On the Effects of the Robot Configuration on Evolving Coordinated Motion Behaviors

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Lakeside Labs
SELF-ORGANIZING NETWORKED SYSTEMS

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Research Topics:

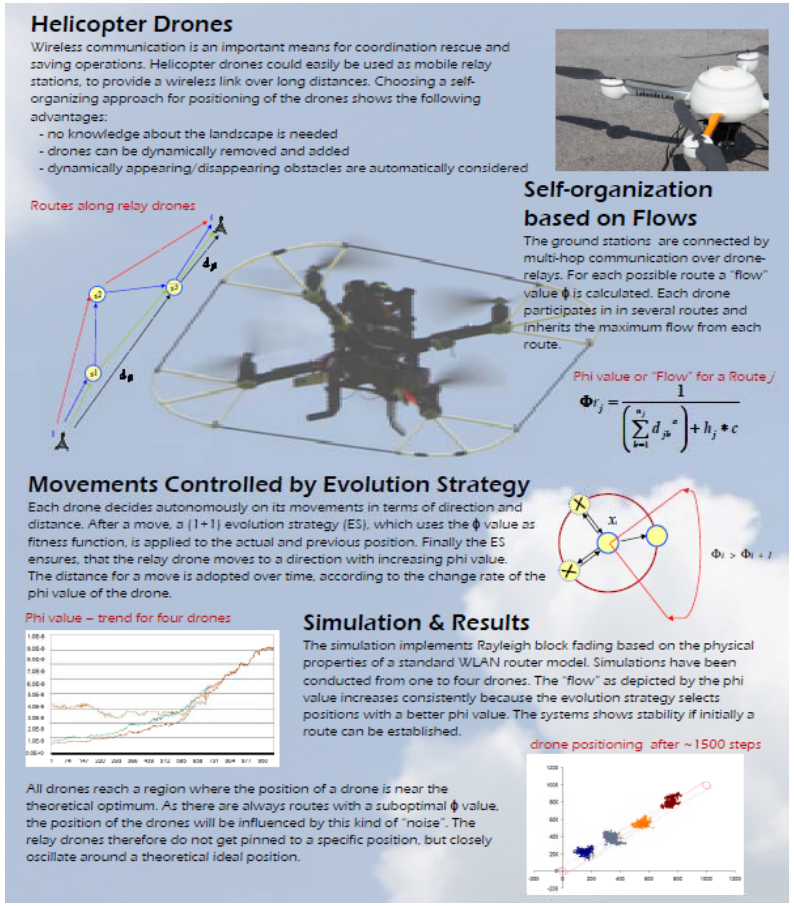
- Smart Grids
  - http://smartmicrogrid.blogspot.co.at/
- Complex and Self-organizing Systems
  - http://www.demesos.blogspot.co.at/
- Networked Embedded Systems
  - https://netwerkt.wordpress.com/

- This talk is supported by projects MESON (KWF) and EVOSOS (FFG).

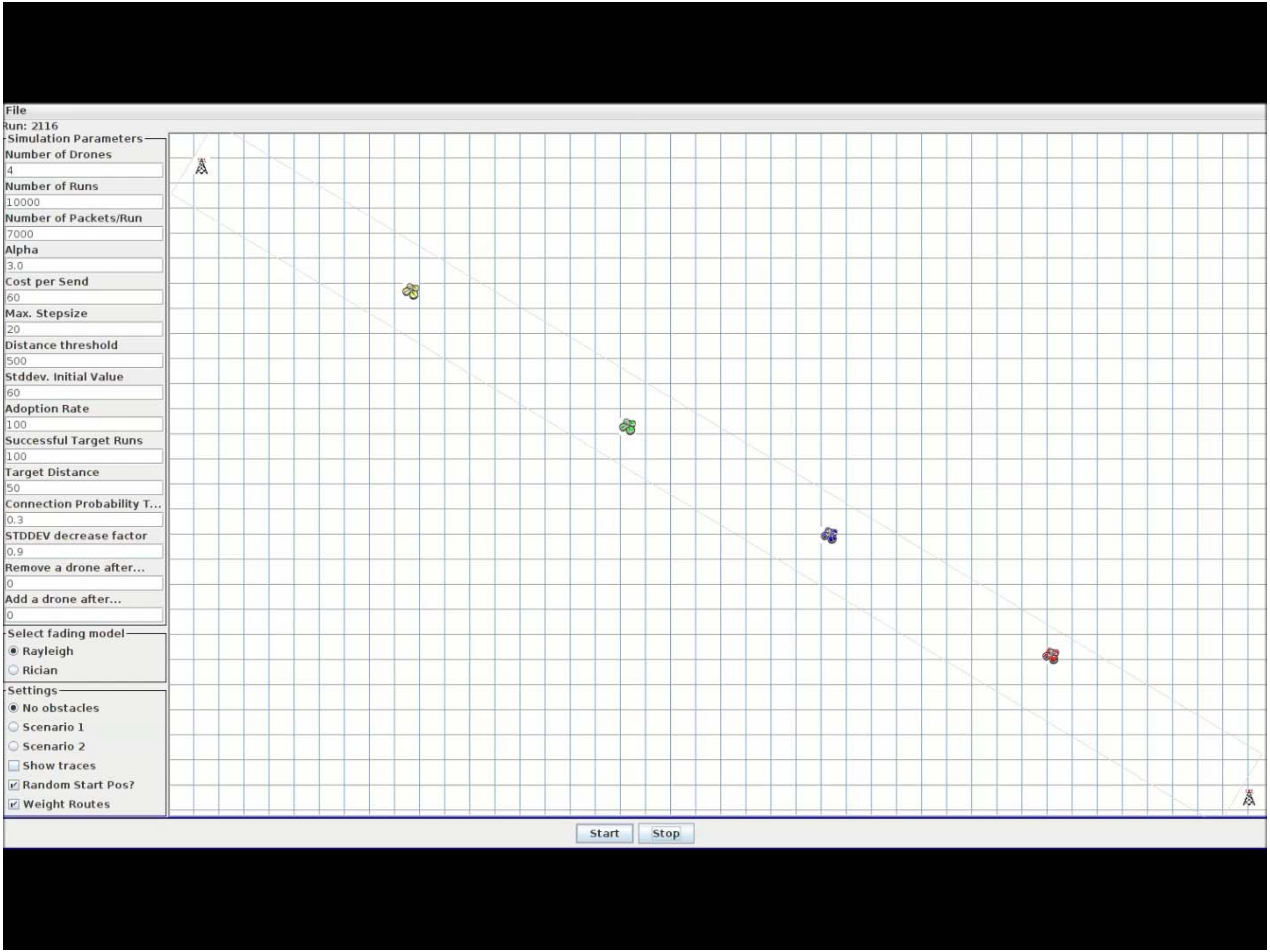
Smart Grid Group

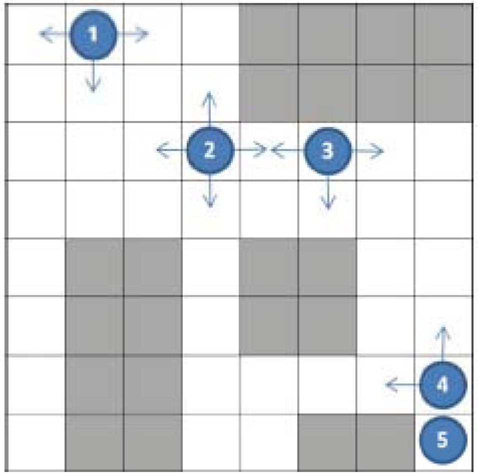
- Goal:
  - place drones as relays for supporting an efficient multi-hop communication
  - e.g. for disaster management operations (no existing infrastructure)
- Algorithm:
  - move randomly to a new spot
  - check if throughput increased
  - move back if not
- Emergent service:
  - optimization of the relays position
- Each robot executes a local evolution strategy (Rechenberg '94)
- Over time they self-organize into a (sub-)optimal positioning
- If a robot is added or removed, they others adjust

H. Lindner, W. Elmenreich. Self-organized Positioning of Mobile Relays, Poster at Fifth International Workshop on Self-Organizing Systems (IWSOS 2011), Karlsruhe, Germany, 2011



Self-organizing flying relays


File
Run: 2116
Simulation Parameters
Number of Drones
4
Number of Runs
10000
Number of Packets/Run
7000
Alpha
3.0
Cost per Send
60
Max. Stepsize
20
Distance threshold
500
Stddev. Initial Value
60
Adoption Rate
100
Successful Target Runs
100
Target Distance
50
Connection Probability T...
0.3
STDDEV decrease factor
0.9
Remove a drone after...
0
Add a drone after...
0
Select fading model
Rayleigh
Rician
Settings
No obstacles
Scenario 1
Scenario 2
Show traces
Random Start Pos?
Weight Routes
Start
Stop



- Goal:
  - flying robots should sweep an unknown area
  - e.g. for disaster management operations
  - no a priori planning possible due to unknown obstacles
- Approach
  - problem modeled in FREVO tool
  - outcome is similar to a random direction algorithm
  - but with different behavior upon detection of other drones

http://www.youtube.com/watch?v=rkXZcbi2KpM&t=3m38s

I. Fehérvári, W. Elmenreich, and E. Yanmaz. Evolving a team of self-organizing uavs to address spatial coverage problems. In R. M. Bichler, S. Blachfellner, and W. Hofkirchner, editors, European Meeting on Cybernetics and Systems Research Book of Abstracts, pages 201–204, Vienna, Austria, April 2012.

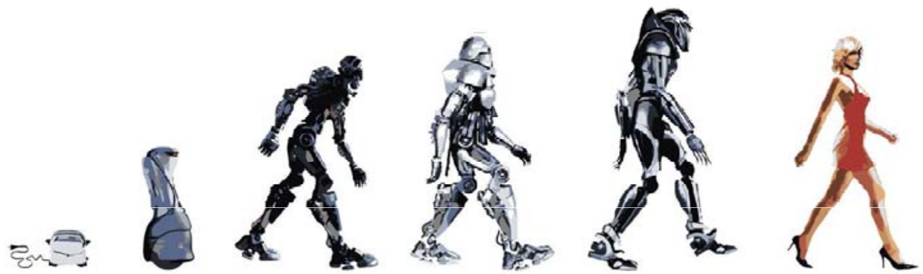
Evolving a distributed search algorithm

- A set of autonomous robots

- Equipped with a number of sensors / actuators

- With an onboard decision unit (brain)

- That is being evolved in order to obtain the desired collective behavior



Evolutionary swarm robotics

- The designer of an ER experiment has to make many choices on
  - experimental setup (ecology)
  - genotype-to-phenotype mapping
  - sensory motor system
  - fitness function
- … that is mostly based only on experience
- Luckily, evolution sometimes counterbalances bad design choices… but it is not guaranteed

Design of an ER experiment

- The designer of an ER experiment has to make many choices on
  - experimental setup (ecology)
  - genotype-to-phenotype mapping
  - sensory motor system
  - fitness function

- Everything that is at the *interface* between the control system of a robot and the robot's environment

Design of an ER experiment

- Usually the sensory-motor system is chosen through intuition or experience relying on

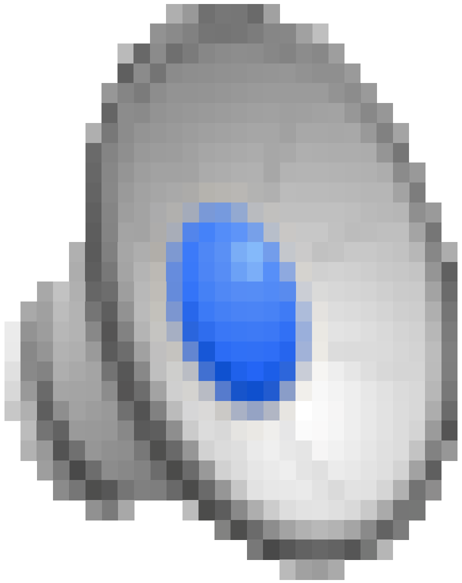
  - smallest set of sensors and actuators
  - minimizing pre- and post-processing of raw data

- This approach is ill-posed for evolving robotic swarms
  - Such systems are very sensitive even to minor changes to their configuration
  - a proper choice can hardly be done without *a priori* information on its effects

The effect of the robot configuration

- Do slightly different configurations effect the quality of the evolved solutions?
- If yes, how?

The effect of the robot configuration



Source: A bird ballet by Neels Castillon [http://vimeo.com/58291553]

Flocking in nature

- Flocking is probably the simplest, most understood self-organizing behavior
- There exists many studies on the simulation of flocking
- It can be obtained by three basic individual rules:

1. collision avoidance
2. flock centering

<ins>Group cohesion</ins>
distance, bearing

3. velocity matching

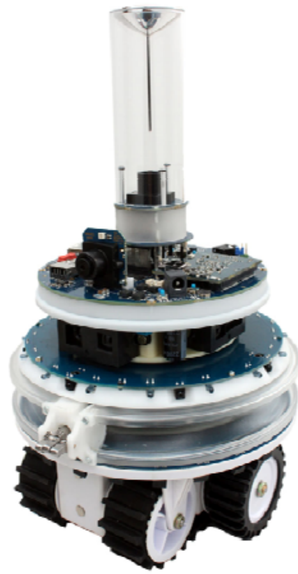
<ins>Group motion</ins>
heading

Why flocking?

- We evolve the neural controllers of 10 marXbot robots using ARGoS

- Robots are equipped with
  - a belt of evenly distributed RGB LEDs that allow signaling with different colors
  - an omnidirectional camera
  - proximity sensors

- We exploit the LEDs to define several robot configurations



Evolving flocking behavior

What is the best configuration for the LEDs?
Do empirical decisions prevail?

LED configuration

0	1	2	3	4	5	6	7	8	9	10	11	
0	0	0	0	0	0	0	0	0	0	0	0	Only proximity sensor
B	B	B	B	B	B	B	B	B	B	B	B	All LEDs are blue
0	0	B	0	0	0	0	0	R	0	0	0	Single LED on both sides
0	0	B	B	0	0	0	0	R	R	0	0	Double LEDs on both sides
0	B	B	B	B	0	0	R	R	R	R	0	Four LEDs on both sides
B	B	B	B	B	B	R	R	R	R	R	R	Full side on
R	0	0	0	0	0	B	0	0	0	0	0	Single LED front-back
R	0	0	0	0	B	B	0	0	0	0	R	Double LEDs front-back
R	R	0	0	B	B	B	B	0	0	R	R	Four LEDs front back
R	R	R	B	B	B	B	B	B	R	R	R	Full front-back

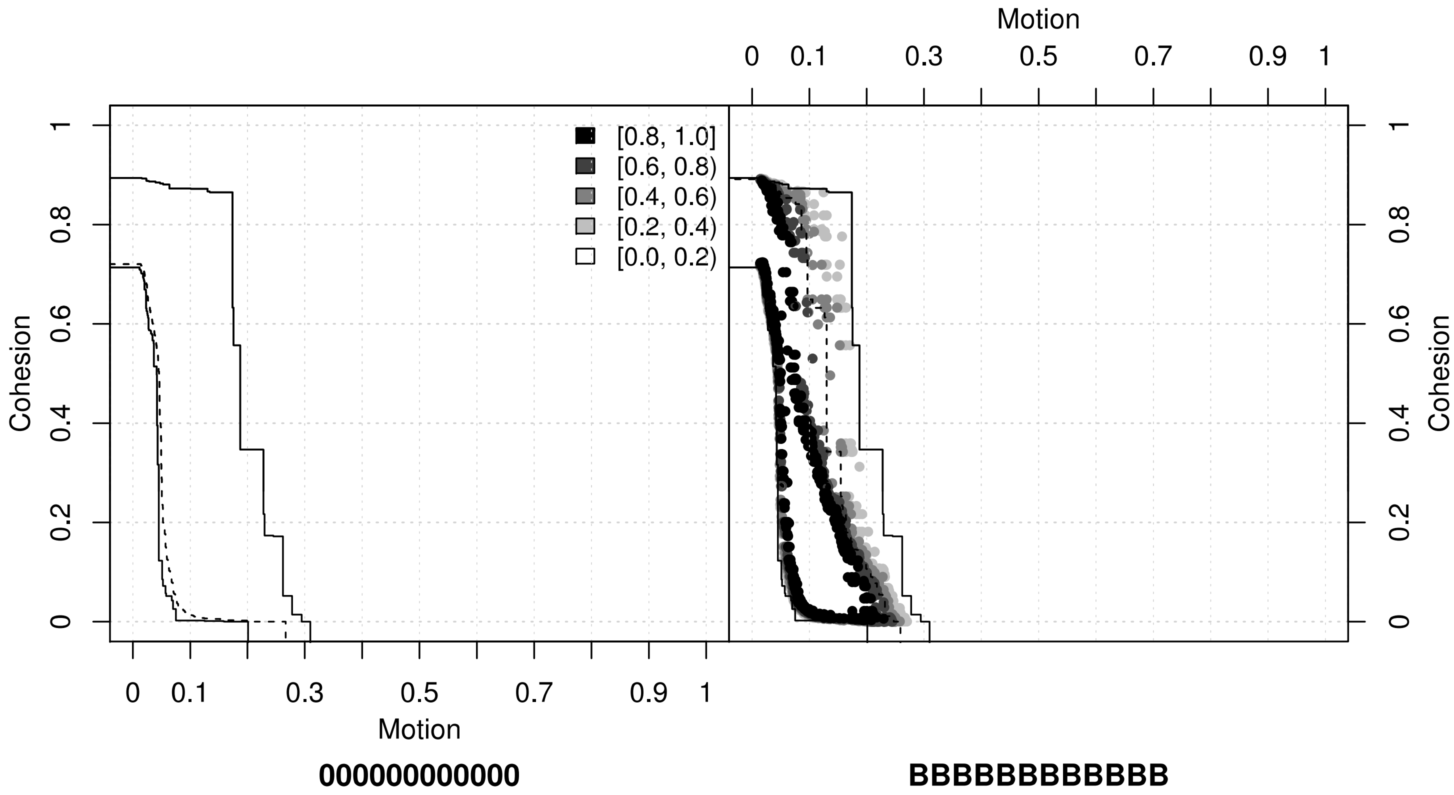
LED setups

- Robot controller is a fully-connected feedforward neural network with 18 inputs and 2 outputs
- We use a simple biobjective evolutionary algorithm with a population size of 100 for 200 generations
- Best 25 is kept for reproduction, only mutation operator
- Robots are rewarded for *cohesion* and *motion*

Evolving flocking behavior

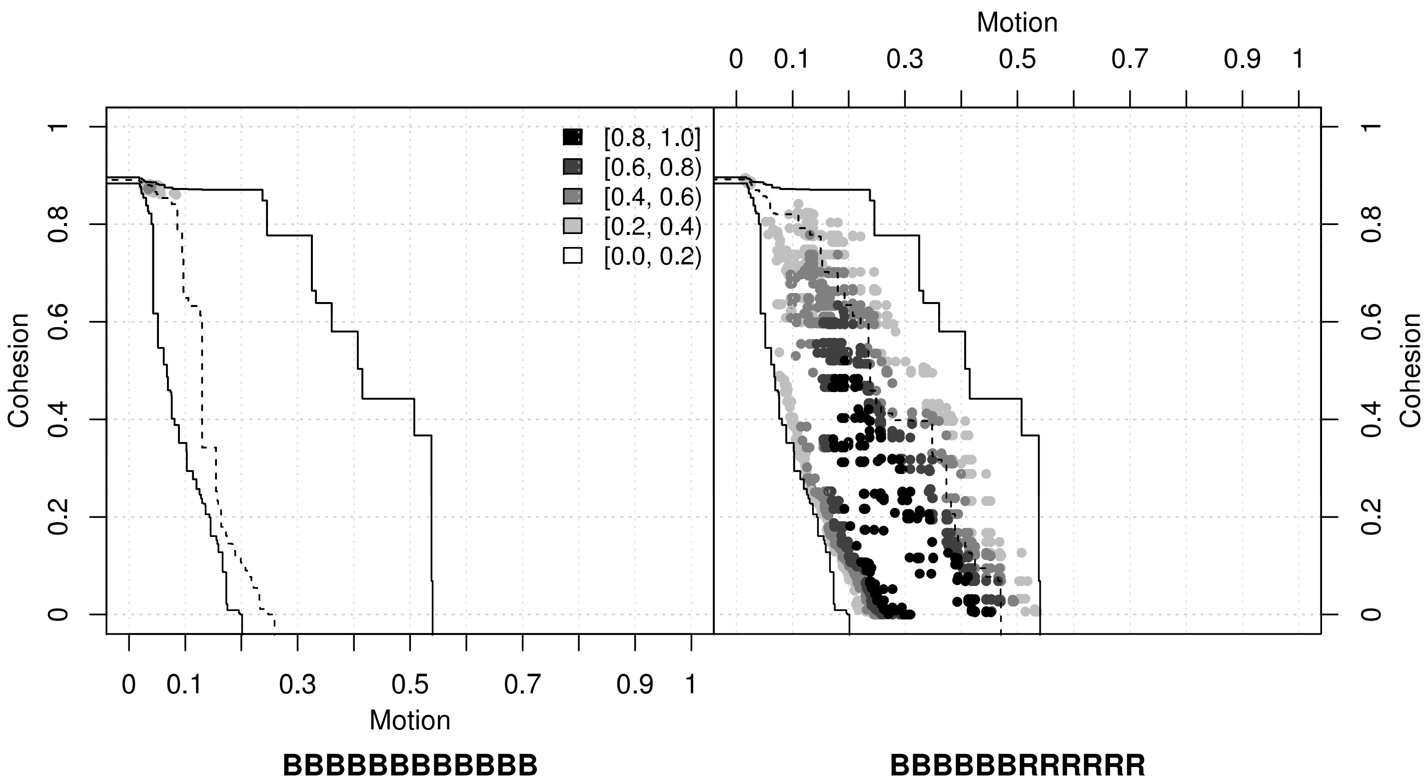
- Pareto-optimality provides a reliable way to compare the results of different runs
- If there is no clear advantage, then direct comparison is probably infeasible
- In this case we use EAF (empirical attainment function) to compare
- It represents the probability that an arbitrary objective vector in the search space is dominated in a single run

Evolving flocking behavior



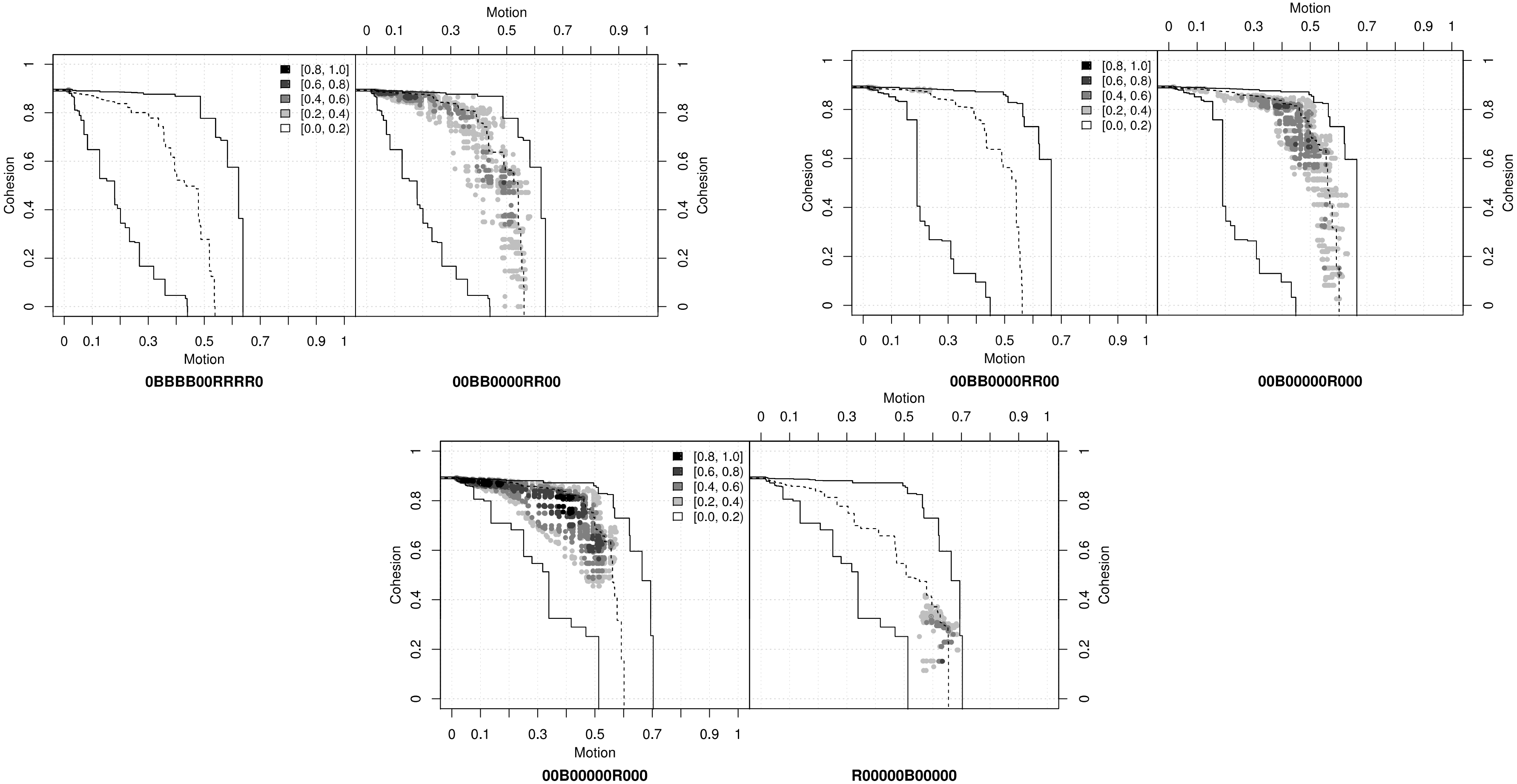
- Both configurations perform poorly
- LEDs only help to detect bots that are farther away

Results: comparison of control configurations



- Heading information clearly helps

Results: comparison of control configurations



- Less LEDs per side perform better
- Sidewise and front-back configurations perform better on different parts of the pareto front

Results: comparison of LED configurations

Evolved behavior

- Different parts of the pareto front might correspond to different group behavior:

  - Aggregation (robots do not move)
  - Disperse (robots spread around)

  - Wavefront (robots move together in a single arc)
  - Train (robots follow each other)
  - Flocking (objective)

- Define metrics to identify behaviors

Behavior analysis

```
if Q3(K) > 1 then
  | return Disperse
end
if Q_3(M) ≤ D_a then
  | return Aggregation
end
if Q_1(C) > D_c then
  | return Flocking
end
if Q_2(Θ) ≤ π/4 then
  | return Train
end
return Wavefront
```

- Regions corresponding to different group behavior can be separated

Behavior analysis

- The selection of the robot configuration can determine the success or the failure of the evolutionary experiment.

- Empirical decisions might result to sub-optimal solutions

- Co-evolution of LED configuration might reveal more information

- However, suitable encoding must be devised to ensure the co-evolvability of configuration and behavior.