Three papers were chosen for study in the field of natural computing with a common theme of systems of communicating agents. The papers are [Gigliotta2014], [Hoverd2014], and [Massaro2014]. These papers are listed in the References section.

# [Gigliotta2014]

## Summary

### Introduction

[Gigliotta2014] used an evolutionary algorithm to develop optimal role differentiation in a group of robots. They say that role differentiation is an issue which needs resolution when a homogeneous group is to perform a collaborative task. Collaborative, being defined as consisting of different activities performed by specialized individuals. Collaborative, as opposed to coordinated, cooperative, or collective behaviors. Coordinated behavior consists of the group of agents organizing their locations or behavior based on that of the other agents. [Particle swarm optimization?] Cooperative behavior means the agents are interacting so to perform a task demanding more than any individual agent’s abilities. Lastly, collective behavior is when groups of agents make choices on the basis of the outcome for the group.

One might propose using an inhomogeneous group of robots if different roles are required. This does not work in cases where the optimal agent operation parameters are not known. In cases where an evolutionary algorithm is used to search for optimal parameters, multiple agent types necessitates altruism; to find the optimal overall behavior, different agent types must evolve in such a way to improve each other’s fitness, not reflected in their own fitness which is driving their evolution. This problem is avoided if homogeneous robots can differentiate their roles. As this work involves robots differentiating between leaders and non-leaders, and fitness being based on the level of distinction between the leader and other robots, it represents something of an impulse-response test on role-differentiation systems.

### Methods

The robots’ were placed in a virtual arena as shown in Figure 1 [Gigliotta2014], and allowed to interact. Leadership was established via infrared signal communication. Robots’ signals ranged from 0 to 1. The robots behavior consisted of how its two motors respond to non-leader, leader, and self infrared communication signals and how its communication output responded to leader and self communication signals. All incoming communication signals had random noise in the   
range -0.05 to 0.05 added to it. This behavior was encoded in a neural network, the free parameters of which were represented by evolvable genes.

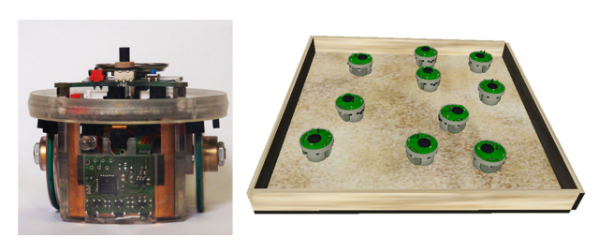


Figure 1 – taken from [Gigliotta2014]: “The experimental set up. Left the e-puck robot. Right the arena with ten simulated robots”

The fitness measure for the evolutionary algorithm is the sum of the differences between the leader, having the largest output signal, and each other robot’s signal, averaged over the number of robots and lifecycles per trial. That is,

(1)

Where C is the total number of cycles for each individual, 40 trials times 1000 cycles per trial for 40000. N is the number of robots in the group, 10. Max is the signal value of the current leader, and O­i is the signal value of robot i.

The initial population consisted of 100 genotypes, each of which was tested for 40 trials each of 1000 lifecycles. The 20 best individuals of each generation are selected for asexual reproduction by making 5 copies of each. Variation is introduced by having 2% of their genes’ bits replaced with random values. They used the best evolved individual resulting from 10 replications of the evolutionary process for subsequent result generation.

### Results

To verify the robustness of their evolutionary method’s solution with respect to scale, they ran 25 trials, each of 3000 lifecycles, for groups of 2, 4, 6, 8, 10, and 12 robots embodying the solution genotype. Average numbers of leaders throughout the trials, and at the ends of trials for the various group sizes were computed. Leaders were defined as robots with outputs higher than 0.5. Groups typically settled on 1 leader eventually, regardless of size. However, as size became too large, this took longer to occur as the arena became crowded. This experiment was also performed with groups of 20, 30, 40, and 50 agents, with standard 150mm communication ranges, and extended 400mm ranges. Despite increasing arena sizes to accommodate these larger groups, performance degraded (average number of leaders increased) with group size. The result of extending the robots’ communication ranges was a mitigation of the group-size related performance

Communicative behavior was investigated by placing two robots facing each other, and running the trial. Each robot’s communication signal value was recorded throughout the lifecycles of this test. The result was that both robots progressively decrease their output until the symmetry breaks at a bifurcation point at 0.5. After this, the output difference becomes amplified and the leader is decided. Without the random noise added to each robot’s perception of the other robots’ outputs, the symmetry is not broken and both robots’ outputs continue to drop.

Non-communicative (motor) behavior was investigated with two tests. In the first, the average speed, and number of robots within communication range were compared between leaders and non-leaders over 100 tests each lasting 3000 cycles with groups of 10 robots. The leaders’ average speeds and connectivities were slightly, but significantly higher than those of non-leaders’. In the second, the average number of leaders throughout and after 10 trials of 3000 cycles each, done on two groups. One group had the usual, best-evolved controlled, and the other had the same with all motor outputs fixed at 0. Being deprived of evolved motor behavior substantially increased the average number of leaders to emerge.

To investigate the importance of interaction topology in this role-differentiation problem, they repeated the evolutionary process with the robots not allowed to move. Robots were initially placed in random locations in the arena subject to the condition that none of them are isolated. The fittest individual typically emerged within 50 generations, with fitnesses around 0.8. Evolution converged more quickly and more consistently than for the standard experiment. Solutions evolved from fixed topology did not perform as well. More leaders were present on average throughout tests, and groups did not converge on a single leader.

# [Hoverd2014]

## Summary

### Introduction

Direct agent-agent communication methods result in deadlock when there is a circular request chain for communication resources among agents. For guaranteed deadlock prevention in a client-server type system, the graph of client-server interactions must be acyclic. This imposes strict constraints on simulations. Such acyclic graphs do not arise in many naturally inspired simulations; one expects many if not all of the agents to be able to interact. Barrier synchronization is described as an unnatural solution to the deadlocking problem. Such solutions might work for certain applications, however barrier synchronization implies a collective coordination. A scripted collective coordination, rather than an emergent one.

To address issues of computational expense and potential deadlock arising from direct agent-agent interaction in complex agent-based systems, [Hoverd2014] proposes the environment orientation approach. Environment orientation is a more natural approach to complex agent-based systems simulation. It reflects reality in that information is passed between agents via the environment. Rather than each agent send messages reminiscent of action-at-a-distance to each other agent requiring that information, each agent passes their external state to the environment. Other agents can perceive other external states subject to environmental modifications or constraints, such as distance or line of sight. Agents repeatedly update their internal state based on their current internal state and the relevant environmental information, followed by their external state and behavior based on their new internal state.

### Methods

To demonstrate that emergent properties observed in conventional direct communication simulations, they simulated Reynold’s boids with the usual rules. The information required for individual cohesion, alignment, and separation behavior is conveyed between agents via the visual environment. Objects of FlockingNeighborhood class were formed and an object of FlockingAgent class associated with one if the FlockingNeighborhood has at least 10 associated FlockingAgents for at least 20 time steps, and if at least 80% of the FlockingAgents of the FlockingNeighborhood were the same for those steps.

They investigate extending simulations to ones containing multiple environments. In this context, multiple environments means agents have access to multiple sources of environmental information. To do this, they simulated Reynold’s boids again, with a “visual” information in the ProximityEnvironment, and “auditory” information in the SpeciesEnvironment. This experiment used multiple species of boids. In addition to the usual rules for flocking behavior, members of a common species are attracted to each other by auditory song information.

### Results

# [Massaro2014]

## Summary

### Introduction

### Methods

### Results

# References

[Gigliotta2014] O. Gigliotta, M. Mirolli, and S. Nolfi, “Communication based dynamic role allocation in a group of homogeneous robots”, Natural Computing 2014; 13:391-402.

[Hoverd2014] T. Hoverd, and S. Stepney, “Environment orientation: a structured simulation approach for agent-based complex systems”, Natural Computing 2014; 14:83-97.

[Massaro2014] E. Massaro, F. Bagnoli, A. Guazzini, and H. Olsson, “A cognitive-inspired algorithm for growing networks”, Natural Computing 2014; 13:379-390.