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Bio-inspired algorithms for distributed control in small teams of autonomous underwater vehicles

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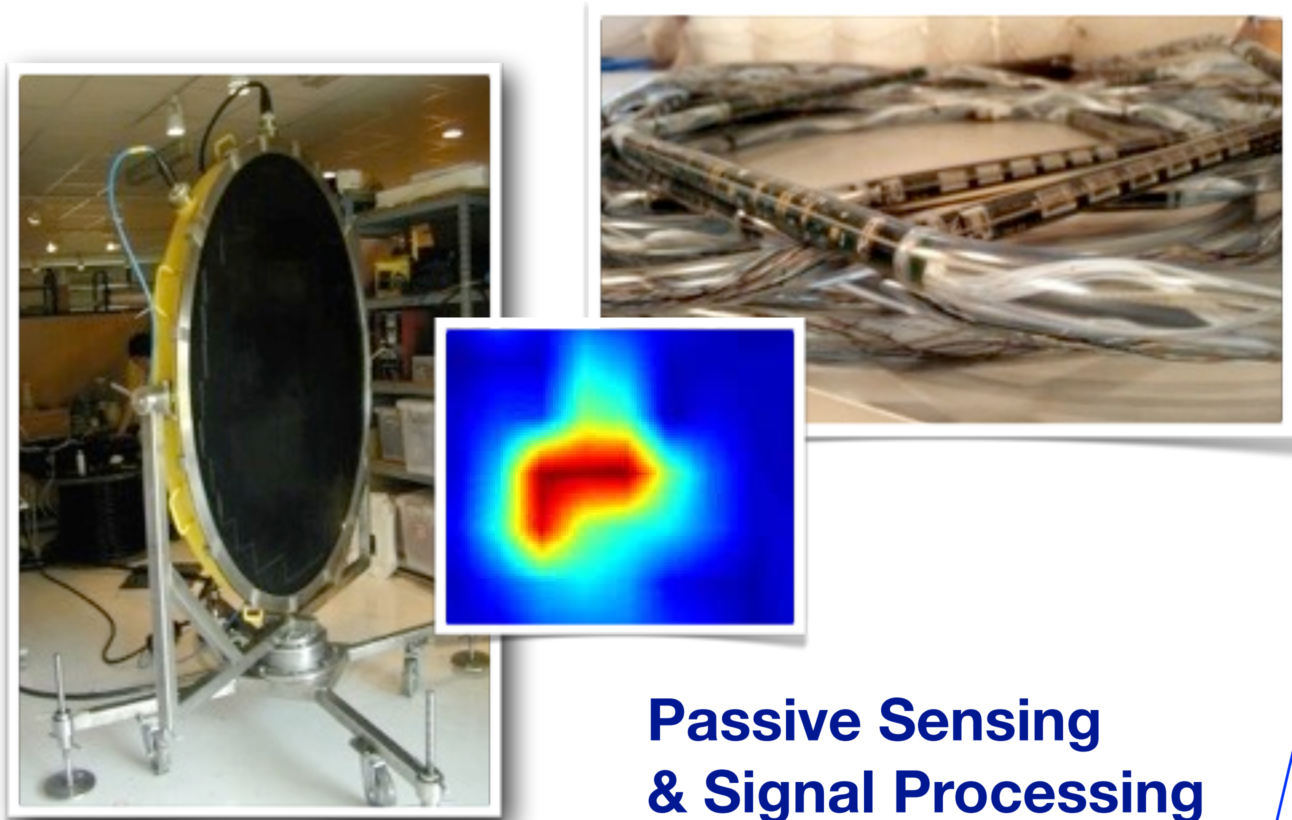
Background



Passive Sensing
& Signal Processing

Autonomous sensing
& platform technology

Underwater
communication
& networking

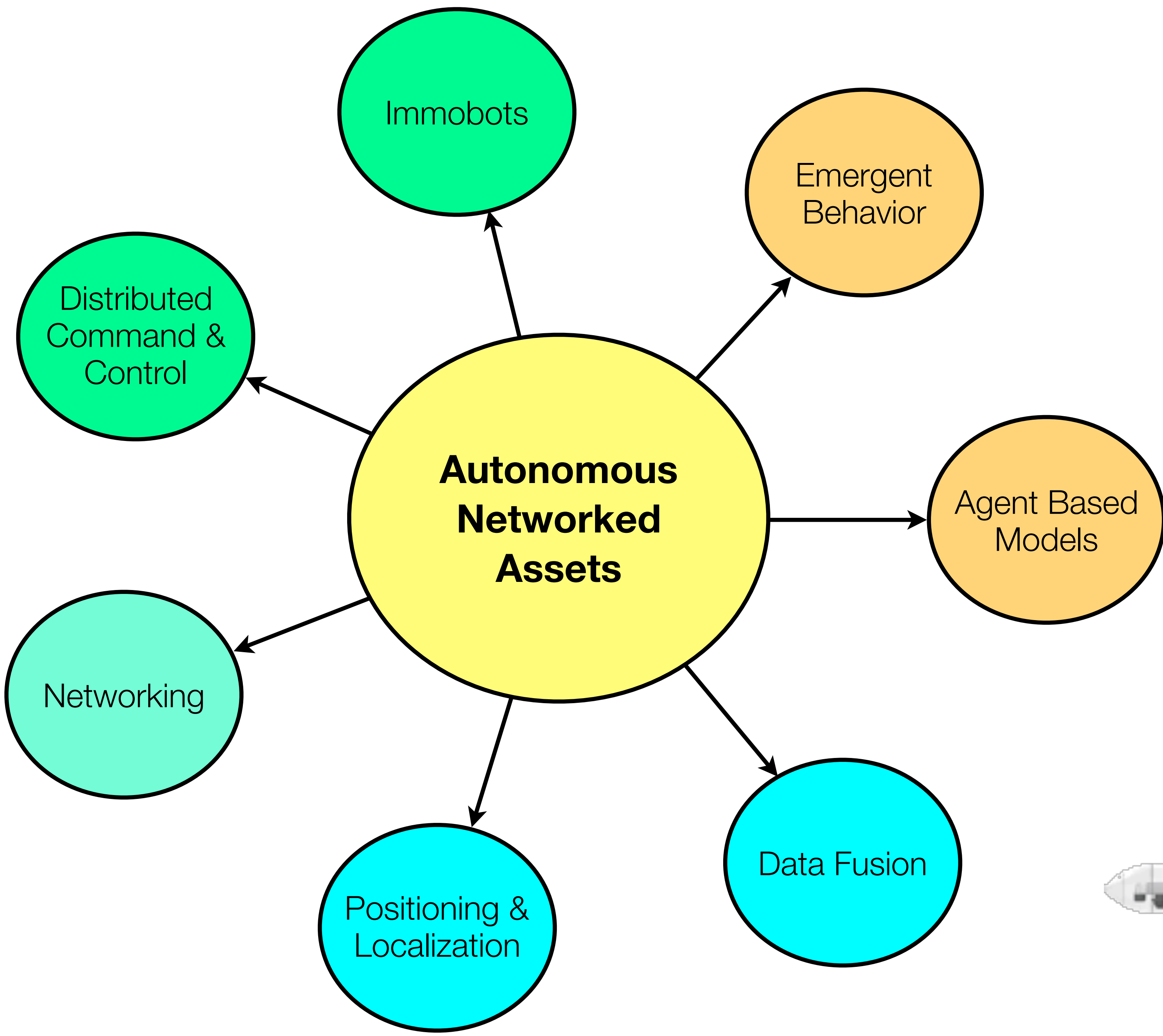
Dolphin
Bioacoustics

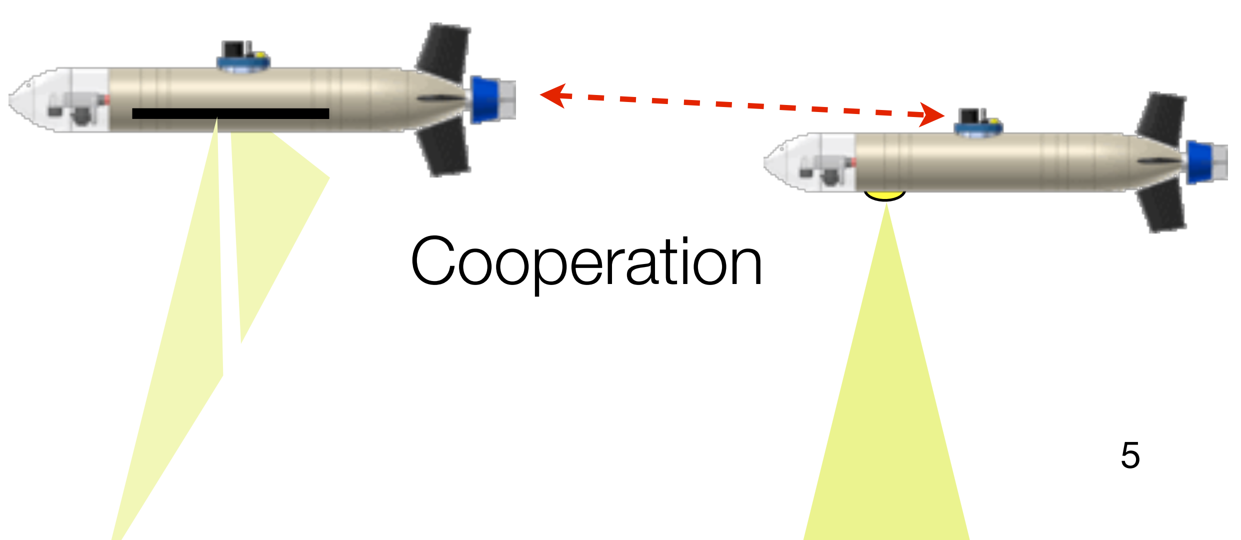
Project STARFISH

"Small Team of Autonomous Robotic Fish"

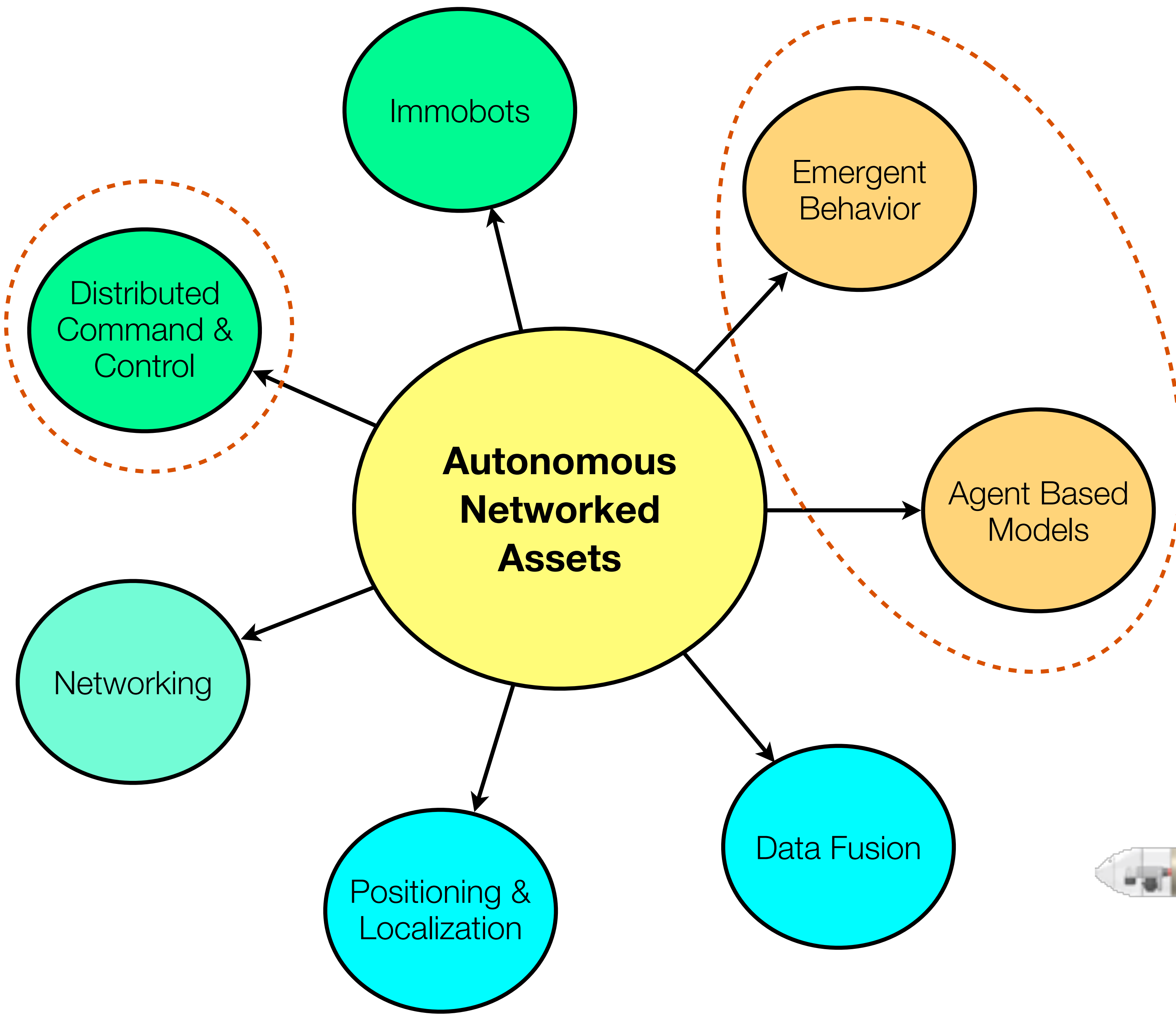
Phase I – 2006-2009
Phase II – 2010-2014

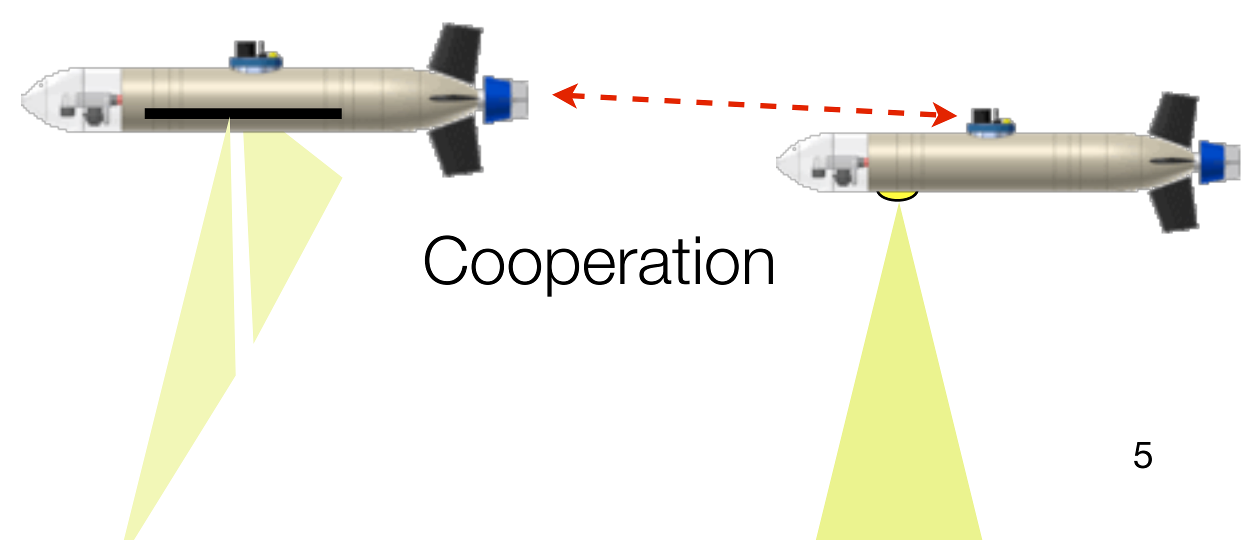
Project STARFISH





Project STARFISH





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.

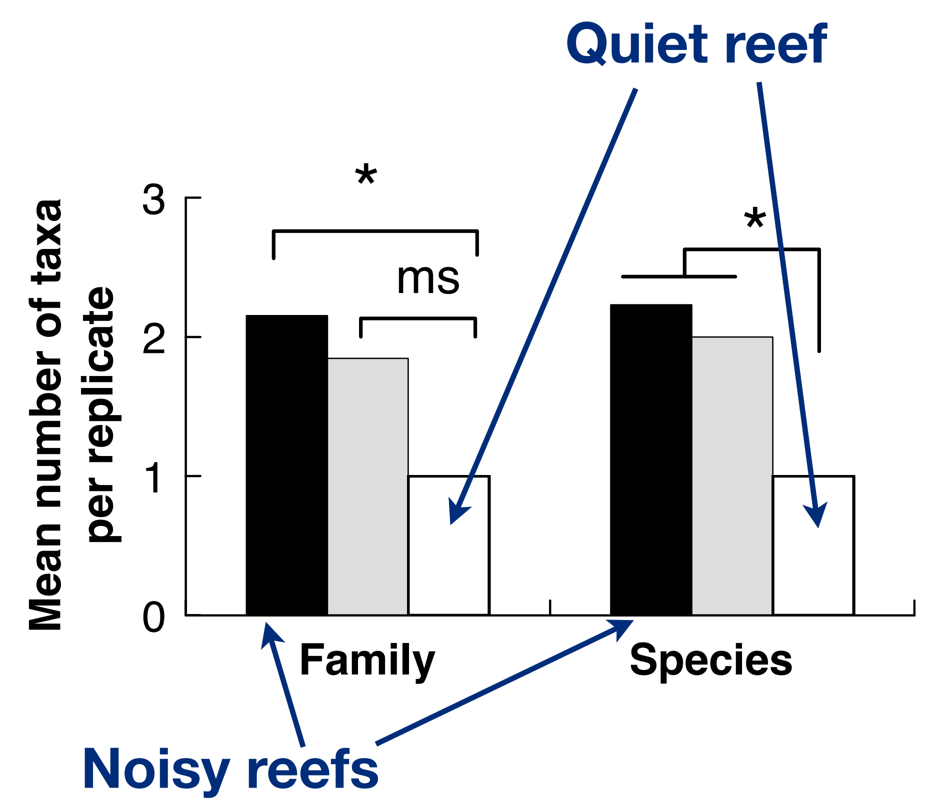


Figure reproduced from [1]

[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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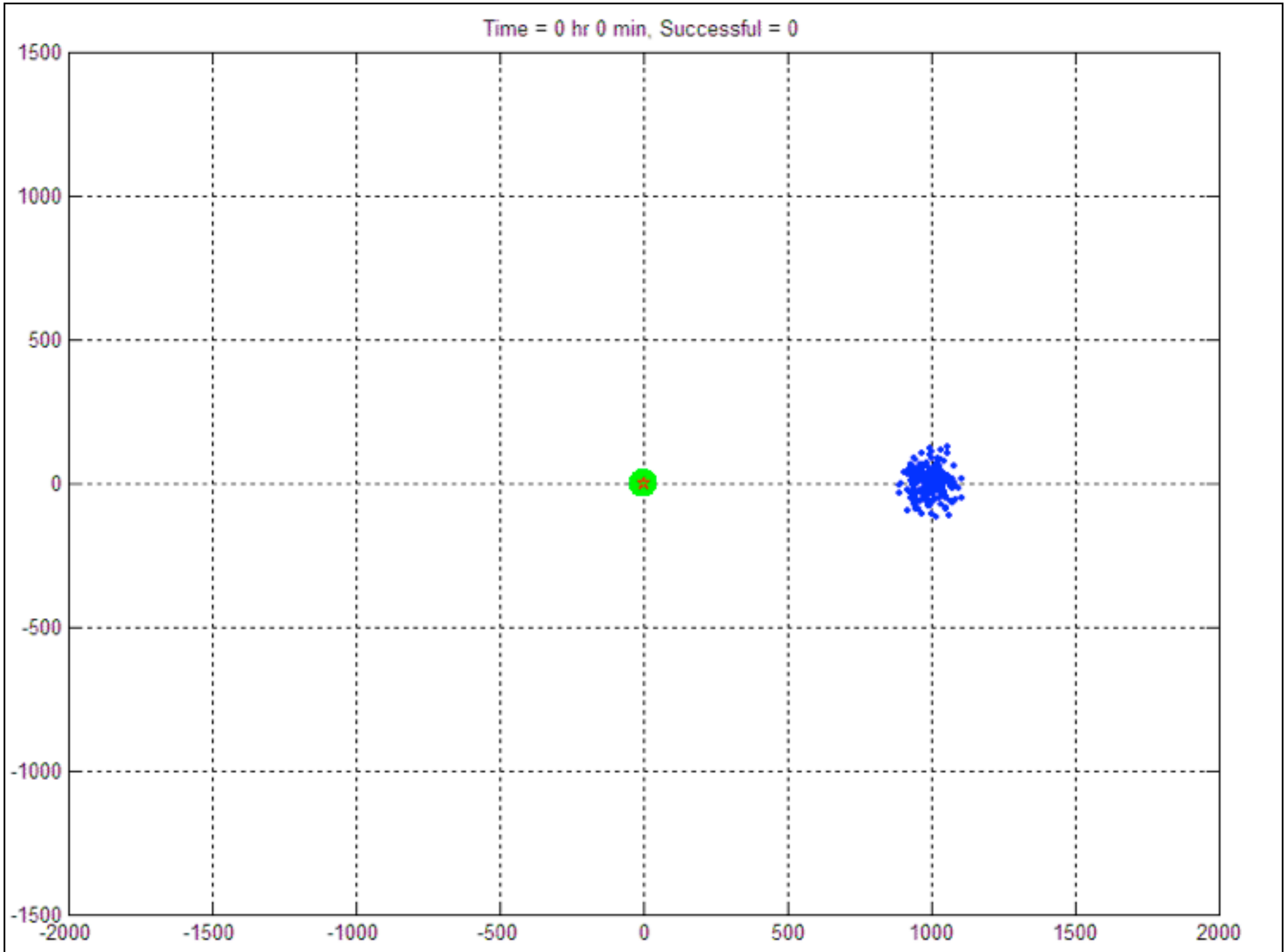

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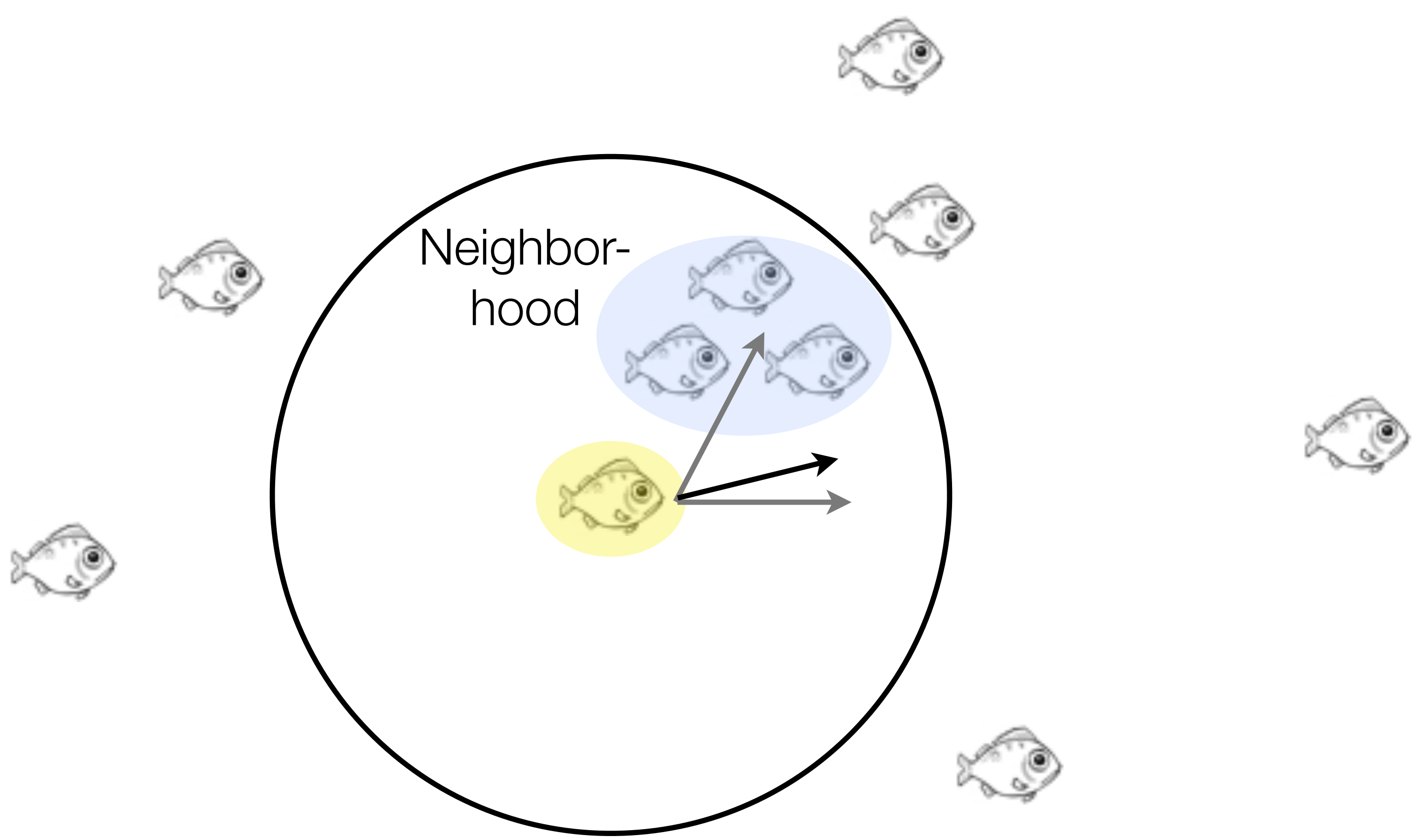
Simulation #2: Schooling Model

- 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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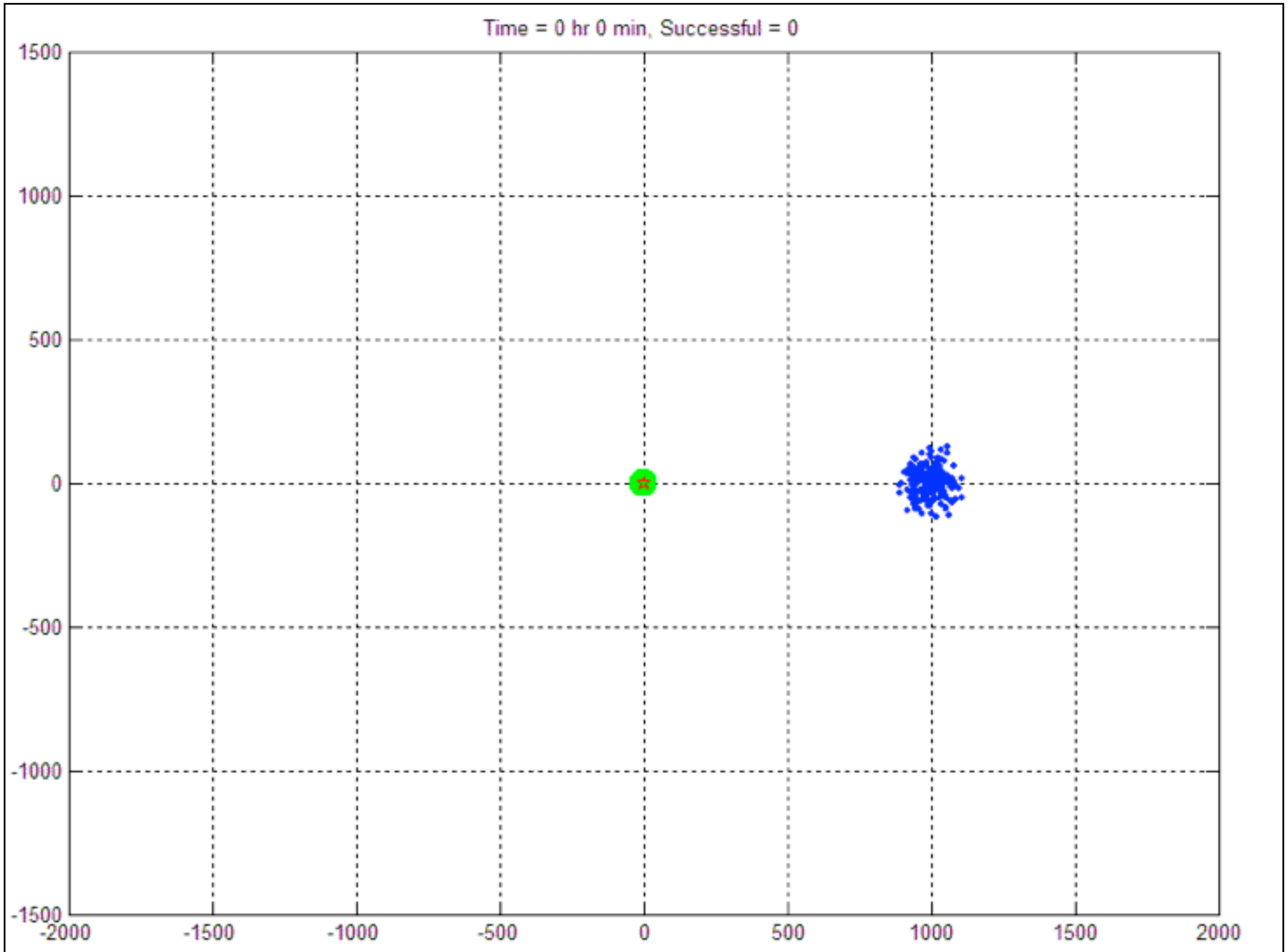

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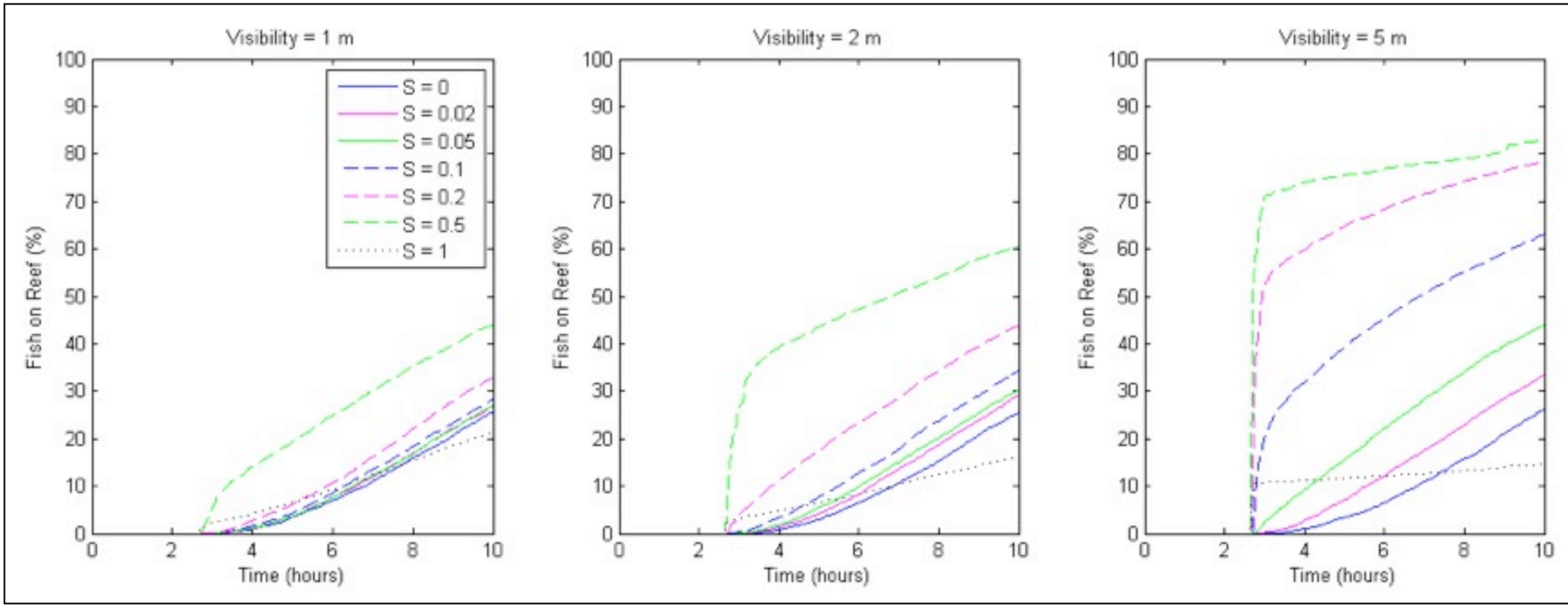
Simulation Results



Key Takeaways

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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.

Group behaviors

are commonly employed in nature

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

Bio-inspired algorithms
for groups of AUVs

Problem Statement

Key Research Question

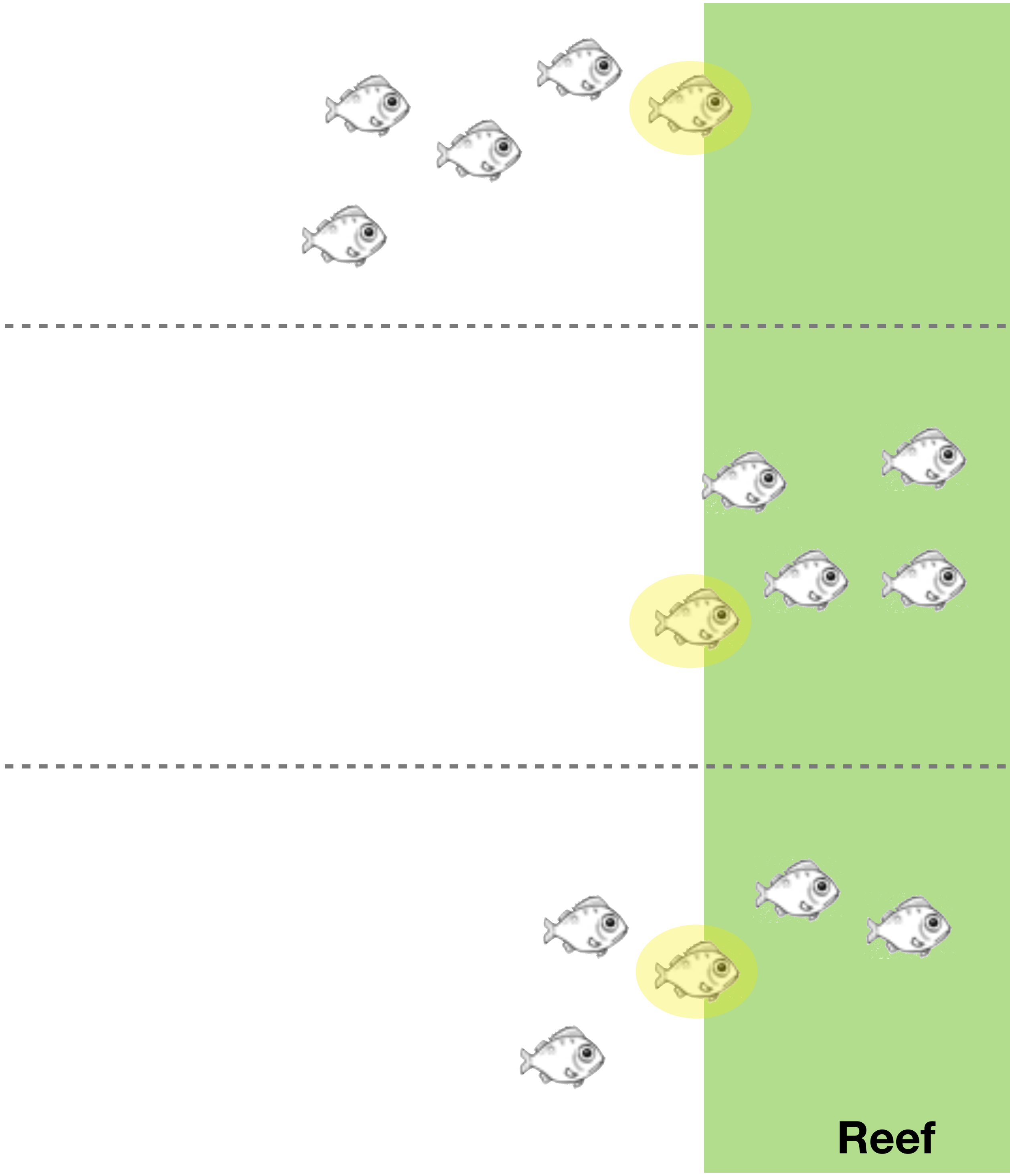
Can we employ <u>emergent behaviors</u> in a <u>small team</u> of AUVs to solve <u>useful</u> problems?

Problem Statement

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

Sub-problems

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



Applications

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

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

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

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

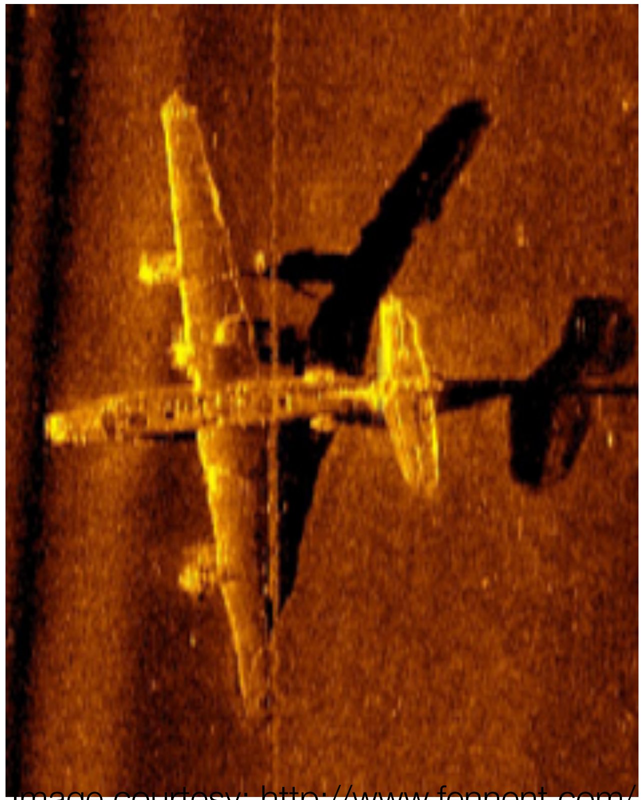


Image courtesy: http://www.fennent.com/

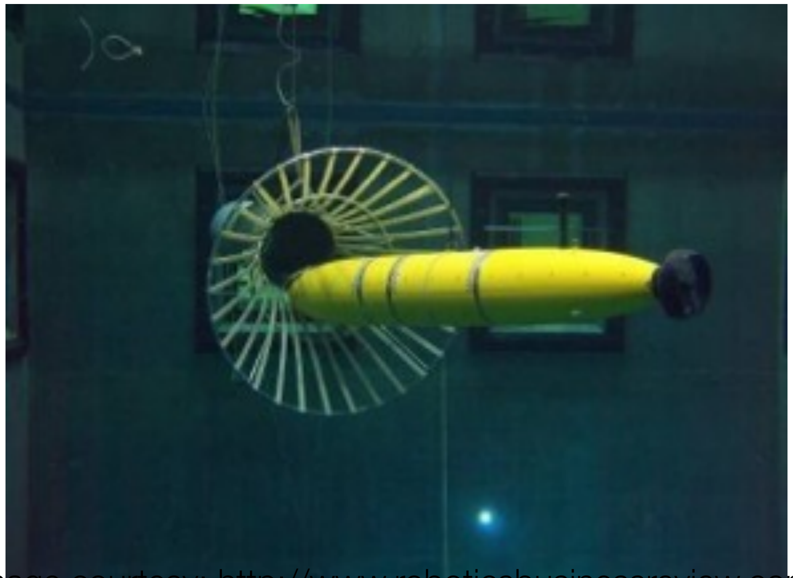
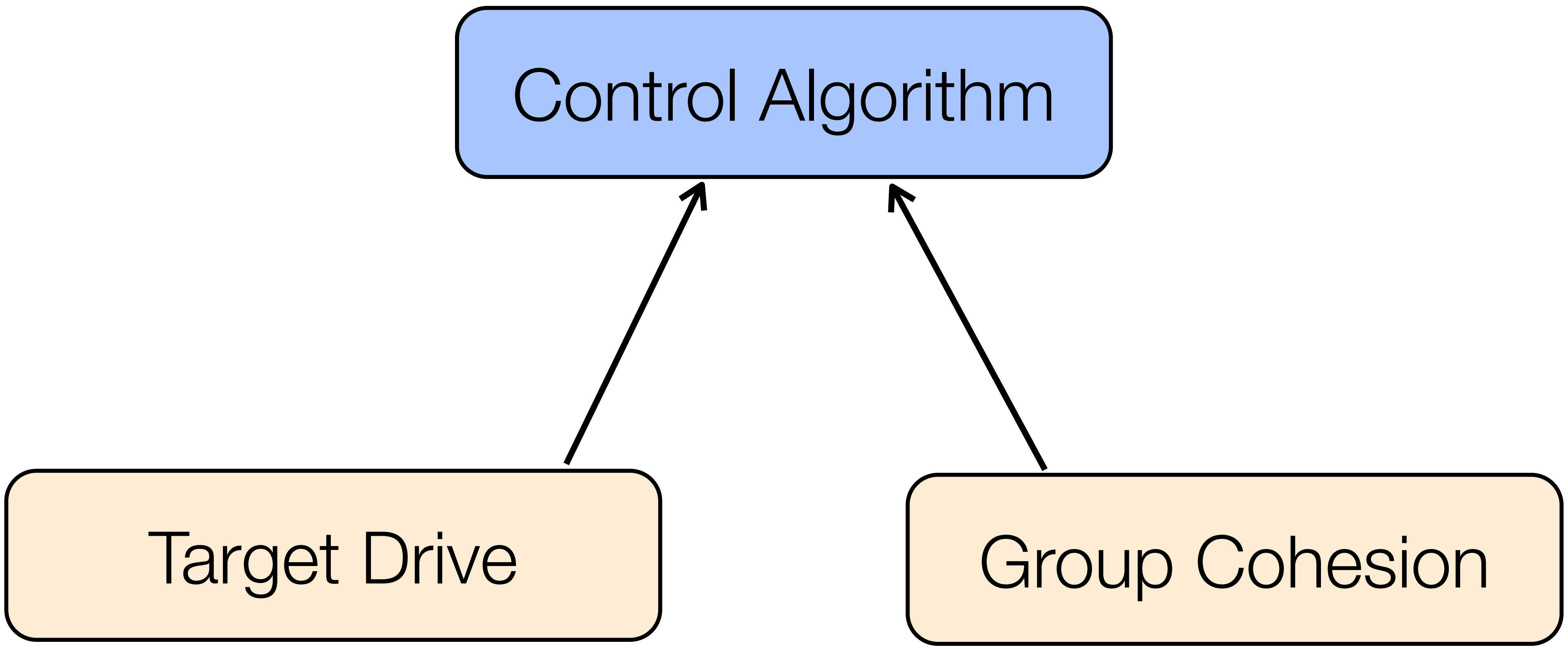


Image courtesy: http://www.roboticsbusinessreview.com/

Bio-inspired algorithms for groups of AUVs

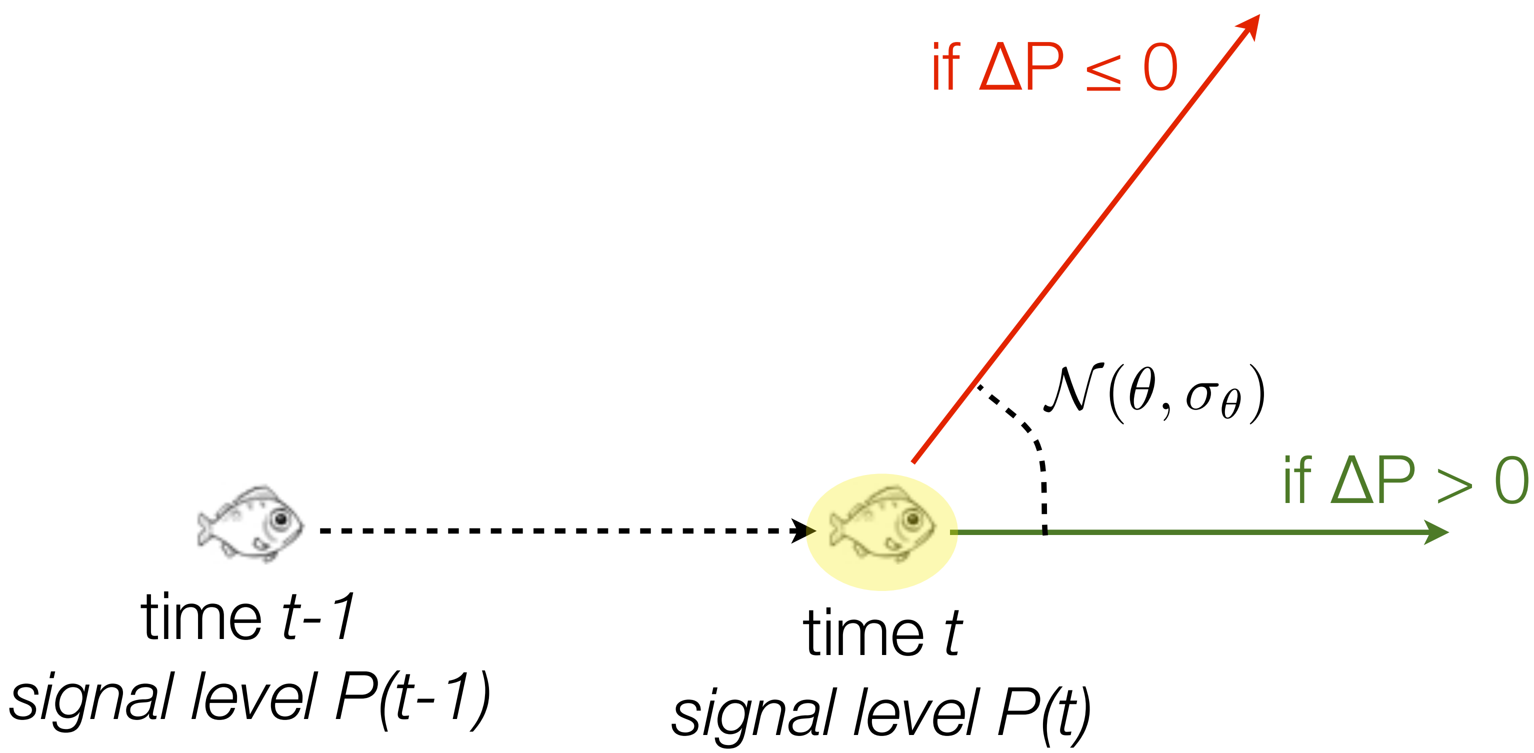
Control Algorithm

Algorithm Overview



Target Drive

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

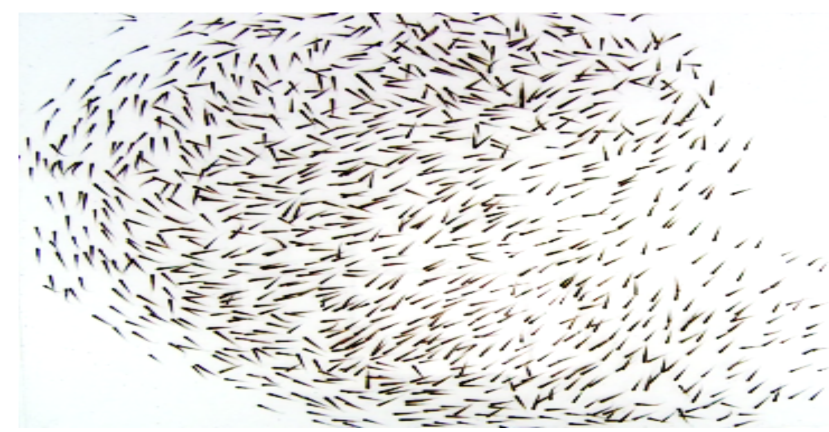


$\Delta P = P(t) - P(t-1)$

Group Cohesion

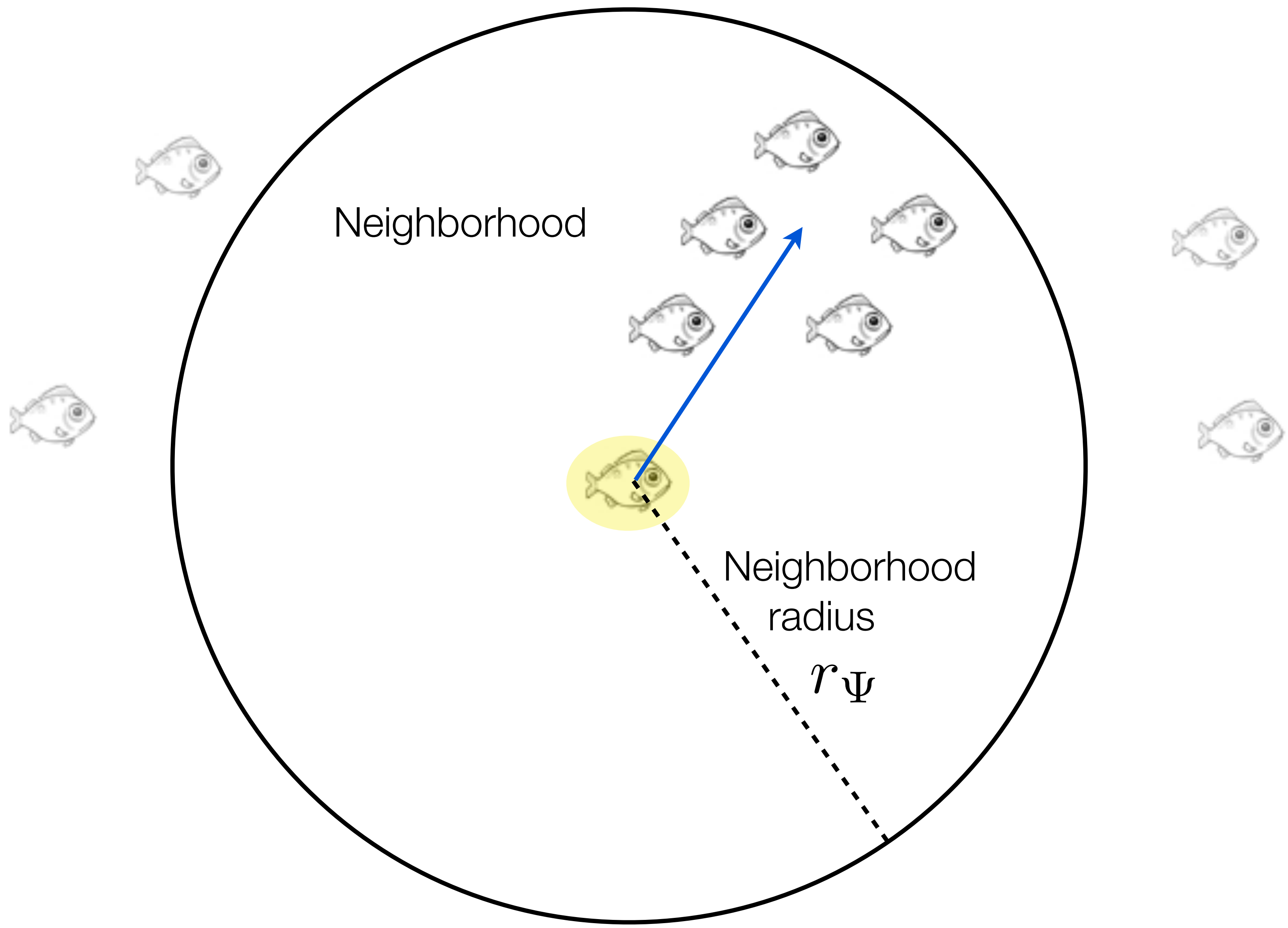
- Based on studies on Golden shiners:

Y. Katz, K. Tunstrm, C. Ioannou, C. Huepe and I. Couzin, "Inferring the structure and dynamics of interactions in schooling fish," Proceedings of the National Academy of Sciences, vol. 108, no. 46, pp. 18720-18725, 2011.



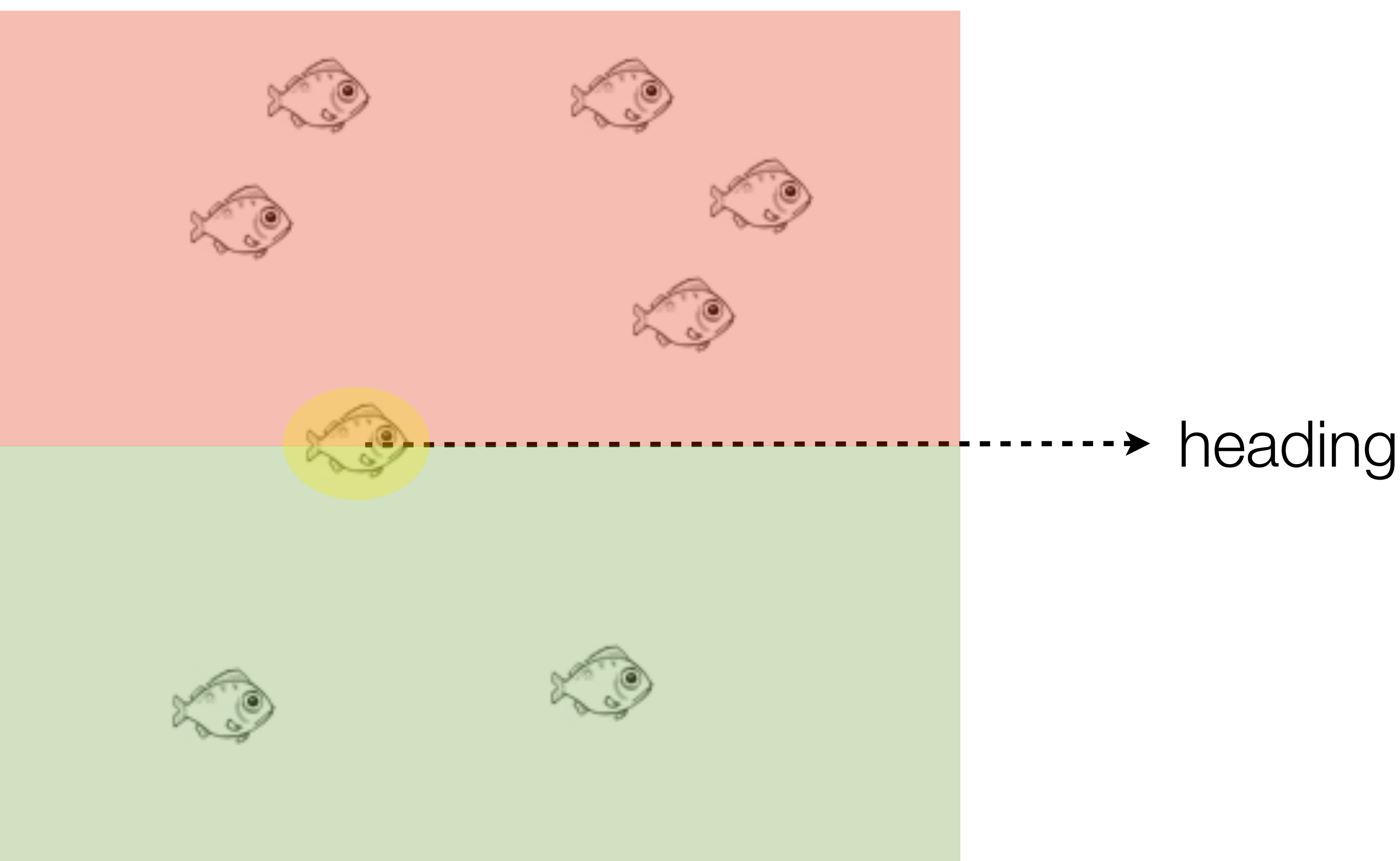
Group Cohesion

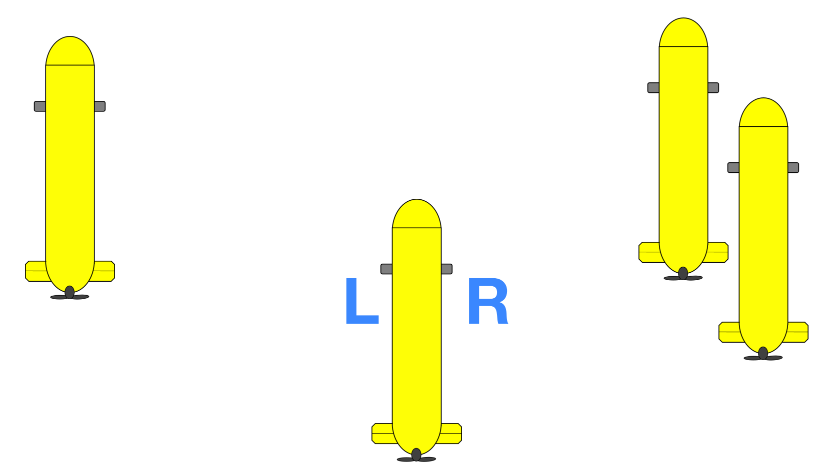
Move towards the centroid of the neighbors



Group Cohesion: Left-Right (LR) Model

- Group cohesion model requires accurate knowledge of neighbor positions
- Further simplification possible without significant loss of performance by estimating which side has more neighbors

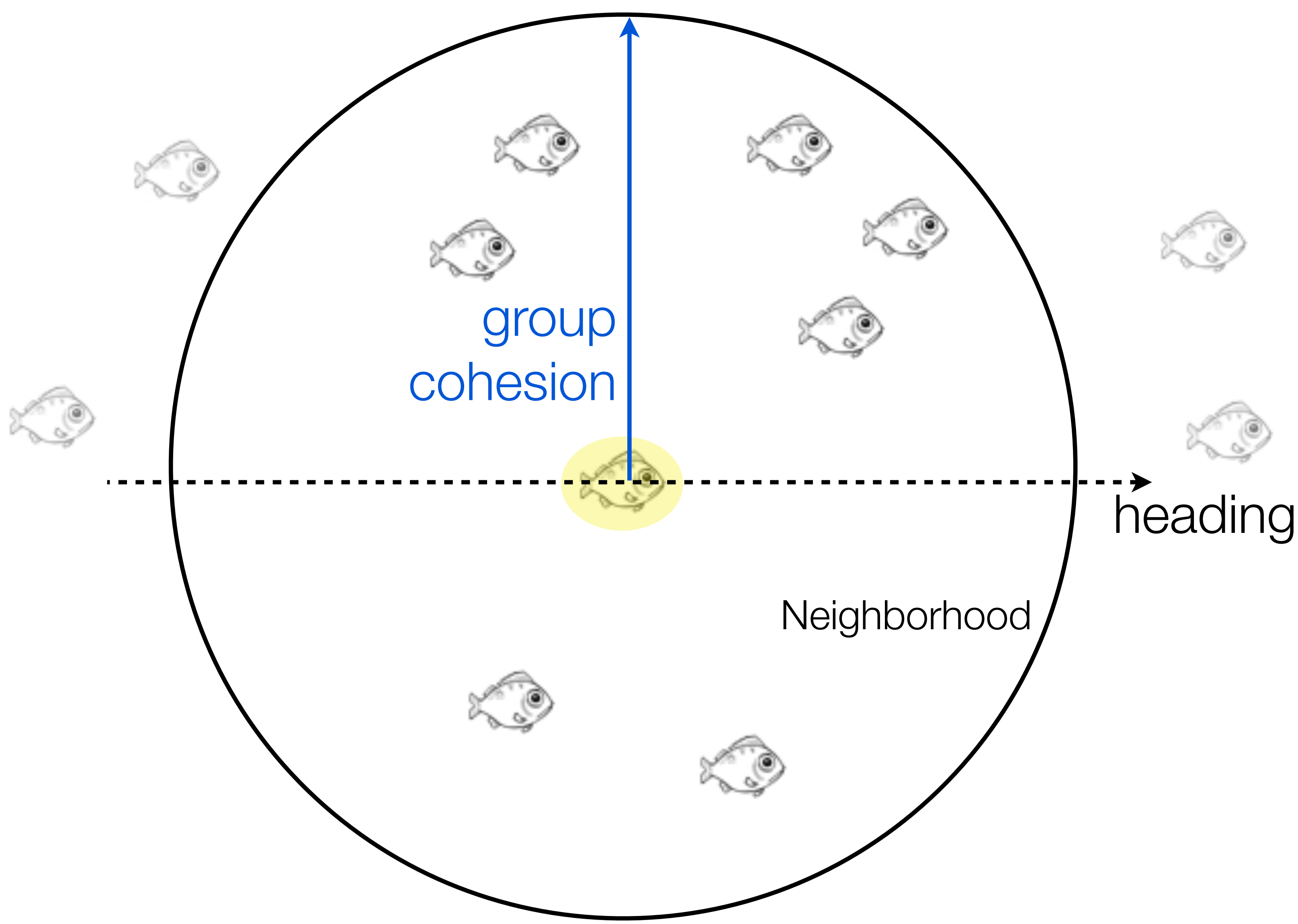




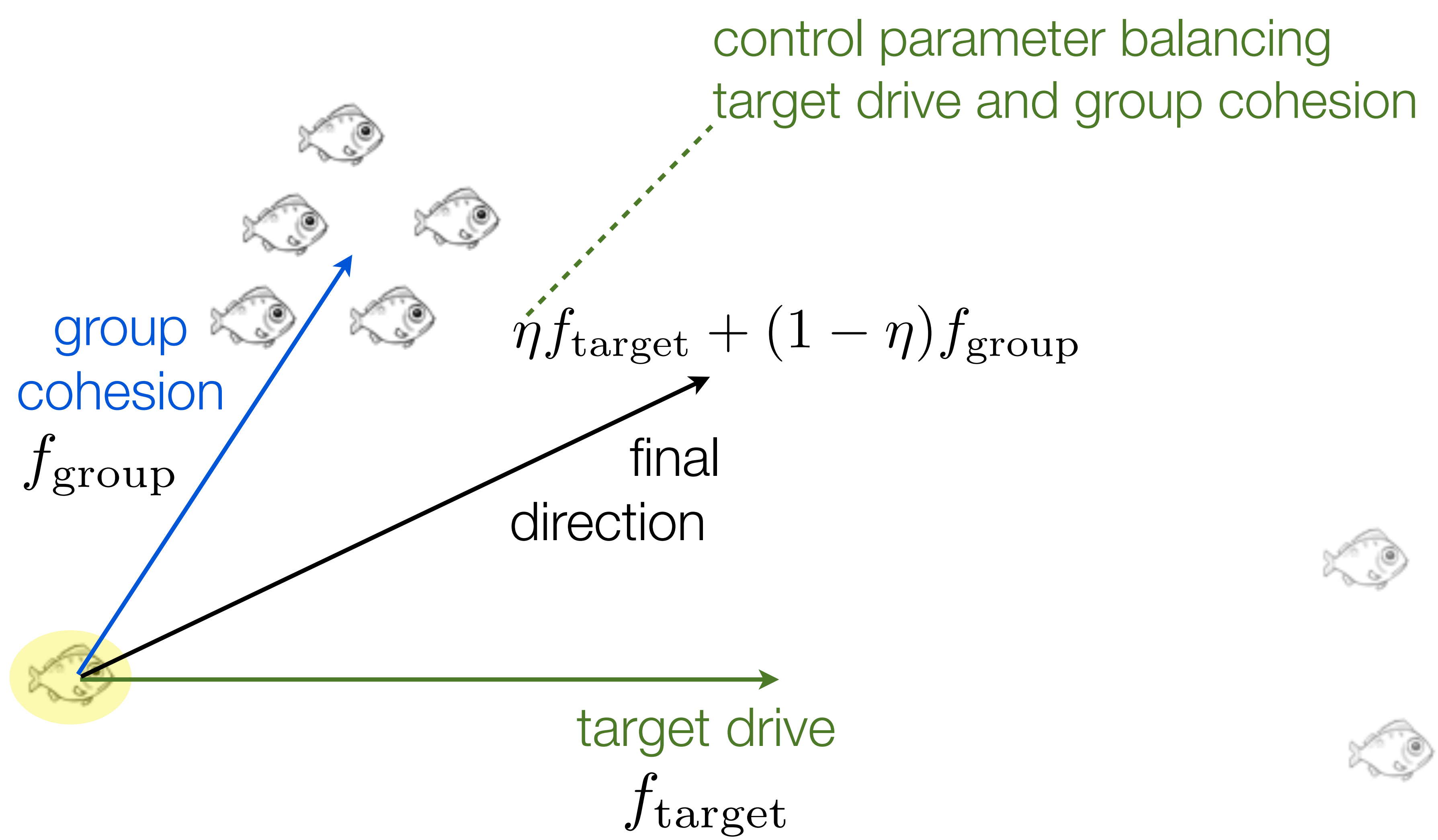
Implementation on an AUV may involve sensors (camera/ hydrophone) on either side of the AUV

Group Cohesion: LR Model

Turn towards larger number of neighbors

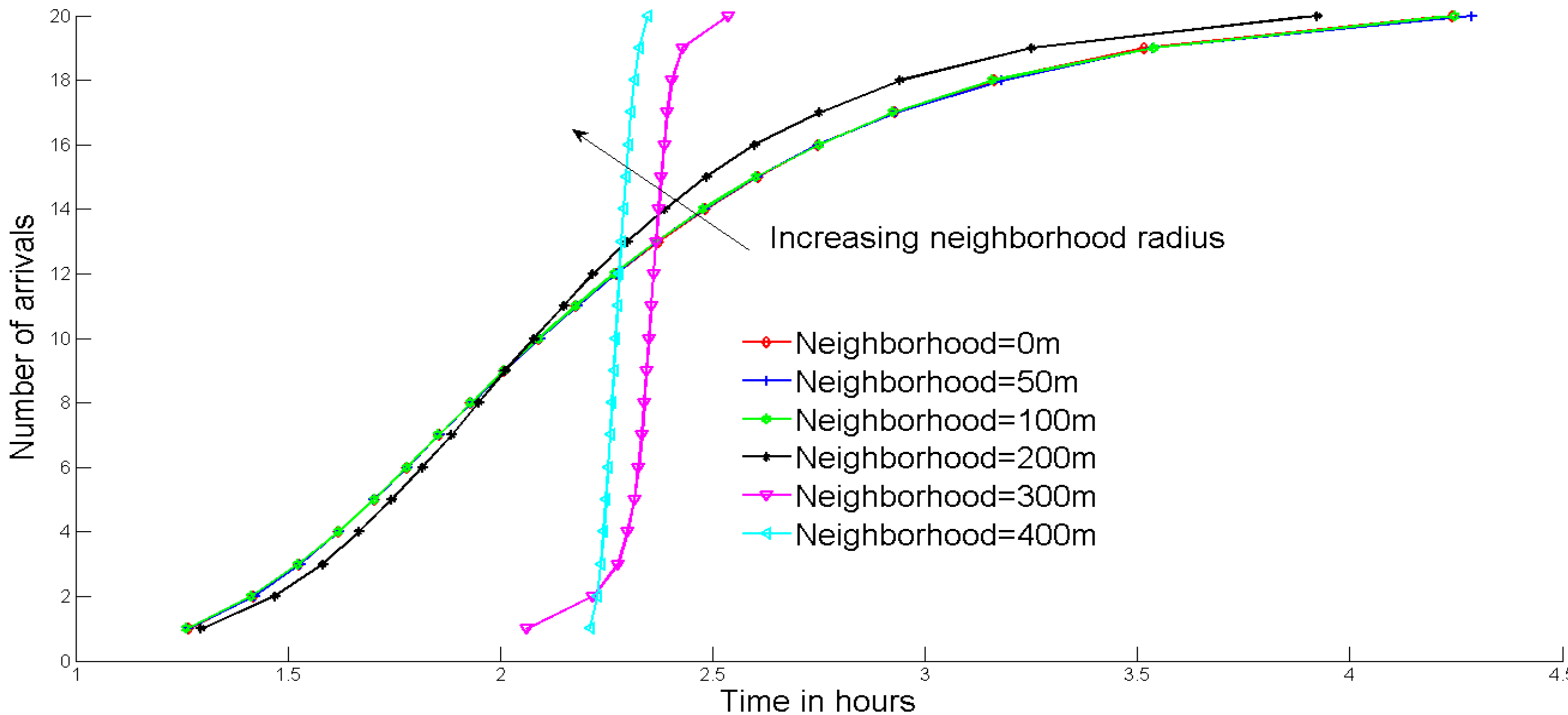


Target Drive + Group Cohesion

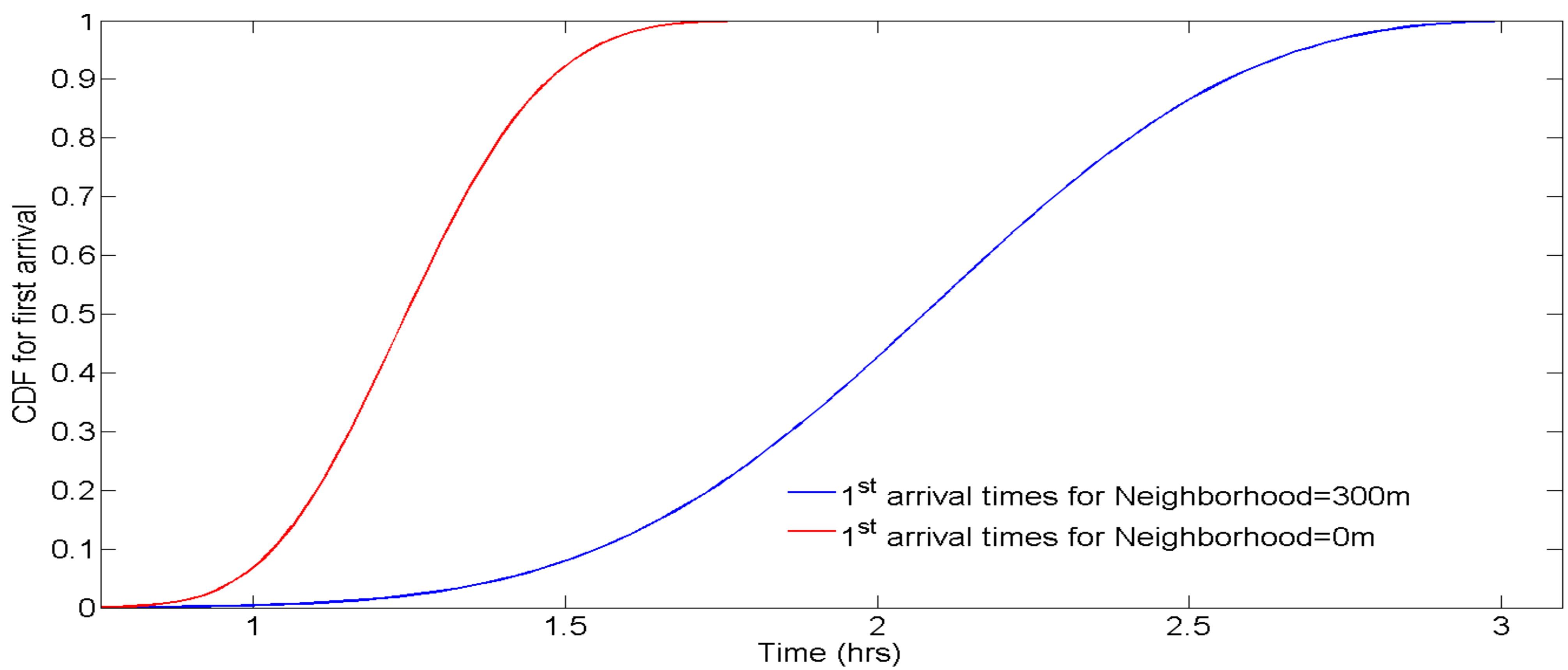


Results:
Fixed parameters

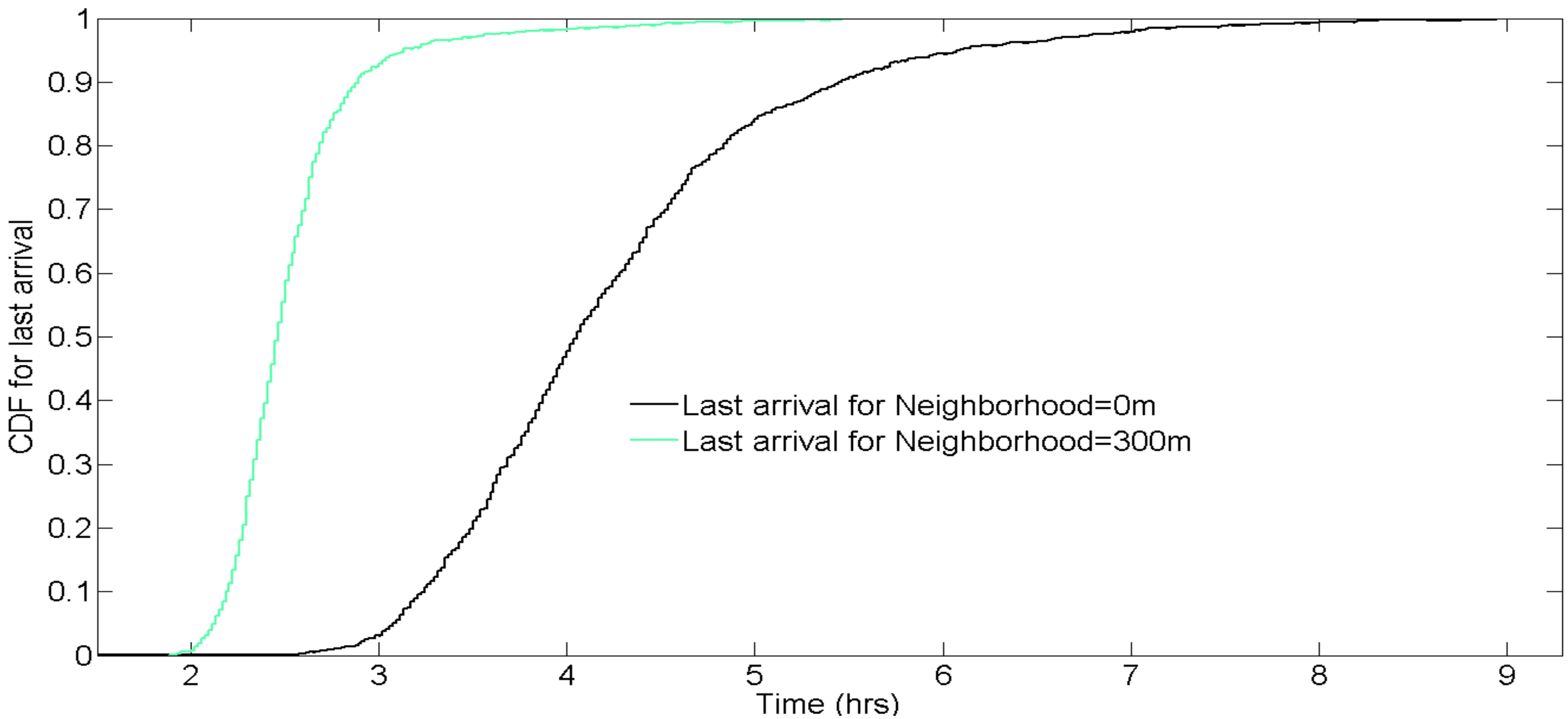
Performance – Neighborhood



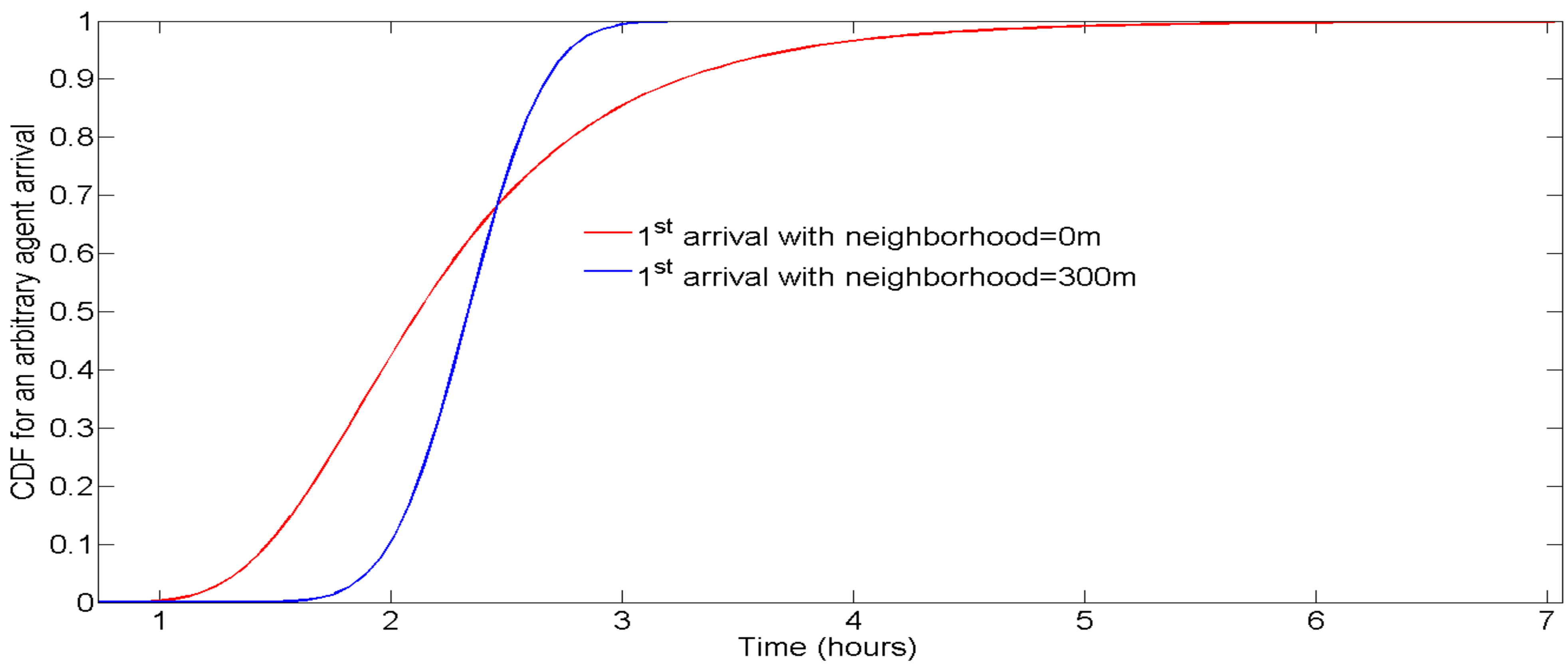
Performance – First Arrival (FAT)



Performance – Last Arrival (LAT)



Performance – Specific Arrival (SAT)



Summary of Results

- For the FAT problem, it is best to have no group cohesion.
- The LAT problem benefits significantly from group cohesion.
- Performance of the SAT problem becomes more deterministic with group cohesion.

Bio-inspired algorithms for groups of AUVs

Parameter Tuning

Control Algorithm Parameters

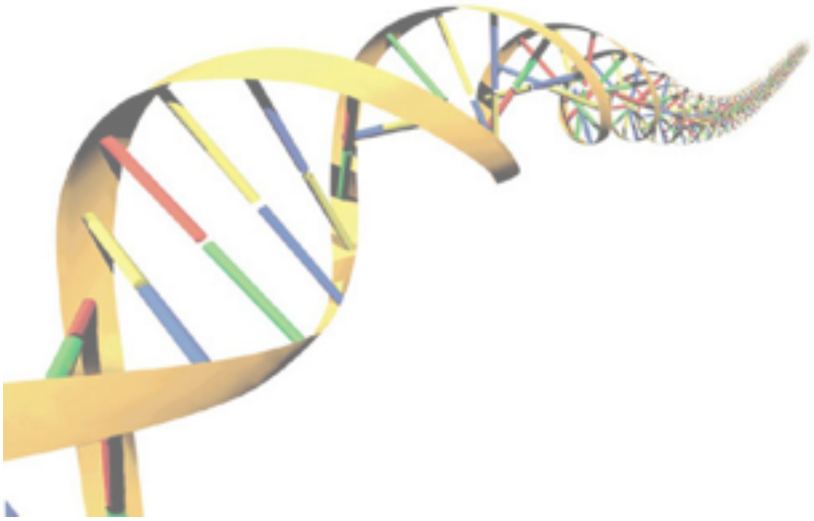
- Number of AUVs – N (range: 1 to 30)
- Drive coefficient – η (range: 0 to 1)
- Turning angle distribution parameters – θ, σ_θ

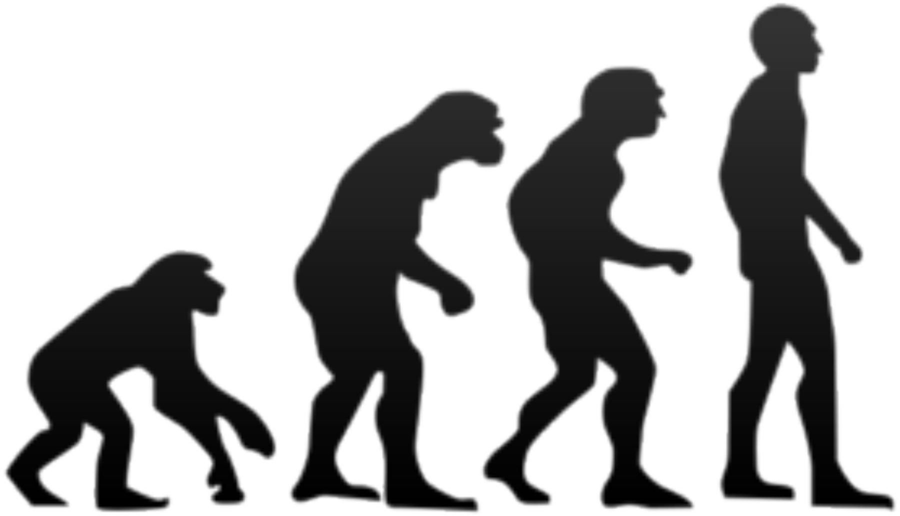
Optimization Objectives

- **Mean first arrival time (FAT)**
- **Mean last arrival time (LAT)**
- Mean specific arrival time (SAT)

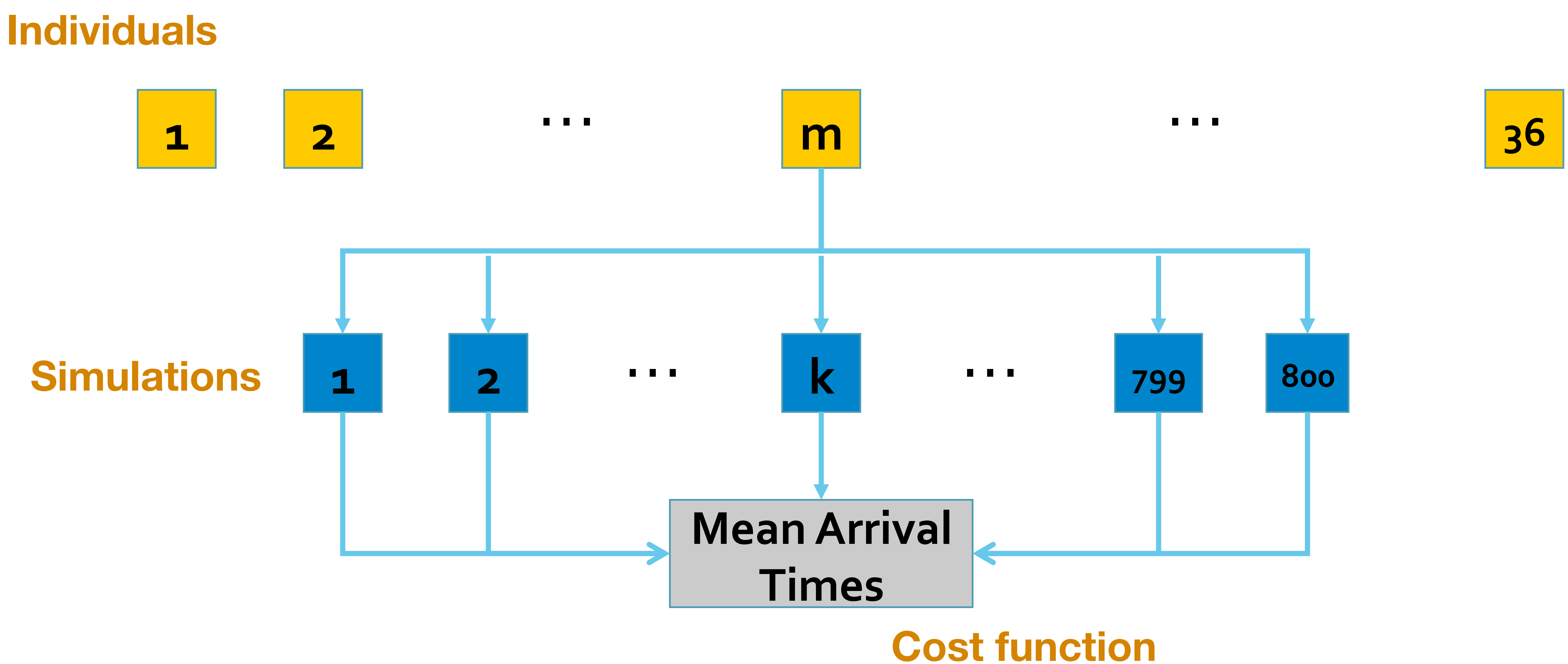
Optimization Framework

- Evolutionary Optimization
  - Population size = 36
  - Real-valued genes: (N, η, θ, σ_θ)
  - Crossover + Mutation
  - Binary tournament selection
  - Elitism

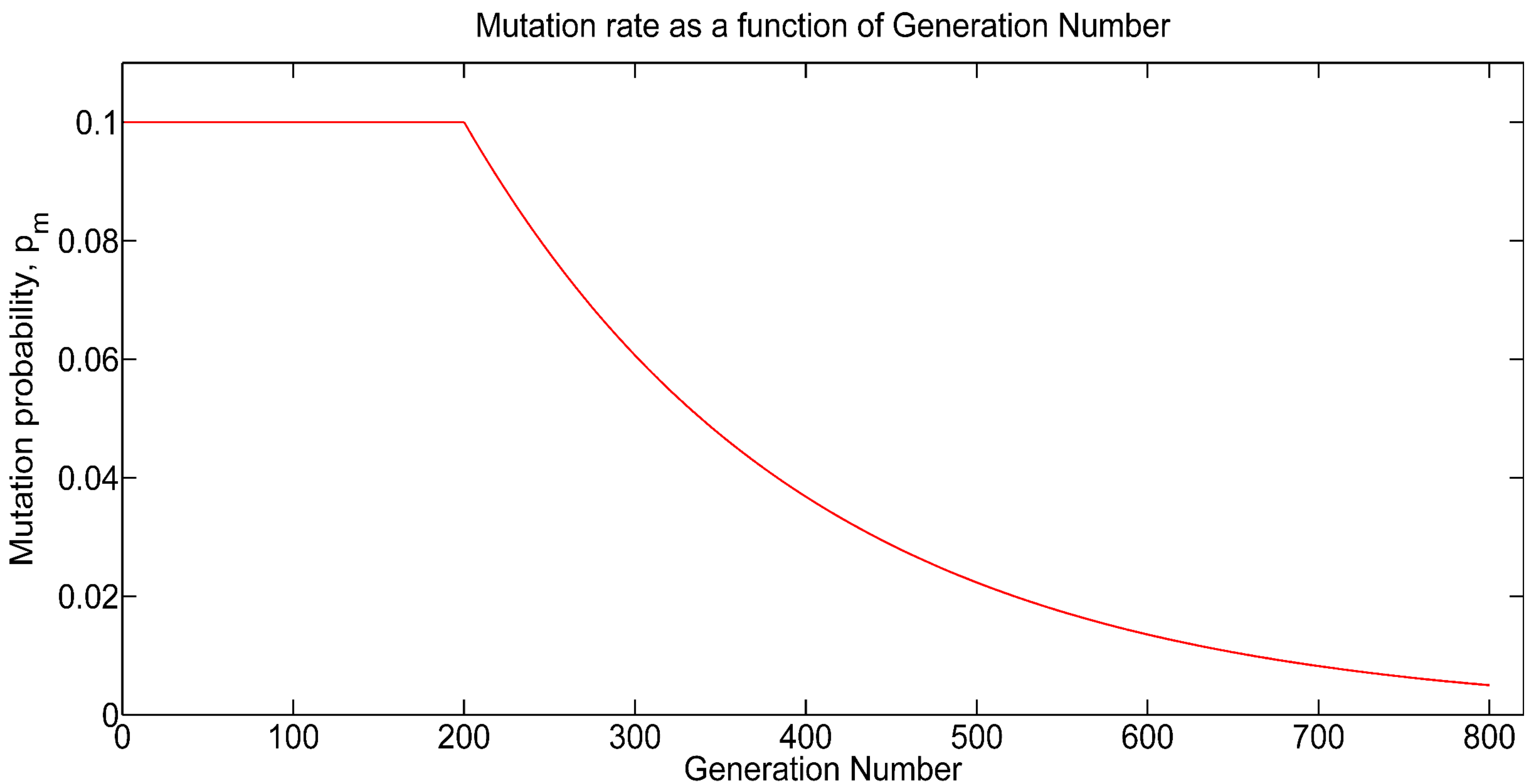




Optimization Framework



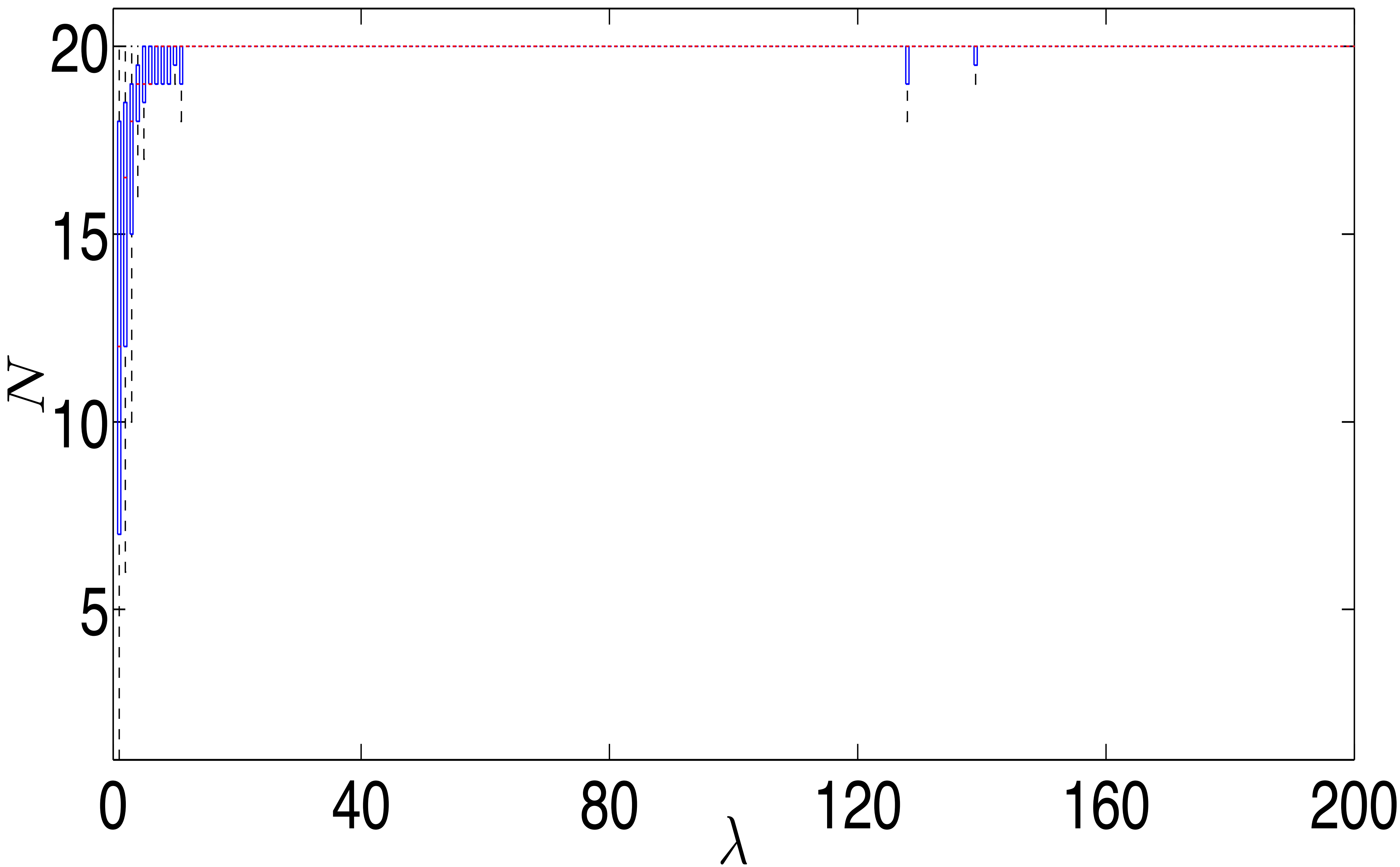
Optimization Framework



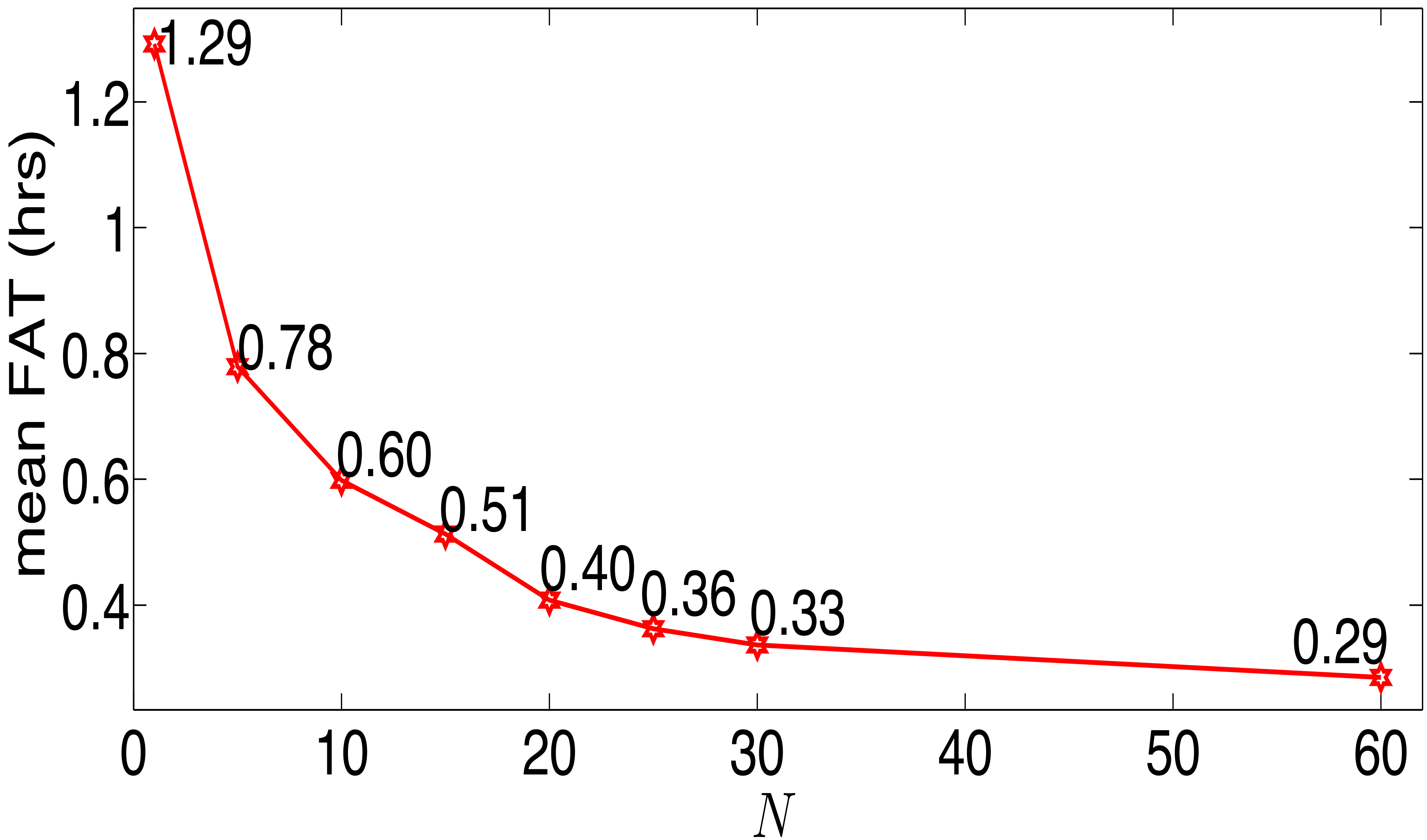
Results:

First Arrival Time (FAT)
with optimized parameters

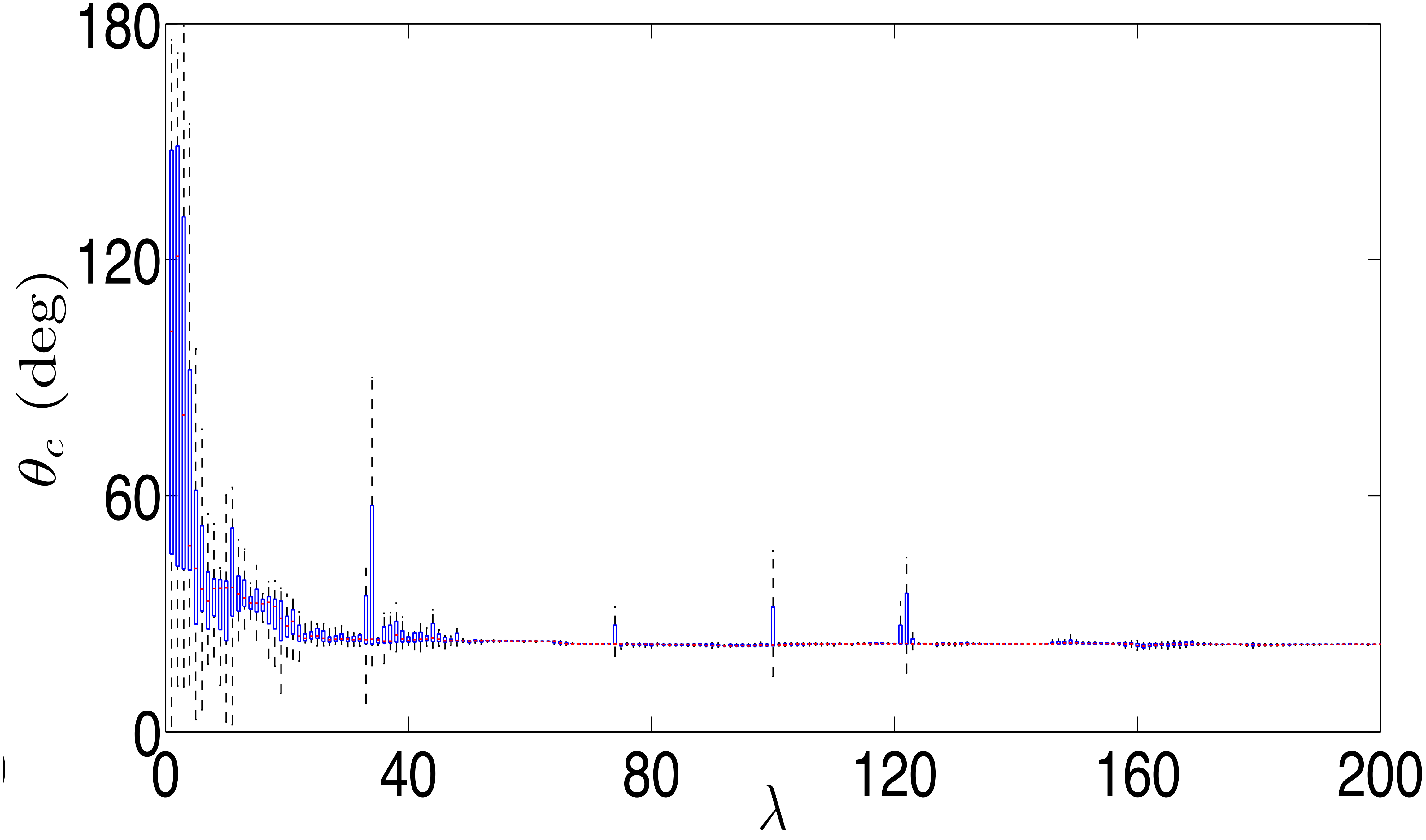
Optimization – Number of AUVs



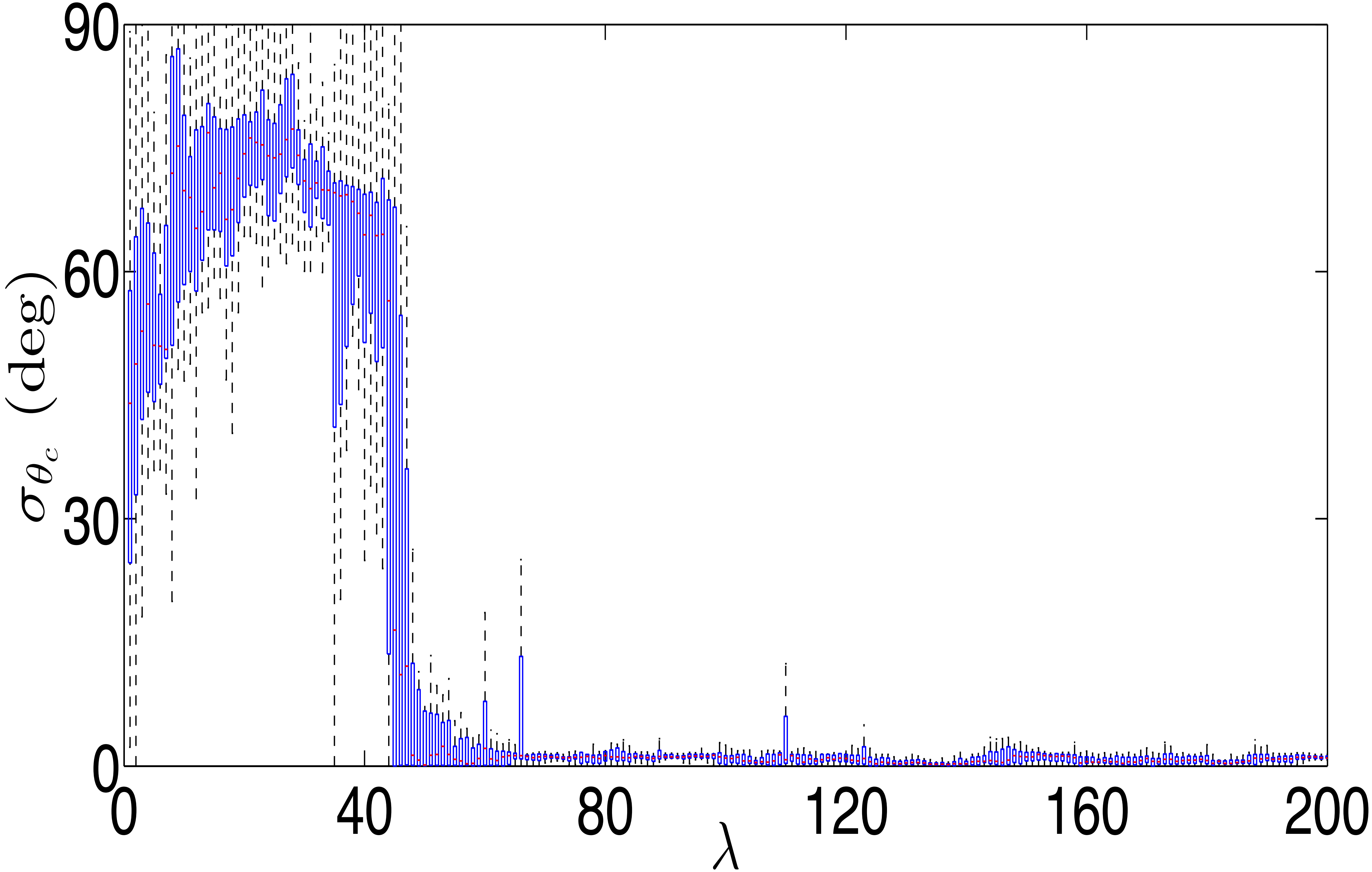
Performance – Group Size



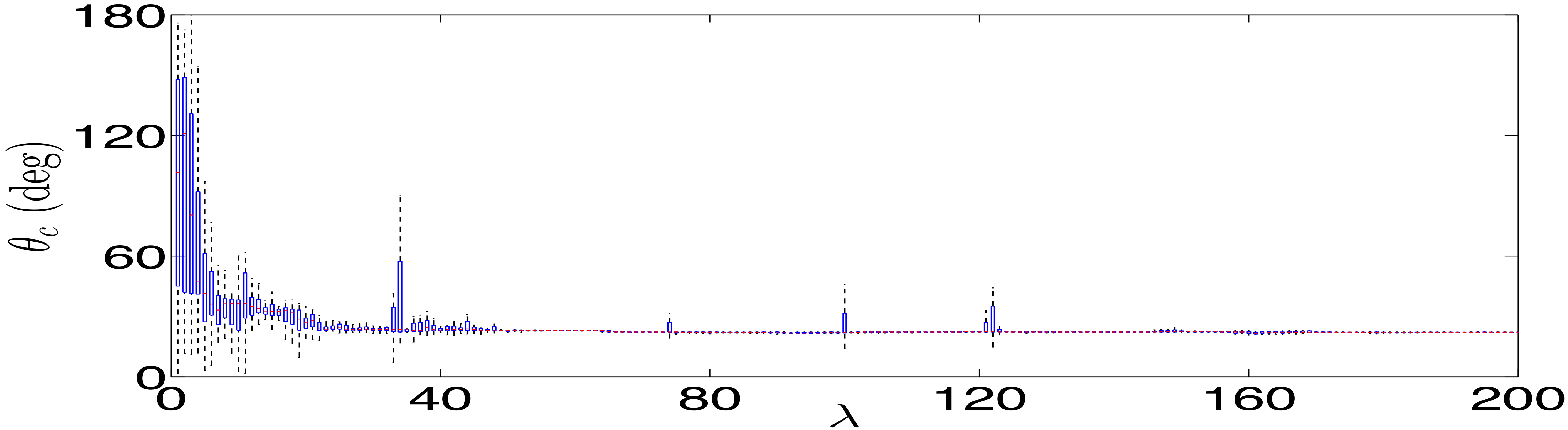
Optimization – Turning Angle

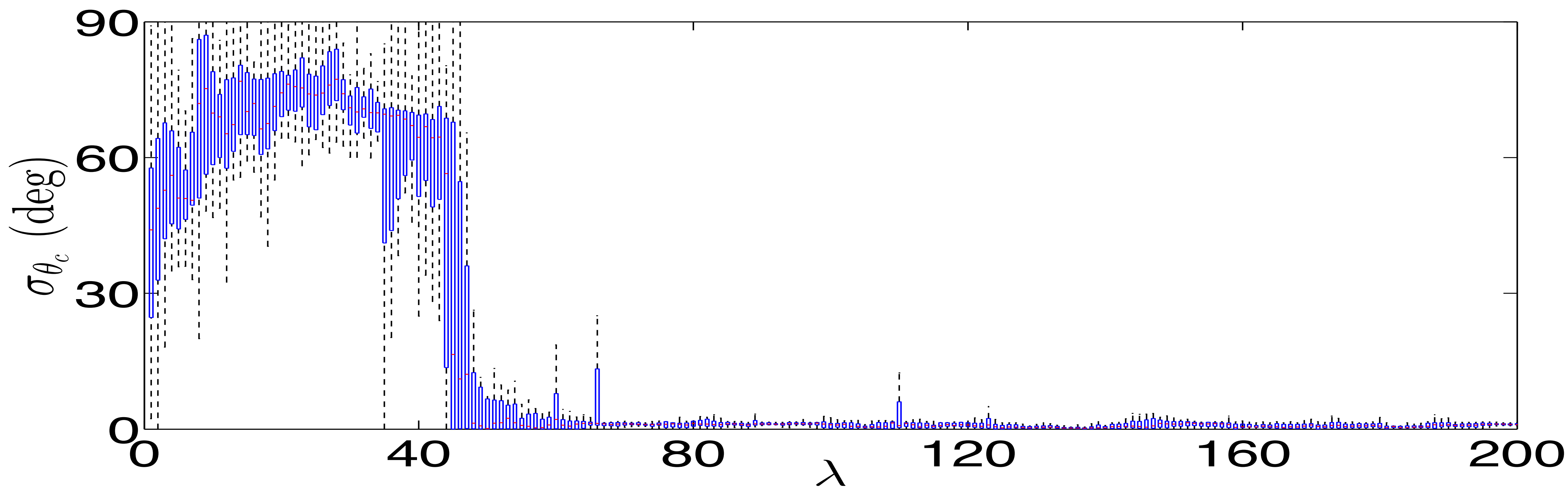


Optimization – Turning Angle Variability

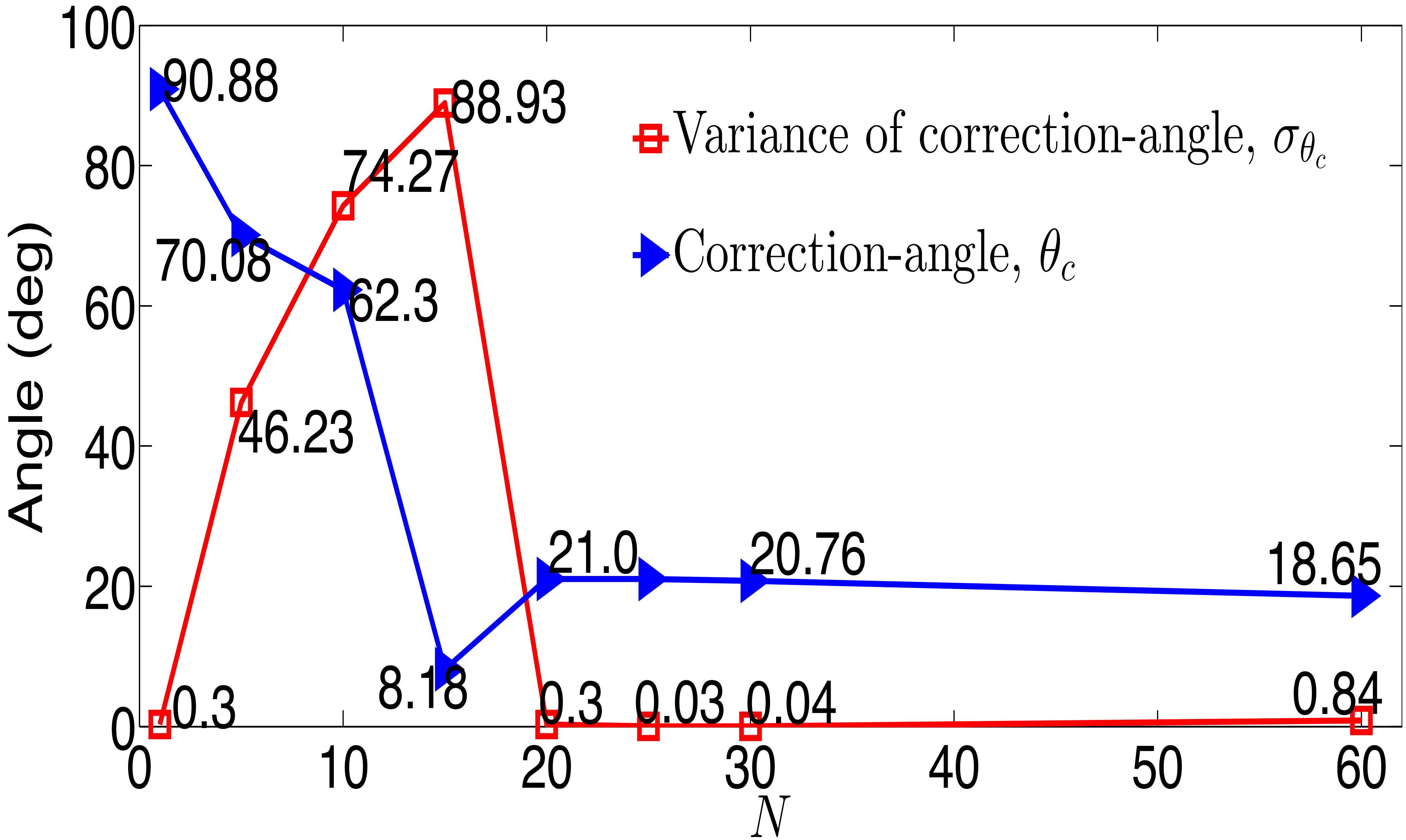


Optimization – Turning Angle

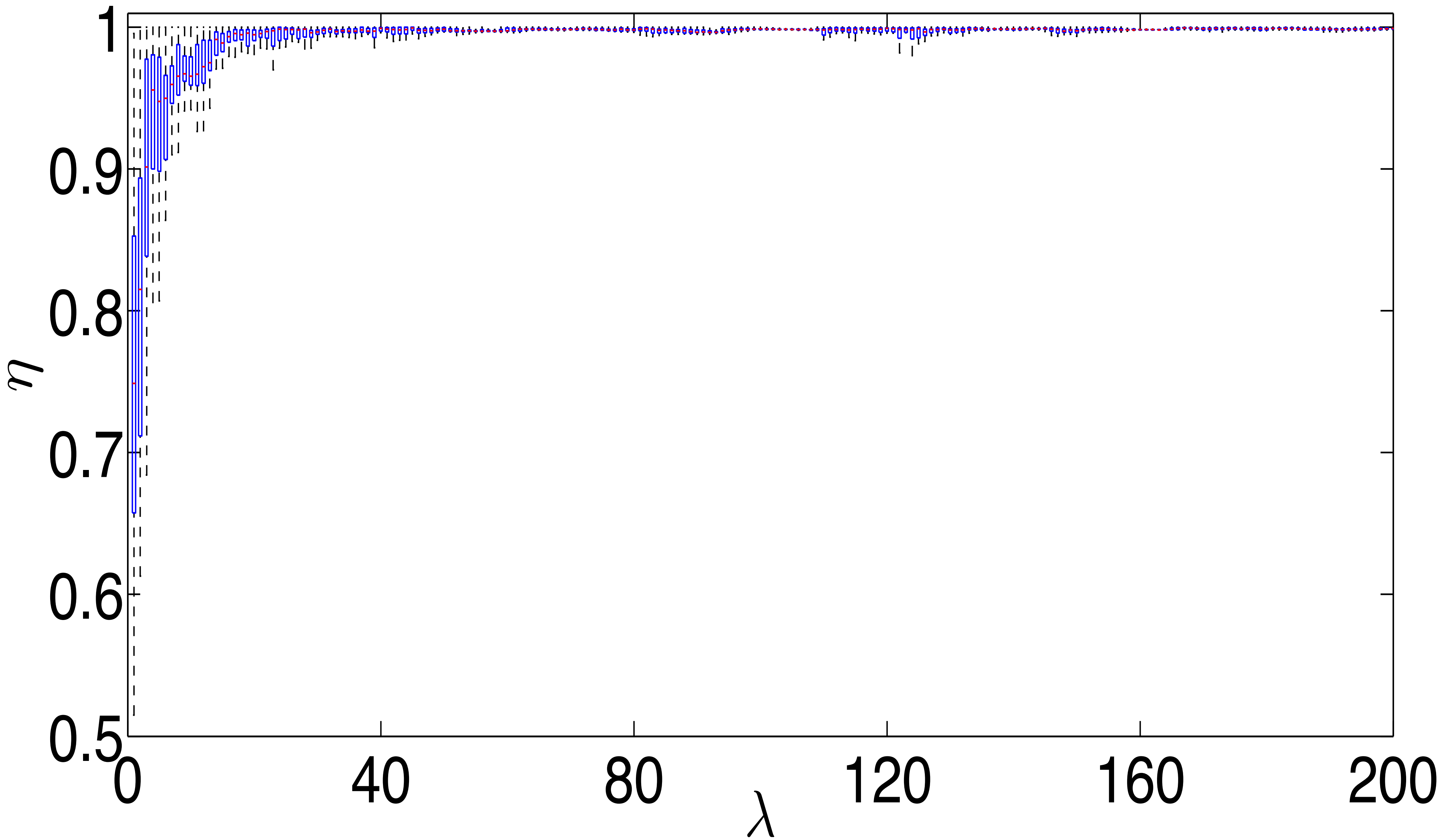




Optimal Turning Angle v/s Group Size



Optimization – Target Drive



FAT – Simulations

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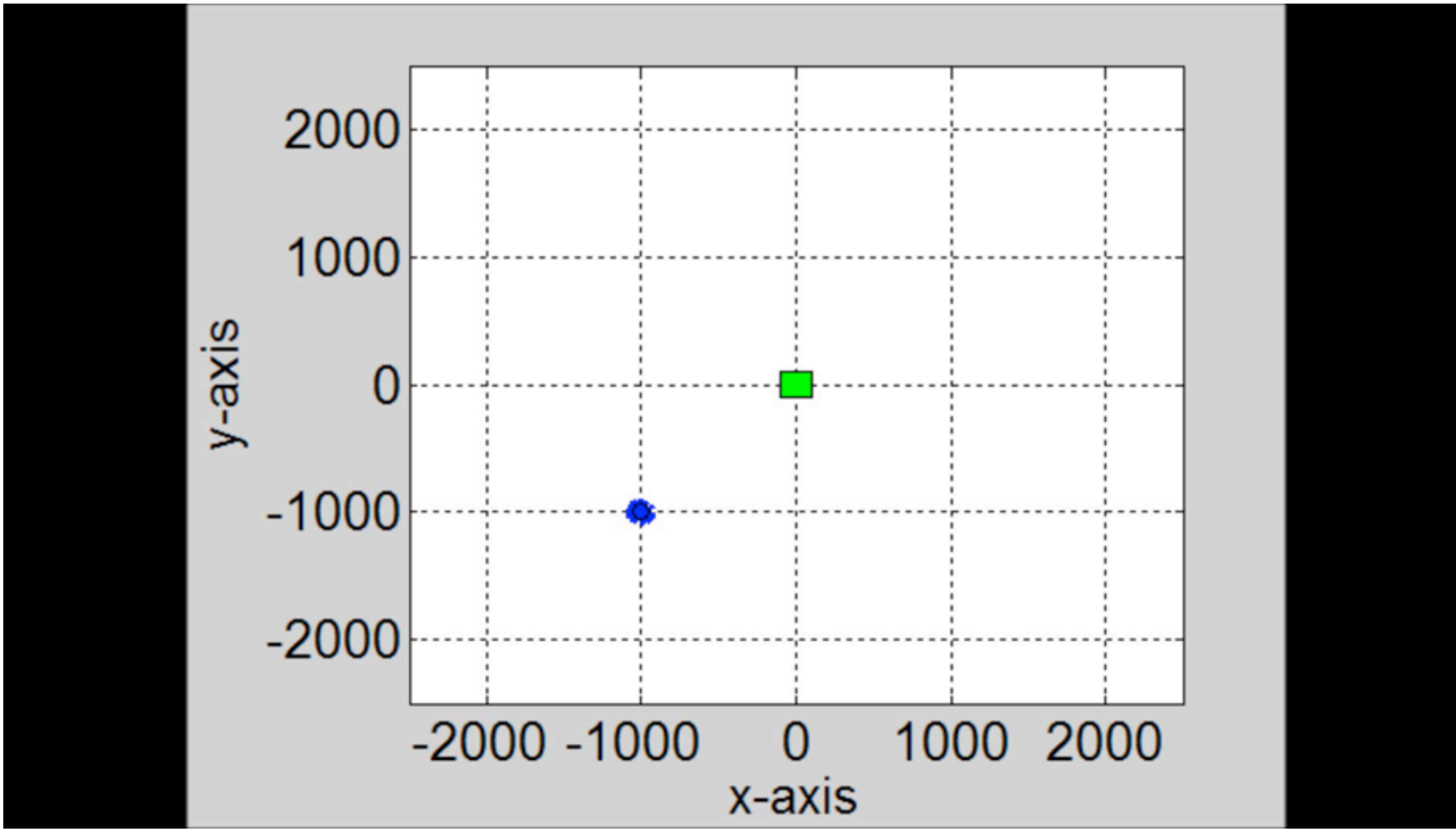

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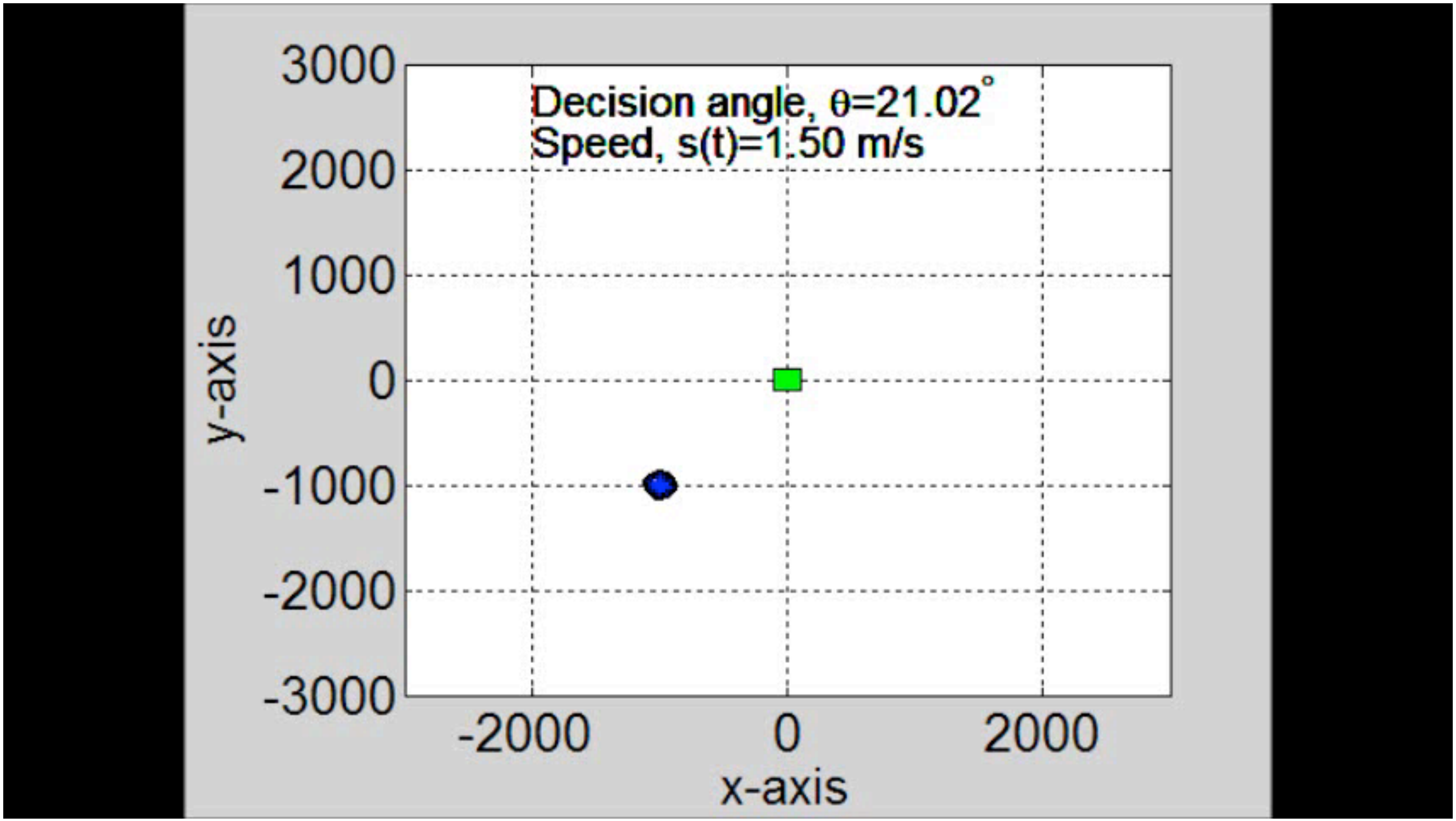
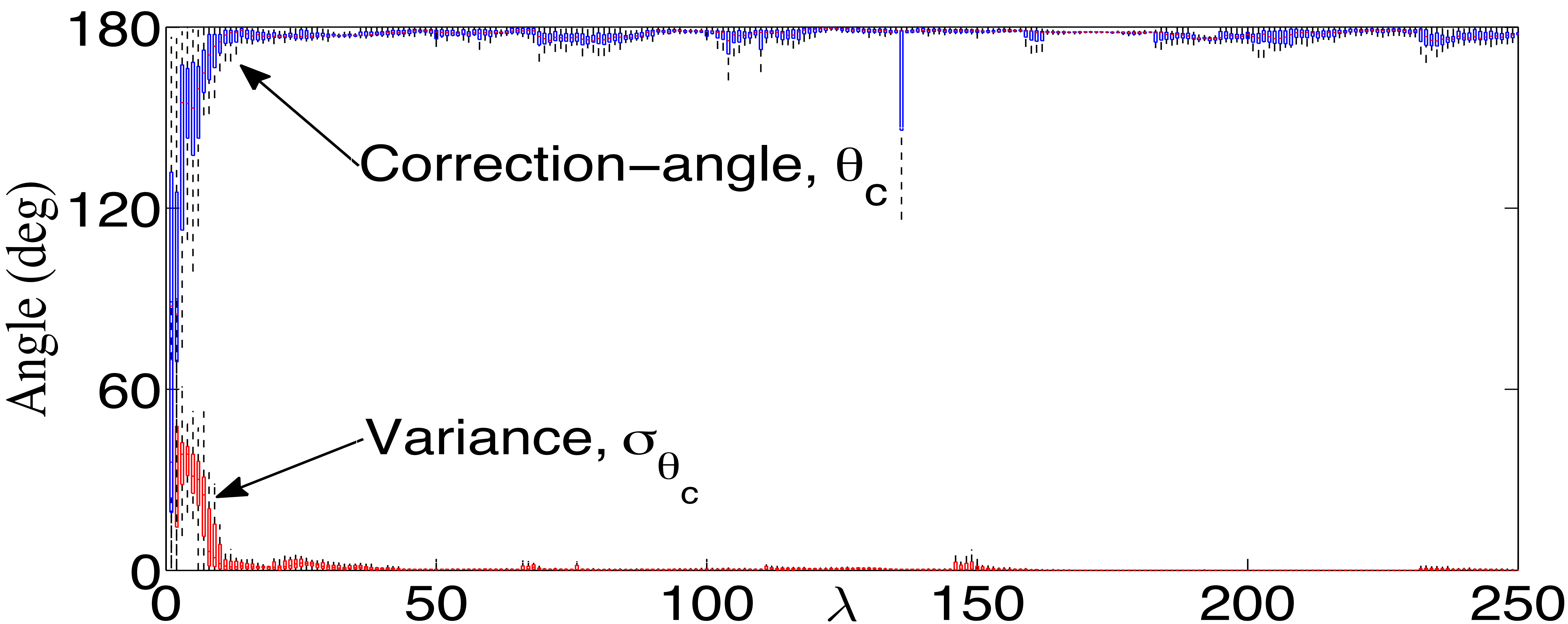
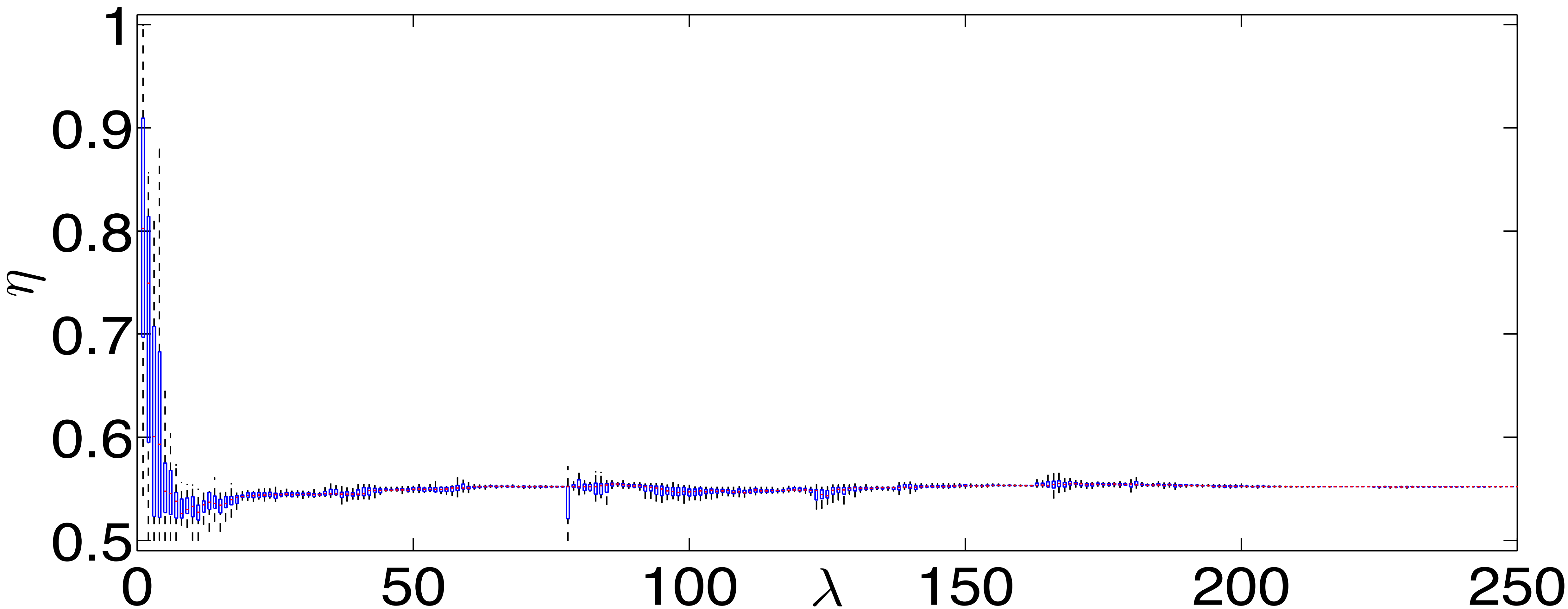


Results:
Last Arrival Time (LAT) with optimized parameters

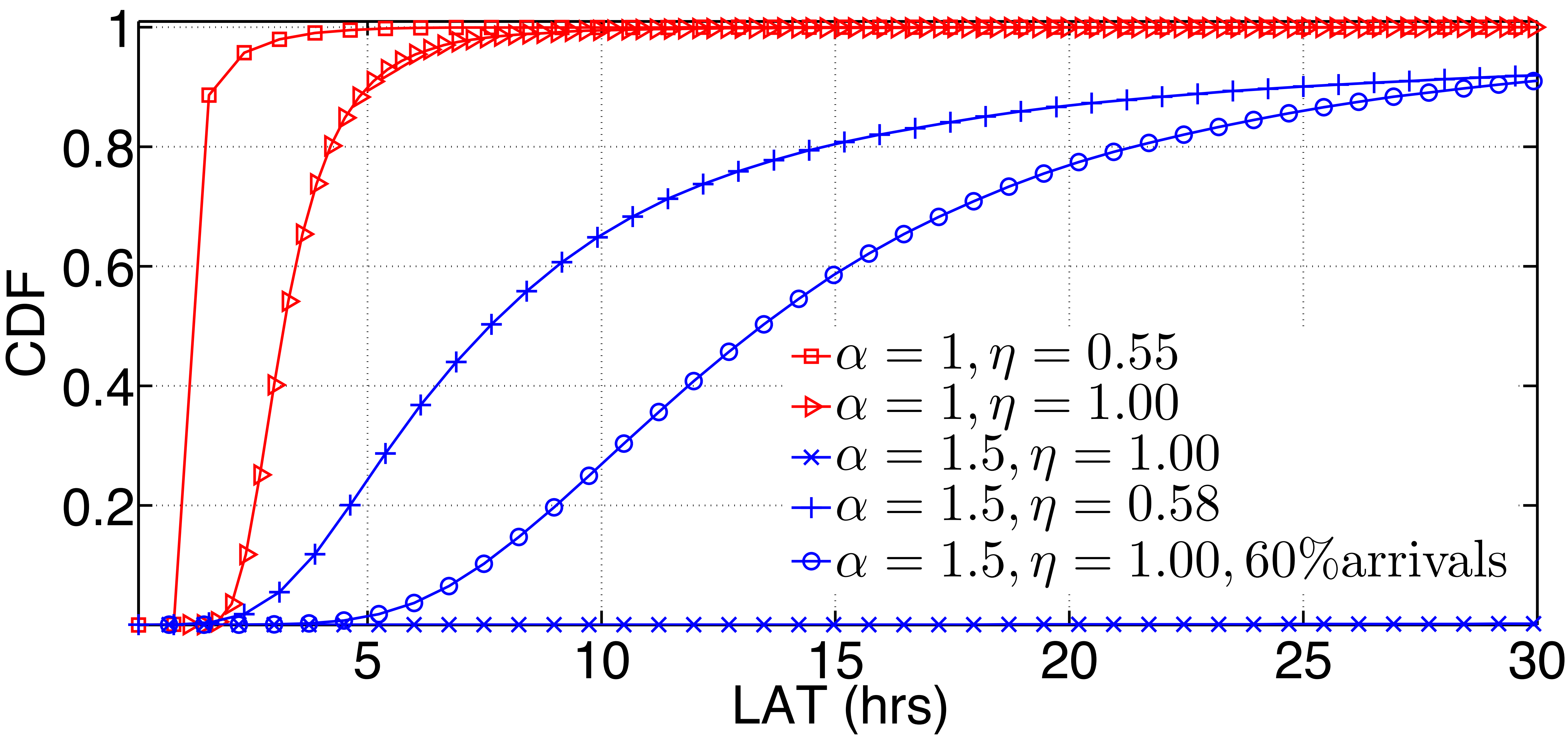
Optimization – Turning Angle



Optimization – Target Drive



Last Arrival Time CDF



LAT – Simulations (N = 1)

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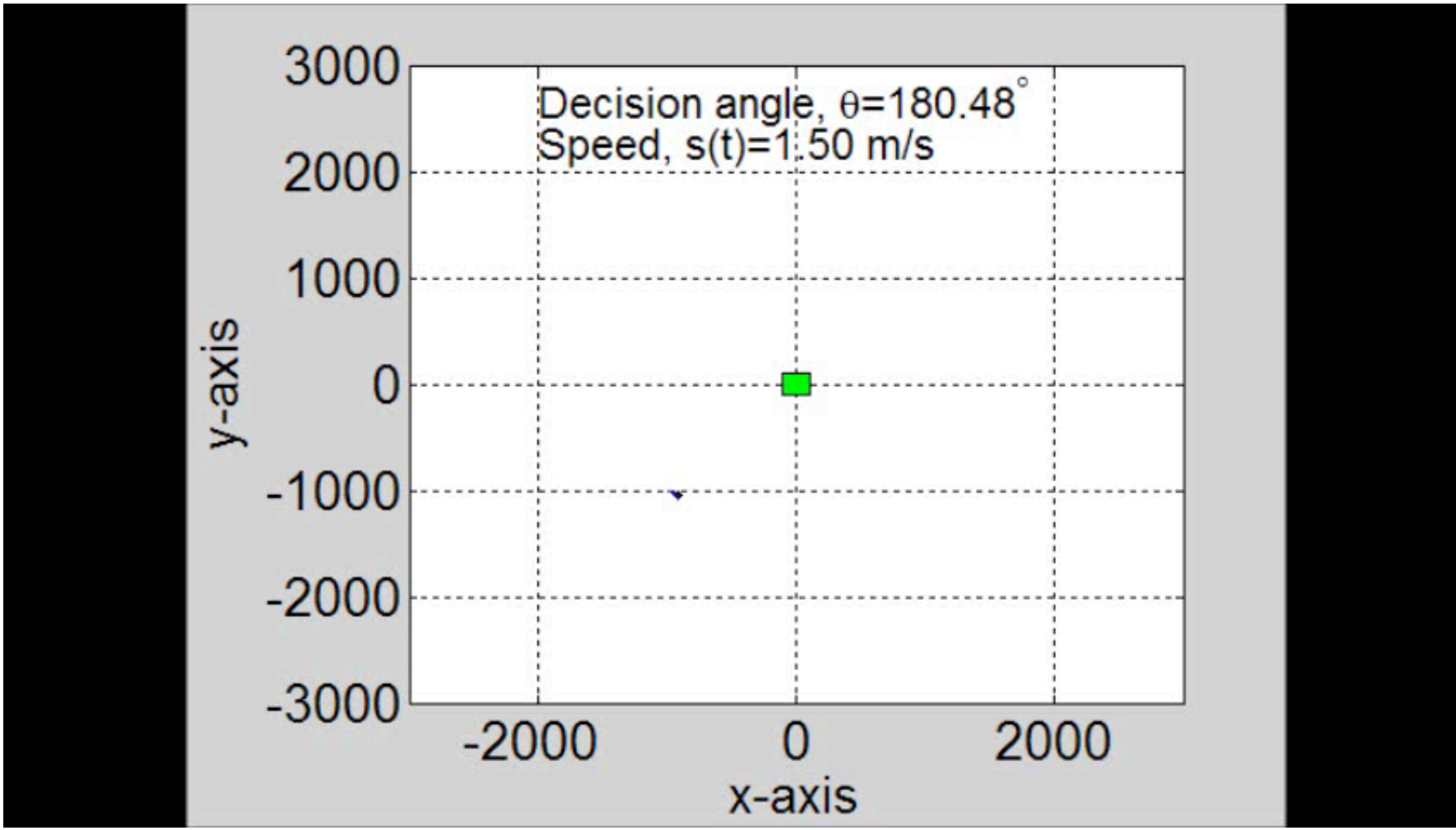

LAT – Simulations (N = 1, Optimized)

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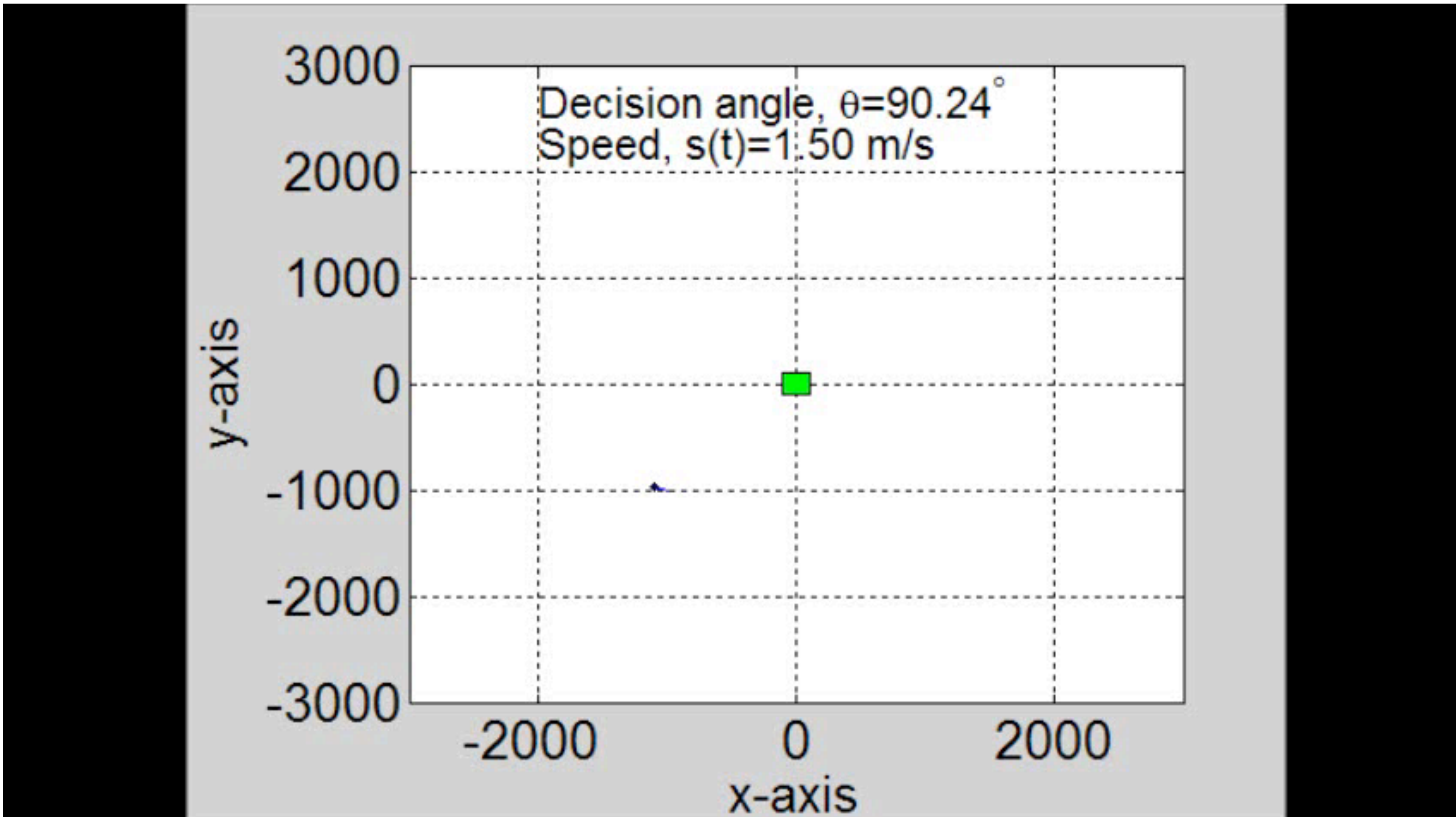

LAT – Simulations (No Schooling, N = 20)

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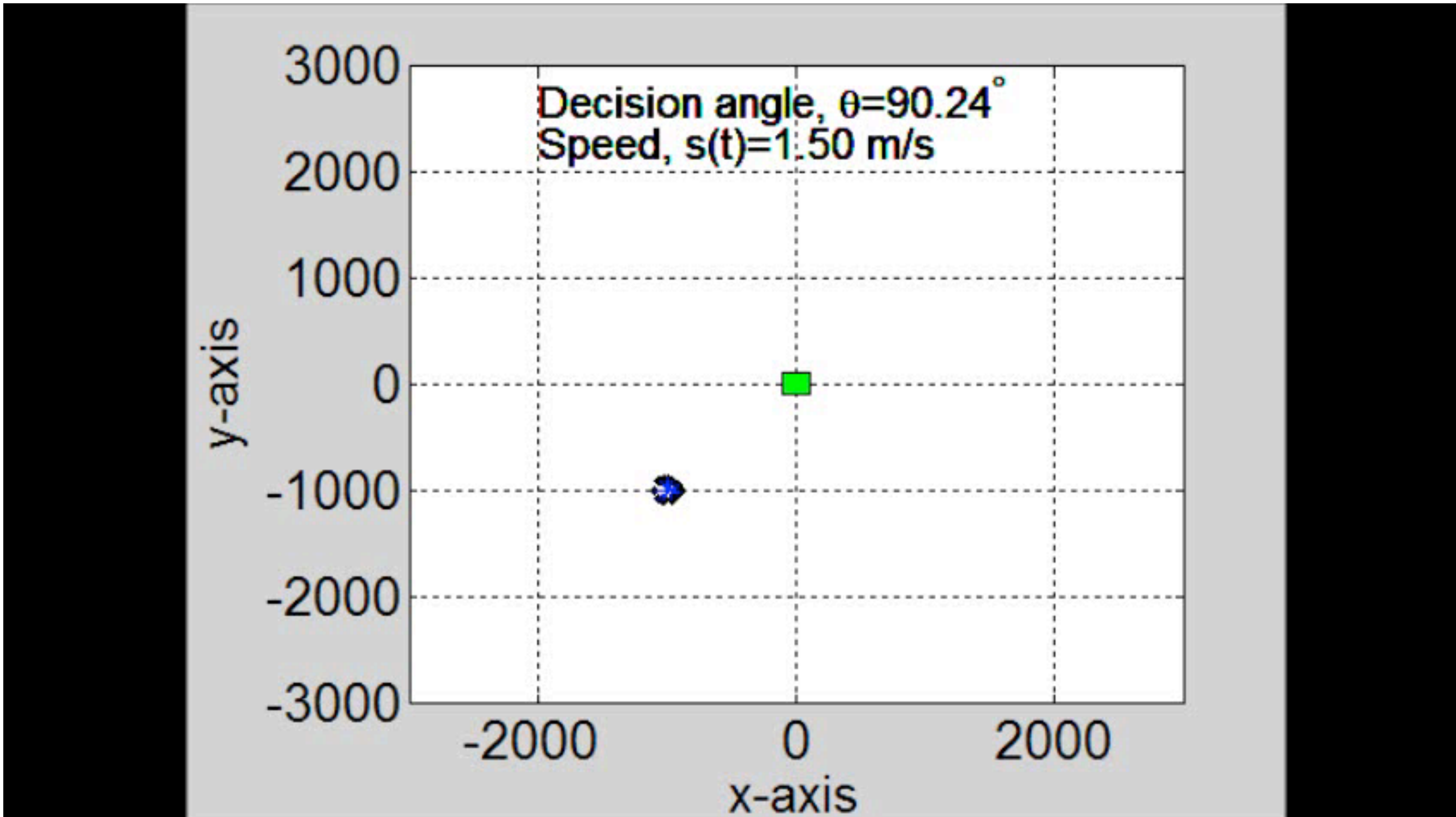

LAT – Simulations (Schooling, N = 20)

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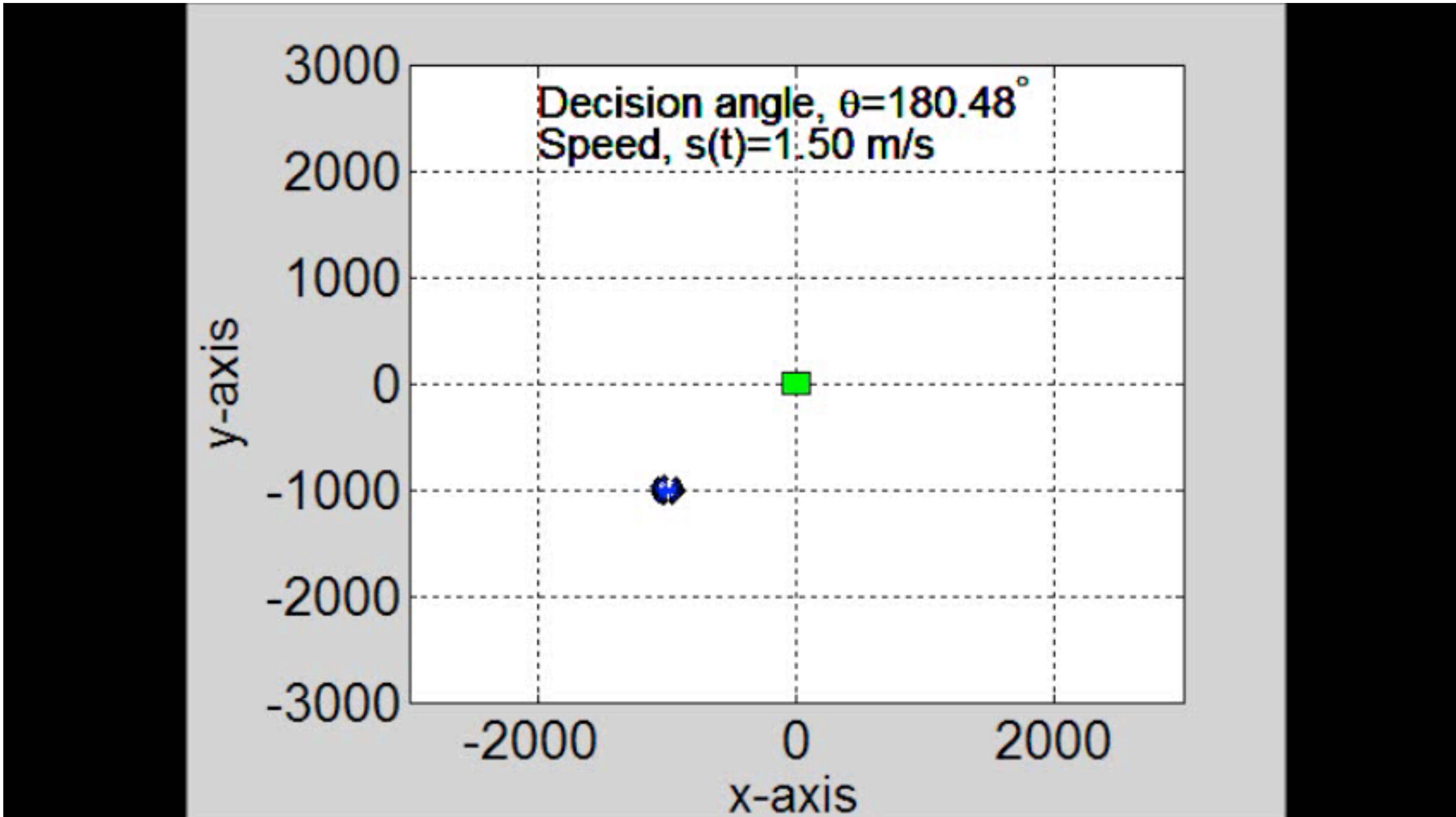

LAT– Simulations (Schooling, N = 80)

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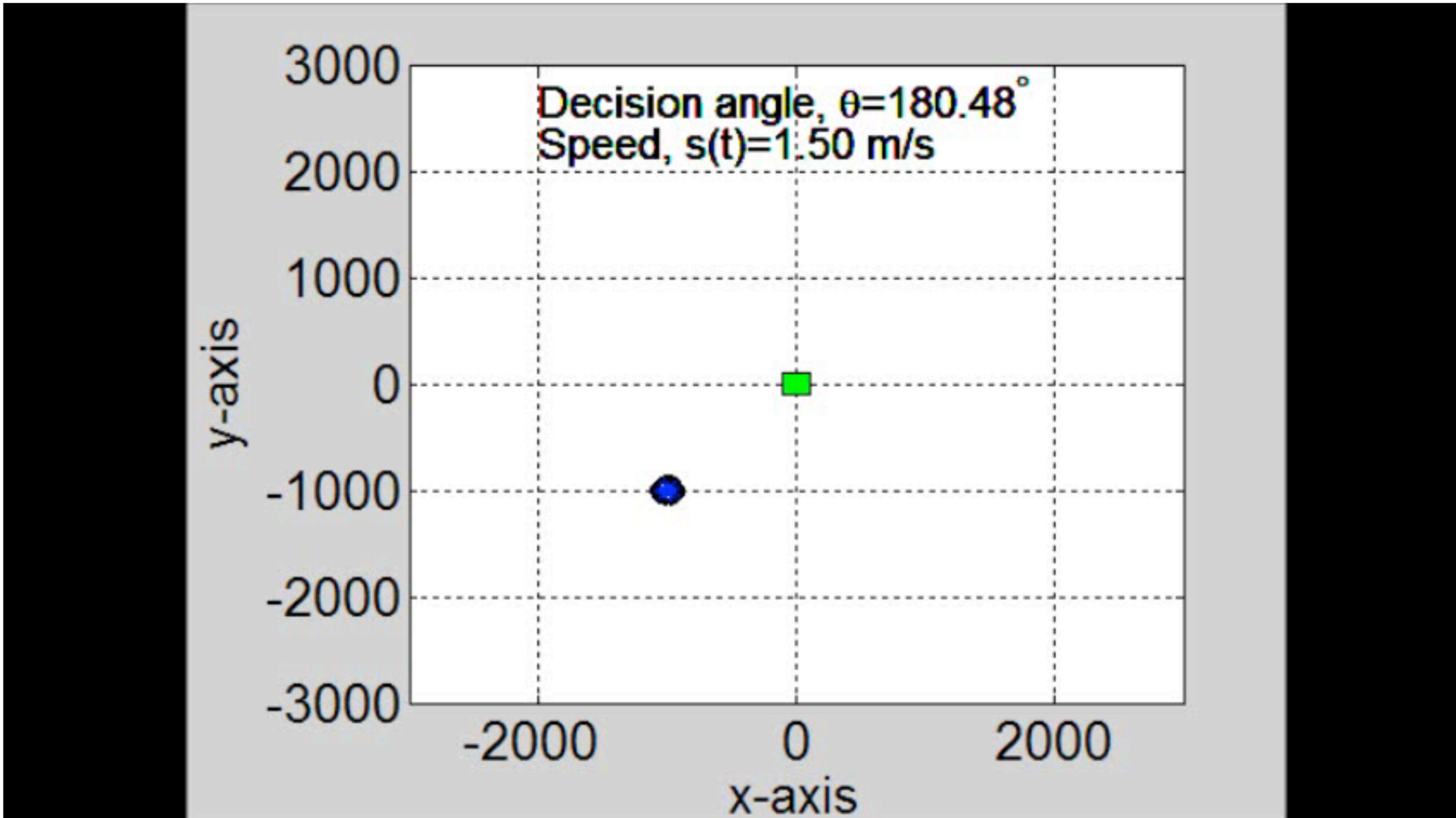


Conclusions

Conclusions

- Small teams can demonstrate effective group synergy.
- Evolutionary optimization can effectively find parameters yielding good performance given a search space.
- The FAT problem does not require group cohesion, but needs many AUVs. The LAT problem benefits from a large team size, and plenty of cohesion.
- Interesting high-level behaviors emerge from the algorithm parameters learned through evolutionary optimization.

Key Takeaways [again!]

1. The team “knows” more than each of the individual in the team.

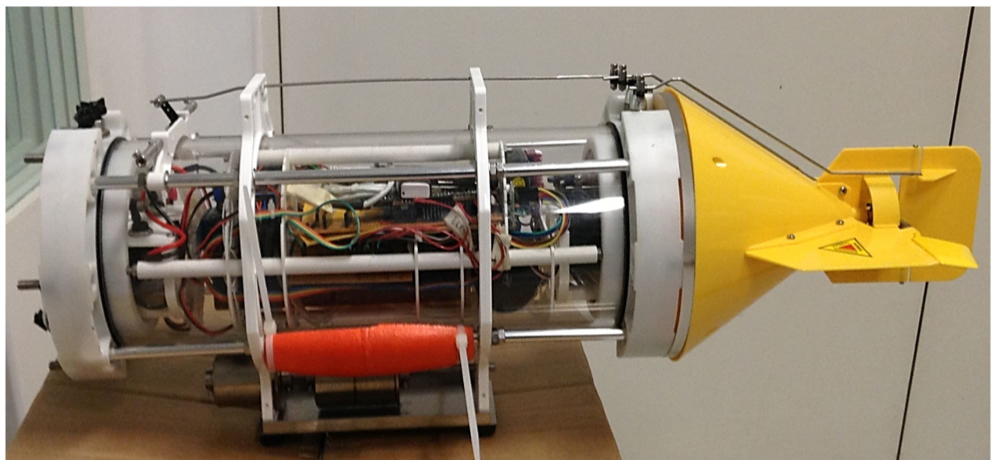
2. A bunch of noisy sensors may be sufficient, if the sensors can cooperate.

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.

Future Directions

Experiments



SwarmBot

Small, portable
Low cost
Near-surface AUV
Group behavior tests

Lake Tests

Other Problems

- Specific Arrival Time (SAT)

Algorithmic Enhancements

- **Dynamic schooling**:
  Change η based on confidence level of an AUV

- **Variable speed**:
  Vary AUV speed based on signal strength improvement ΔP or confidence level