Evolutionary coordination system for fixed-wing communications unmanned aerial vehicles

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Abstract. A system to coordinate the movement of a group of unmanned aerial vehicles that provide a network backbone over mobile ground-based vehicles with communication needs is presented. Using evolutionary algorithms, the system evolves flying manoeuvres that position the aerial vehicles by fulfilling two key requirements; i) they maximise net coverage and ii) they minimise the power consumption. Experimental results show that the proposed coordination system is able to offer a desirable level of adaptability with respect to the objectives set, providing useful feedback for future research directions.

Keywords: Evolutionary algorithms, unmanned aerial vehicles, coordination strategies.

1 Introduction

This paper presents an initial investigation into the coordination of multiple unmanned aerial vehicles (UAVs) that provide network coverage for multiple independent ground-based vehicles, when imperfect connectivity is experienced. Imperfect communication can be due to the mobility of ground-based vehicles thus leading to long distances between them and the aerial vehicles, limited radio frequency (RF) power, and other communication failures. Under these conditions, defining flying strategies able to react to topological changes and ensure relaying of data between ground-based vehicles is a complex problem. Fig. 1 is an illustration of a scenario of a group of 3 aerial vehicles that provide network coverage to a number of ground-based vehicles.

Rapid, unexpected changes to the topology require a coordination system of a high level of adaptability. It has to be able to generate flying manoeuvres and formations according to the movement patterns of the ground-based vehicles and their communication needs. Power consumption plays a key role in the success of such a demanding mission. The aim of this research work is to design a decision unit that generates flying manoeuvres that offer network coverage to support as

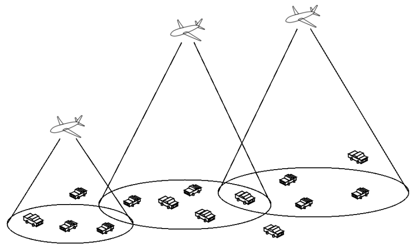


Fig. 1. Communication links are provided to ground-based vehicles. The overlap coverage is found at intersections.

many ground-based vehicles as possible, while the power management follows a reasonable trend. Two objectives are identified. Firstly, to maximise the net coverage by decreasing the overlaps between two or more aerial vehicles. Secondly, as the power consumption is related to the distance between the antennae of the transmitter and the receiver, it is important to control the vertical flying of the aerial vehicles such that the slant distances between them and the ground-based vehicles are minimised. The proposed system employs evolutionary algorithms (EAs) [2] as the adaptable decision unit. The results of a first series of simulation experiments are presented in this paper, illustrating the effectiveness of EAs in solving the problem by relocating the groups of aerial vehicles. The outcome of the study indicates that EAs are an efficient way of coordination that fulfils the two research objectives.

The rest of the paper is structured as follows. Examples of related works is presented in section 1.1, followed by a brief discussion of the aerial vehicle models in terms of performing feasible manoeuvres and communication link budget in section 2 and 3, respectively. Experimental results and their discussion is given in section 4, and in section 5 the paper concludes by addressing the future research directions.

1.1 Background

Researchers have explored the possibility of using evolutionary computation to solve path planning and coordination problems for single or groups of aerial vehicles. In [12], a flyable path plan for multiple UAV systems using genetic algorithms (GAs) is presented, suitable for controlling a specific mission area with vehicles flying at a constant altitude via a number of control points. The Bézier curves technique is used to smooth flying trajectories, resulting in a flight that allows each UAV to move very close to the control points.

[1] considers the coordination of multiple permanently flying (in small circles) UAVs in order to support an ad hoc communication network over multiple ground-based users. The authors propose an EA-based solution that allows each UAV agent to adjust its output power levels and antenna orientation, such that the download effectiveness to the end users will be maximised. The ground area

covered by each UAV is determined by the gain of the vehicles antenna. Low boresight gain allows a wider area to be covered but with a lower signal, whereas high gain antenna transmits with higher signal power in the centre of line-of-sight target, but covers a smaller area.

In [8], the authors employ a GA-based approach for a UAV path planning problem within dynamic environments. The authors define a good solution as the path that optimises three components (distance, obstacles, and path length). The genetic representation consists of a series of manoeuvres that are planned according to a maximum turn rate as well as an acceleration/deceleration maximum value, corresponding to the UAV flight.

The work described in [11] proposes the use of B-Spline curves [7] as the way to represent the trajectory of a UAV flight. Generally, the continuous curve of a B-Spline is defined by control points, which delimit the smoothly joined B-Spline curve's segments. The authors argue that unlike Bézier curves, B-Spline curves are more suitable to represent a feasible UAV route, as an update in one of the control points changes only its adjacent segments due to its local propagation.

In [3], the authors investigate a search method for multi-UAV missions related to surveillance and searching unknown areas, using EAs. Their work allows several UAVs to dynamically fly throughout a search space and autonomously navigate by avoiding unforeseen obstacles, without a priori knowledge of the environment. Although the proposal assumes central administration and user control from take-off time to the end of the mission, the authors employ an EA-based approach to generate appropriate coordinates for UAV relocation.

After studying the evolutionary path planner for single UAVs in realistic environments, [5] propose a solution to the coordination of multiple UAV flying simultaneously, while minimising the costs of global cooperative objectives. As long as the UAVs are able to exchange some information during their evaluation step, the proposed system is able to provide off-line as well as on-line solutions, global and local respectively.

2 The UAV kinematics and communication models

The main methodological aspects with respect to the kinematics of the aerial vehicles and the link budget that characterises the communication links, are briefly described in this section. A more detailed description of the methods used for this study can be found in [9].

In the simulation model, an aerial vehicle is treated as a point object in the three-dimensional space with an associated direction vector. At each time step, the position of an aerial vehicle is defined by a latitude, longitude, altitude and heading $(\phi_c, \lambda_c, h_c, \theta_c)$ in the geographic coordination system. A fixed-wing aerial vehicle flies according to a 6DOF model with several restrictions, ranging from weight and drag forces to atmospheric phenomena, that affect its motion. However, as this work focuses on the adaptive coordination of a group of aerial vehicles with respect to the communication network, a simplified, decoupled, realistic kinematics model based on simple turns is considered for the restrictions

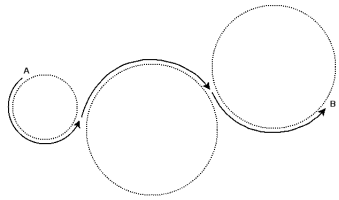


Fig. 2. A manoeuvre of 3 segments of different durations and bank angles, from a starting point A and the finishing point B. Direction of flying is dictated by the bank angle.

of both horizontal and vertical motions [4]. For security and safety reasons, the model is designed to allow flight within a pre-defined corridor, such that the model denies altitude additions or subtractions in cases where the maximum or minimum permitted altitude is reached.

As the flying vehicle is fixed-wing, it may either perform a turn circle manoeuvre with a tight bank angle in order to keep its current position, or implement a manoeuvre generated by the EA decision unit. Taking inspiration from the Dubins curves and paths [6], when implemented, a manoeuvre will generate a trajectory consisting of 3 segments, as depicted in figure 2. Each segment can be a straight line, turn left or turn right curve, depending on the given bank angle.

The EA is free to select the duration for any of the segments as long as the overall duration remains equal to the time of one revolution circle manoeuvre. This strategy ensures synchronisation between all aerial vehicles within the group. With a bank angle of 75 degrees and a constant speed of 110 knots, one revolution time is approximately 6 seconds. The aerial vehicles perform 2 turn circle manoeuvres before they are allowed to implement the latest generated solution from the EA. This time window ensures that the artificial evolution will have reached a result, while at the same time the aerial vehicles will fly in a controlled and synchronised way, keeping their previous formation. Furthermore, the time window ensures that the aerial vehicles will have enough time to exchange fresh GPS data and ultimately communicate the resulting solution on time.

Networking is achieved by maintaining communication links between the aerial backbone and as many ground-based vehicles as possible. The communication links are treated independently and a transmission is considered successful when the transmitter is able to feed its antenna with enough power, such that it satisfies the desirable quality requirements. It is assumed that aerial vehicles are equipped with two radio antennae. One isotropic able to transmit in all directions, and a horn-shaped one able to directionally cover an area on the ground. It is also assumed that all vehicles are equipped with a GPS and can broadcast information about their current position at a reasonable interval (default 3 seconds). In this section, focus is primarily given to the communication between aerial vehicles and ground-based vehicles using the former horn-shaped

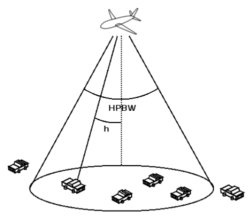


Fig. 3. Slant distance d and angle h of a communication link.

antennae, as it dictates the effectiveness of the communication coverage of the mission and the power consumption of a flying mission.

In order for a ground-based vehicle to be covered, it needs to lie within the footprint of at least one aerial vehicle. As shown in figure 3, a footprint is determined by the altitude of the aerial vehicle as well as its antenna's half-power beamwidth angle. The higher the aerial vehicle flies, the wider its footprint is on the ground, the greater the area covered. The slant angle h of the ground-based vehicle with respect to the aerial vehicle is calculated by applying spherical trigonometry on the available GPS data that each network participant broadcasts. The following piecewise function is then used to decide whether a ground-based vehicle lies within the footprint.

$$L(p) = \begin{cases} 1 : h <^{HPBW} /_2 \\ 0 : h \geq^{HPBW} /_2 \end{cases}$$

Similarly, the slant distance d can be calculated. The greater the distance between the transmitter and the receiver, the higher the signal power required to support the communication.

3 The evolutionary algorithm and fitness function

A centralized, on-line, EA-based approach is considered for the coordination of the group of aerial vehicles. The decision making for the next set of manoeuvres

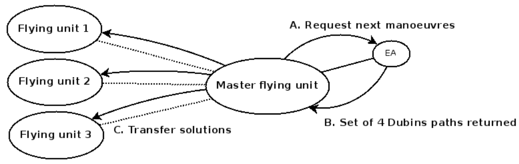


Fig. 4. At the completion of a turn circle manoeuvre, the master aerial vehicle queries the EA for the next set of manoeuvres for the whole group. The solution is then communicated to the rest of the group using the network. If the EA is not ready to generate a solution due to lack of up-to-date information, the returned solution is a set of turn circle manoeuvres, forcing the group to maintain its current position.

for the group is made by a single aerial vehicle, nominated as master. Taking advantage of the underlying network, it is assumed that every 3 seconds the master aerial vehicle is able to receive messages carrying the last known positions and direction vectors of the group as well as the ground-based vehicles. Data updates may be received from relaying aerial vehicles and directly from the ground-based vehicles within the master's footprint, and are tagged such as the master aerial vehicle and in turn the EA decision unit is fed with up-to-date knowledge of the topology. Once the EA has evolved a new set of manoeuvres, the master aerial vehicle is responsible for broadcasting the solutions to the whole group, using the network. As this work mainly focuses providing network coverage to ground customers, it is assumed that there is no packet loss and that a dynamic routing protocol allows flawless data relaying within the topology. The process flow of receiving, generating and distributing solutions amongst the group members is depicted in figure 4. Notice that the EA runs independently from the controller of the master aerial vehicle (threaded), which in practice allows the master aerial vehicle to complete its turn circle manoeuvre, while waiting for a solution.

As described in section 2, a flying manoeuvre is described by a Dubins path of 3 segments. Each segment comprises a bank angle and the duration for which the segment's manoeuvre is to be performed. Furthermore, a Dubins path may request a change to the vertical plane, thus require an alteration to the current aerial vehicle altitude. The information is stored to the chromosome's genes, as shown below.

β_1	δt_1	β_2	δt_2	β_3	δt_3	b	δh

The first six genes describe the horizontal motion and the duration of each of the 3 segments of the Dubins path and are stored as floating point values. The seventh gene b, as well as the last Δh, control the vertical behaviour of the aerial vehicle. When the former is set to 0, the aerial vehicle flies at the same altitude (level flight). If it is set to 1, then the vertical motion is considered and the aerial vehicle is expected to change its altitude by Δh within the duration of the Dubins path, $\sum_{i=1}^{3}(\delta t_i)$.

An evolutionary algorithm using linear ranking is employed to set the parameters of the paths [10]. We consider populations composed of $M = 100$ teams, each consisting of $N = 4$ individuals (the number of aerial vehicles in the flying group). At generation 0 each of the M teams is formed by generating N random chromosomes. For each new generation following the first one, the chromosomes of the best team ("the elite") are retained unchanged and copied to the new population. Each of the chromosomes of the other teams is formed by first selecting two old teams using roulette wheel selection. Then, two chromosomes, each randomly selected among the members of the selected teams are recombined with a probability of 0.3 to reproduce one new chromosome. The resulting new chromosome is mutated with a probability of 0.05. This process is repeated to form $M - 1$ new teams of N chromosomes each.

The fitness function f is designed to optimise two objectives. Firstly, it maximises the net coverage by minimising overlap (i.e., the footprints' intersections).

This is in favour of supporting as many ground-based vehicles as possible using the available number of aerial vehicles. Secondly, it minimises the average altitude of the group. Reducing altitude also reduces the slant distances between the supporting aerial vehicle and the supported ground-based vehicles which in turn lowers the power consumption. The fitness f is used to compute the performance of a group, thus the fitness score of a set of flying manoeuvres, and is expressed as:

$$f = \frac{C_{net} - C_{overlap}}{G} \times \left(1 - norm\left(\frac{\sum_{i=0}^{U}(h_i)}{U}\right)\right) \tag{1}$$

where U is the number of aerial vehicles or genomes per group, G the number of ground-based vehicles, and h_i the resulting altitude of the i^{th} aerial vehicle. Finally, $norm$ returns the normalised mean of the altitudes within the permitted flying corridor, and is a value between 0 and 1.

In order to measure power consumption, an abstract network traffic model is implemented. As previously stated, it is assumed that the communication link between a aerial vehicle and a supported ground-based vehicle is successful when the former is able to feed its antenna with enough power to satisfy the desired link quality. That is, at each time step the transmission of 3 UDP datagrams from each aerial vehicle down to any ground-based vehicle it currently covers is simulated, using a downline data rate of 2Mbit/s and frequency of 5GHz to finally ensure ${}^{E_b}/_{N_0}$ of 10db. Ultimately, the number the available communication links that can be accessed depends on the position of the aerial backbone and the number of ground-based vehicles being currently covered. In this way, the power consumption per time step is measured.

4 Experiments and results

The experiments presented in this paper target aerial missions where both aerial vehicles and ground-based vehicles are placed randomly around a centre point of pre-defined latitude and longitude. All ground-based vehicles move according to a biased Random Way Point model (see [9] for details). Biases in the movements are introduced according to the following strategy. Each time a ground-based vehicle has to generate a new random bearing, there is a 75% chance of moving towards a bounded range of angles. Hence, although individual ground-based vehicles travel randomly in different directions, as a cluster they move in a biased fashion towards a random direction, which is selected in every interval. For the experiments presented in this paper, this interval is set to the duration of the simulation divided by 3. All aerial vehicles start with an initial available power of 250 Watts and fly within the flying corridor of altitudes between 1500 and 22000 ft. An angle of 75° is defined as a turn circle manoeuvre bank angle. Simulations last for 1800 seconds, enough time for the EA to produce a number of manoeuvres that lead to formations of interesting behaviours.

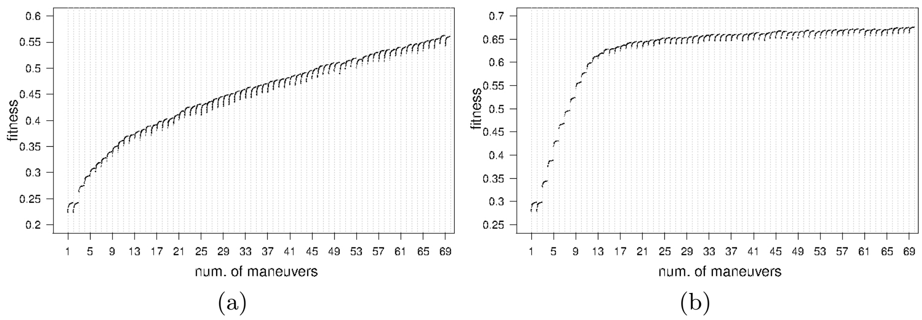


Fig. 5. Fitness of the best solutions after 200 generations for 69 generated consequence sets of flying manoeuvres are shown, for (a) *Exp A*and (b) *Exp B*. Each segment represents the averaged fitness scores (over 20 simulation experiments) and its growth from the first to the last generation.

Two sets of simulation experiments targeted to slightly different scenarios designed to illustrate the adaptability of the system are presented. In *Exp A*, all aerial vehicles start by flying at low altitude and support a small number of ground-based vehicles. In this scenario, the aerial vehicles are expected to increase their altitude in order to subsequently increase the net coverage. In *Exp B*, all aerial vehicles start by flying at high altitude and support a big number of ground-based vehicles with increased overlaps between the aerial vehicles footprints. The system is expected to push the aerial vehicles to decrease their altitude, saving power and reducing the number of ground-based vehicles that lie within the overlapping footprint areas.

Table 1 summarises the configuration parameters of the experiments in terms of initial positions and manoeuvres. For each scenario, 20 differently seeded simulations experiments were conducted. Fig. 5 summarises the dynamics observed in both scenarios from an evolutionary algorithm point of view. In particular, the figures depict the fitness trend for each set of flying manoeuvres over 200 generations. Each segment represents the average fitness of the best solution (i.e., the set of manoeuvres), averaged over 20 simulation runs, for *Exp A* (Fig. 5a), and *Exp B* (Fig. 5b) respectively. For each scenario, the aerial vehicles are asked to execute a sequence of 69 flying manoeuvres, generated by the EA decision

Table 1. Initial configuration of the two experiments.

Parameter	*Exp A*		*Exp B*	
	Aerial	Ground	Aerial	Ground
No. of units:	4	300	4	300
Radius:	6 km	6 km	3 km	3km
Altitude:	2000-2300 ft	0 ft	6000-6500 ft	0 ft
Heading:	80°	0-360°	80°	0-360°
Speed:	110 kts	5-20 mph	110 kts	5-20 mph

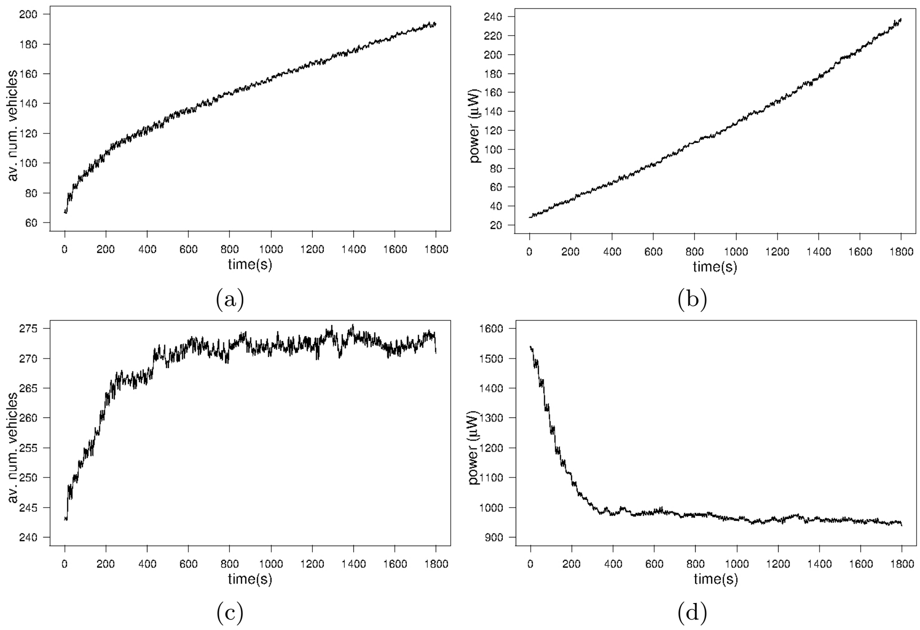
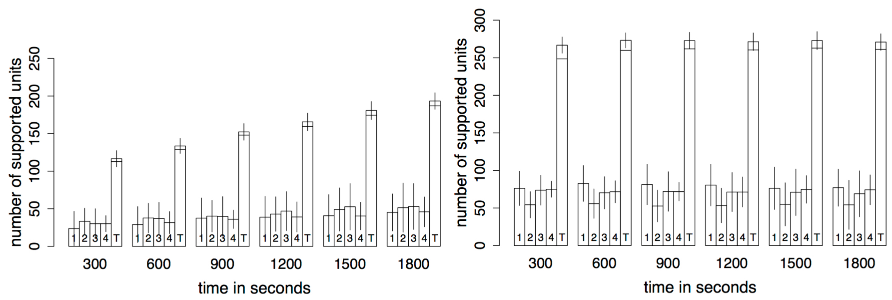


Fig. 6. Average coverage and power consumptions are depicted, for *Exp A* (Fig. a and b) and *Exp B* (Fig. c and d) respectively. Coverage is expressed in term of number of ground-based vehicles that are covered by at least one aerial vehicle.

unit. The starting point of each segment refers to the average fitness of the best solution at generation 1. The end point of each segment refers to the average fitness of the best solution at generation 200.

Looking at the segments in both figures, it can be clearly shown that at each new solution, the EA tends to progressively find a better set of manoeuvres. This indicates that the decision unit is able to efficiently relocate the aerial vehicles in order to find good positions with respect to the current status of the system (i.e., the distribution of ground-based vehicles, the current coverage and the current relative positions of the aerial vehicles). Notice that the initial score of each segment is always lower than the final point of the previous. This is reasoned due to the fact that by the time the aerial vehicles reached the desired position, the ground-based vehicles have already changed theirs, unexpectedly altering the dynamics of the system. This leads to the conclusion that the previously best solution yields less fitness than that predicted by the EA. However, it is shown that the EA tends to increase the fitness score for the sequence of solutions and thus is shown to progressively return better results during the cruise flight of the aerial vehicles. This important observation is made when looking at the general trends in both figures, as they reason about the strategies that aerial vehicles exploit to perform the task. In *Exp A*, the best solution at the end of



(a) (b)

Fig. 7. Individual and total coverage as a function of time. The horizontal segment line in the total bars shows the overlapping number of ground-based vehicles. Error bars show the standard deviation from the means over 20 runs.

the 200 generations for each consequence solution (i.e., set of manoeuvres) is progressively better than the previous best (Fig. 5a).

In Fig. 6a and 6b, where the average coverage and average power consumption are depicted, it is seen that the increase in coverage indicates that the aerial vehicles gradually build better formations and keep them to fulfil the two objectives. Initially, when starting from relatively low altitudes (*Exp A*) the group of aerial vehicles tends to fly higher in order to support more ground-based vehicles (Fig. 6a). As expected, better coverage comes with a small increase in power consumption (Fig. 6b). After starting from high altitudes (*Exp B*) the EA returns solutions that tend to fly lower (Fig. 6c) with a consequent decrease in the power required to provide the communication links (Fig. 6d). The behaviour of minimising the altitude seems to last for the first 20 solutions (Fig. 5b), after which the group of aerial vehicles has reached optimal flying altitudes and formation that offer the possibility of a good coverage to power consumption trade-off. Furthermore, the solutions after the first 20 tend to optimise only the relative positions of aerial vehicles, in order to track the movement of the ground-based vehicles and minimise overlap. This seems to have a minor effect on the power consumption which tends to be constant after the first 400s of simulation time (Fig. 6d).

Network coverage management is clearly shown in Fig. 7a and 7b, for *Exp A* and *Exp B* respectively. The results complement the previous observations as they depict an increment to the group's net coverage (marked as "T"). It is seen that the latter is rather insensitive to the rapid changes of the flying formation. Particularly in *Exp B* the overlap coverage is found to decrease even though the aerial vehicles are asked to decrease their altitude.

Finally, Fig. 8 shows the trajectories of aerial vehicles and ground-based vehicles in terms of their average positions. The centroids of the ground-based vehicles cluster as well as the one of the group of aerial vehicles are shown to follow a similar trend and move closely, highlighting the success of the algorithm in adapting according to the movement and needs of the ground-based vehicles.

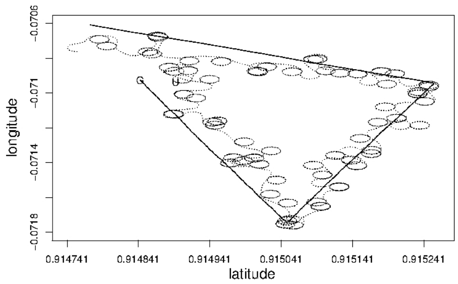


Fig. 8. Continuous line represents the trajectory of the centroid of the ground-based vehicles (as estimated by the whole cluster), whereas the dotted line refers to the movement of the centroid of the airborne group. Letters "G" and "U" indicate the starting points of the two centroids, ground-based vehicles and aerial vehicles respectively.

This figure refers to a single experimental run in *Exp A*. The ground-based vehicles change their overall direction twice during the simulation, as defined by their biased random waypoint mobility model described in previous sections.

5 Conclusion

This paper proposes a coordination system for a group of aerial vehicles designed to form a communication network backbone that connects ground-based vehicles in an ad hoc, highly dynamic fashion. An EA is used as the decision unit responsible for generating relocation information for the group. The EA's fitness function aims to optimise two objectives. Namely, to maximise the net coverage by reducing the overlap between the footprints of each aerial vehicle, whilst minimising the average power consumption to support the communication network. Altitude is strongly related to the power required to provide a link of a satisfactory quality. First developments and experimental results are reported, illustrating promising adaptive behaviour.

There are two future directions that are considered for this research work. Due to the strong dependence on the underlying network, a fully decentralised approach is required. Although several communication and decision protocols may be added to the system to reduce the risk of losing the master aerial vehicle (use of cluster heads, token, etc.), the system should be able to minimise inter-aerial vehicle control overhead communication and thus maximise utilisation of the links for data payload transmissions.

In addition, the use of multi-objective evolutionary algorthm (MOEA) in the system is undoubtedly expected to try to increase the efficiency of the group evaluation within the EA, by allowing multiple objectives to be clearly defined and optimised simultaneously based on the desired flying strategies subject to mission-related, group-based, and individual-based constraints.

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