

## Evolving swarm of UAVs

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**Abstract.** This paper reports on an ongoing study investigating the feasibility of using an evolutionary method to develop the rules governing Self-Organised (SO) systems for use in swarms of unmanned aerial vehicles. In general, it is difficult to design swarm systems that follow explicit global behaviour. Unlike optimising a predefined objective function, the solution to the problem is the emergent behaviour in the SO systems which results from simultaneous interactions among agents and between agents and their environment. In this study, evolutionary algorithms are used to investigate their control and effectiveness in synthesising the weighting of different rules on SO emergent behaviour. Both homogeneous swarms and heterogeneous swarms were considered though the results provided are for a case study investigating the simplest problem a homogeneous swarm without mutation. Though simple this study does indicate the potential of the approach.

**Keywords:** evolution; multi-agent; self-organising swarms; search and rescue

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### 1. Introduction

Swarms of aerial vehicles have advantages over single vehicles in a number of situations that exploit their unique characteristics. They are able to distribute their sensors more widely, require less sophistication and are robust in that the failure of one element leads to the degradation of the unmanned aerial system rather than complete failure. When significant autonomy is transferred to the individual vehicles further advantages appear in the reduction in data transfer and computing required.

The design of cooperative controllers by means of Self-Organisation can be found in literature (Ergnac 2007, Gazi 2005, Hauret *et al.* 2009 and Nowak 2008). The applications include: persistent coverage, wide area search, communication relay, formation control, and target sets engagement. The previous research that applies swarm methodology was limited to relative simple scenarios which lack complex task constraints. The reasons for the lack of successful applications in relative complex scenarios are as follows: First, the swarm intelligent systems are hard to develop. As opposed to the centralised algorithm, the path to the problem solving is not the

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minimisation of an objective function, but the emergent properties in this system due to the interactions among agents and between agents and the environment. The emergent properties can only be observed through the simulation of multiple scenarios. Therefore for the development of control algorithm based on swarm intelligence not only must individual behaviours be determined but also what interactions are required to generate the desired global behaviours (Bonabeau *et al.* 1999). Second, it is difficult to enforce task constraints using any decentralised controller. This is mainly due to the absence of global communication and coordinating information. Optimality is impossible to achieve if high level cooperation among the agents is required. Thus, developing swarm intelligence based systems usually adopts a bottom-up process and focuses the development of interactive sets and the rules that govern their interaction. It is the aim of this paper to examine one possible methodology based on evolution for improving their performance.

The remainder of this paper is structured as follows. Section 2 describes the underlying mechanism for the self-organised swarms. In section 3, the swarm design methodology based on evolution is presented. Section 4 investigates the application of using evolution to design a UAV swarm carrying out search and rescue mission. A summary of this study is given in section 5.

## 2. Self-organised swarms

Swarms of vehicles operating largely autonomously have developed based on bio-mimicry (Fig.1). Social insects and indeed large social mammals have developed the ability to cooperate to achieve an outcome that would be beyond the individual. In the case of social insects such as ants this has

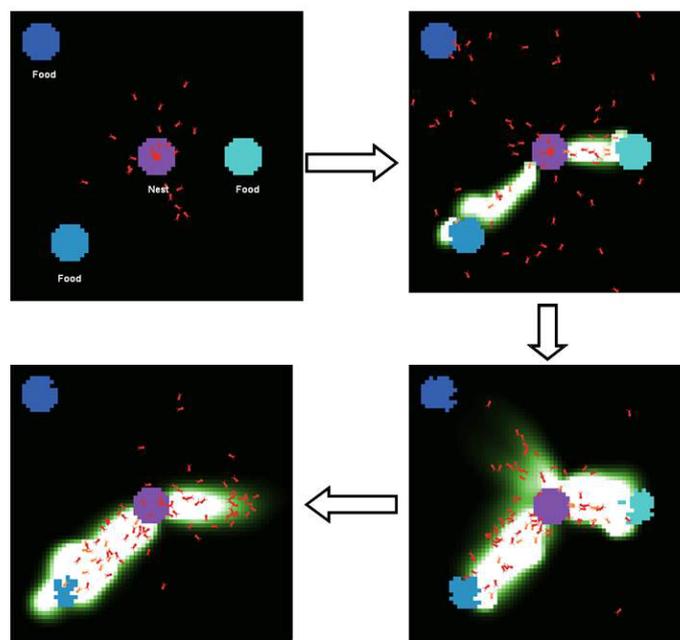


Fig. 1 Simulation of Ant Foraging Using NetLogo (Wilensky 1999)

been achieved with very limited cognitive capacity. Investigation into how this is achieved is well understood. In the work by Bonabeau, *et al.* (1999), several abstract models of the collective behaviour of the social insects are presented. In general, the mechanism by which individuals coordinate their activities relies on stigmergy. Stigmergy is the mechanism within which individual behaviour modifies the environment, which in turn modifies the behaviour of other individuals.

The coordination mechanism using pheromones can be demonstrated using ant foraging activities. The ants initially move in a random direction looking for food. When the ants find a food source, they carry the food back to their nest, dropping a chemical substance called pheromone as they move other foragers follow such pheromone trails. As more ants carry food to the nest, the more chemical is deposited, and hence the higher the probability of recruiting additional ants. Also ants that use the shortest route return to both food and nest more quickly resulting in a stronger pheromones track. Fig. 1 shows the simulation of trail-laying and trail-following behaviour when ants are foraging. The use of digital pheromones for controlling and coordinating swarms of unmanned vehicles can be found in literatures (Erignac 2007, Sauter *et al.* 2009, Parunak *et al.* 2005). The pheromone information, exchanged through shared environment, changes dynamically over time via propagation and evaporation this allows new information to be spread and removes old information. The dynamic nature of the mechanism yields solutions that can adapt to rapidly changing environments.

Fig. 2 shows the flocking of a swarm of agents as simulated in NetLogo® software versus the visualisation of a swarm of starlings in Rome (Wilenski 1999). In this simulation, a number of parameters are varied. The emergent swarming behaviour is thought to be deterministically chaotic. The results show, that the nature of the formation of a global flock is sensitive to the initial starting positions of the agents. Thus, it can be surmised that the flocking system has the inherent property of sensitivity to initial conditions with maximum turn rate, velocity and sensor range. It should be noted in the real world, and indeed in most simulations, it is extremely rare, if possible, to know the starting conditions with sufficient accuracy that the exact later formation can be predicted. Also, each parameter's influence on the other is nonlinear as well as unpredictable. From this

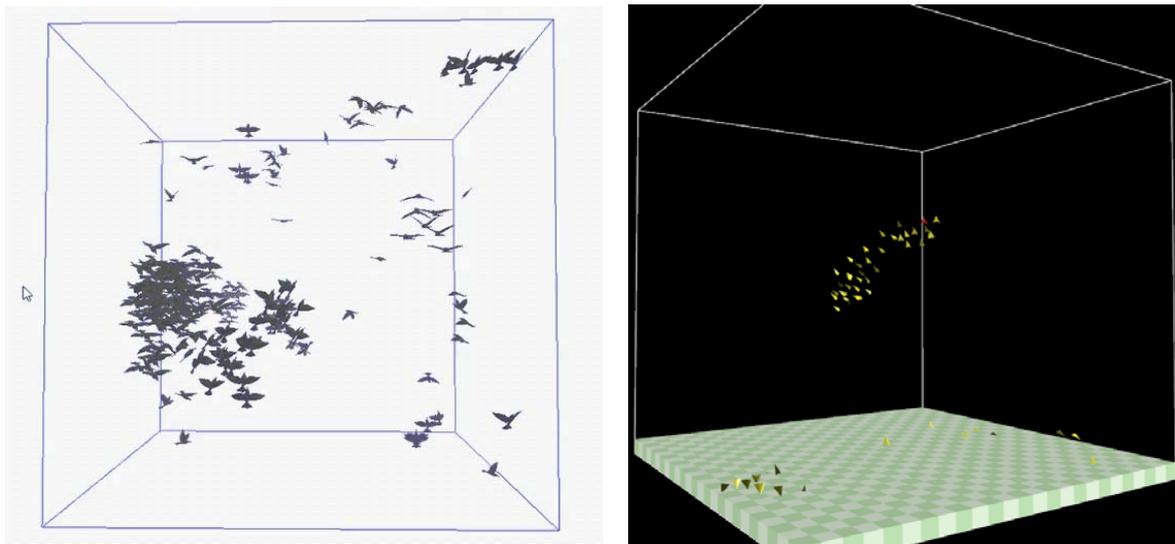


Fig. 2 Starlings of Rome versus simulation of flocking birds

investigation, we were able to obtain the critical parameters that influenced the swarm formation and control; these parameters were then used as the evolving parameters in the case study.

### 3. Swarm design based on evolution

Since Darwin first postulated evolution by natural selection and refined it in his famous book “On the Origin of Species”, the idea that biological systems mutate to increase their fitness for purpose has been generally accepted. There are from the system designer’s point of view a couple of often misunderstood areas the primary one being what is meant by a biological system and where does one draw the boundaries. It is often assumed that the boundary is drawn around an individual entity though Darwin himself argued that swarms of bees acted as one entity. In practice, like in thermodynamics, the boundary can be placed wherever it best allows the phenomena to be investigated. Richard Dawkins placed a boundary in his book “The Selfish Gene” at the level of the Genes (Dawkins 1990). The other issue that has to be addressed is does the process have a direction. There is often a miss held belief that biological evolution can be predicted from the evolutionary history. It is not that simple though it can be argued that the system purely attempts to find a closer match to the fitness thus some birds loose the power to fly and some mammals return to the sea but this is disputed. Thus to mutate an engineering system, some form of fitness factor has to be defined but it may be dynamic and change during the process.

The individuals that make up a swarm can have a single entity with common characteristics (homogeneous swarm) or genetically unique individuals within the swarm (heterogeneous swarm). There are a number of different techniques that can be deployed to improve either type of the swarm involving the evolution of either the individuals within the swarm or the evolution of the swarm itself. The main working principle for evolutionary algorithms is to maintain and evolve a population through selection, recombination and mutation.

#### 3.1 Homogeneous swarm

These types of swarms are the easiest to mutate to success. All the agents are identical and thus the swarm approaches its fitness by making identical changes to each individual within the swarm. Such swarms are often less efficient than those that contain individual agents with different strengths and weaknesses and in particular they do not gain the advantages associated with the wisdom of crowds. As each behaves in a close to identical fashion any generic weakness will be reflected in all vehicles and a given input will lead to an identical output. The major advantage of this approach is because the vehicles are identical they are interchangeable so any one vehicle can replace any other adding to the ruggedness of the swarm. Most of our work to date has concentrated on this type of swarm and due to their inherent simplicity they are the most likely to find early applications in the real world.

#### 3.2 Heterogeneous swarm

These are much more difficult to evolve but have greater potential. By evolving the individual agents the performance of the whole swarm is increased. Most social insect evolution (ants, bees etc.) has not followed this route with all the agents being clones or at least siblings despite the risks of inbreeding and very slow mutation. Social animals with greater cognitive capability

(wolves and starlings) tend to evolve separately though still retaining a collective structure. Such swarms are much more able to deal with a dynamic environment and have the built in advantage of wisdom of crowds.

In a heterogeneous swarm such as a group of people a phenomena can be detected that is very advantageous. When asked to make a decision on which they have limited knowledge as a group they are able to get close to the correct answer. The graph, Fig.3, shows the result of such a test. In this case we asked first year engineering students to guess the number of marbles in a non-cylindrical jar. There were 899 students which made a reasonable sample and the average, 90, was very close to the actual value despite only about forty students guessing correctly. This is defined as the wisdom of crowds.

We expect these same phenomena to exist in heterogeneous swarms though we have yet to clearly demonstrate it. If this does prove to be a characteristic of such a UAS it will open up new possibilities of missions into less predictable environments.

#### 4. Case study: UAV swarm applied to search and rescue mission

The use of evolutionary algorithms enables the ability to control and synthesise the weighting of different rules on self-organising behaviours. This is done by the formation of proper evolutionary algorithm chromosomes such that its mapping relates to the control parameters or the weighting of the rule sets. Genetic algorithms are used in evolving the search agents through changing their attraction and repulsion parameters, such as those that were introduced by Goldberg(1989) and Stnedahl *et al.* (2008) Evolutionary algorithms are versatile in their ability to

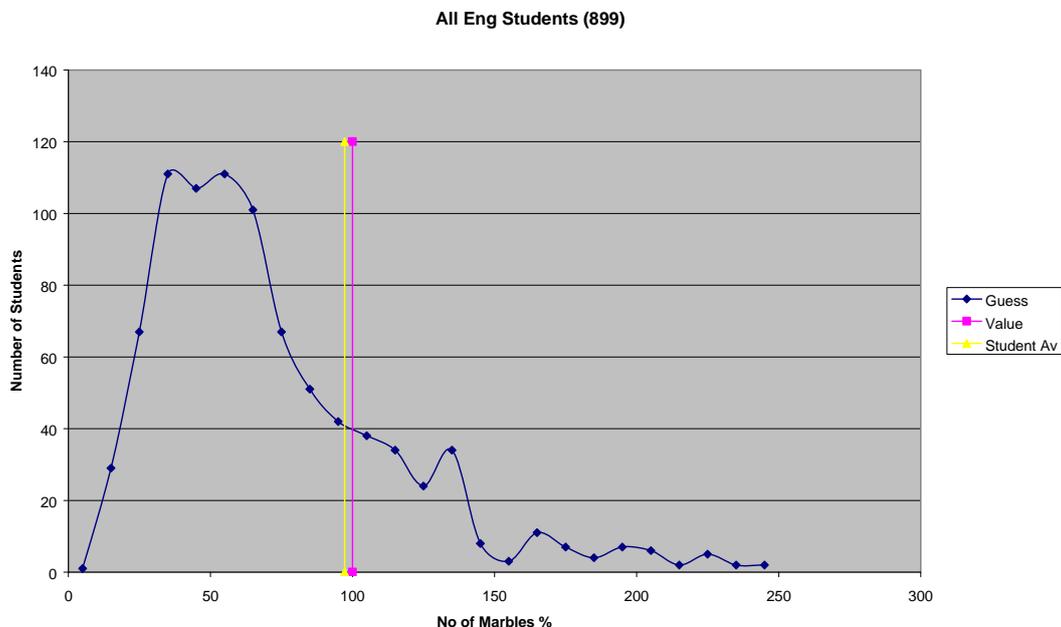


Fig. 3 Wisdom of mass experiment results

find a solution to many complex problems, and are capable of being incorporated into many different types of data structure, such as integer, symbolic, finite state values and binary. The ray-coding technique used in genetic mutation is similar to that proposed by Weinstein (2011).

#### 4.1 Simulation model development

##### 4.1.1 Assumptions and simplifications

- The different formations for the swarm were first simulated in a two-dimensional model to enable us to evaluate their behaviour with the least amount of computational resources. However, the three-dimensional model will need to be further developed to gain a more realistic simulation before final implementation with real UAVs.
- The formations and the controlling algorithms developed were not tailored to be used by a particular aircraft and thus used basic flight dynamics, the turning rate, rate of acceleration, velocity and sensor range. The UAVs used in the models are simplified agents called “turtles”. The sensors on the models are greatly simplified such that each UAV would have a fixed sensor radius, in which 100% certainty is assumed for identification of targets. Furthermore there it is assumed that neighbouring UAVs would not block the line-of-sight of other UAVs in target detection, i.e. there is no “sensor shadow”.
- It is assumed that the search area is bounded thus making it a finite space in which the vehicles can operate.

##### 4.1.2 Model requirements

The model is intended to allow the UAVs to exhibit certain behaviours as listed which are in effect the rule set governing the swarm behaviour:

- UAVs patrol the map area in search of targets.
- UAVs avoid collisions with other UAVs targets, and stay within the bounded area.
- When the target is sighted by the UAV, it is required by the UAV to track the target until rescuers arrive.

The concept of the evolutionary algorithm is that it allows for new solutions/generations based on how good the previous solutions (feedback loop) are, via mutation or crossover, Fig. 4.

##### 4.1.3 Swarm behaviour control

Different behavioural rules and weighting are applied to the swarm to investigate its ability to

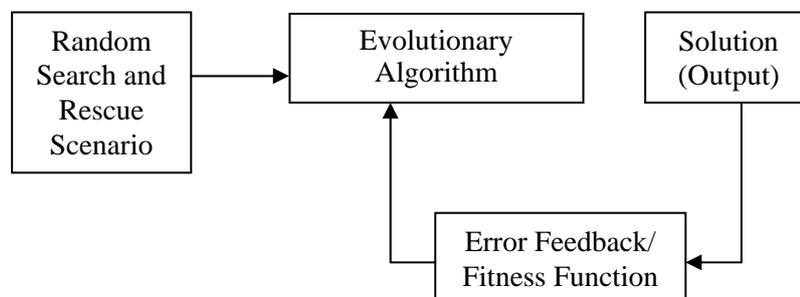


Fig. 4 Schematic of genetic algorithm

fulfil the search element of a search and rescue mission. Evolutionary algorithms, namely genetic algorithms are used to improve the performance of the swarming and search behaviour of each agent. The genetic algorithm that was used is based on the algorithms presented by Price and Lamont (2006).

#### 4.1.4 Genetic algorithms

Genetic Algorithms are adaptive search algorithms. They are based on the evolutionary ideas of natural selection and genetics. They represent an intelligent exploitation of random search within a defined search space to solve a problem. The individuals that make up a swarm can have a single entity with common characteristics (homogeneous swarm) or have each individual within the swarm to be genetically unique (heterogeneous swarm). There are a number of different techniques that can be deployed to improve either type of the swarm involving the evolution of either the individuals within the swarm or the evolution of the swarm itself. The main working principle for evolutionary algorithms is to maintain and evolve a population through selection, recombination and mutation.

Computational evolutionary algorithms generate populations as a number of entities such that each individual in the population influences the performance of the population in each cycle, called a generation. The evolution starts from a population of initially randomly generated individuals with the fitness of every individual in that generation being evaluated both as an individual and as a participant in a swarm. The next generation population is generated by first selecting the relatively fitter individuals or swarms from the current generation and then re-applying certain aspects of their characteristics to the next generation. The fitter swarm is decided relative to the fitness value or cost function of the swarm generation (homogeneous swarm) or individual agent (heterogeneous swarm). This can be done either by deterministic means (recombination) or random mutation.

The genetic algorithm is based on similar algorithms developed by (Price and Lamont 2006) and (Stinedahl, Rand *et al.* 2008). Essentially this genetic algorithm allows teams of UAVs to compete against each other, rather than competing as individuals. Caution is required when incorporating Gray coding, as required by NetLogo, into simulations as there is often extended amount of computational time required for a whole evolution cycle. However, an excellent way to speed up the computation of each generation is the use of parallel computation on each individual. This is also another advantage of evolutionary algorithms.

New UAV teams are created using crossover-recombination and random mutation. For each pair of “parent” chromosomes, the genetic algorithm randomly selects two crossover points.

The fitness of every individual within a generation will be evaluated both as an individual and as a participant in a swarm. The bit strings are encoded using Gray code which is an alternative binary representation where successive numbers differ only by a single bit. This is done to reduce the effect of Hamming cliffs - where the genetic algorithm is unable to reach an “adjacent” solution due the number of bits that need to change.

In the homogenous swarm experiment, there are four force coefficients being evolved, as the UAVs on any particular team are identical. In the heterogeneous swarm experiment, the representation is slightly more complicated. Each UAV is allowed to evolve individually, so the chromosome describing each team must be extended to include genes for each of the individual UAVs.

Initially, a random population of UAV teams is generated. The “fitness” of each team is evaluated by allowing them to execute the search-and-track simulation several times. The team is

then awarded a fitness score between 0 and 1, based on how quickly it was able to find the targets.

The most successful teams are then selected as “parents” for the next generation using a tournament selection procedure.

#### *4.2 Methodology of evolution*

The characteristics of the swarms may be initially randomly selected but if there is information that indicates particular properties will be beneficial they can be used to initiate the swarms. The swarms that prove to be the best performers are then randomly blended and the exercise rerun with a number of blended swarms and the process repeated. This should lead to an improvement in performance until an acceptable level is reached. There are a number of questions and fundamental problems that arise from this approach. The first question is how many parent swarms, or agents, should have their characteristics blended to maximise the chance of success. Nature exclusively uses two parents to blend half the genes of each to create the children but it is not obvious why a better result may not be obtained by a greater number of parents. In the case of the nurture part of the evolution a number of individuals both formally and informally contribute to the final characteristics of more evolved mammals. The main weakness of the mutation approach is that valuable properties are discarded simply because they have not been randomly selected, from the parents that might prove beneficial to the mission. This can to some extent be mitigated by sheer brute force running a large number of simulations but if the vehicle is defined by a significant number of parameters this soon become overwhelming. It is also possible to insert a random or directed mutation that may allow a discarded characteristic to be resurrected.

Fig. 4 shows the application of genetic algorithms through the use of an error feedback loop from the output as a performance measure to improve subsequent generations. That is, new solutions/generations (Fig. 5) are the result of how good the current solutions (feedback loop) are via mutation or crossover.

The determination of an appropriate fitness factor and the initial conditions set are the only variables available to the designer and thus must be chosen with great care. There are normally a number of constraints on a UAS. Take a simple search mission. There may well be a need to accomplish the mission as quickly as possible but this will normally be constrained by the financial cost associated with success or failure. Once one goes to the search level is it better to cover the terrain more times or less times with a greater chance of success each sweep. All these and many other factors will affect the mutation of the vehicle and its control laws. The ability to find the target of interest may also depend on time of day, state of sea in a marine search etc. so the optimum mutation may change during the mission. This is of course again analogues to nature where environmental changes may drive evolution in a particular manner for a period of time and then reverse. This can be clearly observed in the weather cycle where an approaching cold period, ice age, may well suite some mutations while they will be disadvantaged when the Earth goes into a warm period. There is a well-known scenario used to explain this. Assume there is a small animal that lives on the coastal plain of a mythical mountainous island. If global warming occurs, for whatever reason, the plain will start to get inundated with water. Over a period of evolutionary time the animal may adapt to life in the water or in the mountains. In both cases the evolution is driven by fitness for purpose but the two fitness values will lead to a divergence in the animal's structure and behaviour. An interesting area of investigation for UAS developers is to look at mutating their vehicles to a number of distinct fitness factors so a number of vehicles with divergent capabilities emerge.

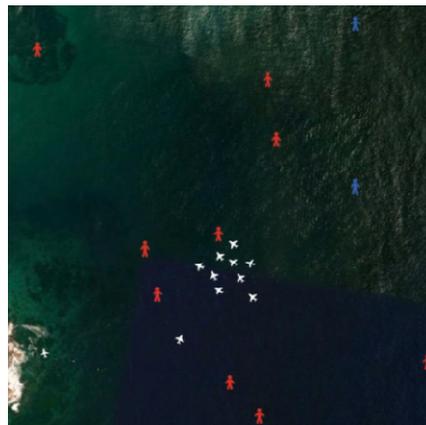
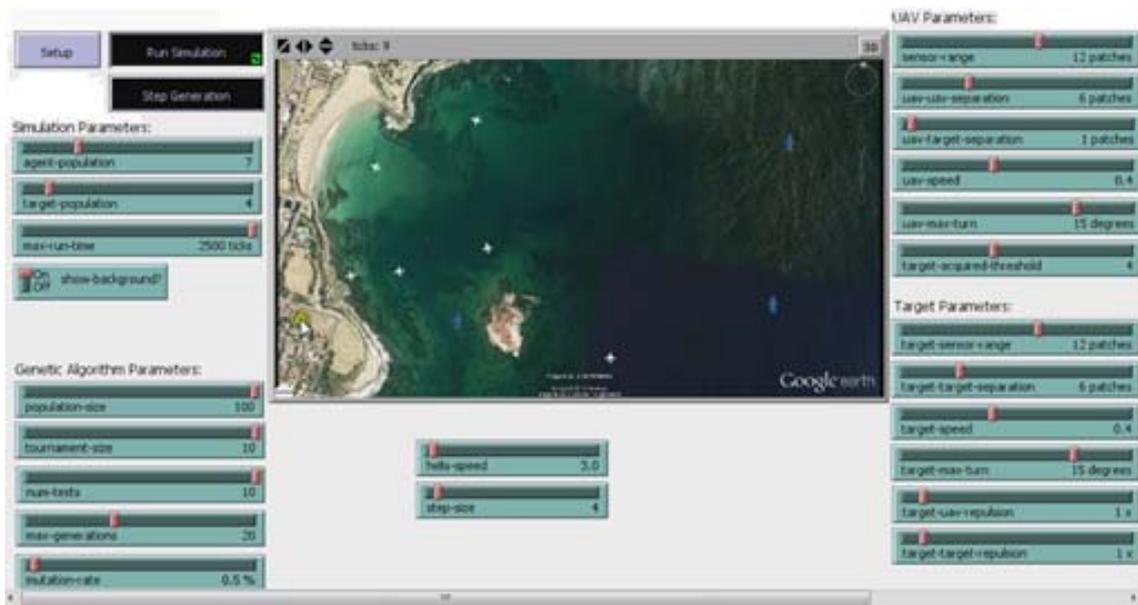


Fig.5 Simulation model interface

### 4.3 Agent behaviour

The basic laws that each search agent follows are outlined below:

**Cohesion-** search agents are attracted to each other in the sense that it would try and fly within its neighbour's boundary.

**Repulsion-** each search agent have a repulsion sphere in which neighbouring agents would change direction if within the sphere to avoid the loss of UAVs due to collision.

**Alignment-** is the urge for each search agent to fly at the same speed and direction as its neighbouring search agents.

**Identify Targets-** targets within the sensor range of the search vehicles are identified visually, on the screen, by the change in the target's colour from blue to red, at which point the search agent would update the coordinates of the red targets to the rescue helicopters and engage in tracking.

Target Tracking- attraction and repulsion rules are used to enable the tracking property of search agents when they switch operation rules from “search” to “track” at the discovery of the victims. The new rule set allows for the search agents to circle the victim at a desired distance until rescue (target-agent repulsion and target-agent attraction) and repulsion is used to stop search agents from tracking the same human, minimise local convergence, via the use of repulsion between the target-agent-agent, the agent would be repelled by the other agent that is already tracking the target. This is similar to Price and Lamont (2006) use of pheromones to indicate when an agent has spotted a target.

In this paper, only the behaviour of the search and tracking agents is considered, the human agents and recovery agents (helicopters) are assumed to follow predefined rules.

#### 4.4 Genetic swam experiment

Genetic algorithms were utilised in homogeneous swarms and the average of their fitness function was recorded for further analysis.

The swarms were initially randomly generated with 100 teams and repeated 100 times in order to gain a normalised value of the results. The fitness function is taken as the average time for each team to converge towards a solution with respect to the maximum simulation time allowed. The testing of a homogeneous swarm undergoing evolution through a genetic algorithm allows for the determination of swarm performance as a result of the genetic algorithm. The genetic algorithm parameters that were used in the experiment are shown in Table 1.

The first set of tests run looked at the homogeneous case as this is the simplest and the most likely to find an early application in the real world.

As can be clearly seen the time taken to complete the mission rapidly decreases until after about 37 generations the time is equal to the predicted time from which the fitness factor was derived. As expected there are some generations that do not do as well as their parents but that is fully expected in an evolutionary model. In this particular case there was no mutation included in the model so each generation breeds true, that is combines the behaviour of their successful parents.

Table 1 Initial search swam parameters

Parameter	Value
Population Size	100
Number of Tests	100
Maximum Number of Generations	50
Maximum Simulation Time	1000 iterations
Number of Search Agents	7
Number of Rescue Helicopters	4
Number of Humans	4
Forces that are evolved	UAV-Target Attraction UAV-Target Repulsion UAV-UAV Repulsion UAV-UAV Attraction

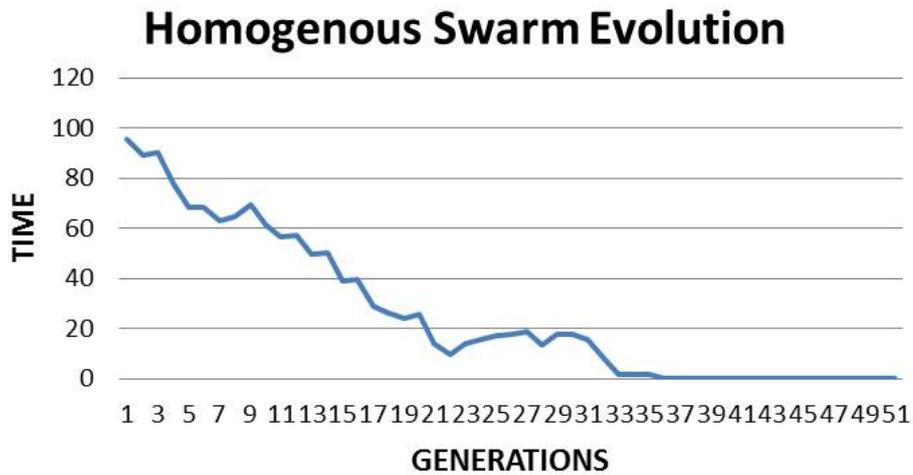


Fig. 6 Simulation of homogenous swarm evolution to success

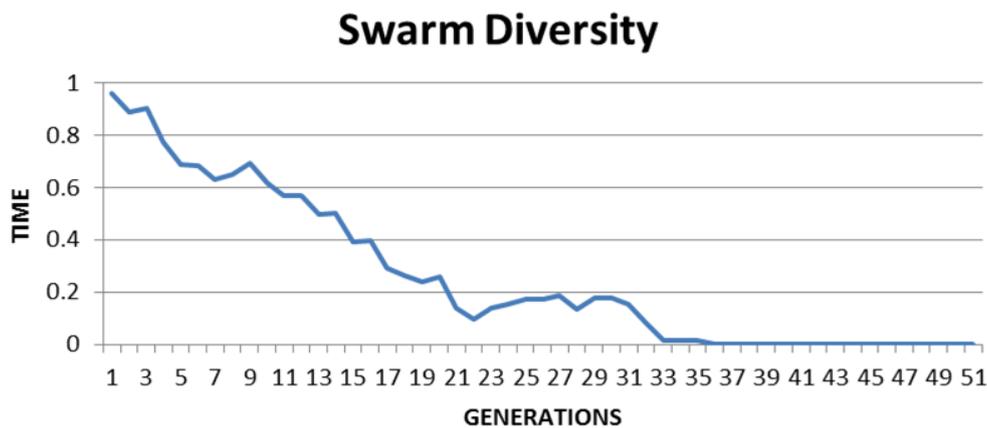


Fig. 7 Simulation of homogenous swarm showing declining diversity

In Fig. 7 it can be seen that the diversity, that is the genetic variation of the swarm declines as their efficiency increases. While this is to be expected as the less successful swarms are rejected what is far less clear the two plots mimic each other so directly. This may well be a product of this case where there was no mutation so after each run the diversity could only decline.

Other experiments we have conducted indicate that if new genetic possibilities are brought into the swarm through mutation the diversity behaves in a distinctly different manner. There is of course an as yet unresolved relationship between efficiency and diversity were diverse systems while less efficient have greater flexibility when faced with an unexpected event.

## 5. Conclusions

Bio-mimicry offers useful insights to those attempting to make engineering entities collaborate.

This is particularly important in the case of Unmanned Aerial Vehicles where there are potentially great gains to be made in terms of adaptability and ruggedness by using self-organising techniques. It is believed that greater diversity both in and between swarms is also an advantage as it should be better able to respond to a changing environment while maintaining baseline fitness, with little variation between fitness values between each simulation run. The capability is, however, in its infancy requiring a great deal of research before practical systems will emerge. The Aerospace group of the University of New South Wales has been exploring various modes of enquiry (Ahmed *et al.* 1990, 1992, Findanis and Ahmed 2011, Pisasales and Ahmed 2002, 2002a, 2003, Lien and Ahmed 2010, 2011, 2011a) to seek answer to a variety of problems (Ahmed and Wagner 2003, Findanis and Ahmed 2008, 2011a, Gatto *et al.*, 2000, 2000a, Shun and Ahmed 2011, Simpson, *et al.*, 2002, Wu and Ahmed 2011, 2012) of practical significance of which real-time simulation (Ahmed and Page 2011, 2011a, Chi *et al.*, 2012, Chi and Page 2013, Michael *et al.* 2012, Sammons and Page 2008) is one. We believe simulation to be very important and probably the most appropriate emerging technology to investigate these types of control system but it is far from clear what mutation strategies will prove to be the most productive or even whether homogeneous or heterogeneous swarms offer the most promise. Our future work will be directed towards answering these questions and in particular trying to determine whether swarms of UAVs can possess wisdom of crowds.

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