SWARMS IN THE MACHINE:
Mimicking Biological Systems in Distributed Artificial Intelligence

Cameo Wood
Bennington College
Bennington, VT 05201
cwood@bennington.edu
http://student.bennington.edu/~cameo

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Abstract

Complex behaviour, from the molecular to the ecological, can be the result or parallel local interactions of many simpler individual agents. The swarm, which is a collection of simple locally interacting organisms with global adaptive behaviour, is an emergent behaviour that is able to be modelled with accuracy within a computer simulation.

Swarm or Distributed intelligence can be defined as the exhibition of collective intelligence by groups of simple agents. The Swarm Intelligence approach to Distributed Artificial Intelligence (DAI) argues an alternative approach to problem solving exists and operates at a different level than the problem solving processes that are traditionally used. The basic premise of the Swarm Intelligence premise is presented in the computerised modelling of "dumb" artificial agents modelled after biological entities that are not programmed with intentional goals individually and yet exhibit problem solving abilities as a collective behaviour. Two core concepts of Swarm intelligences are stigmergy[1] and allelomimesis; stigmergy meaning communication through the environment, and allelomimesis meaning an individual's reaction it's neighbour. Stigmergy is a common term within DAI as it describes the computation that needs to occur ever time an individual responds to and therefore modifies its environment, causing all rule sets for all neighbouring individuals to be recomputed.

[1] Kassabalidis, 1

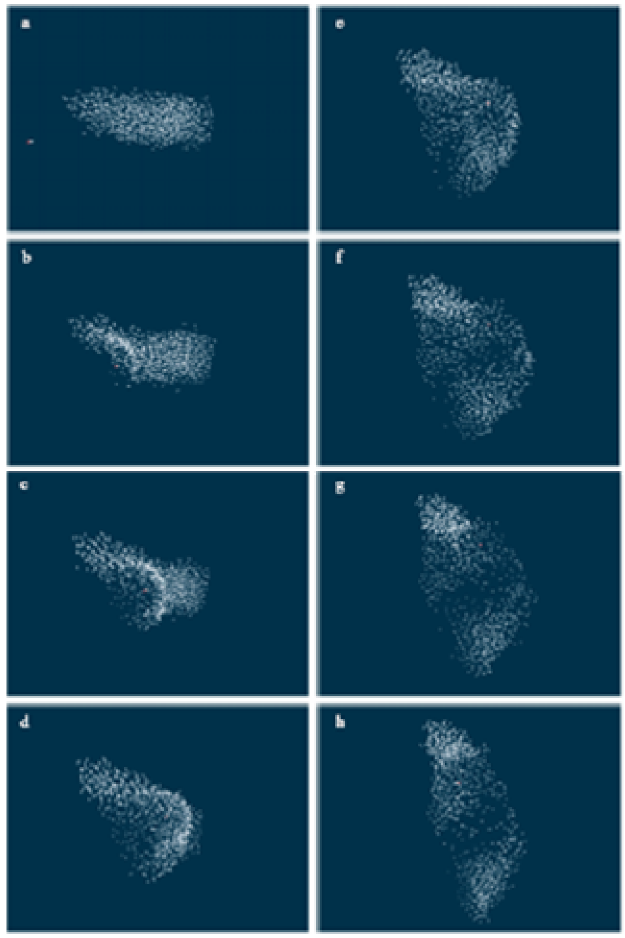
Swarm behaviour is characterised by collective phenomena such as flocks of birds, schools of fish, swarms of bees and schools of ants exhibit identifiable group behaviour whose complex migration, hunting, and gathering behaviour appears to be wholly integrated and is seen as a single coherent entity. Computer simulations of individual members of such collective phenomena has proven to be a useful heuristic in analysing the group as a whole, however, this understanding appears to be contingent upon the modelling of the very large number of interactions that occur between the individuals. Using these tools, it has been demonstrated that group leadership, hierarchical control, and global information is not necessary for collective behaviour.[2] It is critical to realise that this "collective" behaviour is not limited to just spatial motion, but the actual behaviour of the individuals within the group.

Simple rule sets can be applied to many different types of DI (Distributed Intelligence) in computer simulations and illustrate simple actions for collective groups. Models of such behaviour range from abstract cellular automata to more physically realistic computer simulations. An example of this is a two rule set for a termite to build a dome. The existing condition is that each termite will take some dirt into its mouth to moisten it, and then follow two rules: Move in the direction of the strongest pheromone concentration, deposit what you are carrying where the smell is strongest.[3] Such models of behaviour for collective groups assume that each individual is moving at a constant speed and is moving in a relative proximity to its neighbours. This kind of collective behaviour exhibits allelomimesis, in which an individual's actions are determined by its neighbours which is often one of the main influences on a decentralized system.

The observation of DI in animals assists in understanding the evolution of cooperative behaviour and understanding emergent phenomena of many different types. For example, fish schools appear to move as one entity, moving together as an identifiable single organism. It is now understood that there is no set of group-level rules for the exhibited movement, or even a set

[2] Couzin, 1.
[3] Kennedy, 103.

of rules for collective behaviour for the individual. There is no leader or hierarchy that steers and controls the movement—instead it is a mechanism by which individuals interact to the behaviours of their immediate neighbours and as a result of such local interactions, the collective group-level pattern of activity emerges spontaneously; an example of biological self-organisation.



Collective phenomena is not to be misconstrued as a term or a technology specific to Artificial Intelligence or biological systems; it exhibits emergent behaviour wherein simple interactions of autonomous agents, with simple primitives, give rise to a complex behaviour that has not been specified explicitly.[4] Distributed Intelligence systems use resilient, decentralised emergent techniques based on the systems of social insects. A social insect colony has three main attributes that define its behaviour as DI:

- Global order from local interactions: The system has a correlation between the elements of the system and is not controlled by a non-local (external) force.
- Distributed Control: Corollary to the first characteristic; local interactions emerge from the distributed control among the system elements.
- Robustness: The system is resistant to perturbations and has a strong capacity to restore itself after damage.

The main problem in designing DAI after biological distributed systems lies in creating a system with emergent properties; how can individual behaviour and interactions be defined in order to produce desirable emergent patterns. In a study of two similar types of organisms, desert

[4] Kassabalidis, 1

and army ants, it is possible to understand the possible connection between the number of individuals and the subsequent effect on behaviour. Desert ants generally evolve into small colonies of one thousand individuals, and army ants into large colonies of one million individuals.[5] In small colonies like the desert ants, the individuals exhibit complex behaviour, with demands for specialised behaviours. Large colonies like army ants, however, follow very few rules of a very simple behaviour. However, both groups have nearly the same behaviour in such simple tasks as path planning:

1. Avoid obstacles
2. Wander randomly (with a weighting towards pheromone trails).
3. If holding food, drop a pheromone trail.
4. If find food (if not carrying) and pick it up.
5. If find nest, drop food.

The complexity dynamic, however, reflects an individual's threshold reinforcement dynamic, wherein the more a specialist within a colony performs the same task, the less possibility that it will respond to a new task. While new specialists can be generated in response to perturbations, they take longer as each individual waits for another individual to rise to the task. The paradigms within emergent behaviours of self-organisation raise questions about what environmental and local conditions must be in place for a leader or specialist to emerge. In some cases the difference between a non-leader and a leader can be threshold responses to environmental external stimuli such as air or water currents, light, and temperature. Groups which effectively utilise leaders such as flocks of geese or some schools of fish follow three different rules:

1. Leader issues orders- all turn now.
2. Lead by example—I turn, you turn.
3. The most reasonable action.

[5] McShea, 220

There are problems with the leader-led paradigm; within flocks, a perturbation of flock bifurcations and coalescing raises problems of leadership. Also, there are certain costs within leading, and how the fitness of the group best served, and by which leader. Leaders become a form of specialisation, and pay certain costs in effort. There are also difficulties of communication within a flock that relies on visual contact for cohesion. Perturbations occur within the system which leads to challenges of leadership, and waiting for threshold values to be exceeded. In leading, a "front" is created when leaders are decided upon. However, as illustrated below in figure 1, when there is a local environment change that seems to inspire a reaction, allelomimesis takes over and causes direction or some other kind of pattern change in the group. During a change in direction, the leaders are no longer at the "front," and there is a need for new leaders to emerge, and another threshold waiting period begins.

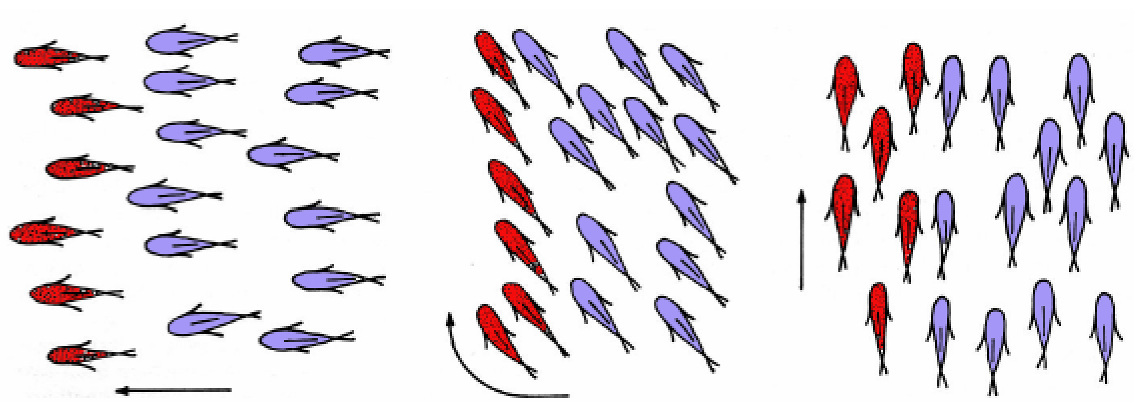


Figure 1. Leadership in a direction change.

Conversely, the advantages to flocking are many, which why it is such a successful collective behaviour. Predators are less likely to be able to track individuals within a group, which relates to the idea that individuals in a herd are acting selfishly, and use the herd as a way of escaping the notice of predators through confusion.[6] Animals in a flock also have an advantage in their ability to concentrate prey by working as terms. While flying, birds in a flock can

[6] Hamilton, 295

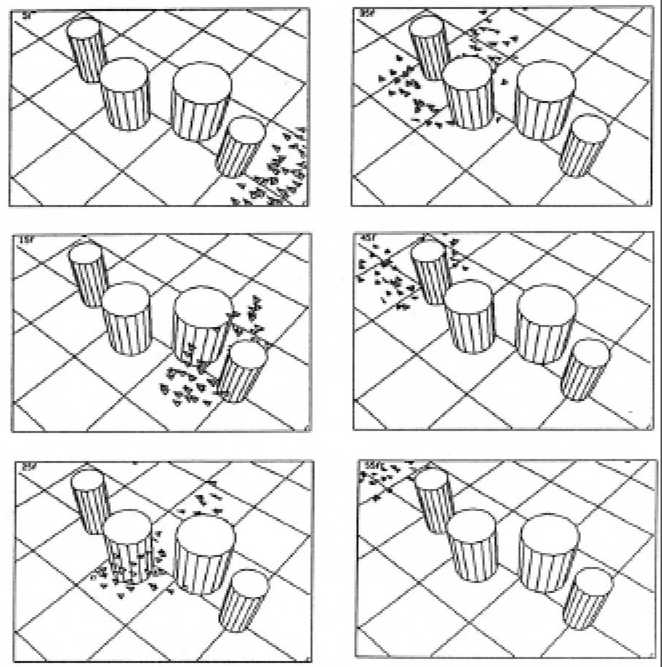


FIGURE 6 A flock of "Boids" negotiating a field of columns. Sequence generated by Craig Reynolds.

conserve energy by practising slipstreaming. Individuals in a flock are also at a close proximity, facilitating the need to find a mate.

Craig Reynolds, a computer programmer, found various ways of applying rule sets to biological systems and developed a simple flock modelling system that was able to realistically portray bird-like elements in a distributed system, which he dubbed “boids”. He addressed the problem of how allelomimesis works in a flock given only very simple rule sets. However, in order to realistically animate the flock, each flight path for each individual had to be constantly recalculated upon the changes that earlier recalculations had imposed upon the group as a whole.

There is also a swarming behaviour which is the antithesis of flocking, repulsion. This is mainly used in biological systems for tasks that require a task in a large geographic region. A lot of these methods are being utilised in robots for similar tasks. Ants use repulsion for tasks such as Foraging, and exploration for new sites. Robots that use similar techniques are being designed for environment exploration in order to perform rescue, landmine and trash search and collection.

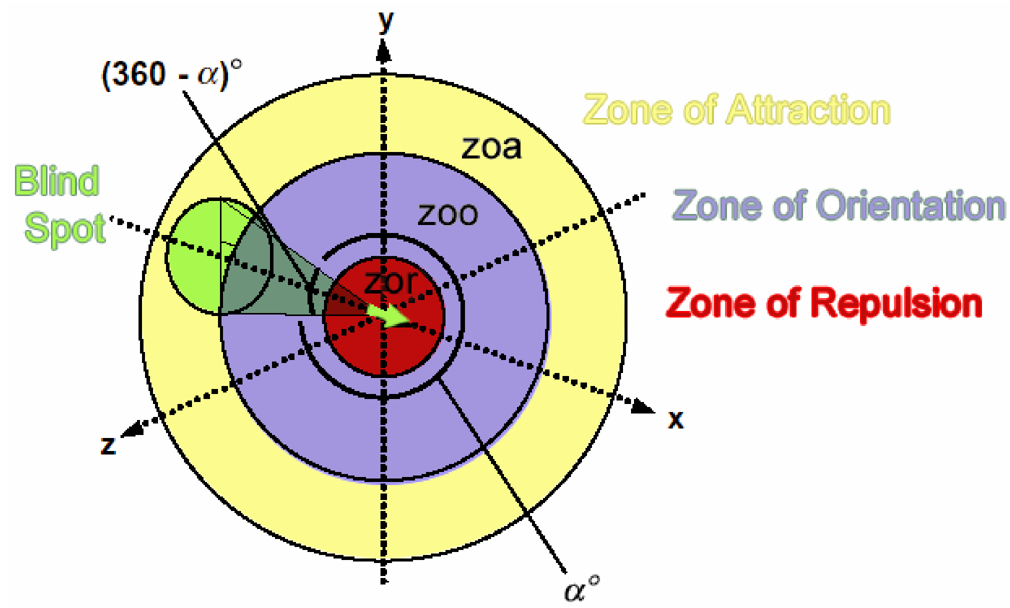


Figure 2. Couzin's representation of an individual

Within Couzin's ground breaking paper in 2002 which presented a model of the collective behaviour of animal groups, he specifies individual level rules within the construct above in Figure 2. This paper illustrated four types of self-emergent behaviour of group formation within a three dimensional space, as well as presenting an argument for collective memory within groups. In the figure above, the individual is centred at the green arrow facing toward x and follows five basic rules:

1. Maintain minimum distance and position your centre so that there are no others within your ZOR.
2. If any other individuals enter your ZOR, move away.
3. If there are no individuals within your ZOR, respond to any others in the ZOO and ZOA except those in the blind spot.
4. Align yourself with neighbours in ZOO.
5. Orient towards neighbours in ZOA.

As Couzin changed the area of the behavioural zones of repulsion, orientation and attraction, four collective behaviours of group formation emerged: swarm, torus, dynamic parallel group, and the highly parallel group.

Swarms:

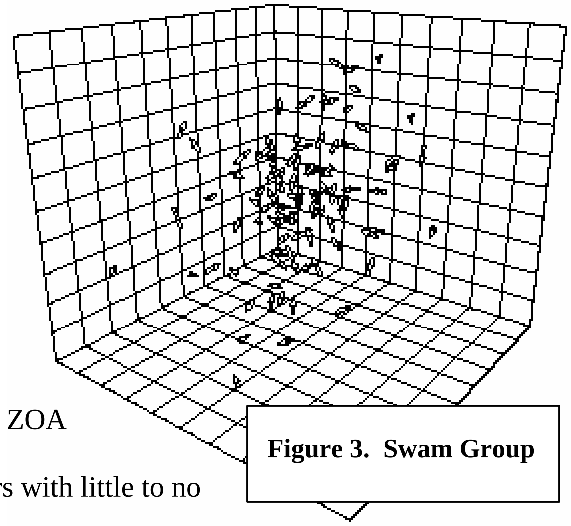


Figure 3. Swam Group

The swarm group is an aggregate with cohesion, and a low level of parallel alignment among the individuals, and a low angular momentum. This type emerges when individuals perform ZOA and ZOO behaviours with little to no parallel orientation. This behaviour is mainly exhibited in insects such as locusts, mosquitoes and midges, and can also be seen within fish schools.

Figure 4. midges in a swarm

Torus:

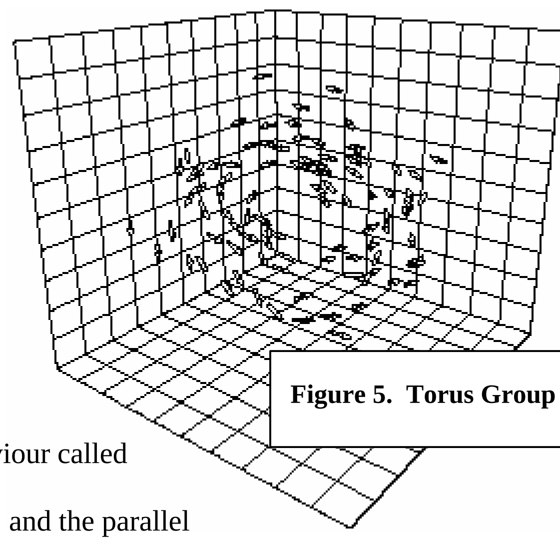
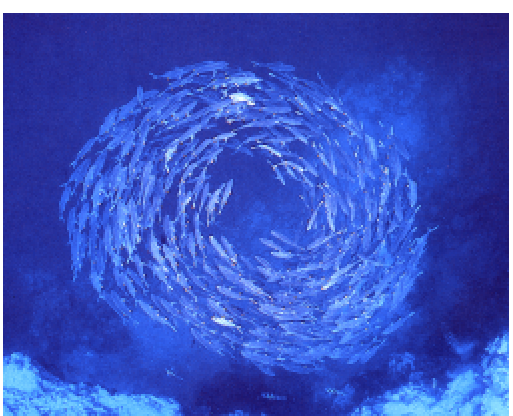


Figure 5. Torus Group

The individuals within this group continually rotate around an empty core in a behaviour called "milling". The direction of the rotation is random, and the parallel alignment within the group is low, but the angular momentum is high. This type occurs when the ZOO is small and the ZOA is large. While this may seem to be uncharacteristic of real animal movement within groups, it is a natural formation exhibited by barracuda, jack and tuna.



Dynamic parallel group:

This group has a high level of parallel alignment among individuals, but a low angular momentum. This group type is much more mobile than the swarm or torus, and occurs at intermediate values of the ZOO with intermediate or high values of ZOA. This type exhibits many of the same characteristics associated with aggregations such as flocks of birds and schools of fish. The individuals are polarised and move as a coherent group, however, the individuals can move within the group, allowing fluctuations in group density and shape.

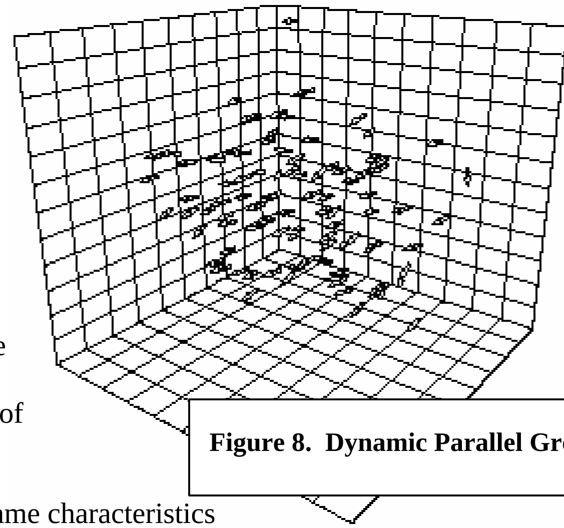


Figure 8. Dynamic Parallel Group

Figure 7. Midges in a Dynamic Parallel Group

Highly Parallel Group:

As the ZOO increases, this type self-organises into a highly aligned arrangement with very high parallel orientation with rectilinear movement. This type is much more static than the other three in terms of the individual's spatial

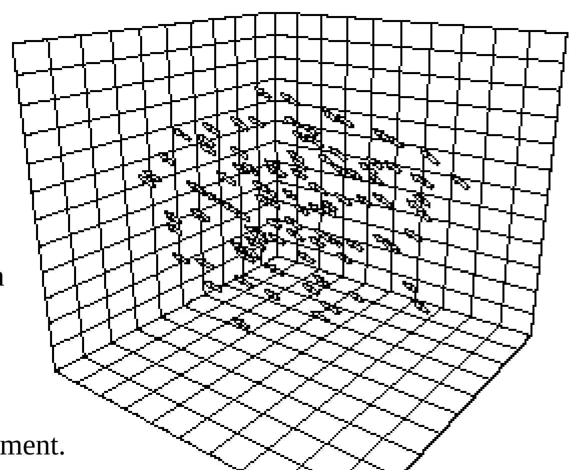


Figure 10. Highly Parallel Group

Figure 9. School of fish in a Highly Parallel Group

orientation within the group, making the fluctuations in density and the shape of the form very consistent.

Using these tools in order to better understand how swarms function in biology, it is therefore possible to model these same individual rules of the biological systems in order to better understand how swarms develop, and how slight changes in an individual's rule sets in response to allelomimesis can reform a swarm into a new type in order to best deal with the current situation. The four types of groups,

a. swarm
b. torus
c. dynamic parallel
d. highly parallel

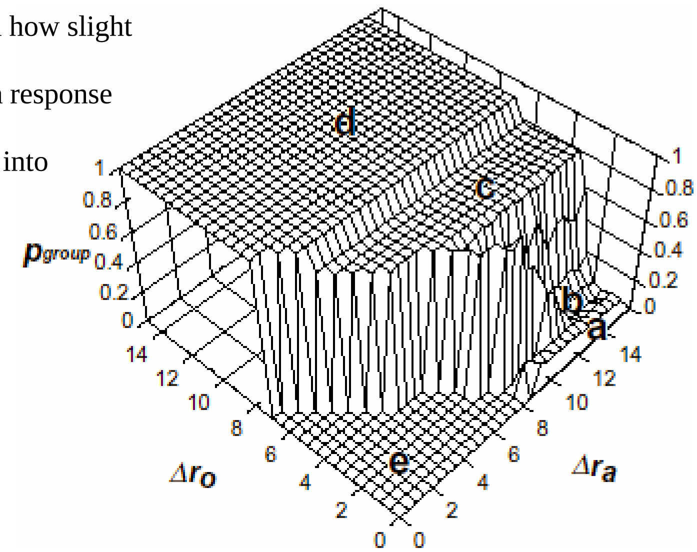


Figure 11. Polarisation graph

Each has a unique signature of movement, form and orientation. The polarisation graph shows the amount of parallel alignment (P group) between neighbouring individuals locally interacting in any one group type. The two axis are measured by the width of repulsion in ZOO (Δr_O) and attraction in ZOA (Δr_a). The most polarised group is group **d.**, the aptly named "highly parallel group" and the least being the swarm.

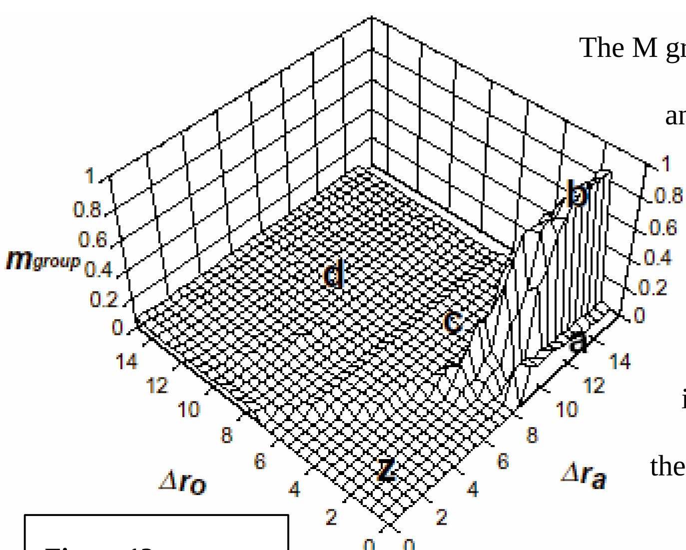


Figure 12. Angular Movement

The M group of motion shows the amount of angular momentum that one group has, showing the Torus group to be within a very small criticality range of Δr_O and Δr_a, showing the importance of movement to turning in the characteristic milling fashion.

The use of collective behaviour in Artificial Intelligence and robotics has been traditionally centralised with globally defined parameters. This is because of a belief that in order to achieve global level “intelligence”, the intelligence must be engineered globally. As discussed earlier in regard to the Boids, the exponential state space in computing the stigmergy of each individual agent makes this kind of global intelligence prohibitive, as each state change needs to be modelled and fed back to each individual.

One thing that might be learned in understanding biological systems in terms of their application to Distributed AI is the notion that a few simple rules have the ability to generate the complexity we see in the world. As Kauffman insinuated, the origin of life could be simple under the right circumstances and self-organisation is likely a major driving force.

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