Simulation of Cooperative Behavioral Trends by Local Interaction Rules

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Abstract

We explore the creation of cooperative behavioral trends in a group of agents, within the framework of an artificial physics simulation. Local interaction rules, that have "selfish" interpretations, were specifically designed to engender cooperative behavior. Although we conclude that it is necessary to further refine our specific set of interaction rules, our results support the view that it is indeed possible to simulate sophisticated cooperative behavior via a set of selfish local interactions.

1 Introduction

Imagine a blue, open sea, where a pack of orcas ("killer whales") senses a school of fish at a distance. The orcas move closer and closer to the school, encircling it with a pincer movement (a highly cooperative maneuver), and continue circling until the school compresses into a tight mass of fish. All this maneuvering requires a great deal of communication and teamwork among the orcas. In this paper, we explore whether this kind of highly cooperative behavior can be simulated by local interactions, that have selfish interpretations.

There have been many previous examinations of similar cooperative behavior in the field of multiagent systems (e.g., [3, 4, 8, 6]), including some older predator-prey experiments (using an evolutionary model [5], designed rules [7], and other approaches [2]), and even including predator-prey experiments with self-motivated agents (e.g., [9]). The current work differs in the sophistication of the coordination and difficulty of the hunting task, as well as in the model used to engender ostensibly cooperative behavior.

Local interactions are well-simulated by physical systems of charged particles [10, 11]; for example, [12] discusses a simulated world with artificial rules of physics in which a complex regular structure was formed by particles, using only particle-centered local rules of interaction. In fact, this appears to be very similar to what happens within a school of fish, and inspired the use of a similar technique in our simulation.

We extended the physicomimetic simulation of [12], and represented fish and orcas by different types of artificial particles. Hunting requires coordination among the orcas; each individual should act in correlation with the others, and react to the actions of others. Our simulation of this activity was based only on physical, local rules of interaction.

There were three rules governing action: greed, envy, and cowardice. These are seemingly in direct opposition to cooperative teamwork. Our results show, however, that they can successfully simulate sophisticated cooperative behavior, in particular the kind exhibited in the complex hunting pattern of orcas. While the interaction rules could be interpreted in other, non-selfish ways, it is still interesting that self-interested behavior — local to individual agents — *could* give rise to the appearance of such complex, meaningful coordination. Although our experiments did not achieve the complete efficiency or elegance of orca hunting, they successfully demonstrated that externally observed cooperative behavior might have selfish origins.

2 Artificial Physics

In [12] by Spears et al., a simulation tool is described that uses Artificial Physics to create an environment of agents responding to local interaction rules. Spears' simulation uses physical forces to drive a set of agents to a desired configuration or state. The parameters of the simulation (physical forces) are tuned so that the desired configuration will be achieved when the system gets to a stable state that minimizes the potential energy of the overall system.

Spears' system works according to basic Newtonian formulas of motion, and simulates particles subject to different fields that affect them. This is done on a discrete virtual time scale; after each time lapse of Δt, the locations of the particles in the system are recalculated. Each particle is modeled with mass, position, velocity and acceleration. Positional change is calculated as $\Delta x = v\Delta t$, where v denotes the last recorded speed of the particle. In turn, the new velocity is formed by the formula $v = \frac{F}{m}\Delta t$, where m is the mass of the particle and F is the force that affects it.

The force that affects any particle is computed based on the relative position of the particle within fields created by other particles. The basic formula used is $F = \frac{G}{r^2}$, where G is a parameter of the field, and r is the distance between the affected particle and the particle that produced the affecting field. However, the simulation needs the force to be reasonable, and thus limits it to some maximal value, F_{max}. It also considers the field to reverse its effect at some range R — from an attractive force, it becomes a repulsive one. G, R, and F_{max} form the parameter set of the pseudo-physical fields in Spears' simulation.

To make the particle motion reasonable, Spears also introduces viscosity type friction, sensor limitation (the maximal distance at which a force would have *any* effect), and V_{max}, a limit on a particle's speed.

One of Spears' results was the ability to place any number of agents in random locations on the screen, and (in reaction to local interactions) have the agents eventually be set in a symmetric network of triangles.

To create this effect, that simulation created a well-tuned field among the agents, making them react to one another in the appropriate fashion. As mentioned above, the model of inter-agent force established an attraction among the agents if they were far from one another, and became repulsive when they get closer. [13] formally proved that the system stabilized at the state with least potential energy, and this state is a regular mesh.

The resulting "net of triangles" was reminiscent of a school of fish, and inspired our use of an artificial physics approach as a theoretical basis for the simulation of fish and orca pack behavior. We have also made use of theoretical and numerical conclusions made in [13].

3 Model of the World of Orcas and Fish

The National Geographic Society [1] describes the following peculiar behavior of orca whales: "*Orcas in the northern part of the Atlantic have developed a highly organized predation technique that has rarely been seen by human eyes. A large school of fish are 'corralled' into a ball. Perimeters of the ball are guarded by the orca pack members…Soon the massive ball is clustered so tightly, the fish's escape response breaks down. Oxygen levels in the ball drop and the fish become confused. At that point orcas use their powerful tails to knock out fish at the edges of the 'fish-ball', and eat them one by one.*"

During this impressive act, orcas exhibit very high cooperation skills. They communicate to improve their synchronization and positioning, take turns at feeding and guarding the ball, and the "corralling" itself includes such maneuvers as "pincers".

These orca behaviors, unlike maintenance of the structure of a fish school, do not seem to stem from local interactions, but rather from some high-level cooperative strategy. This is confirmed by the fact that older members of the pack seem to repeatedly demonstrate to younger orcas what to do, creating the impression that a complex skill is being taught and learned.

In this research however, we would like to consider orcas' behavior from a different angle, and investigate whether their complex hunting strategy can be created or simulated by simple selfish local interactions among orcas. It may be the case that this was the original reason that the joint behavior appeared, and that it was only later transformed into a regular ("conscious") practice.

For example, the very fact that orcas keep at a regular distance from one another during their school encirclement could appear as a result of mutual dislike among orcas, or even fear and **cowardice**. But assuming the dislike, the only reason that they do not split and move away from each other is that they are hunting a school of fish — in other words, their **greed** keeps them together near the fish. The constant circling could also be a result of **envy**; once an orca gets close to a fish, another one begins to envy it and moves in closer to the fish in question. However, since they fear one another and the fish itself is not keen to stay close to orcas, a circling motion results.

The question then becomes whether three selfish local interactions such as greed, envy, and cowardice can result in a behavior similar to the cooperative hunting moves of orcas. Note that in a sense it places orcas into a model similar to that of fish, which seem to form their schools based on local interaction rules.

As an example, a school of fish could be modeled as being formed by two kinds of fear: fear of separation, and fear of conflict. Fear of separation stems from the “safety in numbers” survival strategy — a fish would not want to be too far from other fish around it (a local property). Fear of conflict stems from the fact that fish fear one another because they compete over basic resources, such as food and oxygen.

Composition of these basic qualities of fish and orcas are extremely similar to interactions among physical particles within a field. This abetted the creation of a simulation using artificial physics tools, including such features as the screening of internal members of the fish school by the outer boundary.

4 Simulation

4.1 Technical description

The basic ideas of the tool we have created are similar to the tool in [12]. We used Newtonian formulas to calculate velocities and particle position variations; the simulation enabled us to define various kinds of particles. Each particle has two constant properties: a mass, and a volume. The mass is used to calculate the acceleration and velocity of particles: $v = \frac{F}{m}\Delta t$ (just as in [12]). However, our simulation extends the notion of friction, and simulates its effects independently for every particle based on its volume: $F_{fric} = -\rho\mu v$, where ρ is the volume of the particle, μ is the constant friction coefficient, and v is the particle’s speed.

We have also generalized the notion of fields — we do not use fields that flip their effect (from repulsion to attraction) midway. The field has constant effect, either attractive or repulsive. However, any particle can emit or be affected by any customized set of fields. The fields are now parameterized by strength G, sign (attraction or repulsion), maximal feasible force created by the field F_{max}, and the fading-away distance after which the force is considered to be ineffective R_{max}.

Our simulation also introduced the notion of interference. These forces do not influence particles directly, instead modifying the effects of other fields within the system. Such fields have an additional coefficient ξ (IC in our data tables), that dictates the degree of interference created by the field. The basic interference diagram can be seen in Figure 1; the interference effect is computed using the formula $F_{inter} = F\left(1 + \xi\cos(\alpha)\right)^{\nu}$, where F_{inter} is the force after the interference application, F is the original force created by the field between the affecting and affected particles, ξ is the interference coefficient, ν is the sign of the interference, and α is the angle between the lines of sight from the effected particle to the interfering one and the effecting one.

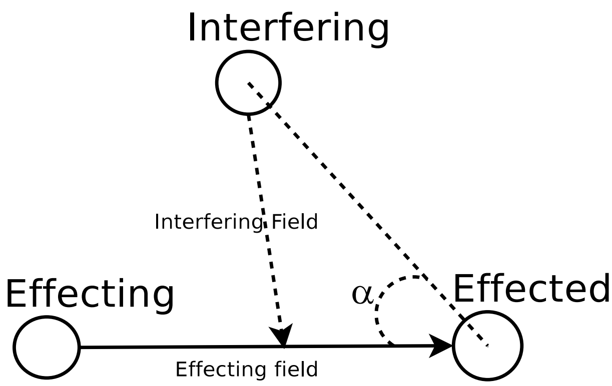

Figure 1: Field Interference Diagram

As in [12], we also limit the maximal particle speed, thus introducing the V_{max} parameter; however, in our simulation particles can have different speed limitations. Other calculations are performed just as in [12], based on the laws of Newtonian motion.

4.2 Implementing Desired Behavior in the Simulation

As was mentioned in Section 3, the cooperative behaviors in which we are interested are to be engendered by local interaction rules.

The first task is to translate the fish school formation rules into the language of artificial physics. It is obvious that fear of separation can be modeled by an attractive field, and fear of conflict can be modeled by a repulsive field. In fact, this is exactly what happens in [13] and in our simulation, which results in a school of fish that keeps a regular triangular mesh-like formation. We introduce two fields: FishPullFish and FishPushFish, with their respective parameters computed as dictated by [13].

However, a school is not an ordinary triangular mesh. We introduce an interference field, FishMaskFish, that masks the interior of the fish school. The field affected by FishMaskFish is the first field that affects orca pack behavior: FishPullOrca. This field comes to model *greed* as was discussed in Section 3. We introduced OrcaPushOrca (to model *cowardice*), and the OrcaEnvyOrca interference field (to model *envy*). Finally, the obvious effect of fish moving away from orcas is modeled by a repulsive field, OrcaPushFish.

While FishMaskFish is a negative interference field that weakens the effects of FishPullOrca, the OrcaEnvyOrca is a positive interference field that increases the effects of the FishPullOrca field.

Note that all these fields and effects could not have been implemented in the original artificial physics work [12]. In addition, although the initial values for the FishPullFish and FishPushFish fields (responsible for fish school creation and maintenance) were calculated based on [13], the rest of the fields were uncharted territory, and were fitted using multiple experimentation sets.

5 Finding Parameter Values

Our first goal was to build a stable school of fish, similar to Spears' net of particles described in Section 2, i.e., finding the right parameter values for FishPushFish and FishPullFish. Initially, we considered the parameters of Spears, and tried to use them in our simulation. Spears used one force between the particles with the following values: $F_{max} = 1, \ \ G = 0.12$. In our simulation, this had to be replaced by two counteracting forces, as seen in Table 1.

Force vs. Parameter	F_{max}	R_{max}	**G**
Attractive force	1	0.5	0.12
Repulsive force	3	0.3	0.24

Table 1: Values for forces of fish among themselves

With these values, we got results similar to those of Spears: when the particles are far from each other (more than 0.3), they only pull each other closer together, since at that range the repulsive force FishPushFish is not activated. When they pass the distance of $r = 0.3$, both forces are activated, and as the repulsive force coefficient G is double the pulling force coefficient, we get a repulsion of the same value that Spears' field version had. However, the division of forces in our simulation allows for greater flexibility; for instance, the F_{max} value in the repulsive force can vary independently, and the more it is increased, the more regular and uniform the school becomes.

After establishing a stable school of fish, we turned to the main goal of finding the correct values of the set of fields described in Section 4.2, the fields that involve orcas. This was done based on the following initial assumptions:

- Orcas should sense the fish pulling force from very far, but its impact should be rather limited.
- When any orca is getting close to a fish, other orcas begin to envy it; that is, the pulling field of that fish is enhanced.
- For the school to have a group sensory response to orcas, the effective radius of the orca fish-repulsive field should be larger than the basic distance between fish within the school. However, this radius has to remain small enough to simulate limited fish sensory range.

With these assumptions, and after performing a large number of experiments with different field parameter settings, we arrived at the basic value set that resulted in a success rate of approximately 80% — in 80% of the trials, the orcas encircled the fish and compressed the school.

The basic values we used as field parameters are described in Table 2. Other parameters were set as follows: the friction coefficient was set to 0.5, the mass and volume of the orcas was set to 4, and their V_{max} was 1.5.

Field name	F_{max}	R_{max}	**G**	**IC**
Orca Push Orca	1.5	2.2	0.3	
Fish Pull Orca	0.4	6	1	
Orca Push Fish	0.8	0.8	0.19	
Fish Mask Fish		0.8		2
Orca Envy Orca		0.8		2

Table 2: Basic values used as field parameters

It is important to note the initial geometric configuration of our experiments. Orcas and fish were randomly placed in two non-intersecting rectangular areas, and the group of fish and orcas were initially separated by a distance significant with respect to the maximal sensory range of orcas.

There were two main problems we encountered with respect to the desired orca behavior:

- Occasionally, the school of fish was divided into two parts. In these cases, sometimes the orcas encircled the larger part, but sometimes they did not stick to one goal, and did not succeed in 'catching' either of the fish schools.
- Even when the orcas succeeded in encircling the fish, in some of the tests orcas passed through the school, while the fish stayed in a school configuration.[1]

To try and solve these problems, we performed further experiments, modifying various field parameter values. Our general strategy was to start by experimenting on one parameter each time, making a small change in its value. If the change improved the performance, we tried a few more values for the same parameter. We then created more complex experiment sets, combining the changes that showed improvement, taking for each parameter the value that gave the most successful results.

A summary of experiment sets and their respective results can be seen in Table 3. For each experiment the table shows the number of trials; success (percentage of trials in which the orcas encircled the fish), division (percentage of trials in which the orcas divided the school of fish), cut through (percentage of trials in which the orcas passed through the school of fish and the fish stayed in a school).[2] Since our visualization tool had a limited perception range, in some trials the fish school and orca formation moved out of the observable area; this is the reason for two numbers in the number of trials column in Table 3, and also the reason for the range of success rate values. The minimum value of the range was obtained with the unobserved trials treated as complete failures, while the maximum value of the range was obtained with the unobserved trials discarded from the experiment set.

5.1 Solving the Division Problem

The first experiment set was created in order to solve the school division problem. In this set, we reduced the influence of the FishMaskFish interference field. This field masks the interior of the fish school, and we initially assumed that this made orcas rather insensitive to the school as a whole, which in turn caused the division problem. Therefore, reducing the impact of the masking interference field might remedy the problem. However, this experiment set did not yield any improvement: the number of divisions did not decrease, and furthermore, the number of orcas cutting through the school got very high (see Table 3).

Trying another approach in the next experiment set, we increased the attraction between the fish (FishPullFish field), in order to improve the school integrity properties. This change led to a great improvement: when the orcas came close to the fish, the fish school stuck together and roughly maintained its form, moving as an integral unit — much like this happens in nature. The orcas could not penetrate into the school of fish, and the school hardly ever divided. Note that this makes the fish school parameterization and behavior differ from the original Spears' value setting and particle network. In fact, since in our simulation we had the ability to separate between the forces, we could make changes only in the attractive force and leave the repulsive force as is, gaining further flexibility in forming the school's behavior. With the change we made,

[1] Although this type of behavior may be typical for dogs herding sheep, or wolves hunting, we were simulating orca behavior, and considered this something of a problem. This issue is also discussed below.

[2] Experiments of this last kind that *ended* with the desired goal are treated as a success, and will be counted in the 'success percentage'.

Set #	Experiment	Trials # (visible)	Success %	Division %	Cut through %
Base	Basic Values	40(37)	77.5-83.78	16.22	45.96
1	Reduce influence of Fish Mask Fish	40(40)	78	22.5	52.5
2a	Increase attraction between fish (0.12→0.145)	40(37)	90-97.3	2.7	43.24
2b	Increase attraction between fish (0.12→0.135)	20(16)	75-93.75	6.25	12.5
3	Reduce influence of Orca Envy Orca	40(36)	72.5-80.6	19.44	11.11
4a	Increase Orca Volume (4→5)	40(30)	65-86.7	13.33	10
4b	Increase Orca Volume (4→4.5)	40(29)	55-75.86	24.13	13.79
5	Combination: change fish attraction (0.12→0.145), increase orcas volume (4→5)	40(35)	87.5-100	0	5.71
6a	Combination: change fish attraction (0.12→0.145), orcas volume (4→5), and orcas V_{max} (1.5→1.2)	40(25)	60-96	4	4
6b	Combination: change fish attraction (0.12→0.145), Orca volume (4→5), and Orca V_{max} (1.5→1.35)	20(17)	85-100	0	5.88
6c	Combination: change fish attraction (0.12→0.145), Orca volume (4→5), and Orca V_{max} (1.5→1.4)	20(17)	85-100	0	11.76

Table 3: Summary of Experiment Variations

the fish school remained stable, but performed better with respect to the outer influences and restrictions of our simulation targets.

As seen in Table 3, this experiment had a very high percentage of success, but in many of the trials the orcas succeeded in encircling the fish while still cutting through the school — as seen in the table, the percentage of 'cutting through' is high. So the first problem is solved in most cases by the experiment sets 2a and 2b, where there is hardly any division, but the second problem of 'cutting through' persisted, and became the center of attention in the following experiment sets.

5.2 Solving the Cut-Through Problem

As described in Section 3, during their hunting, orcas encircle the school of fish, but at no stage do orcas cut through the fish school. One question we considered was whether this phenomena is actually a problem — as long as the the same final result is reached. After all, this phenomenon can be observed in other real-world examples, such as dogs herding sheep, or wolves hunting. In these cases, dogs (or wolves) use the exact same technique; one pack member passes through the herd to the other side, while the rest of the pack keeps the herd from disintegrating. Some shepherd dog breeds actually run on the backs of the sheep to complete the encircling. However, as the original goal was to simulate a specific activity in nature and be faithful to the processes at work, we considered this a problem for orca hunting patterns, and experimented with ways to reduce 'cutting through' behavior.

Observing the trials, it seemed that cutting through the school of fish resulted from situations in which orcas accumulated too much acceleration and got to high velocities. We tested two different approaches to improve performance. In experiment set 3 (see Table 3), we reduced the influence of the OrcaEnvyOrca interference field, as envy was one of the reasons for the orcas' high acceleration. This experiment value setting did indeed reduce the percentage of trials in which orcas cut through the school, but unfortunately the success ratio also dropped relative to the basic field parameter settings. On the other hand, the following two experiment sets (4a and 4b), in which we increased the volume of an orca, reduced the percentage of cutting through even more than in experiment set 3, and also had a higher success ratio compared to the basic set (see Table 3). Since orca velocities directly depend on their volume, increasing volume had the desired effect.

Having reduced both of the initial problems, we attempted to merge the most successful parameter settings among the observed experiment sets. We designed more experiment sets in which we increased fish attraction together with increasing orca volume. This experiment set (set 5 in Table 3) had a very high percentage of success, and quite a low percentage of cutting through.

Encouraged by the success of increasing orca volume, we then decided to test whether a direct speed limitation could have similar (or better) effects and reduce the cutting through percentage even further. To this end we formed a few experiment sets (6a-6c) with parameters taken from the former combined experiment set 5, and augmented it with different values for V_{max}. These experiments showed that direct reduction of V_{max} can indeed improve the percentage of cutting through, but there is a trade-off with the percentage of success. That is, reducing V_{max} too much also resulted in the reduction of the success ratio.

Another effect that could be seen when both increasing the orca volume and decreasing their V_{max} is that the encirclement task takes the orca pack much more time. The orcas move slower and have more difficulty in reaching their goal, in comparison to the experiment sets where they could just cut through the fish school, get to the other side of the school, and complete the encirclement with ease.

All the above experiment sets were done with and without noise added to the system. The results did not show significant differences with noise added, and are not shown in Table 3.

5.3 School Shrinking as the Effect of Orca Activity

As described in Section 1, after successfully encircling fish, orcas in nature shrink the school to a tighter fish formation. Viewing the simulation runs in the above experiments, it looked like the schools of fish indeed got smaller and crowded together after being encircled by orcas. We decided to verify this fact numerically, and measured the school volume in two ways.

First, we measured the maximum distance between the fish within the school at each time step in a few of the above experiment sets. We also measured the distance (in the absence of orcas) of a school of fish, to have a base value for comparison. As seen in Figure 2, in the experiments with orcas around the fish, the maximum distance between the fish stabilizes at a much lower value than when the school of fish stabilizes without outside interference (seen in the graph by the line of ‘only fishes’ and the line of ‘only fishes fitting fish attraction’, which is the school of fish with our change to the attractive force). The graphs were measured only on successful results, as measuring maximal distance among fish in trials with a divided school would not yield a meaningful numerical value.

The second way of measuring fish school volume was to measure the average distance between fish within the school. For this average distance, we saw results similar to those using the maximal distance measure (see Figure 3).

5.4 Geometry of the Initial Position

In addition to the experiment sets of Table 3, we also experimented with different geometries of the initial fish and orca positions, leaving the field parameter settings clipped to the basic values of Table 2. We tried, in these experiments, to create two separated subgroups of orcas instead of one group. In the first geometric experiment set, the orca subgroups were placed roughly on the same side of the fish school, one beside the other, but separated. This initial situation eased the mission for the orcas, as they had the ‘pincer’ maneuver half completed. Another geometric experiment set began with two groups of orcas on opposite sides of the school. This had a potential hidden danger that the fish school would break in two, snapped by the two orca groups. In fact, this did not happen; the job was even easier for the orcas, and almost all trials succeeded.

6 Summary and Conclusions

Our initial goal was to recreate in a simulation a specific cooperative behavior that occurs in nature: the orca hunting pattern. The simulation was based on local rules of interaction among the participating agents; the rules have “selfish” interpretations. As seen in the experiments, orca behavior could be reproduced, although we did not reach 100% success.

Observing the simulation (Figure 4), one does get a sense of complex cooperation among the orcas. For example, when one orca gets close to the fish and initializes the hunt, other orcas hurry to come and ‘help’ — this despite the fact that within the simulation this behavior is motivated by ‘envy’. While of course the

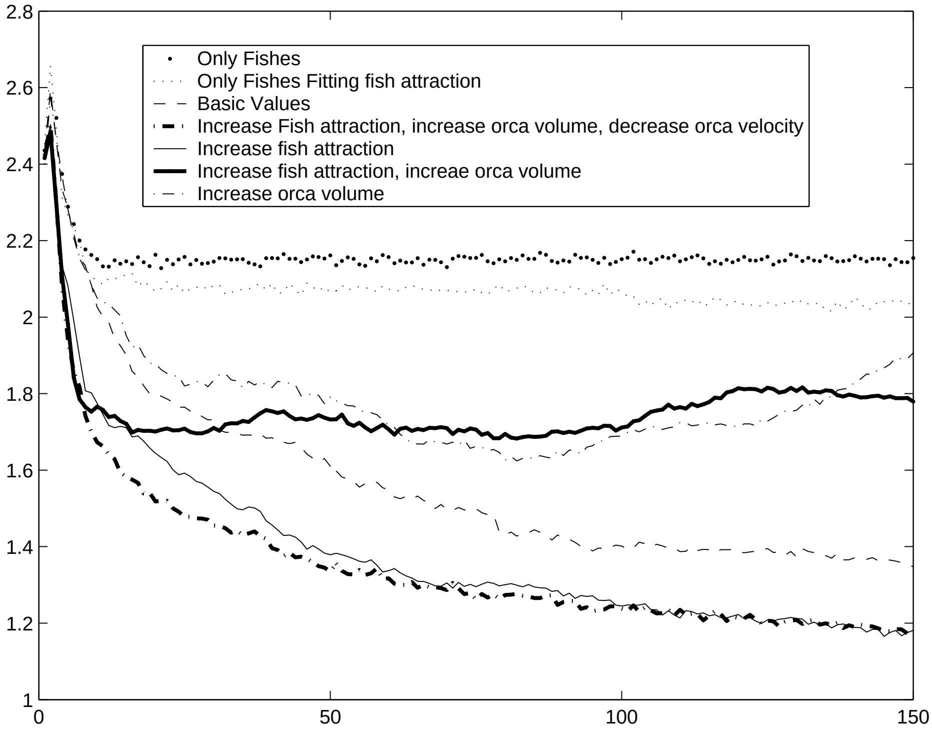

Figure 2: The maximum distance between fish in various experiments

same local interaction rule could also be interpreted in, e.g., an altruistic way, it is still interesting that self-interested behavior — local to individual agents — *could* give rise to the appearance of such sophisticated overall coordination among them.

After finding the basic values for our simulation parameters, most of the trials succeeded in various experiments, i.e., simulated orcas successfully encircling a school of fish. The problems we still had were seen only in a small fragment of the trials, and in nature, activities like the one we considered also do not always succeed. Modifications of simulation parameters improved overall performance.

6.1 Future Work

There is still room for improvement. We believe that further experimentation with different parameter values would lead to even better results, as there are still many more possible experiment variations that have potential benefit. For example, one might make changes to the field FishPullOrca (we tried changing both its interfering forces OrcaEnvyOrca and FishMaskFish, but not the field itself), combined with a modified coefficient of friction (we had a fixed coefficient throughout the experiments).

It is still not clear whether the failures we saw come only from incorrect parameter values, or whether they stem from a more basic issue, a problem in the definition of the physical interactions in the simulation, or even the fact that cooperative behavior of the kind we considered cannot be completely simulated by local interactions of this type.

There are several other directions in which to expand the work. One promising possibility is to use automated processes to fine-tune the simulation parameters. Instead of manual experimentation, we could, for example, use genetic algorithms or other mathematical tools for complex function minimization, which in turn can be guided by a formal physical analysis of the proposed artificial fields (as in [13]).

In addition, there are ways to improve and change the simulation tool itself. Our tool is designed only for 2 dimensions, but it could be expanded to work also with R^3, R^4, R^n. The forces in the simulation are calculated by a simple polynomial formula — a force is inversely proportional to the distance. But other formulas may be used, for example, an exponential decay characteristic of diffusion.

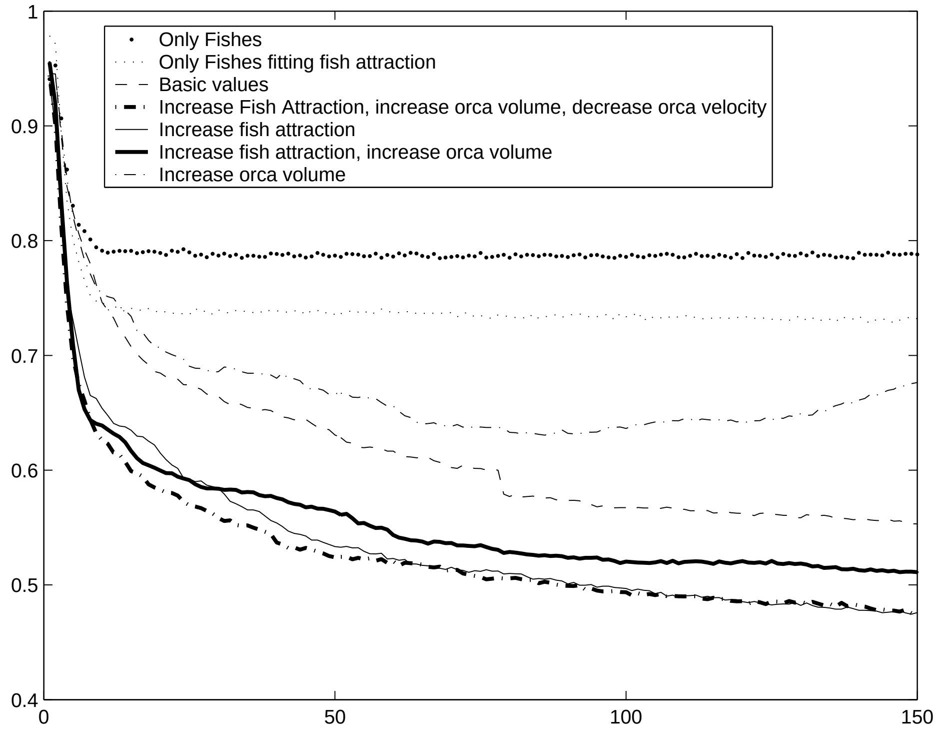

Figure 3: The average distance between fish in various experiments

7 Acknowledgment

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References

[1] National geographic. Web — www.nationalgeographic.com.

[2] Christopher Grinton. A testbed for investigating agent effectiveness in a multi-agent pursuit game. Technical report, Dept. of Computer Science, The University of Melbourne, 1997. BSc Honours Thesis.

[3] Roderich Gross and Marco Dorigo. Evolving a cooperative transport behavior for two simple robots. In *Artificial Evolution: 6th International Conference, Evolution Artificielle, EA 2003*, volume 2936 of *Lecture Notes in Computer Science*, pages 305–316. Springer-Verlag, 2003.

[4] Roderich Gross and Marco Dorigo. Cooperative transport of objects of different shapes and sizes. In *Ant Colony, Optimization and Swarm Intelligence: 4th International Workshop, ANTS 2004*, volume 3172 of *Lecture Notes in Computer Science*, pages 106–117. Springer-Verlag, 2004.

[5] Thomas Haynes and Sandip Sen. Evolving behavioral strategies in predators and prey. In *Proceedings of the Workshop on Adaption and Learning in Multi-Agent Systems (at IJCAI-95)*, volume 1042 of *Lecture Notes In Computer Science*, pages 113–126. Springer-Verlag, 1995.

[6] Auke Jan Ijspeert, Alcherio Martinoli, Aude Billard, and Luca Maria Gambardella. Collaboration through the exploitation of local interactions in autonomous collective robotics: the stick pulling experiment. *Autonomous Robots*, 11:149–171, 2001.

[7] R. Korf. A simple solution to pursuit games. In *Proceedings of the 2nd International Workshop on Distributed Artificial Intelligence*, 1992.

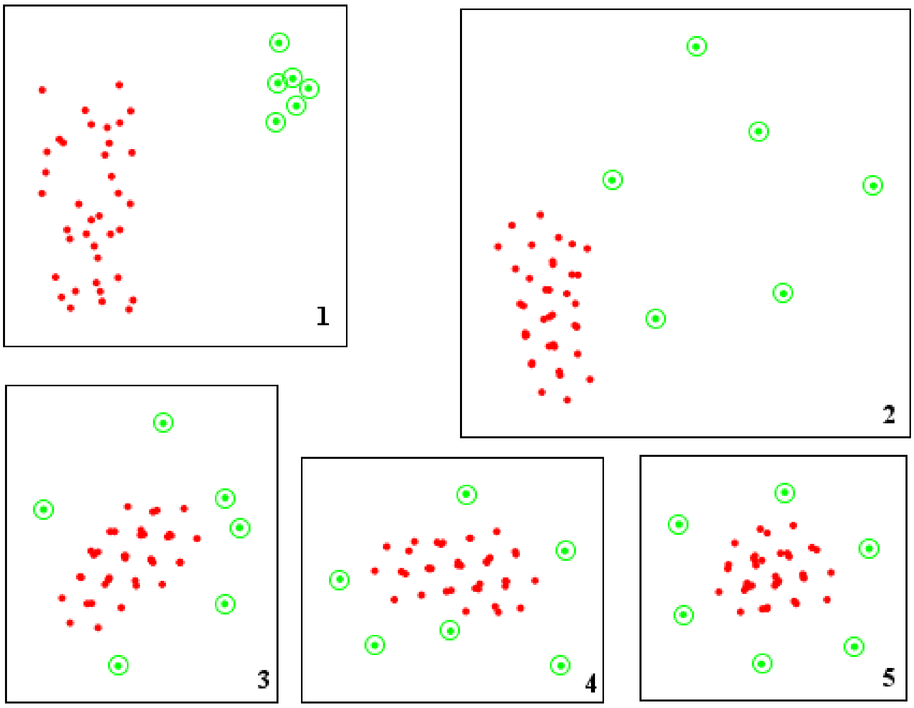

Figure 4: Snapshots of the simulation: different stages of capture from the initial state to the final encirclement (haloed particles are orcas)

[8] C. Ronald Kube and Eric Bonabeau. Cooperative transport by ants and robots. *Robotics and Autonomous Systems*, 30:85–101, 2000.

[9] Ran Levy and Jeffrey S. Rosenschein. A game theoretic approach to distributed artificial intelligence and the pursuit problem. In Y. Demazeau and E. Werner, editors, *Decentralized Artificial Intelligence III*, pages 129–146. Elsevier Science Publishers B.V./North-Holland, 1992. Also published in *Proceedings of the Workshop on Modeling Autonomous Agents in a Multi-Agent World*, Kaiserslautern, Germany, August 1991.

[10] M. Poggio and T. Poggio. Cooperative physics of fly swarms: an emergent behavior. Technical Report A.I. Memo No. 1512, MIT: AI Lab and Center for Biological and computational learning, December 1994.

[11] Onn Shehory, Sarit Kraus, and Osher Yadgar. Emergent cooperative goal-satisfaction in large scale automated-agent systems. *Artificial Intelligence*, 110:1–55, 1999.

[12] W. Spears, D. Spears, R. Heil, W. Kerr, and S. Hettiarachchi. An overview of physicomimetics. In *Swarm Robotics: SAB 2004 International Workshop*, volume 3342 of *Lecture Notes in Computer Science: State of the Art Series*, pages 84–97. Springer-Verlag, 2004.

[13] William M. Spears, Diana F. Spears, and Rodney Heil. A formal analysis of potential energy in a multi-agent system. In *Formal Approaches to Agent-Based Systems: Third International Workshop, FAABS 2004*, volume 3228 of *Lecture Notes in Artificial Intelligence*, pages 131–145. Springer-Verlag, 2004.