Swarm modelling.

The use of Swarm Intelligence to generate architectural form.

Pablo Miranda Carranza Dipl ArchMSc
CECA University of EastLondon
Holbrook rd Stratford
London E15 3EA
e-mail: merluza@altavista.com

Paul Coates AA Dipl
CECA University of EastLondon
Holbrook rd Stratford
London E15 3EA
e-mail: p.s.coates@uel.ac.uk

Abstract

The reason for choosing swarms as a study case is the fascination of the simplicity of its mechanics and its complexity as a phenomenon. It can be compared in that sense with other models such as Cellular Automata, for example, with which shares some similarities (they are parallel systems, they interact at a local level, etc).

This paper describes the swarms understanding them as examples of sensori-motor intelligence. It begins addressing some issues already patent when studying simple turtles, and then it looks at two ways of interaction of the swarm and their implications. It studies the interaction with an environment in relation with learning processes and simple perceptions of forms, and then uses the processes developed in this first cases to look at the possibilities of

interaction of the swarm with a human, and its similarities with other systems such as Genetic Algorithms or social systems.

In general the paper discusses the morphogenetic properties of swarm behaviour, and presents an example of mapping trajectories in the space of forms onto 3d flocking boids. This allows the construction of a kind of analogue to the string writing genetic algorithms and Genetic programming that are more familiar, and which have been reported by CECA [22,23,24,25,26]

Earlier work with autonomous agents at CECA [27, 28] were concerned with the behaviour of agents embedded in an environment, and interactions between perceptive agents and their surrounding form. As elaborated below, the work covered in this paper is a refinement and abstraction of those experiments.

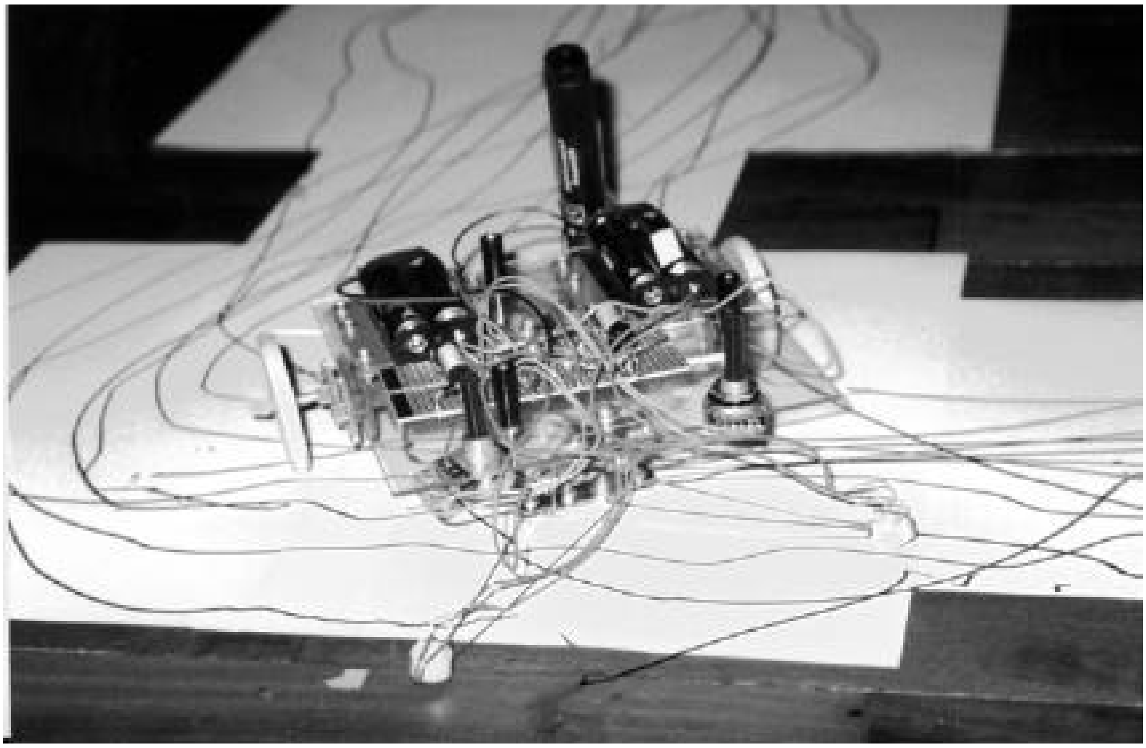
This places the swarm back where perhaps it should have belonged, into the realms of abstract computation, where the emergent behaviours (the familiar flocking effect, and other observable morphologies) are used to control any number of alternative lower level morphological parameters, and to search the space of all possible variants in a directed and parallel way.

1. Simple agents and turtles. Sensori-motor intelligence and perception

W. Grey Walter built in Bristol the first recorded turtles, Elmer and Elsie, just after the second world war. These first turtles raised many questions and opened new paths in the field of early Artificial Live. Walter gave them the mock-biological name Machina speculatrix, because they illustrated particularly the exploratory, speculative behaviour that he found characteristic of most animals. As he wrote, *'Crude though they are, they give an eerie impression of purposefulness, independence and spontaneity.' 'In this way it neatly solves the dilemma of Buridan's ass, which the scholastic philosophers said would die of starvation between two barrels of hay if it did not posses a transcendental free will.' [1]*

Inspired by Grey.W. Walter's turtles, Valentino Braitenberg [2] uses thought experiments in which very intricate behaviours emerge from the interaction of simple component parts, to explore psychological ideas and the nature of intelligence. In a sense, Braitenberg "constructs" intelligent behaviour, a process he calls "synthetic psychology". A similar approach has been taken in the development of this work, starting from very simple agents or turtles interacting in the real world, and then developing the idea further with the use of swarm systems in the computer. Invention and deduction, as in Braitenberg's case, have been preferred over analysis and observation.

To begin with, a simple turtle was built, based in the reflex behaviour by which moths and other insects are attracted to light, known as "positive phototropism". In this mechanism the two halves of the motoric capacity of an insect are alternatively exited and inhibited, depending on the side from which they perceive a strong source of light, having the effect of steering the insect towards the light source.



automaton moving on an environment

The automaton consisted of two light sensors connected each to threshold devices and these to two electric motors (one in each side of the body). The device is thus made of two completely independent effectors (sensory-motor units). The automaton exhibits different behaviours depending on the configuration of its parts. Changing in particular the position of the light sensors respect to the rest of the components, the machine wondered in different ways through a rectangular white area: sometimes groping the edges, another times covering the whole surface, other times stopping at the corners. Although all operations involved in the 'computation' of this automaton were elementary, the organisation of these operations allowed us to appreciate a principle of considerable complexity such as the computation of abstracts. Notions such as the ones of "edge", "corner" or "surface" emerged when different configurations of the body of the automaton were set in the same test environment.

Though Von Foerster [3] already defined this emergence of perception through sensor-motor interaction in the framework of second order cybernetics, the biggest development of this idea of perception-in-doing comes perhaps from the description of perception in autopoietic theory. For Maturana and Varela, cognition is contingent on embodiment, because this ability to discriminate is a consequence of the organism's specific structure. They call this concept Enaction, where *'...knowledge is the result of embodied action'* and *'cognition depends upon the kinds of experience that come from having a body with various sensorimotor capacities ... themselves embedded in a more encompassing biological, psychological, and cultural context '* [4].

1.1 Structural coupling

The most interesting idea in Autopoietic theory referring to perception is the already mentioned Structural coupling, which leads to the concept of enactive perception. It *is '...a historical process leading to the spatio-temporal coincidence between the changes of state in the participants '* [5]. Structural coupling describes ongoing mutual co-adaptation without allusion to a transfer of some ephemeral force or information across the boundaries of the engaged systems. There are two types of structural coupling:

1) A System coupling with its Environment.
2) A System Coupling with Another System.' If the two plastic systems are organisms, the result of the ontogenic structural coupling is a consensual domain.'

Inside this framework it is interesting to observe is how different 'forms' are described by the structural coupling of the automaton and an environment. There is not any explicit description of those formal concepts in the system, instead they are actually distributed through it, in the 'environment' and in the way the light sensors are fixed in relation to the motors. We could say that the device describes different 'gestalts' (a gestalt being some property -such as roundness- common to a set of sense data and appreciated by organisms or artefacts) or universal forms. In the next experiments swarms are implemented to define and find such concepts of shape. These experiments resemble Selfridge and Neisser's Pandemonium machine for pattern recognition, in which 'Each local verdict as to what was seen would be voiced by "demons"(thus, pandemonium), and with enough pieces of local evidence the pattern could be recognised' [6].

2. Swarms

The relative failure of the Artificial Intelligence program and its approach to cognition has forced many computer scientists to reconsider their fundamental paradigm. This paradigm shift has led to the idea that sensori-motor intelligence is as important as reasoning and other higher-level components of cognition. Swarm-based intelligence relies on the anti-classical-AI idea that a group of agents may be able to perform tasks without explicit representations of the environment and of the other agents and that planning may be replaced by reactivity. (R.Kube and E.Bonabeau) [7]. The self-organisation of patterns of flow in social insect swarms is an example of how intelligent and efficient behaviour of the whole can be achieved even in the absence of any particular intelligence. Indeed, such patterns can have functionality even without the awareness of the individual entities themselves. A study of the essential elements of swarm dynamics provides an understanding of such behaviours, where the most important of them is possibly the capacity for self-organisation.

The collective behavioural characteristics of a group of organisms must, of course, be encoded in the behaviour of the individual organisms. Complex adaptive behaviour is the result of interactions between organisms as distinct from behaviour that is a direct result of the actions of individual organisms.

2.1 First case of structural coupling: Systems coupling with an environment

As explained in the introduction the first experiments with swarms are an extension of the work done with the automaton, in the descriptions of form through sensori-motor devices.

There are some different numbers of paradigms of collective intelligence. Perhaps the most simple in principle and many times spectacular is the modelling of flocks, herds and schools, that give rise to quite appealing spatial configurations. Based on Craig Reynolds computer model of co-ordinated animal motion, Boids (1986)[8], a swarm of sensing agents was created, each of them reacting to a geometrical environment through a collision detection algorithm, and combining their actions through flocking. In the flocking or schooling of fish '*individual members of the school can profit from the discoveries and previous experience of all other members of the school during the search for food. This advantage can become decisive, outweighing the disadvantages of competition for food items, whenever the resource is unpredictably distributed in patches'* [9]

The flocking rules were taken straight from Reynolds, and implemented in C and C++, inside AutoCAD 14 first, and using OpenGL later.

2.1.1 The flock algorithm.

Each agent has direct access to the whole scene's geometric description, but reacts only to flock mates within a certain small radius of itself. The basic flocking model consists of three simple steering behaviours:

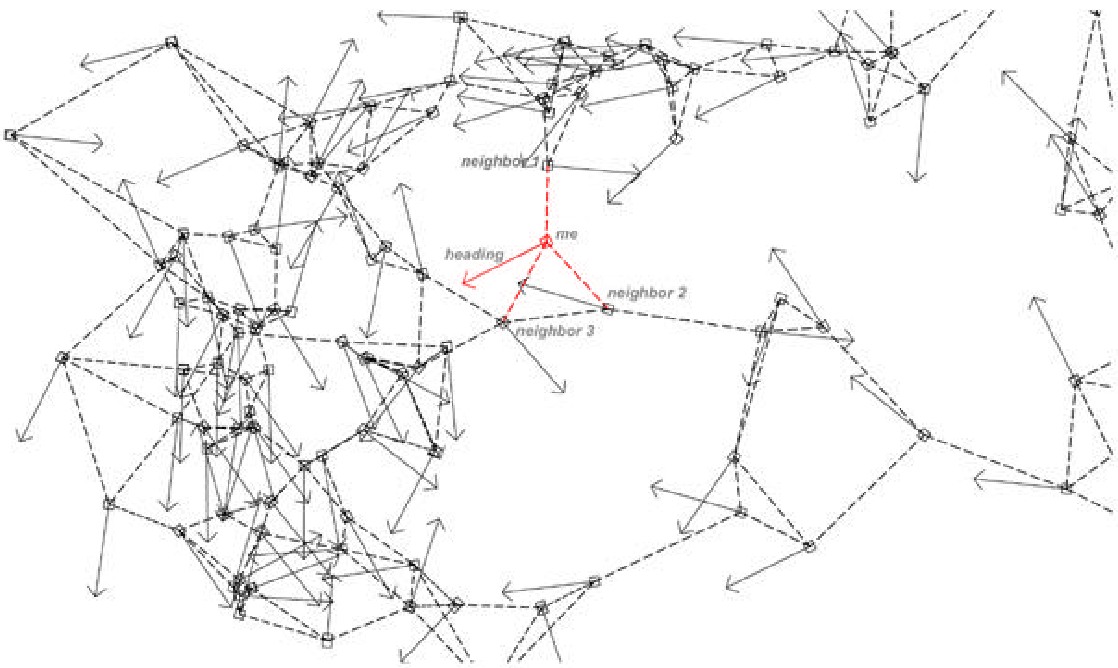


Diagram of the swarm. Arrows represent each agent's heading, dotted lines their closest neighbours.

Separation:

Gives an agent the ability to maintain a certain separation distance from others nearby. This prevents agents from crowding to closely together, allowing them to scan a wider area. To compute steering for separation, first a search is made to find other individuals within the specified neighbourhood. For each nearby agent, a repulsive force is computed by subtracting the positions of our agent and the nearby ones and normalising the resultant vector. These repulsive forces for each nearby character are summed together to produce the overall steering force.

Cohesion:

Gives an agent the ability to cohere (approach and form a group) with other nearby agents. Steering for cohesion can be computed by finding all agents in the local neighbourhood and computing the "average position" of the nearby agents. The steering force is then applied in the direction of that "average position".

Alignment:

Gives an agent the ability to align itself with other nearby characters. Steering for alignment can be computed by finding all agents in the local neighbourhood and averaging together the 'heading' vectors of the nearby agents. This steering will tend to turn our agent so it is aligned with its neighbours.

Obstacle avoidance:

In addition, the behavioural model includes predictive obstacle avoidance. Obstacle avoidance allows the agents to fly through simulated environments while dodging static objects. The behaviour implemented can deal with arbitrary shapes and allows the agents to navigate close to the obstacle's surface. The agents test the space ahead of them with probe points. When a probe point touches an obstacle, it is projected to the nearest point on the surface of the obstacle and the normal to the surface at that point is determined. Steering is determined by taking the component of this surface normal, which is perpendicular to the agent's heading direction. Communication between agent and obstacle is handled by a generic surface protocol: the agent asks the obstacle if a given probe point is inside the surface and if so asks for the nearest point on the surface and the normal at that point. As a result, the steering behaviour needs no knowledge of the surface's shape.

Results:

In this first experiment, as a result of the way the collision detection algorithm worked (slowly rectifying the heading of the agent until it found a collision free trajectory), the individual agents had a tendency to align with the surfaces of the geometric model of the site. This ended in the emergence of the 'smoothest' trajectory on the environment, which in the case of the test model of a site where the meanders of a river. The swarm is able to discriminate the edges of a long wide curvy grove, that is, the geometric form of the river, from any other information such as buildings or building groups or infrastructures.

Traces left by the agents.

2.1.2 Ants, networks and learning swarms.

The second experiment with swarms tried to incorporate the capacity for learning that we find in many social insects. This is many times achieved through their relation with the environment, through stigmergy and sematectonic communication.

Grassé introduced stigmergy (from the Greek stigma: sting, and ergon: work) to explain task co-ordination and regulation in the context of nest reconstruction in termites of the genus Macrotermes[10]. Grassé showed that the co-ordination and regulation of building activities do not depend on the workers themselves but are mainly achieved by the nest structure: a stimulating configuration triggers the response of a termite worker, transforming the configuration into another configuration that may trigger in turn another (possibly different) action performed by the same termite or any other worker in the colony [11]. Individual behaviour modifies the environment, which in turn modifies the behaviour of other individuals. The process is called sematectonic communication [12], when the only relevant interactions between individuals occur through modifications of the environment.

Systems such as these show self-organisation of higher complexity than the initial flock model. Furthermore, it is possible to make a connectionist interpretation of the mechanics of such a system, and realise that it shows the same basic properties of a network [13]. Through this reading, and comparing it with a network it is easy to appreciate the capacity of a sematectonic system in terms of 'learning'.

In Connectionist models structure consists of a discrete set of nodes (neurones), and a specified set of connections between the nodes (synapses). The network unfolds as a dynamic process in which different variables related to the transitions between nodes, or connection strengths, are modified. The dynamics of the whole system is the result of the interaction of all the neurones.

In its most general sense, learning can be described in connectionist models as how the connection strengths, and hence the dynamics, evolves. In general there is a separation of time scales between dynamics and learning, where the dynamical processes are much faster than the learning processes. In addition to neural networks there are many other types of connectionist models, such as autocatalytic chemical reactions, classifier systems, and immune networks, to mention just a few. Swarm networks are just another example.

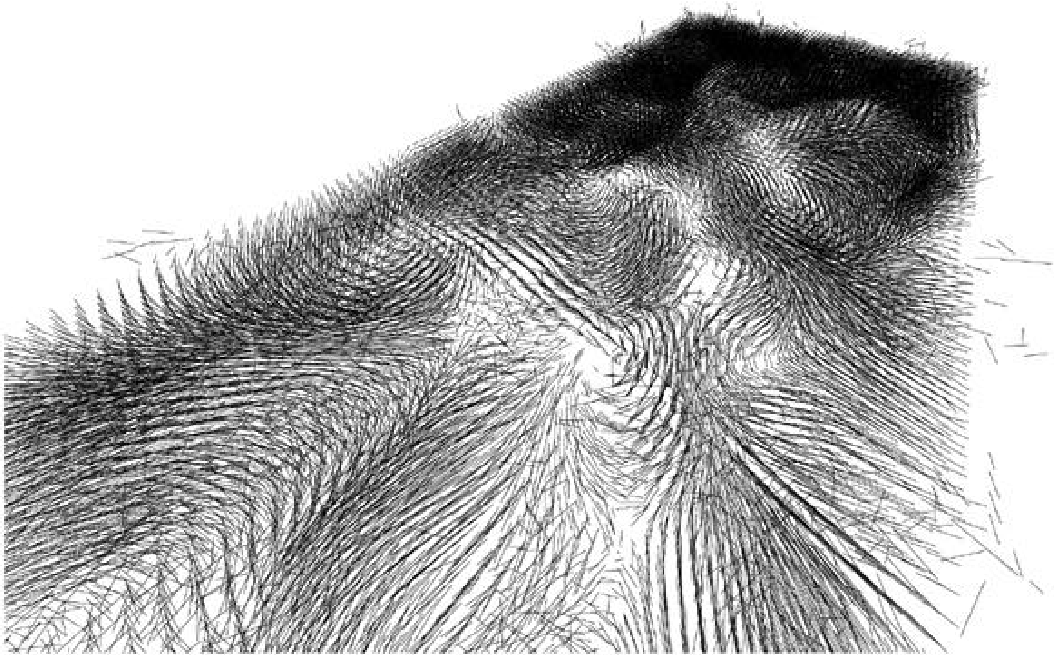
Incorporating these ideas in to the swarm, sematectonic communication was implemented instead of flocking. For this, a three dimensional lattice space was provided. Agents move in this discrete space, each lattice being equivalent to a node in a connectionist system. Each agent leaves a trace in the morphogen variable (from Millonas) on each lattice (or node). The lattice space is also capable of computations on its neighbourhood, similar to Cellular Automata. The computations of the nodes are:

Diffusion: local averaging of the morphogen values, in order to generalise to neighbour nodes, and to generate smoother gradients for the agents.

Evaporation of the morphogen: slow reduction of the morphogen values, as explained earlier, to give the network the capacity of 'forgetting'. Necessary to discriminate the relevance of information, and therefore to learn.

Gradient calculation: This is performed by the nodes themselves instead of by the agents. It corresponds to the 'weights' in the transition probabilities from one node to another (in the case of this lattice space one of the neighbour nodes). Agents read the gradient and add it to their current heading.

The way the gradients modify the possibility of an agent moving from one node to another is understood as the changes in the weights or the strengths of the connections between nodes, and therefore as the learning of the system. The lattice space and the accumulation of morphogen in it work as a memory and the slow "evaporation" of the morphogen as the capacity to 'forget', and therefore to discern significant patterns from irrelevant ones. After some time, areas with bigger concentrations of morphogen differentiated from others.

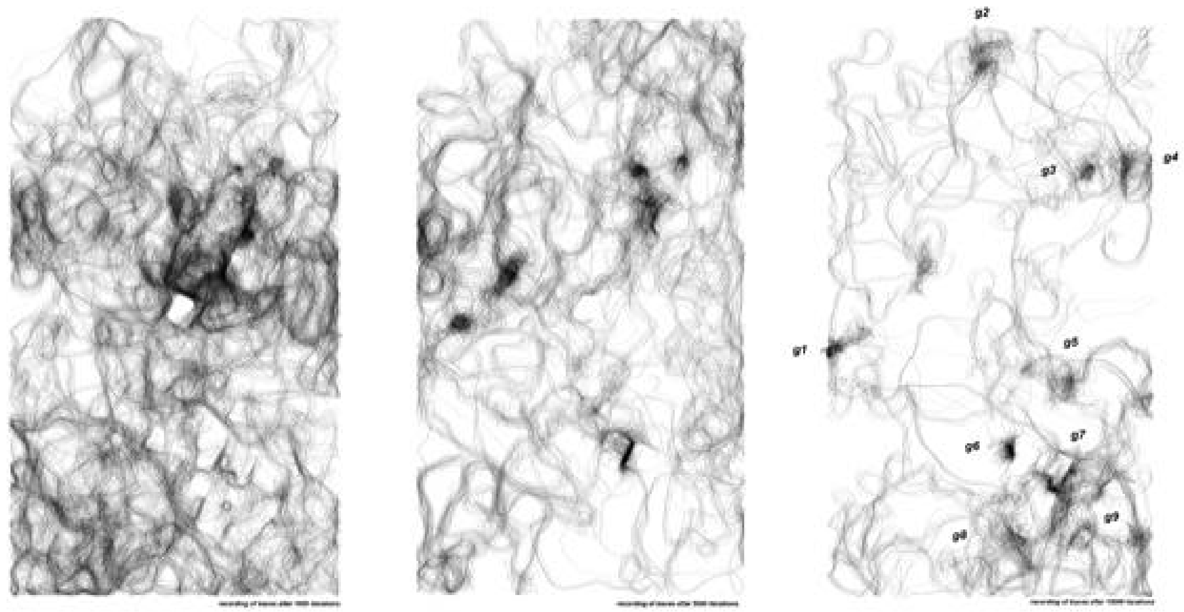


Gradients created by the sematectonic process.

A next step was to differentiate and learn between different "experiences" or sensed data by the agents. The agents would therefore “secrete” more morphogen when they 'sensed' geometry, and less when they had a clear view ahead of them. This ends up with the agents discerning different parts of the geometrical model, and clustering in areas where their collision detection algorithm informed them of higher spatial complexity (in the terms of the agents). In other words, spaces where the agent's collision detection algorithm found conflicts with the geometry (trying to steer away from one collision path and entering in to another, for example) at the same time spaces relatively easy to reach are rarely visited since otherwise the morphogen would evaporate if not visited by any agent.

2.1.2 Adaptative flock

In their paper 'The use of Flocks to drive a Geographic Analysis Machine', J. Macgill and S. Openshaw [14] discuss how the emergent behaviour of interaction between flock members might be used to form an effective search strategy for performing exploratory geographical analysis. The method takes advantage of the parallel search mechanism a flock implies, by which if a member of a flock finds an area of interest, the mechanics of the flock will draw other members to scan that area in more detail.



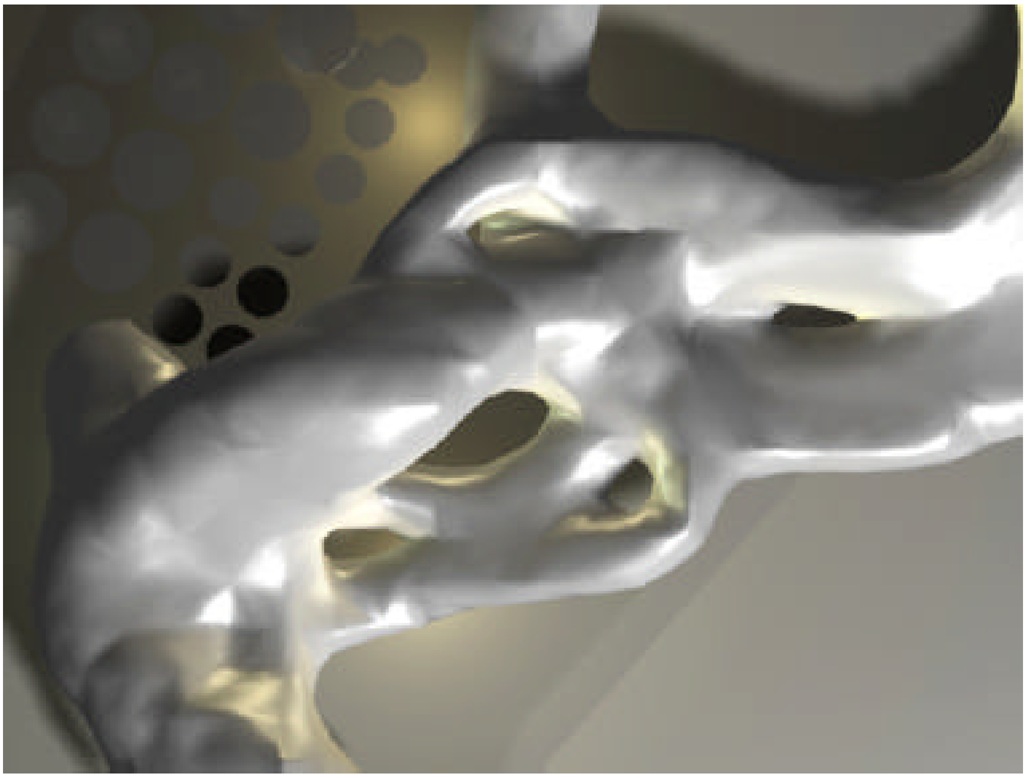
Result of the learning process in the site after 1000 , 5000 and 10000 iterations (8 hours).

The third swarm therefore was again of a flocking kind. One of the advantages of these is that since the lattice space and all its Cellular Automata operations such as diffusion are not needed anymore, it is possible to reduce enormously the amount of computation necessary.

The system shows the same characteristics for cognition explained earlier, that is, the capacity for remembering and forgetting, which we described when describing evaporation of the morphogen as essential in the process of learning.

The Algorithm.

Each agent would have now a variable speed, with a common minimum and maximum for all agents. In case of collision trajectory, the agent will slow down. In the absence of collision, the agent will steadily speed up until it reaches its maximum. This means that in the event of a 'conflict' space, or an area where one agent detects many collisions consecutively, agents will cluster; since their speed is low, they will have the inertia to remain there, where as faster 'free' agents in the neighbourhood will be easily attracted to the area. The information about collision areas is therefore stored in the speed of the agents. Speeding up will be the equivalent of forgetting in the system.



Isosurface wrapping the paths of the agents.

With this mechanism, the swarm will move around detecting collision areas. If the area doesn't have enough weight compared with another, it won't be able to attract enough agents. The system will end up discriminating the areas were most collisions occur and which are more accessible, after a time.

2.2 System Coupling with Another System and consensual domains

Until now, swarms have being moving in geometrical representations of spaces. These swarms have been shown to have the ability to define different qualities of their environment, comparing patterns of collisions and unfolding a learning process.

The space agents move in doesn't necessarily need to be any representation of physical space. It is possible to use the swarms of the different types to perform searches in n-dimensional phase spaces. The possibilities of this approach as an optimisation mechanism have been underlined by Eberhart and Kennedy [15], and their performance compared with similar search engines and devices such as Genetic Algorithms. One possible advantage of this approach is the easy understanding of the relation between the search mechanism and the solution space, and the way this search is performed. It also makes it possible to compare the process with other evolving systems, like the evolution of ideas, opinions and beliefs in social systems.

In the next step such a device has been built and tested for its ability to respond to human interaction. We have in this case the second type of structural coupling described previously as the coupling of two systems, which define a consensual domain. This can be described as the sphere defined by ' *interlocked (intercalated and mutually triggering) sequences of states, established and determined through ontogenic interactions between structurally plastic state-determined systems.'* [16]. We could also find this consensual domain when looking at the relations between agents in the previous swarms. The difference now is that this domain exists also between the swarm as a whole, and a human partner.

2.2.1. The Algorithm

The algorithm for this swarm is also a development of the basic Reynolds Boids algorithm, where each agent has been given a mass variable in order to incorporate the capacity of learning as well. The acceleration the individual agents experience each iteration depends on this variable: light weights mean higher speeds, heavy weights slower ones. The cohesion of the flock is also influenced by the mass: heavy agents will attract others to their neighbourhood stronger than light ones. Light agents will also have less inertia, where heavy ones will tend to keep their variables unmodified.

The system needs the slow "evaporation" of the mass variable in order to be adaptative and therefore to learn.

Some "sympathetic mass transition" has also been implemented, in order to make agents in the close neighbourhood of a very heavy one become also heavier and slower, and consequently clustering in that region (In the previous swarm this happened automatically from the interaction with the environment).

The weight that is assigned to each agent could have its origin in a "fitness function". The position of each individual of the swarm would then be mapped onto a "phenotype" and a fitness value calculated for it. In cases of good fitness a heavy weight would be given to the individual, to indicate the system that that position is worth keeping and mimicking. Bad positions would this way be forgotten, since the agents in those areas would have low inertia and the tendency to move rapidly away from them, towards more successful territories. Regions with good values will compete with others for the attention of the agents, and if not successful enough, they will be forgotten.

The implementation of a strategy based in the assignment of weight seemed appropriate in this particular case where there is interaction with a human. In a more general case it would be possible to evaluate each position for each iteration. In this case the difference of position are very small for each iteration and therefore the communication with the user and testing of the positions must be made at intervals of many iterations. The mechanism for copying some of the weight of heavier neighbours allows agents to react to the result of the "fitness" of those neighbours without direct testing of each particular position for each iteration. Of course this or a similar mechanism would also allow the testing of fitness at separate intervals, and therefore it would improve the economy of calculations of the algorithm.

In this instance of the flocking algorithm no specific fitness function has been assigned, using instead a so-called "eyeball test", in which a human partner decides which position is more fitted. The process of interaction between both defines what has previously been described as a consensual domain.

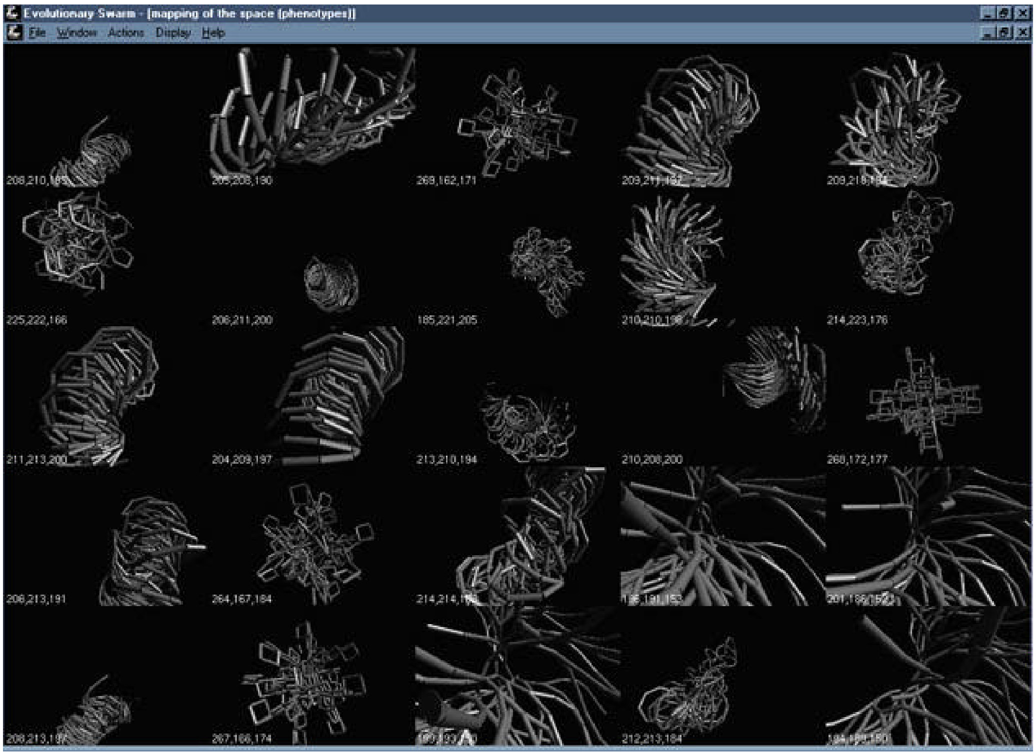
Additionally to Reynolds basic flocking algorithm, the agents choose sometimes one of their neighbours randomly. This rule has been found to be an effective way of avoiding the creation of completely uncommunicated and unrelated clusters of neighbours, allowing the swarm to adapt faster.

The collision avoidance with each other is also worth mentioning again in this context. It introduces slight discrepancies between the positions of the individual agents (they will have similar positions, but not the same one, or in other words, the phenotypes will be very similar but most of the cases not completely identical). This last element is in contrast with what Kennedy and Eberhart explain in their paper, about the possibility of for example two 'opinions' sharing the same space [17]. The introduction of these differences in position allows the agents to scan areas more thoroughly and extensively, particularly helpful when working with design spaces and "eyeball test" kinds of fitness.

The way the space is mapped in to a phenotype is simple: in this case the three-dimensional space defined has been understood as the parameters for a branching algorithm. Each of the values of the position vector of the agents becomes a rotation angle around X, Y and Z in the branching of the phenotype. It is thus not necessary to have an infinite space, but it can be bounded between 0 and 360 in each of the axes. The decision of using such an algorithm as a phenotype is not arbitrary. First it allows to create a big variety of different forms from very few parameters, which was reduced to three in this case to allow the demonstration of the operations of the swarm (the representation of spaces of higher dimensions has obvious difficulties). Secondly, it produces forms with many symmetries, in which patterns can be easily recognised and forms classified by the human partner. Therefore the choice of such a phenotype is not aesthetic, but functional.

2.2.2. The program: Evolutionary Swarm.

Evolutionary Swarm is a Windows application developed to test the capacity of a swarm algorithm to define a consensual domain. It implements the algorithm previously described and provides it with an interface. This interface is made of two basic windows: one in which the swarm is shown in relation with the search space, and another one in which the position of each individual has been mapped in to a phenotype, through a branching algorithm. Each of these phenotypes can be selected by the user, increasing in this way the mass variable of the agent associated with that position. The agent will accordingly slow down and tend to remain in the vicinity of that space. Because of the dynamics of the swarm, the position of the phenotype selected will be 'mimed' by the rest of the individuals and reproduced with more or less accuracy through out the agent population. For generating more diversity among the swarm it is only necessary to evolve it without any particular member selected. This will increase the differences between the individual positions (less consensus) and therefore the variety of the phenotypes.



screensave of the interface of the evolutionary swarm.

2.2.3 Parallels with social systems

Parallels between biological evolutionary systems and the development of ideas have often been made, being perhaps the one implied in the concept of memetic evolution the most popular of such comparisons. The word “meme” was coined by Richard Dawkins in his book The Selfish Gene. Memes tend to make copies of themselves and are therefore “replicators”, like genes. ` *Examples of memes include melodies, icons, fashion statements and phrases. Memes function the same way genes and viruses do, propagating through communication networks and face-to-face contact between people*’ [18].

In this context the flock positions of its individuals could also be compared with opinions, preferences etc, where the movement of the individuals would be equivalent to the shift of those opinions inside a social system. Individuals may hold some ideas or positions, and at the same time show some 'sympathies' or tendencies towards others, often in the close vicinity of the ideas that they currently hold. If these sympathies are sustained for long enough or are very strong, the positions will shift towards the sympathised convictions. This idea of sympathies or tendencies is similar to the direction vectors in the swarm model. The different clusters of agents that emerge and the region they define could be compared in a social system with close sets of ideas, "ideologies" or shared beliefs.

Since there is some kind of 'conversational' human/machine relationship between the swarm and a person interacting with it, the forms work in some way as signs, in the sense that they are interpreted by the person and meanings attached to them, such as good/bad, spider-like, spongy, etc. The swarm tends to 'understand' and 'agree' with the choices made by the person interacting with it, but it also seems to 'disagree' slightly, or at least to not fully understand the preferences of the user. It is only in this way that the conversation is possible, and the consensual domain formed. If the machine would agree immediately, that is, if all agents would converge exactly to the point specified, conversation would be impossible. Through this game of differences the conversation can evolve.

Thus, if we understand the forms of the phenotypes as some kind of sign their relations are similar as the signs in a linguistic system. The mechanics of these resembles the one of the swarm: '*As soon as a certain meaning is generated for a sign, it reverberates through the system. Through the various loops and pathways, this disturbance of the traces is reflected back on the sign in question, shifting its 'original' meaning, even if only imperceptibly. …Each trace is not only delayed, but also subjugated by every other trace'.* [19]

Even more similarities emerge if we think of a phase space of signs, or the space of all their possible meanings. '*Words or signs, do not have fixed positions. The relationships between signs are not stable enough for each sign to be determined exactly. In a way interaction is only possible if there is some 'space' between signs. There are always more possibilities than can be actualized (Luhmann 1985). The meaning of a sign is the result of the play in the space between signs. Signs in a complex system always have an excess of meaning, with only some of the potential meaning realized in specific situations.'* [20]

2.2.4 Comparison between models of adaptation.

As we have seen in comparison with a memetic system the swarm model in relation with the evolution of ideas is more akin to their emergence through smooth changes of opinion than with the actual spontaneous birth of them. The discovery of new 'ideas' in the swarm is performed in a smooth way, by the tendency of the agents to overpass an optimum point and by the amplification of these mistakes. This slow evolution and drift between ideas becomes one of the substantial differences between Genetic systems such as the one constituted by memes, in which there is a random search mechanism involved (mutation) and that of the swarms, in which the shifting towards new ‘ideas’ is smooth. If mutation in memetic systems is thought as the accumulation of miss-replications or memetic drifts, the smoothness of the evolution of the swarm could then be understood as an equivalent continuous and low intensity memetic drift. In the swarm evolutionary paradigm random mechanisms similar to mutation could also be implemented, as perhaps the possibility of random jumps of the agents inside the search space.

But there is also possible to highlight other differences between the genetic and the swarm models. Carl Popper [21] distinguishes between two basic levels of adaptation: genetic adaptation and behavioural adaptation. The main difference between the genetic and the behavioural levels of adaptation is this: mutations at the genetic level are not only aleatory, but also completely “blind”; they are not directed towards an end, and the survival of a mutation can not influence in the posterior mutations, not even in the frequency or in the probabilities of their apparition. In the behavioural level trials are also more or less random, but they are not completely “blind” in any of the ways mentioned. In the first place they are directed towards an end, and in the second, animals can also learn from the production of a trial. According to this, the swarm model could be compared to some extent with the behavioural model of adaptation, in the sense that the direction vectors of each individual can be interpreted as ‘directed towards an end’ (in the abstract space to optimise their positions). The direction vectors, at the same time also influence next ‘mutations’, or shifts in position. Popper also emphasises how behavioural adaptation is in general an intensively active process: in the animal –especially in the play of the young animal –, and even in the case of the plant, which investigates actively and constantly its environment.

Conclusion.

In this paper we have discussed the development of sensori-motor intelligence and its particular instance of the swarms. Those have been extensively studied from this point of view, and different models of them tested. Processes of learning have been developed through different approaches first in swarms that evolve in a geometrical environment, and finally in an abstract representation of a design space. The possibilities of such a model have been explained and then the model has been compared with evolution of ideas in social sitemaps and with other evolutionary systems, in particular genetic systems. Most of the conclusions established about this last model of swarm could also be extended to others. Instead of flocking algorithms, stigmergic swarms could be implemented in similar ways.

References.

1. Walter, W. Grey '*An Imitation of Life'*, Scientific American, 182(5), pages 42-45,1950.

2. Braitenberg, Valentino '*Vehicles: Experiments in Synthetic Psychology'*, MIT Press, (Mass) 1984.

3. Von Foerster, Heinz, *On Constructing a Reality* in '*Observing Systems'*, Intersystems Publications, 1984. Pages 288-309.

4. Maturana, Humberto '*The organization of the living: A theory of the living organization'*, International Journal of Man-Machine Studies, Vol. 7 (1975). From Randal Whitaker,Tutorial Autopoiesis and Enaction, Umeå Universitet (Sweden) http://www.informatik.umu.se/~rwhit/Tutorial.html

5. Ibid 4.

6. Negroponte, Nicholas '*The Architecture Machine'*, MIT Press, (Mass).

7. C. Kube, Ronald and Bonabeau, Eric '*Cooperative transport by ants and robots'* (online paper).

8. Reynolds, C.W. Flocks, herds and schools: a distributed behavioural model. Computer Graphics, 21(4). On line: http://hmt.com/cwr/boids.html

9. Wilson, E.O. '*Sociobiology: the new synthesis.'* Cambridge MA: Belknap Press, 1975.

10. Grasse, P. 'La reconstruction du nid et les coordinations interindividuelles chez Bellicositermes natalensis et Cubitermes sp. La theorie de la stigmergie: essai d'interpretation du Comportament des Termites Constructeurs' Insectes Sociaux 6 (1959). Pages 41-48. 11. in Bonabeau, Eric , Dorigo, Marco and Theraulaz , Guy '*Swarm Intelligence. From Natural to Artificial Systems'* Oxford University Press, 1999.

12. Ibid 9.

13. Millonas Mark M.*'Swarms, Phase Transitions, and Collective Intelligence'* in Artificial Live III Ed. Christopher G. Langton, SFI Studies in the Sciences of Complexity, Proc Vol XVII, Addison-Wesley 1994.

14. MacGill, James and Openshaw, Stan *'The Use of Flocks to drive a Geographic Analysis Machine'* (online paper) www.geog.leeds.ac.uk/pgradspj.mcgill/gis.html.

15. Eberhart, Russ and Kennedy, James '*Computational Intelligence'* PC Tools, AP Professional, USA 1996. http://www.engr.iupui.edu/~shi/Coference/psopap4.hrml

16. Ibid 4.

17. Ibid 15.

18. Dawkins,Richard . *'The Selfish Gene'* Oxford, Oxford University Press, 1976.

19. Cilliers,Paul . *'Complexity and Postmodernism. Understanding complex systems'* Routledge, London, 1998.

20. Ibid 18.

21. Popper, Karl. *'The myth of the framework. In defence of science and rationality'* Routledge, London, 1994.

22. Coates P.S & Amy Tan 'Using Genetic programming to explore design worlds' Middlesex Art & Design research colloquium 1996

23. Coates P.S. A.Tan & T Broughton 'Using Genetic programming to explore design worlds' Caad Futures 97 Munich August 1997

24. Coates P.S. H.Jackson 'Evolving spatial configurations' Eurographics 98 ICST.London 1998

25. Coates Jackson& Broughton in : Ed P.Bentley "Evolutionary design by computers" Chapter 14. Morgan Kaufmann 1999

26. Coates & Makris "Genetic programming and spatial morphogenisis AISB 1999 Edinburgh

27. Coates & Schmidt "Parallel architecture" ECAADE 1999 Liverpool

28. Coates & Thum "Agent based modelling" Greenwich 2000 University of Greenwich London 2000