Swarm Robotics – Final Report

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***Abstract*—This paper is an attempt to examine aggregation behavior in swarm robotics in a broader context. It examines biomimicry and the caution which must be employed therein. Motivated by social behavior among insects, birds, and fish, it seeks to test a potential aggregative swarm model which seeks to mimic the dynamics governing swarm behavior in social animals using an attractant-repellant force interaction formula. Furthermore, the dynamics of predator evasion are likewise examined and potential applications of swarm technology described in this paper are explored.**

I. Introduction

FOR centuries, poets and philosophers have been fascinated by large groups of same-species animals tending to cluster together – flocks of birds, schools of fish, colonies of ants, honey-bee hives. The assumption made is that group dynamics arise from decentralized local interactions between individual agents and between agents and the environment. [1] These swarms form for a number of benefits, including enhanced protection, increased hunting ability, greater ease of travel, predator confusion, or to perform tasks which otherwise would have been impossible for a single such organism, such as carrying heavy objects, or building large and intricate colonies as in the case of ants [2].

In robotics, separate robots can be coordinated together to perform certain tasks as a team which otherwise could not be accomplished using a single robot, or would be prohibitively complex, expensive or time-consuming. [3] Thus, my motivation in pursuing swarm robotics stems from observing self-organizing behavior patterns in social animals and attempting to decode the principles driving their behavior in hope to adapt these principles for potential robotics applications – biomimicry.

In addition to benefits inherited from its motivator, a swarm of robots (autonomous agents) has the potential for a number of advantages over its single-agent-system counterpart, including enhanced failure tolerance, ease of adaptability, versatility, scalability, rapid wide-area coverage, security (due to decentralized information), and of course economy. [4]

A simple and oft-overlooked aspect of swarm robotics containing its own subtle intricacies is aggregation – the process of assembling discrete autonomous entities into a swarm. It is this feature which gives rise to the patterns we see in flocks of birds and schools of fish, and it will be examined thoroughly – using analytical and numerical methods, apparently complex swarm behavior can be modeled and interpreted. [5]

Lastly, I will touch upon practical motivations for swarm robotics – that is, its potential implementations in biomedicine, micro-assembly, mine detection, cleaning tasks, and so forth – and the feasibility of such applications in the near future. [6]

II. Biomimicry

THE inspiration for swarm robotics usually stems from biological sources, so it is apt to examine them in context. Firstly, it is important to note the distinction between pattern and function for swarm characteristics. Human perception can be quite misleading: some obvious features of a 3D swarm, such as a funnel or torus shape, have analogues incarnations in 2D swarms and thus appear to be adaptive to group dynamics, but such shapes occur so frequently in nature that they could be considered evolutionarily neutral. On the other hand, dynamic patterns such as coordinated maneuvers have clear biological interpretations such as predator avoidance and confusion and can be considered group dynamics. [7]

Once essential evolutionary group dynamics are identified, it is possible to create a model to describe the behavior of the group.

III. Modeling

APPROACHES to modeling can be divided into two groups: Eulerian and Lagrangian. Eulerian models do not consider individuals explicitly but instead focus on population densities. Lagrangian models specify the state of each agent in the swarm, and are more pertinent here. [5]

Most swarm aggregation phenomena can be modeled by an attractant-repellant profile, whereby individual interactions are characterized by long range attraction and short-range repulsion. [8] That is, each agent is modeled as an inertial mass upon which various forces act: locomotory forces such as drag, aggregative force such as long range attraction, and random forces due to individual agent motion. [7] Agents are drawn towards other agents to form swarms, are repelled by agents in close proximity to avoid collision, and are repelled from predators to avoid being eaten. Thus, the dynamics of the emergent patterns can be described using Lagrangian models which specify the state of each agent as it undergoes changes in velocity and direction as dictated by said forces.

Some more modeling considerations include numerical preference, or the *rule size*. This refers to the number of neighbor each agent pays attention to – it can be a set number, have a maximum, depend on orientation or simply include all agents within range.

IV. Modeling Applet

THE specific equations used to model the forces vary widely, from square waves to trigonometric functions. I have experimented with various options and have chosen a linear force/distance relationship (Fig 1c) for simplicity.

My modeling testbed – "Red Herring" was created from scratch using the Java 1.4.2.05 SDK. It consists of a functional graphical user interface which allows for selection of swarm size, sensor range, time delay between steps and equilibrium distance – the distance at which 2 swarm agents exert no aggregative "forces" on each other. Each identical agent is displayed as a circle with a line indicating its direction of travel. This aesthetic aspect was partly influenced by a similar but more complicated simulator, *SimbotCity*. [4]

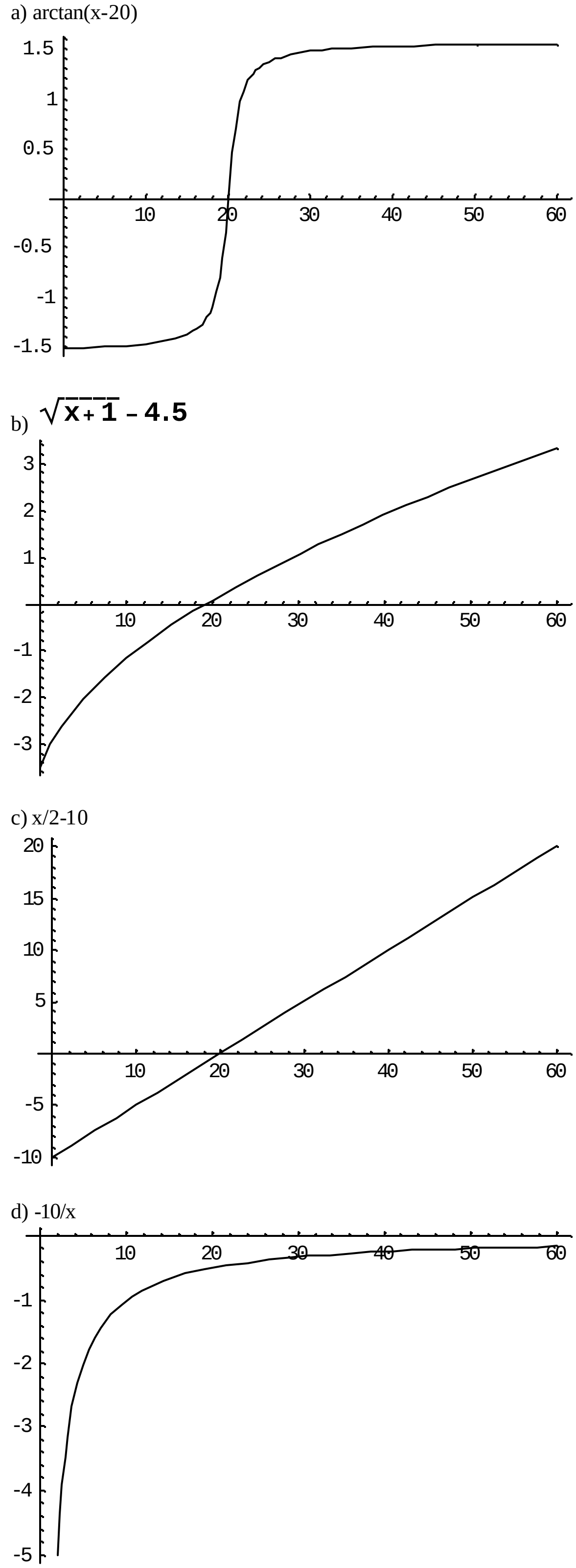

Fig 1: (a-c) various attractive/repellant force/distance curves
(d) predator repulsion curve.

Once the simulation is run, each agent considers each other agent within its sensor range, calculates its relative distance and orientation and determines the corresponding aggregative force it exerts on the agent in question. The total of these forces determines how the agent accelerates and in which direction. The agent is moved accordingly, and the process is repeated for the next “step,” and aggregative behavior is demonstrated using a series of discretely determined steps.

Friction is considered – for each step, the velocity is decreased by 2% to prevent agents from accelerating to infinity or spiraling out of control. A collision detection clause prevents agents from passing through each other: when the distance between two agents decreases to the sum of their radii each experiences a stronger repulsive force.

Owing to these factors, the agents eventually aggregate to form one or more swarm clusters. This simulator effectively models simple sensor-based mobile robots exhibiting collective robotic intelligence with no explicit communication.

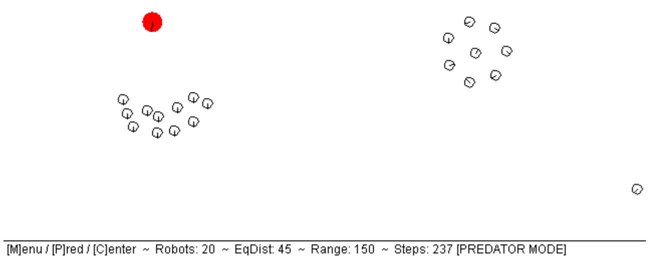

Fig 2. “Red Herring” swarm modeling applet

V. Cluster Characteristics

THE nature of these clusters depends on the various swarm parameters. The greater the population density, the greater the chance that separate developing clusters would merge together to form a single one. The greater the equilibrium distance, the higher the chance of pulling stray agents into the cluster. Increasing sensor range meant that more agents were likely to interact with other agents and thus form smaller numbers of large clusters. Trials are conducted to determine correlation between population density and relative cluster size.

Trials are all conducted on a playing field of 640x468 $\sim 3*10^5 \sim$ c pixels. Population density is thus listed as 1, 2, 3… to represent 1 agent per c pixels, 2 agents per c pixels, etc. – or simply, 1 agent per playing field, 2 agents per playing field, and so forth. 10 trials are conducted for each population density.

Trials show that relative cluster size (average cluster size divided by population) approaches 1 after an initial downward spike due to sparse agent distribution leading to frequent clusters of 1 or 2 agents. (Fig 3a) Similarly, the total number of clusters exhibited an initial spike owing to large numbers of 1- or 2-agent clusters, followed by a gradual decline towards 1 as population density increased to the point where few agents were left outside of sensor range. (Fig 3b)

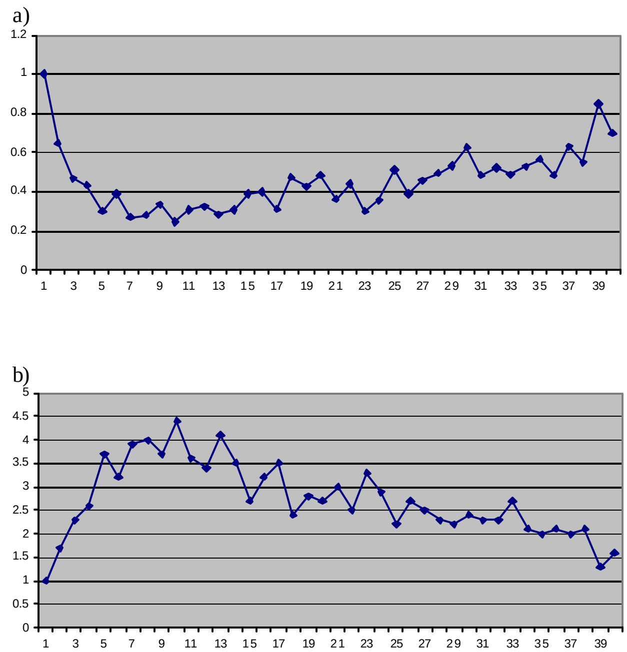

Fig 3. a) relative cluster size vs. population
b) number of clusters vs. population

A more elaborate and harder to quantify cluster characteristic is dynamic vs. static equilibrium. For sufficiently large equilibrium distances, all agents would eventually find a stable equilibrium position, usually forming a configuration which geometrically optimized distances between all agent pairs. (Fig 4a) If the equilibrium distance was relatively small however compared to agent radius (here 5 pixels), the agents would be unable to find a stable equilibrium point and hover around each other continually searching for one. The clusters formed would be stable as a whole, but individual agents were constantly in motion and did not form the geometrically optimal configurations of static equilibrium conditions. (Fig 4b) The distinction between the two can be made analogous to fish school formations – static equilibrium corresponds to normal swimming, and dynamic equilibrium to a tightly-packed ball formation.

These simple analyses are straightforward and somewhat intuitive, but important in outlining the logic of the attractant-repellant swarm model. This model demonstrates that a very simple set of rules – indeed, just one equation – can adequately explain the clustering behavior of many social animals without examining the agents in motion, a state which I have omitted for the sake of clarity and simplicity.

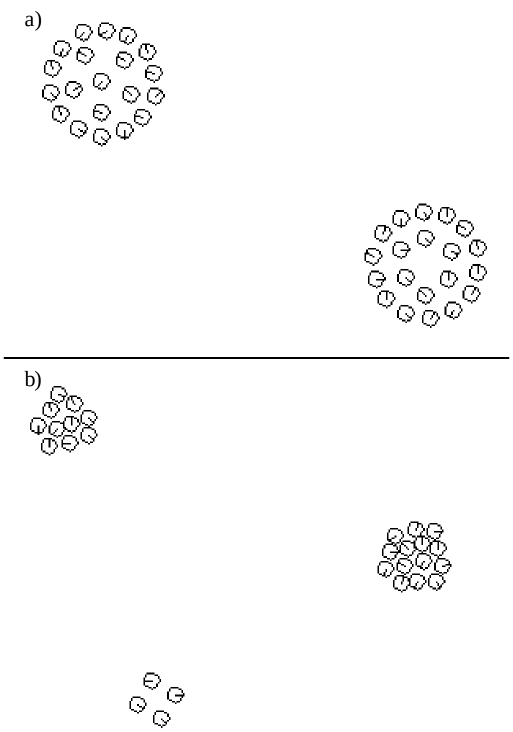

Fig 4. a) static equilibrium b) dynamic equilibrium

VI. Predator Avoidance

ANOTHER property of aggregative swarms occurring in nature is predator avoidance technique. Schools of fish split, rejoin, explode, contract, and swirl around predators to evade and confuse them in a dazzling feat of synchronized swimming. (Fig 5) [7] Such maneuvers are part of an array of defense tactics employed by fish schools, and are considered emergent evolutionary behavior. [7]

I have further developed my "Red Herring" swarm modeling applet to incorporate simple predator avoidance techniques. Each agent now not only considers interaction forces of all other agents in its range, but also those of a special agent named "predator" which travels in a straight line unaffected by the presence of other agents (I have added the ability to steer the predator as per the advice of a friend, but opted not to allow it to eat the other agents in a PacMan-like fashion). All other agents are only repelled by the predator if it is in their sensor range, by a function as the inverse square of the distance between them. This equation was used despite its divergence from the original linear force-distance relationship of agent-agent interaction to illustrate the importance of not being eaten by predators.

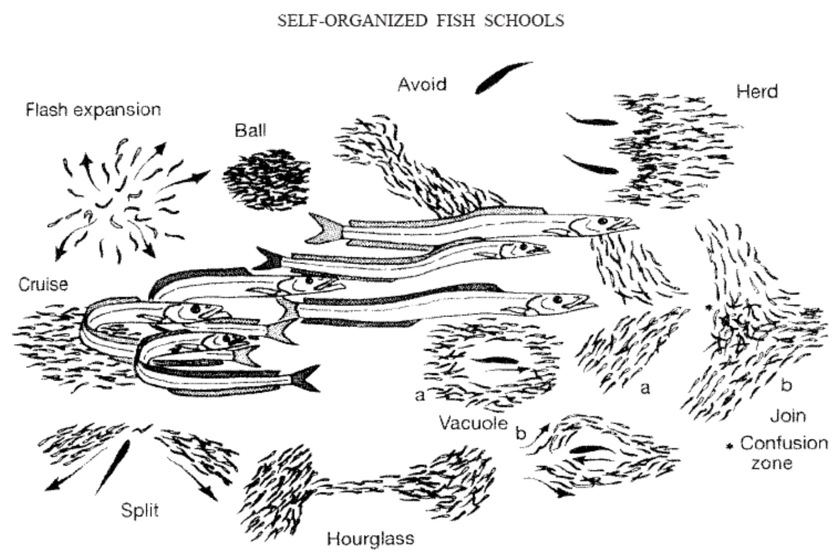

Fig. 5 examples of coordinated movement and directed activity.

While being unable to model directed activity predator avoidance techniques such as flash expansion and hourglass, agents in "Red Herring" exhibited a variety of interesting behavior, including herding, (Fig 6a) splitting, (Fig 6b) avoiding, (Fig 6c) and even vacuole. (Fig 6d) I have not conducted rigorous analysis on predator avoidance due to its overwhelming scale; statistical analysis of random aggregation and predator approach arrangements seems somewhat unfeasible.

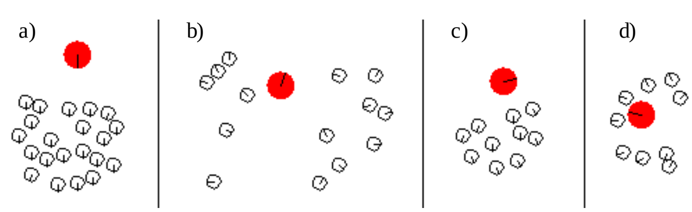

Fig 6. agent behavior: a) herding b) splitting c) avoiding d) vacuole

VII. CONCLUSION

FINALLY, I have shown how a simple rule-set can govern seemingly complex behavior in a swarm of autonomous agents. What we can draw from this is that it is feasible to use simple control methods in a distributed, delocalized manner to dictate autonomous agent behavior. Inexpensive robots with minimalist sensor arrangements could conceivably use such aggregation techniques with minimal intelligence and simple behavior-based decision-making, and ultimately give rise to more complex collective swarm intelligence.

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