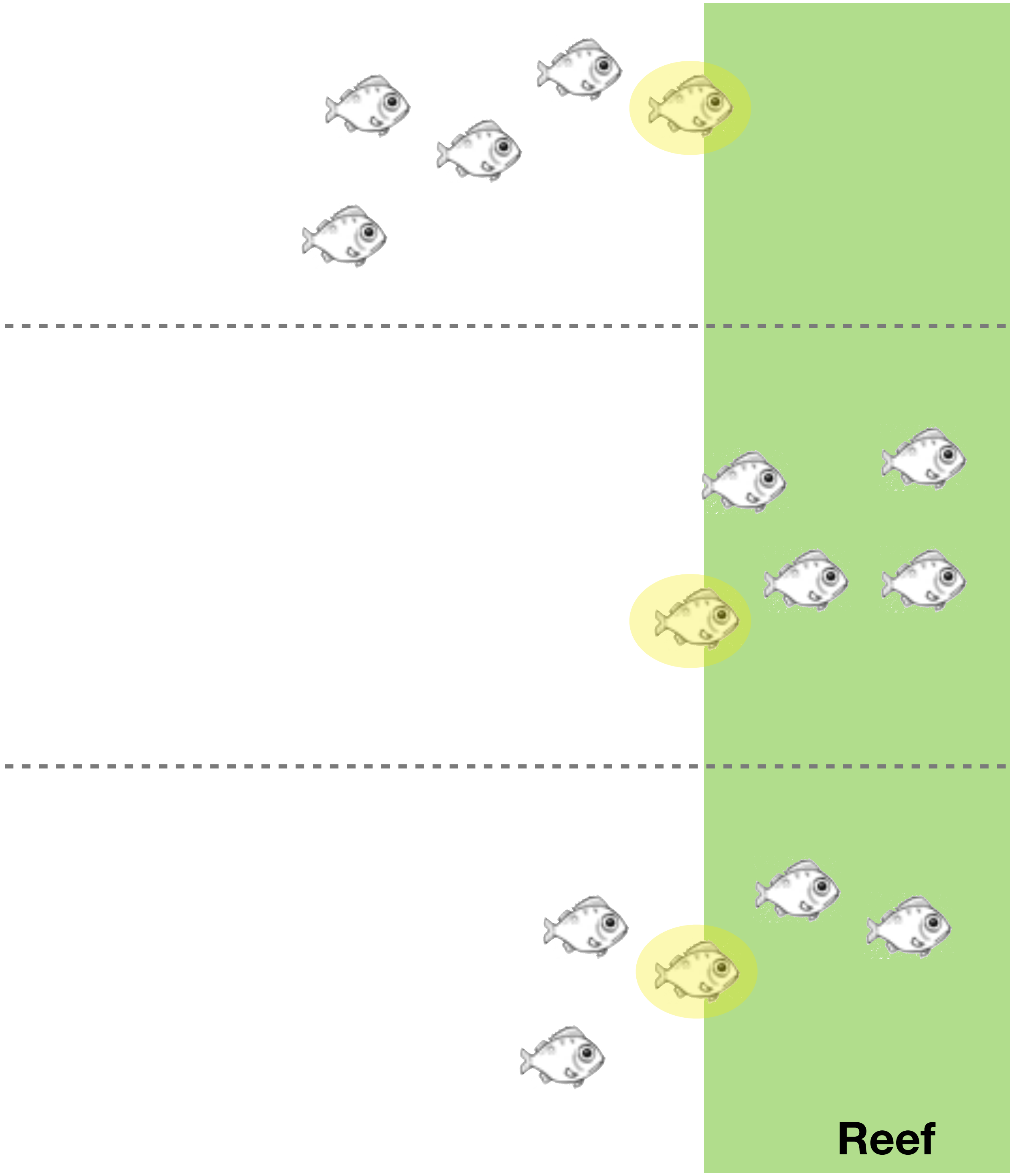
Can we employ <u>emergent behaviors</u> in a <u>small team</u> of aquatic robots to solve <u>useful</u> problems?

Problem Statement

- Localize a source using a small team of aquatic robots.
- Individual robot behavior determined by a set of simple control laws.
  All robots follow the same laws.
- No explicit communication between robots.
  Information is communicated implicitly by observing neighboring robots.

Sub-problems

- First Arrival Time (FAT)
- Last Arrival Time (LAT)
- Specific Arrival Time (SAT)



Applications

- **First Arrival Time**:
  Search Operations
  (first robot to find target)

- **Last Arrival Time**:
  Homing Operations
  (all robots to arrive at dock)

- **Specific Arrival Time**:
  Search & Intervention Operations
  (a specialized robot in the team with intervention capability)

Image courtesy: http://www.mwpower.co.uk/

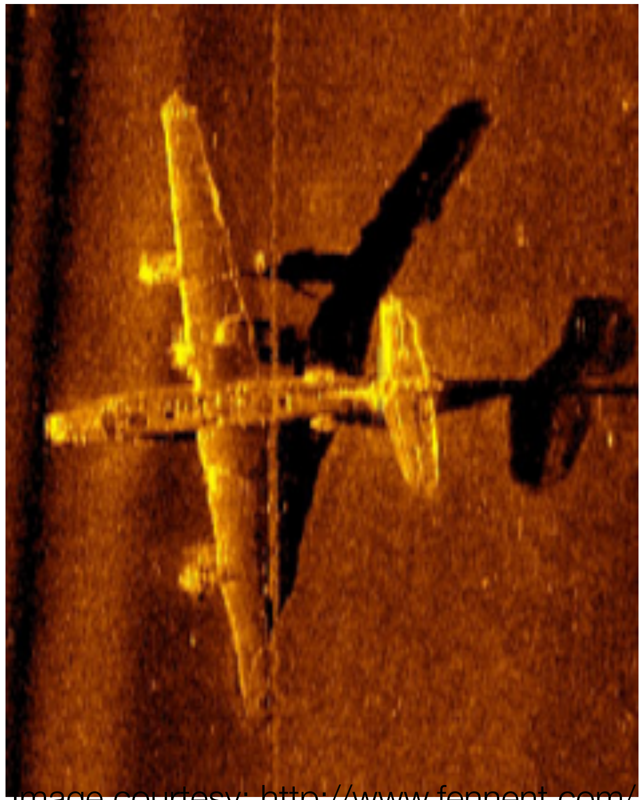


Image courtesy: http://www.fennent.com/

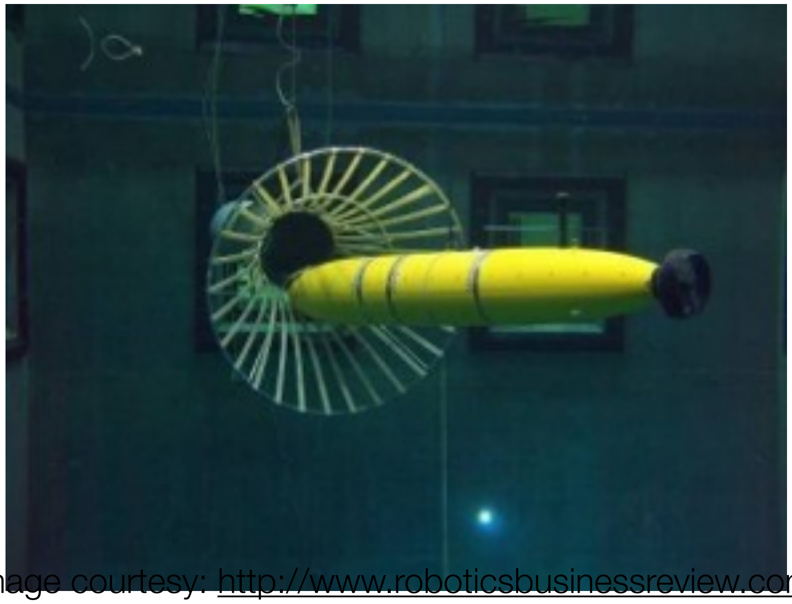
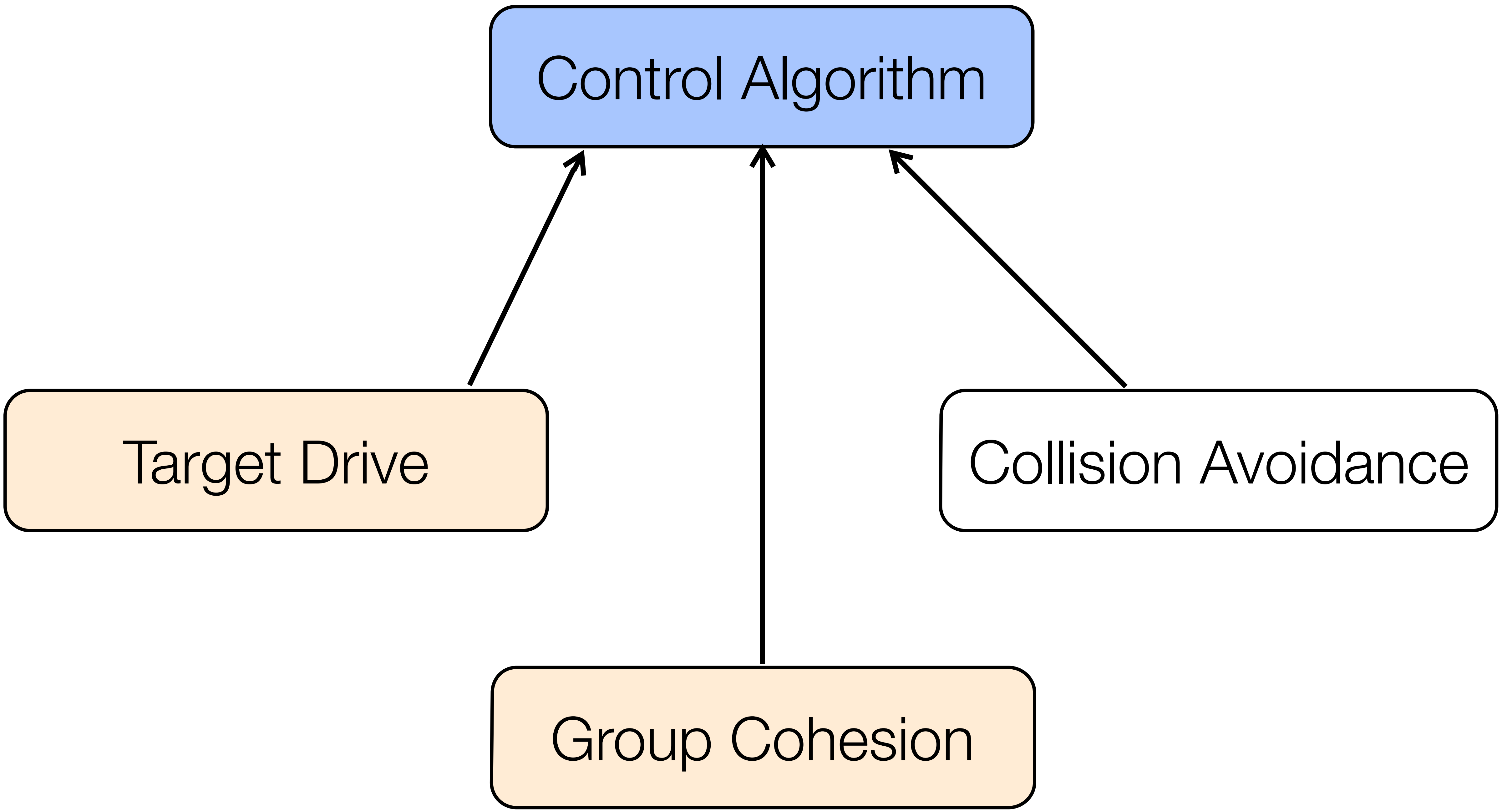


Image courtesy: http://www.roboticsbusinessreview.com/

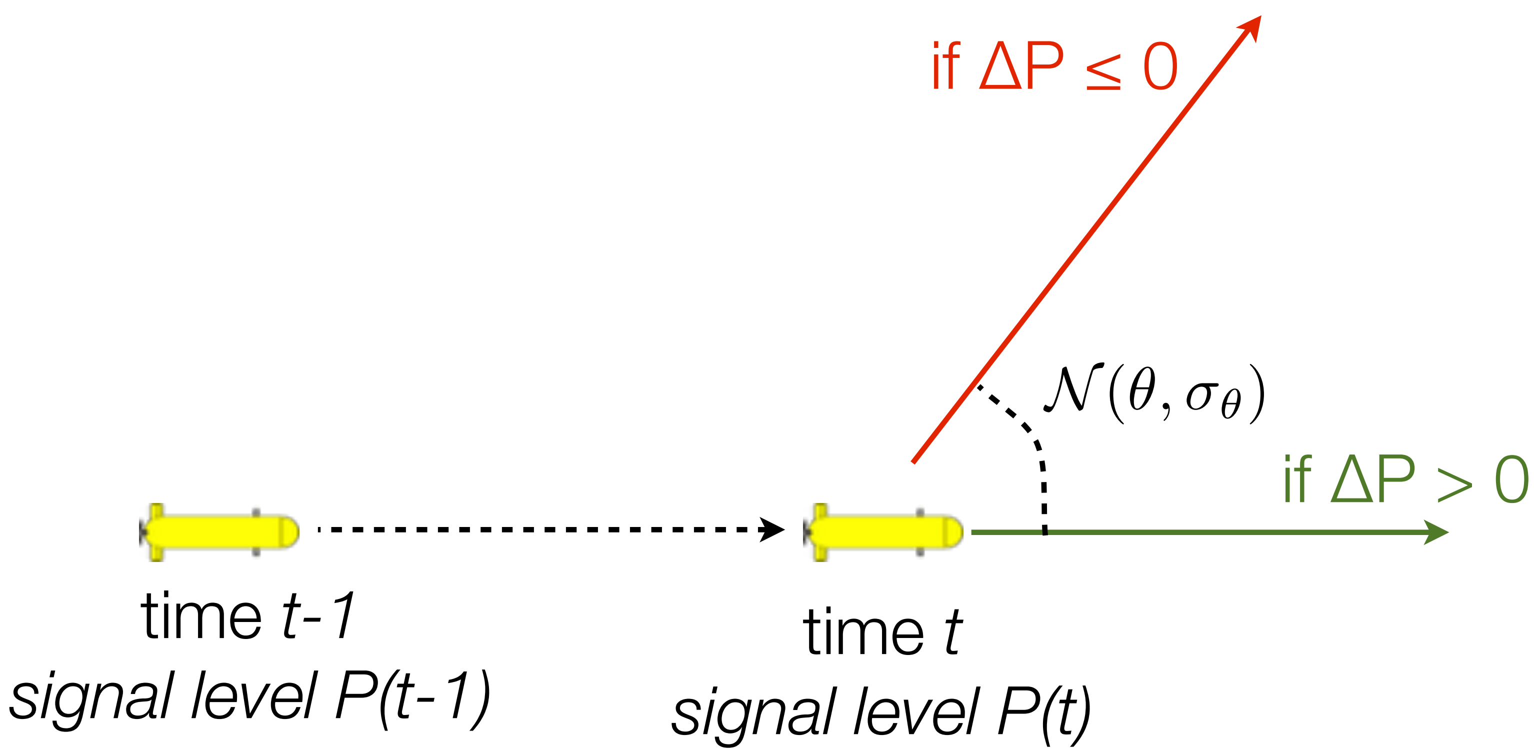
Control Algorithm

Algorithm Overview



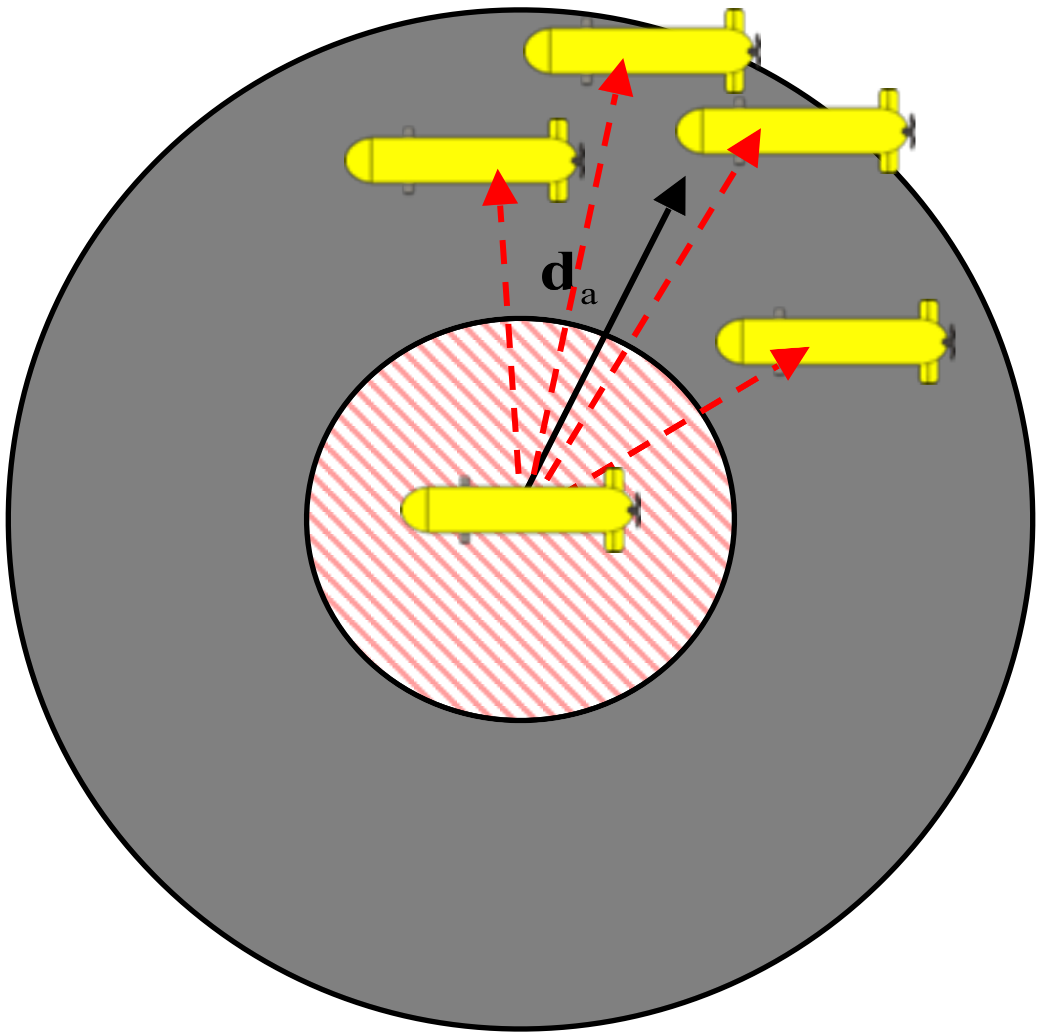
Target Drive

If signal gets stronger, keep going; otherwise make a random turn



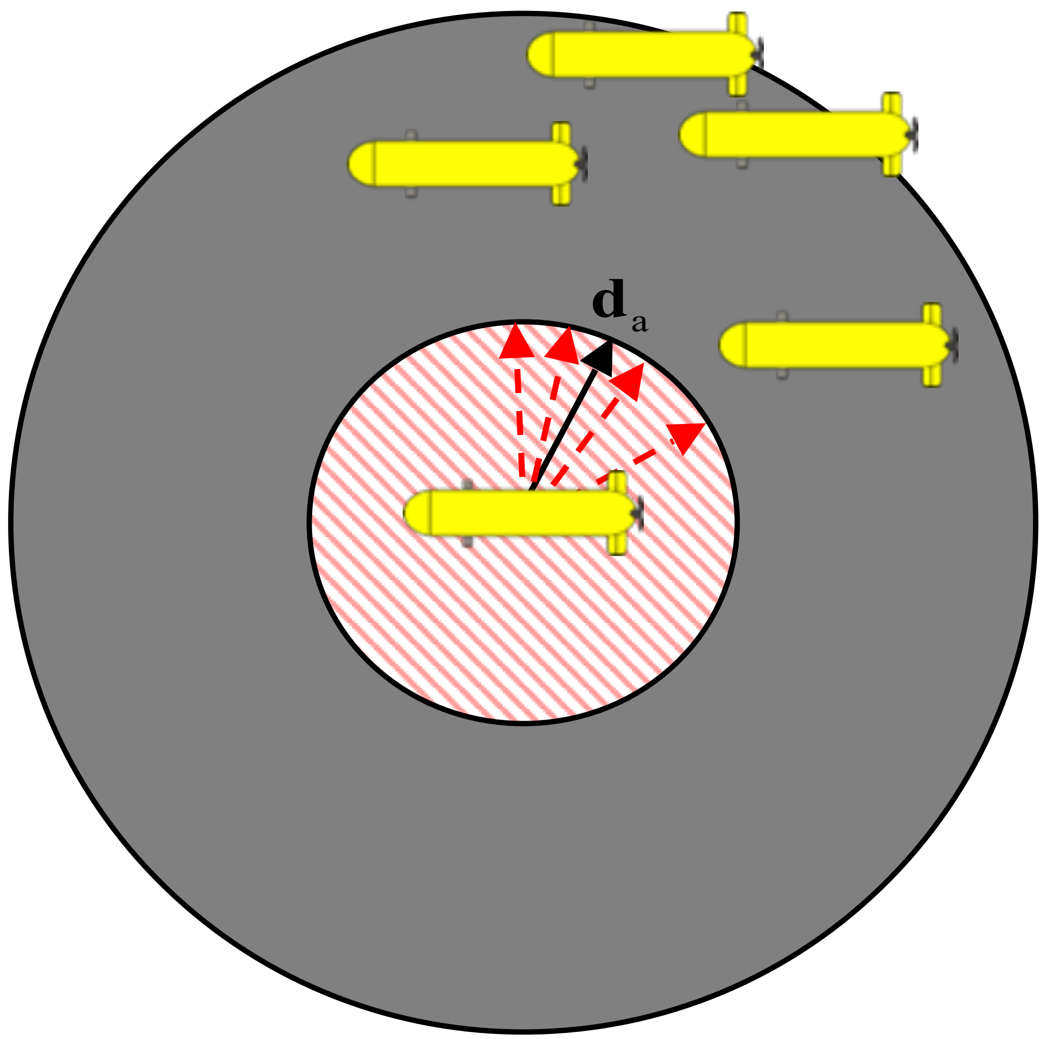
$\Delta P = P(t) - P(t-1)$

Group Cohesion: Centroid Model



Move towards the centroid of the neighbors

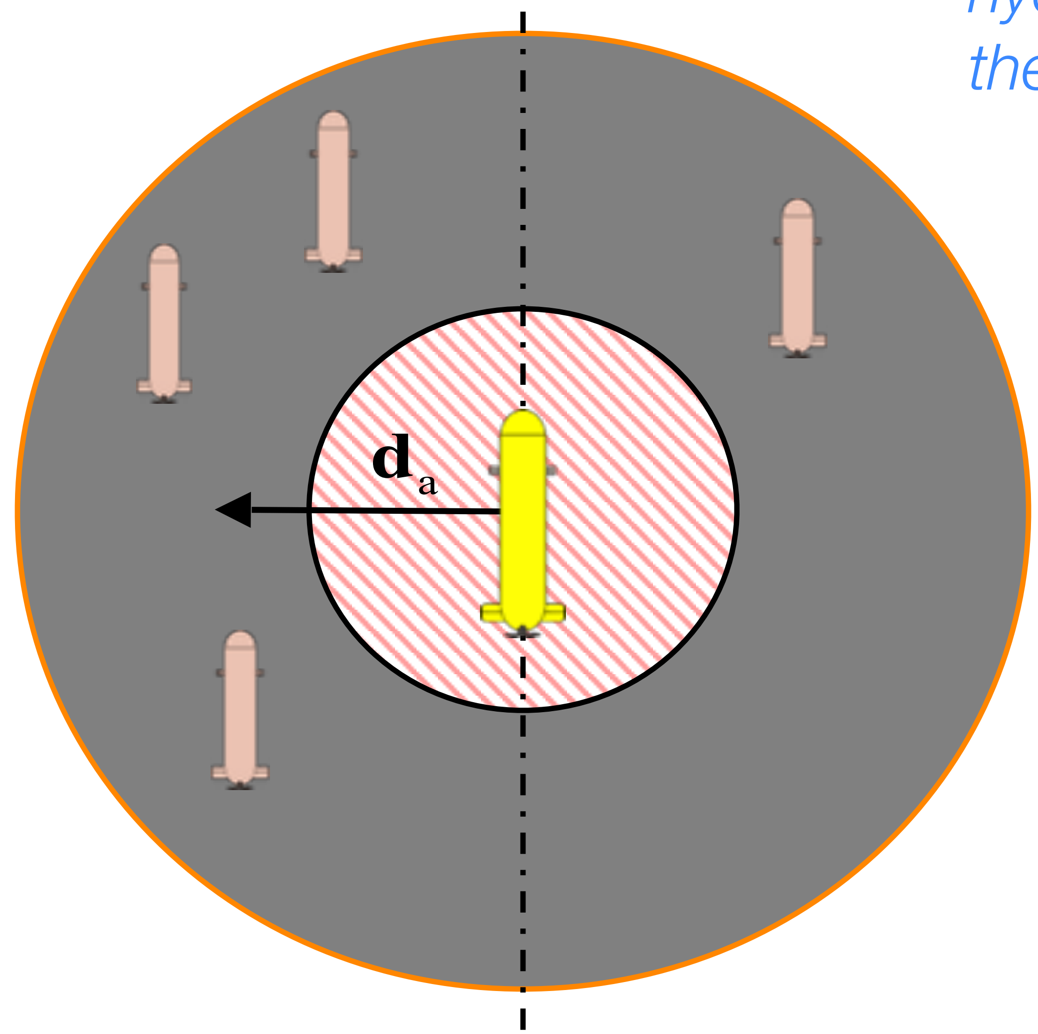
Group Cohesion: Unit Vector Model



Move in the average direction of the neighbors

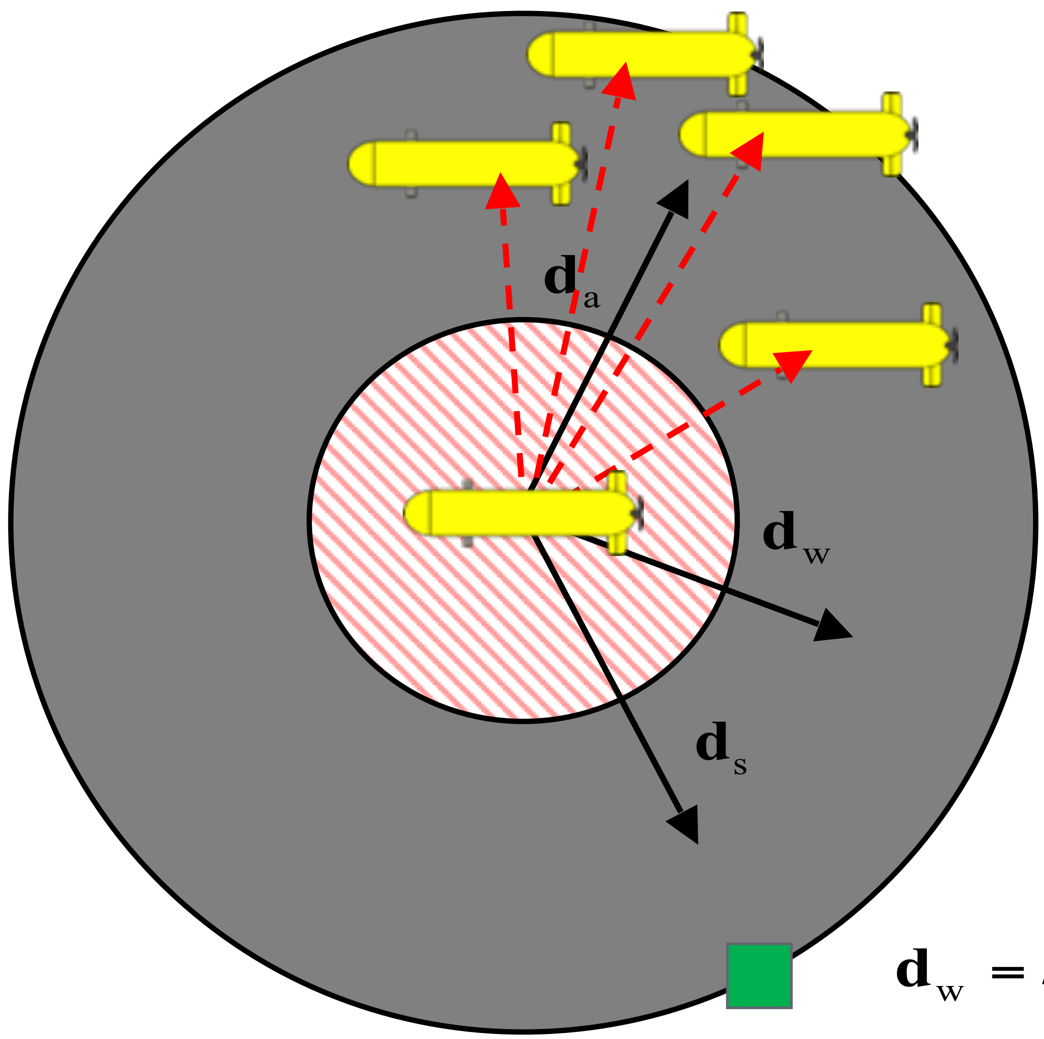
Group Cohesion: Left-Right Model

Implementation on a robot may involve sensors (camera/ hydrophone) on either side of the robot



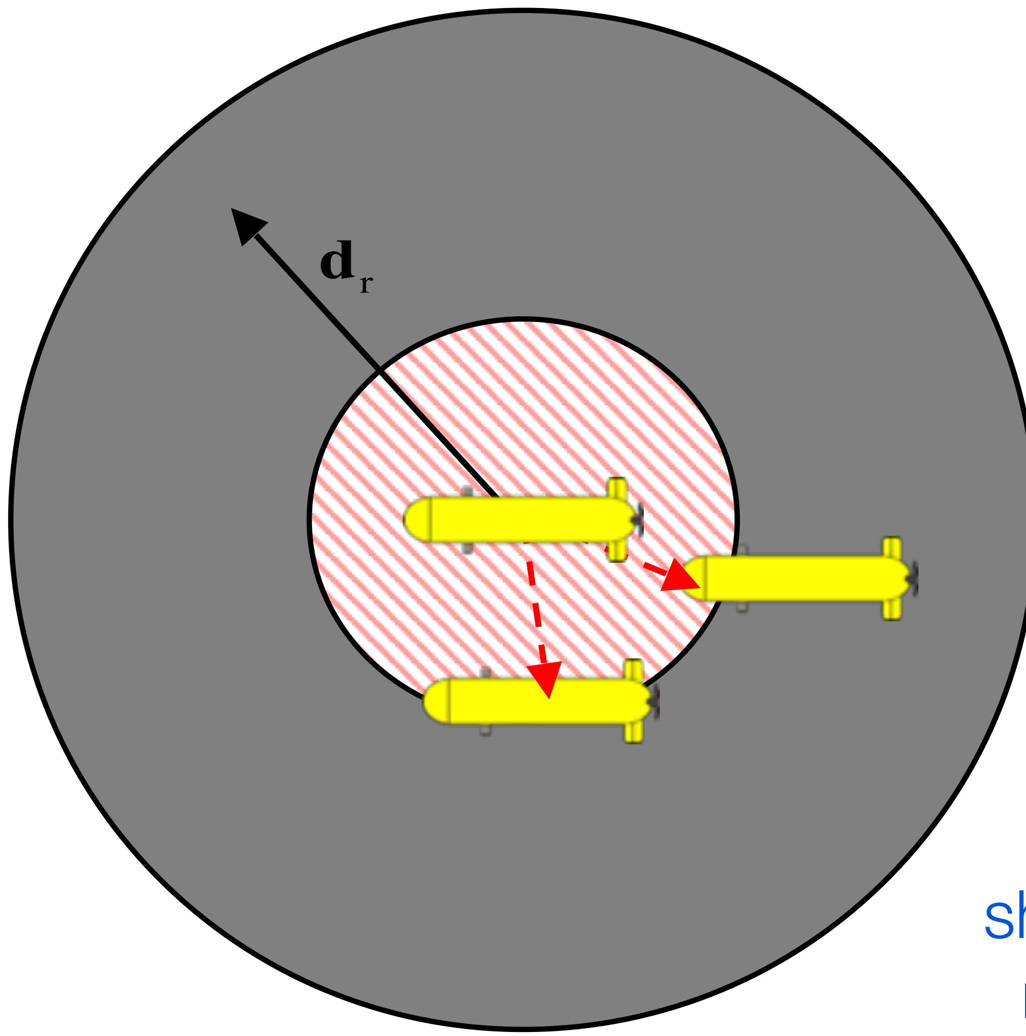
Move in the direction of more neighbors

Combined Behavior



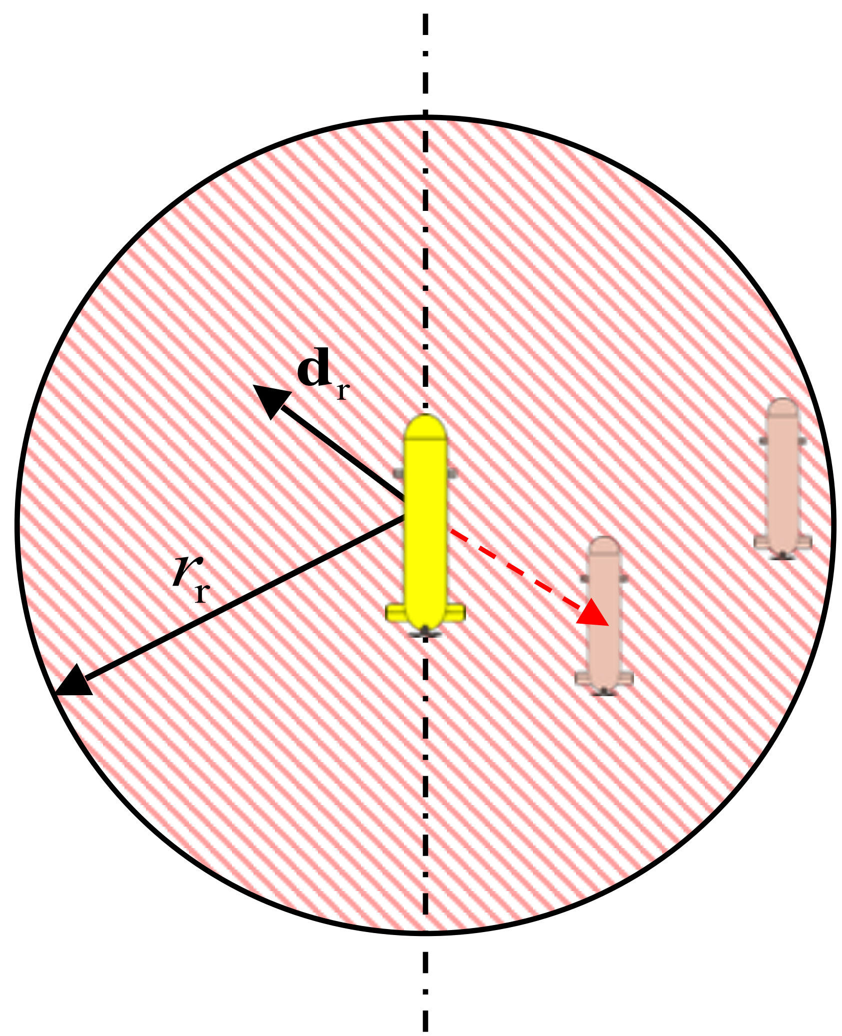
$$\mathbf{d}_w = b_s \mathbf{d}_s + (1 - b_s)\mathbf{d}_a$$

Collision Avoidance: Centroid Model



short-range
repulsion

Collision Avoidance: Nearest-neighbor Model



Learning Optimal Parameters

Parameter Tuning

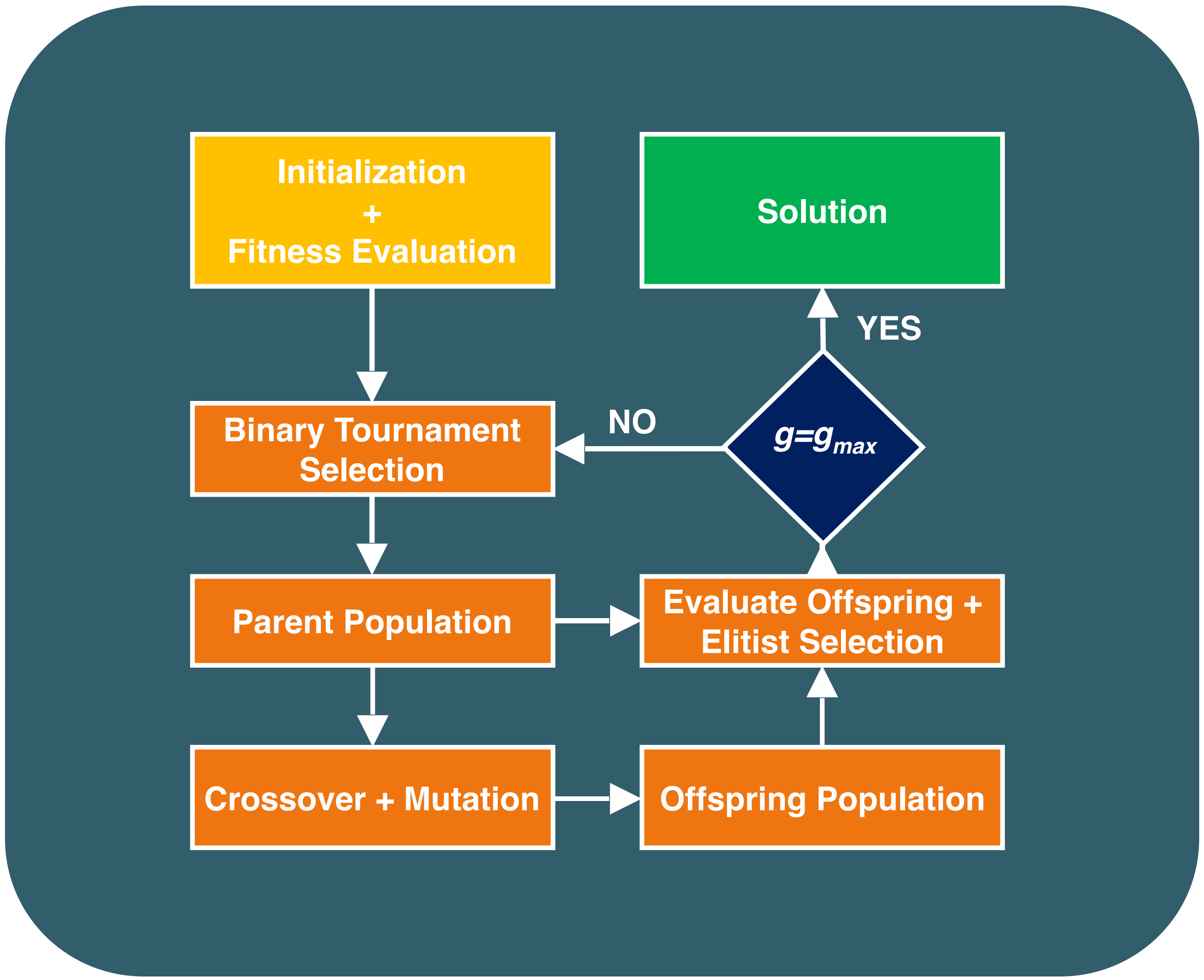
Parameters:

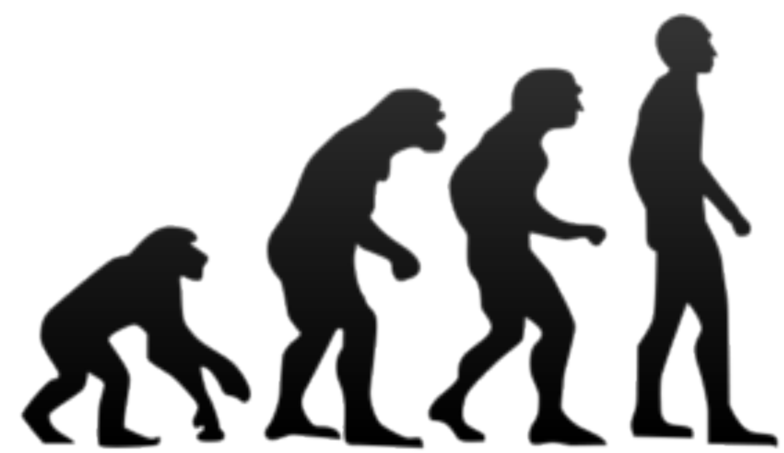
- Number of robots
- Drive coefficient
- Turning angle distribution parameters
- Neighborhood radius
- Sampling interval

Objective functions:

- Mean first arrival time
- Mean last arrival time
- Mean arrival time

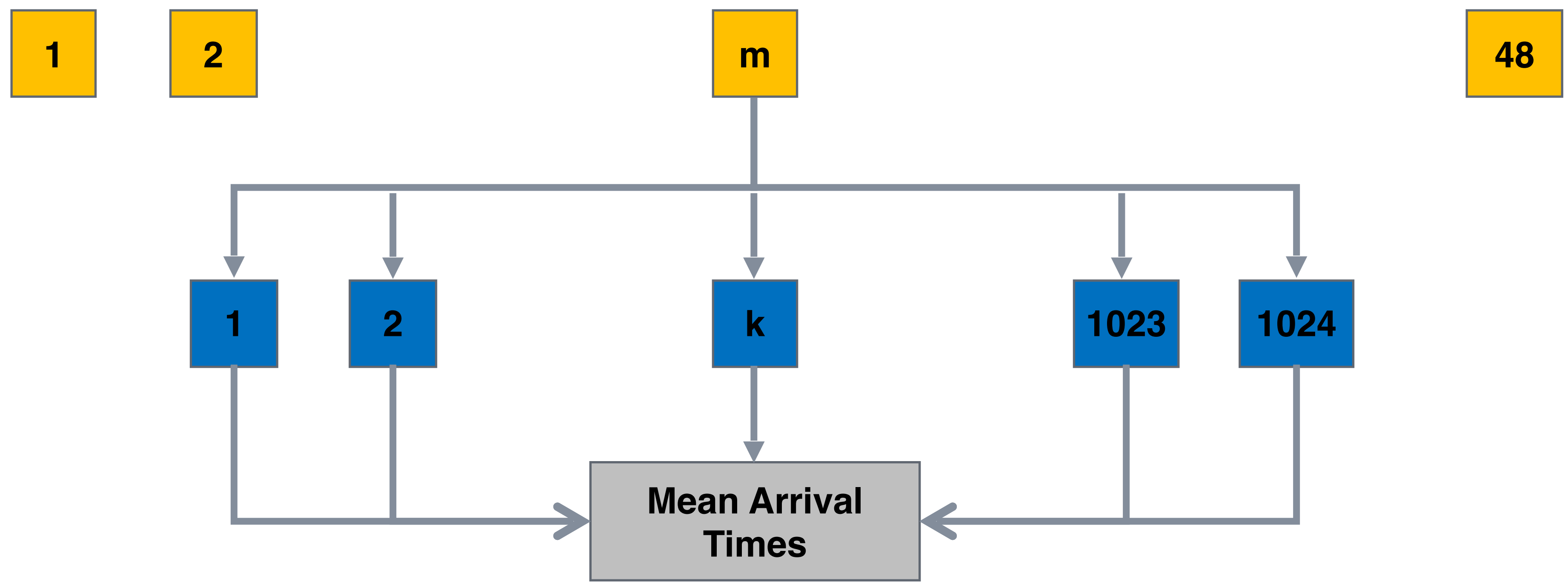
Optimization Framework: Genetic Algorithm





Optimization Framework: Genetic Algorithm

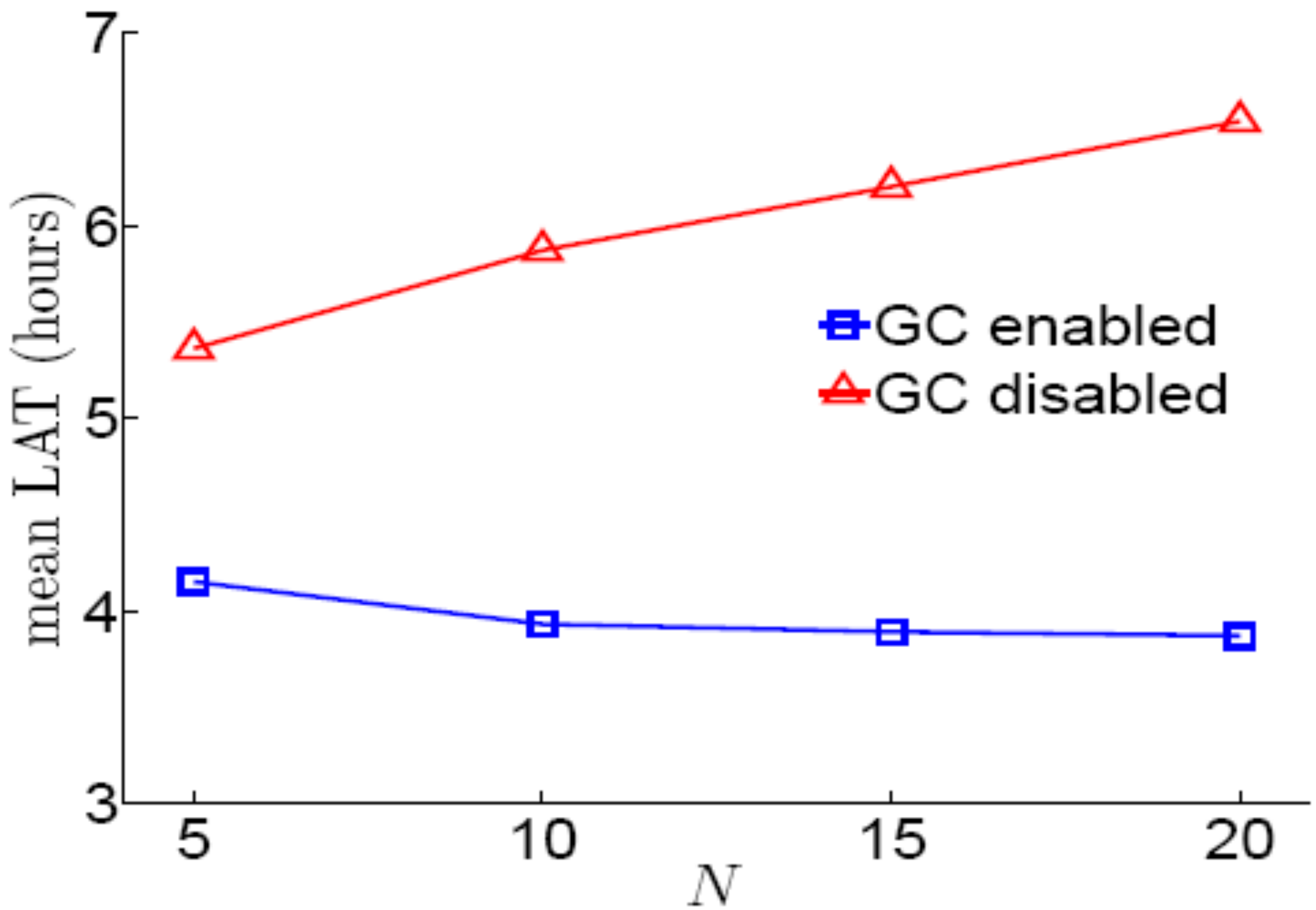
Population of 48 individuals and 1024 simulation runs each



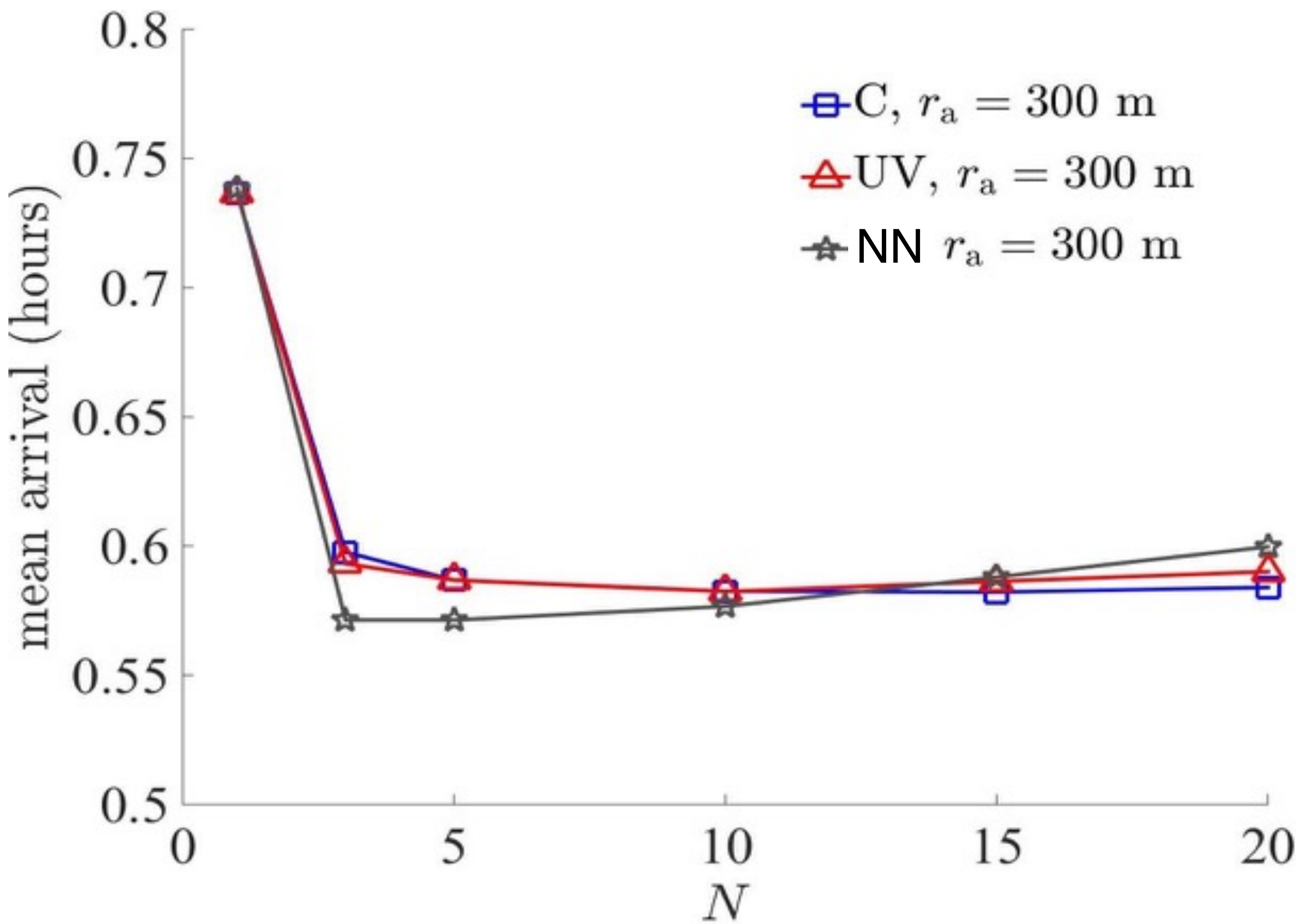
Selected Results

Example Simulation: LAT

Last Arrival Time with/without Schooling



Mean Arrival Time Performance



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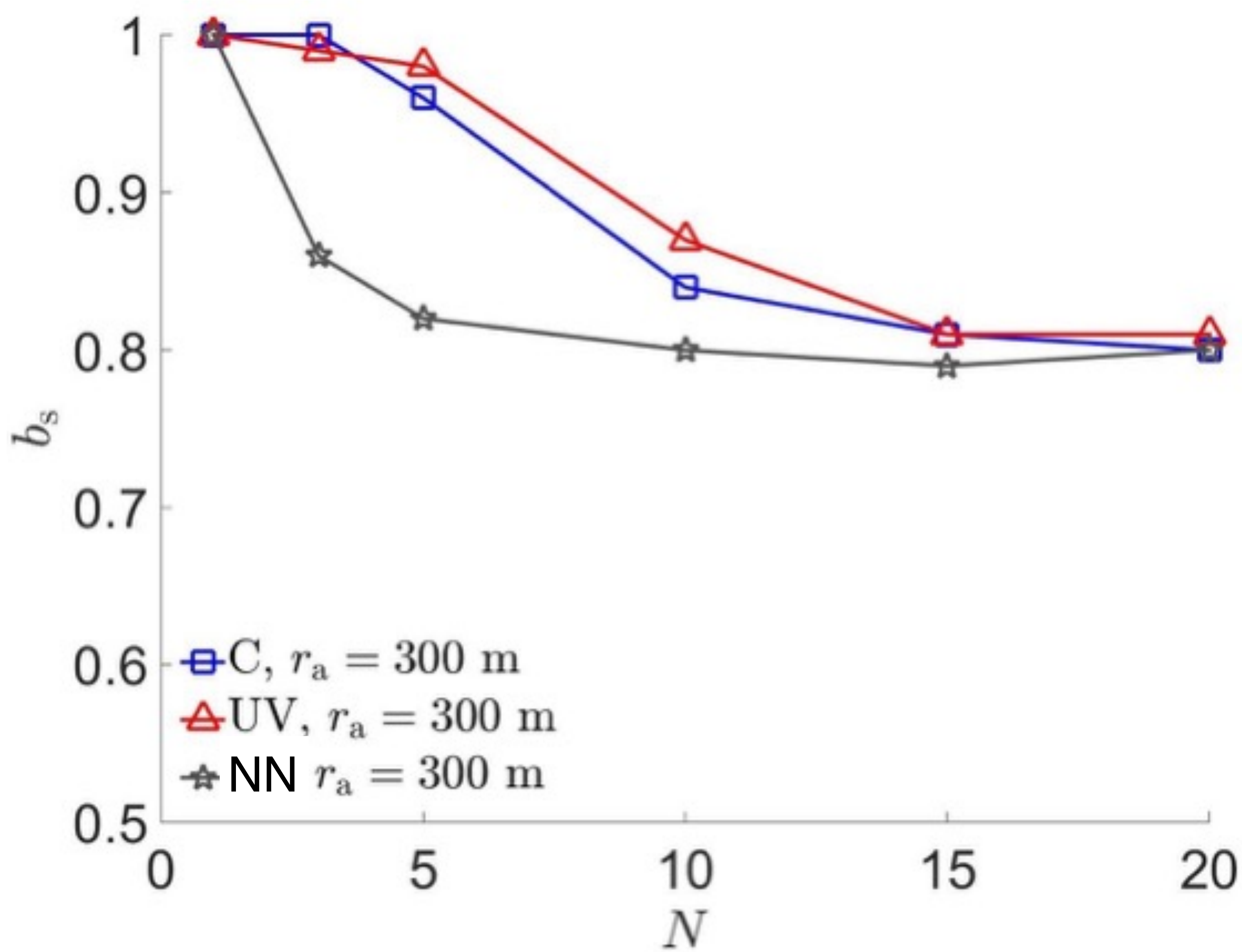
Optimal Schooling



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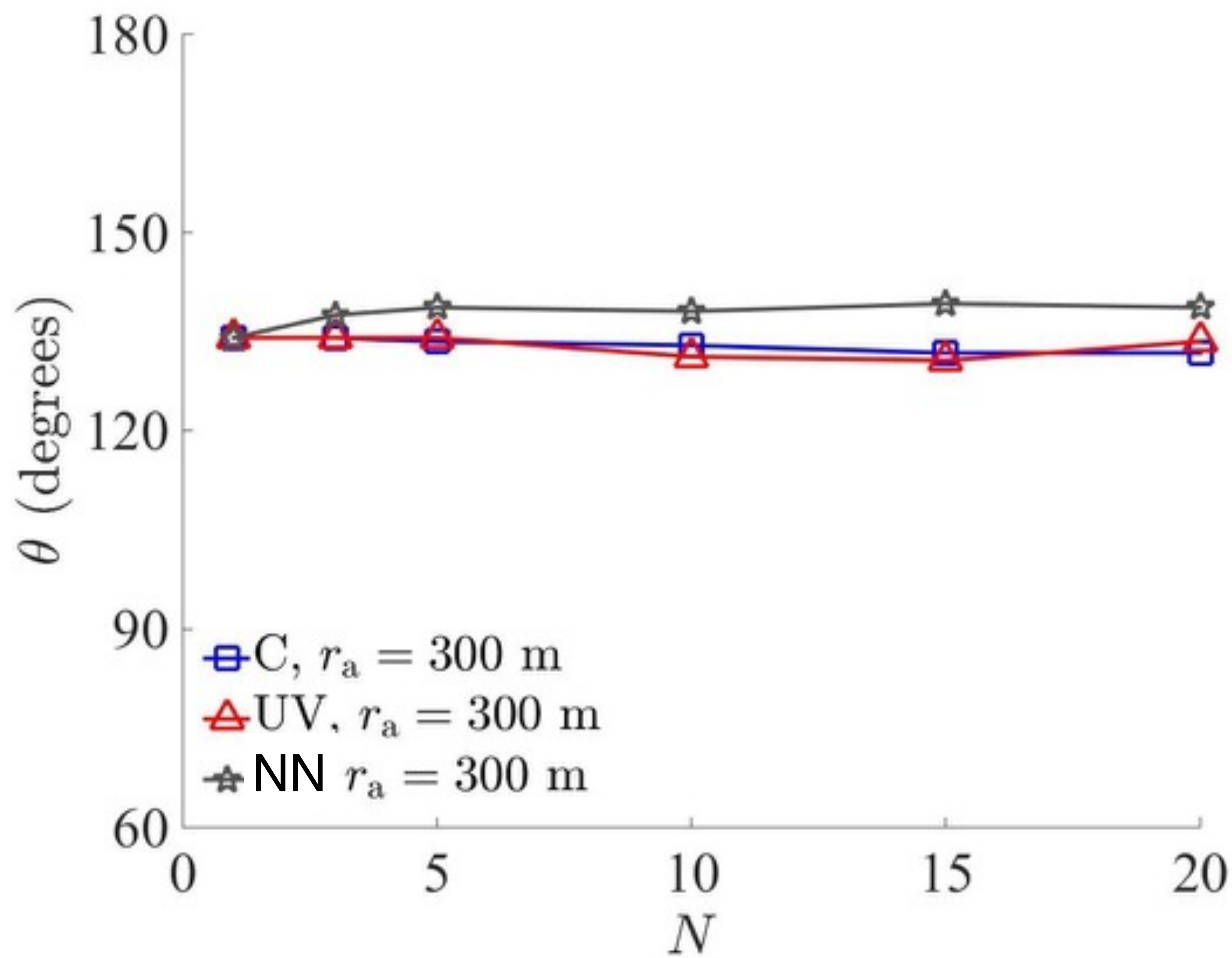
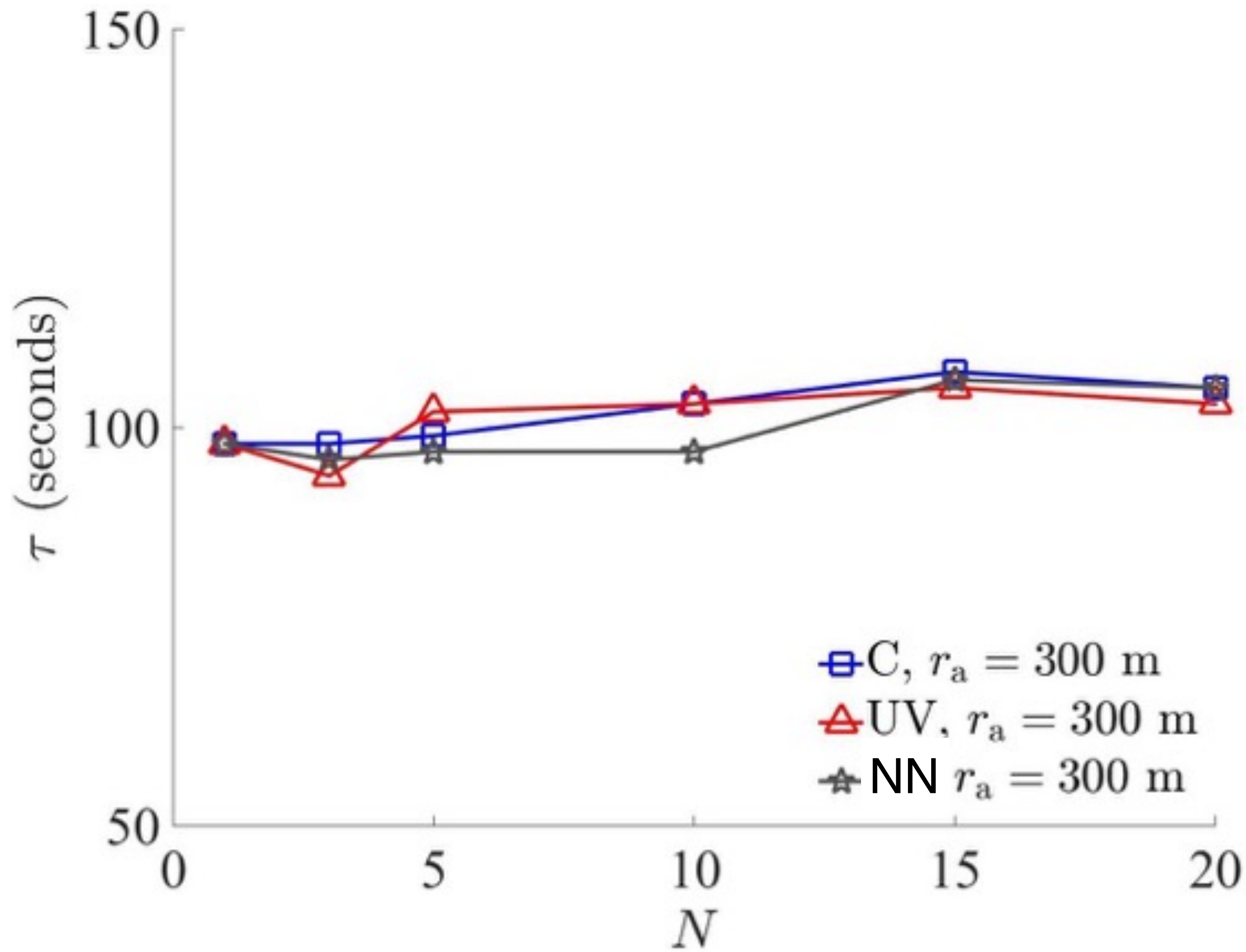
Optimal Turning Angle



Optimal Turning Angle



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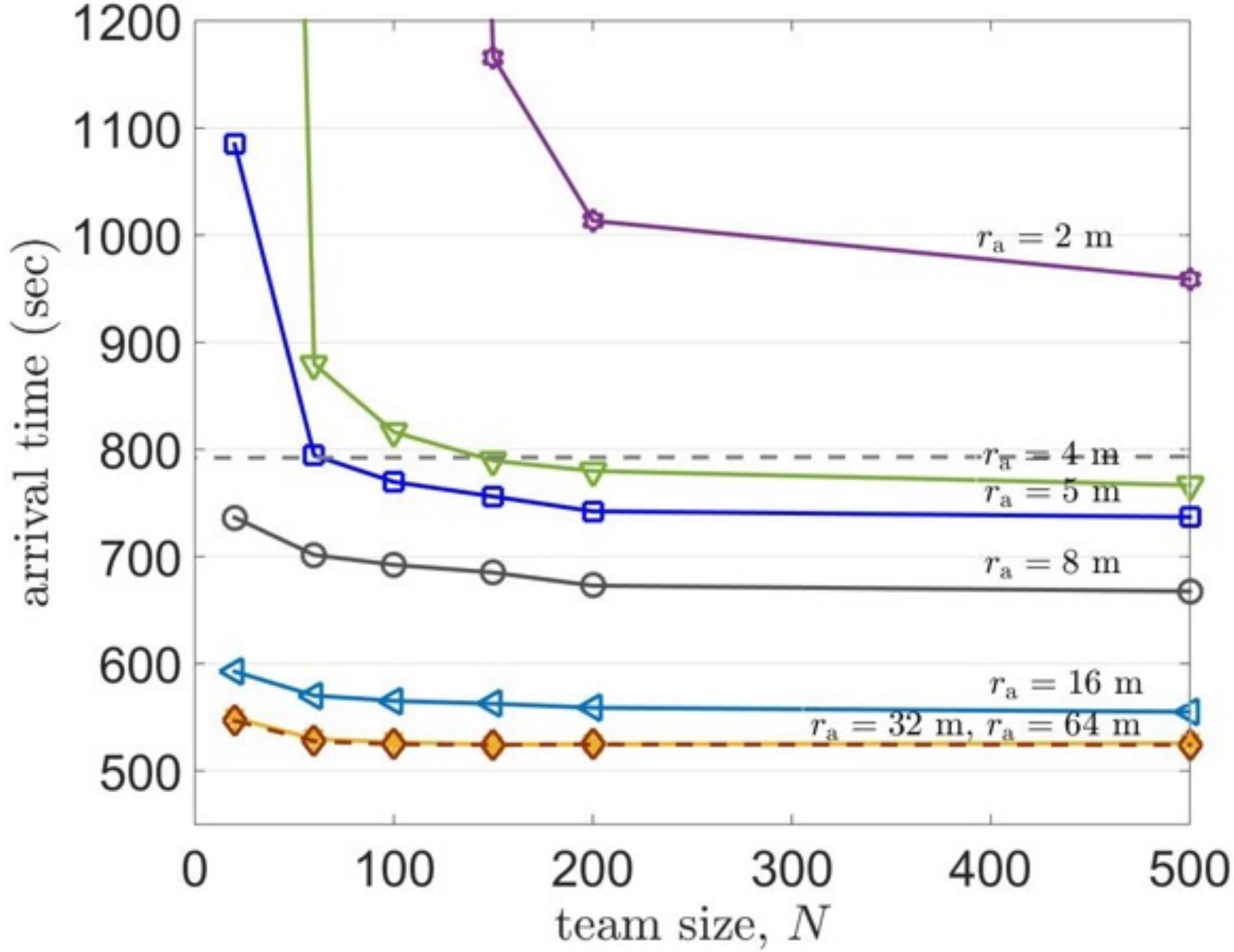
Team Size vs Neighborhood Radius



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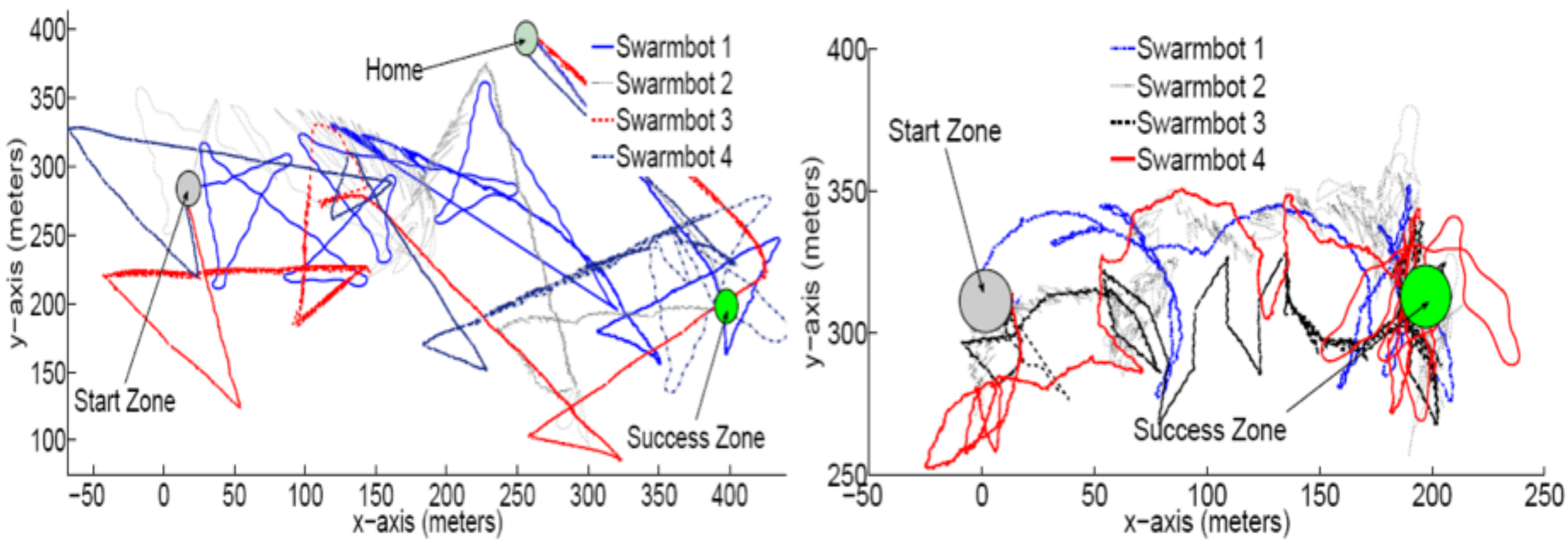
Experimental Testing

SwarmBots

SwarmBots

SwarmBots



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Conclusions

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- Small teams can demonstrate effective group synergy.
- Evolutionary optimization can effectively find parameters yielding good performance given a search space.
- The simple control strategies learned from the evolutionary optimization can be implemented in practical aquatic robots easily with minimal sensing and no explicit communication capability.
- The key ingredients for persistent autonomy (low cost, long endurance and robustness) can be achieved with multi-robot systems with simple robots.