UAV Flight Coordination for Communication Networks

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A comparison between two algorithms for coordination of actions in UAVs based communication network

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Abstract

The autonomous coordinated flying of teams of unmanned aerial vehicles able to maximise their coverage and utilise the available on-board power efficiently, is a complex problem and involves the fulfillment of multiple objectives that are directly dependent on dynamic, unpredictable and uncontrollable phenomena. In this paper, two such systems are discussed and compared based on their ability to reposition fixed-wing unmanned aerial vehicles to form and maintain an effective airborne wireless network topology. Evolutionary Algorithms and Game Theory are employed as the two decision making approaches for the generation of appropriate flying solutions. The results highlight the ability of Evolutionary Algorithms to evolve flexible sets of manoeuvres that keep the vehicles separated and increase coverage, while Game Theory is found to be able to identify strategies of predefined manoeuvres that fulfil the two objectives, especially when the number of ground-based mobiles as well as the number of unmanned aerial vehicles is small.

Keywords: evolutionary algorithms, game theory, unmanned aerial vehicles, fixed-wing, wireless communication

1. Introduction

Unmanned aerial vehicles (UAVs), also known as aerial drones, are experiencing a great success in a variety of domains. Applications span from the film and photo image industry where UAVs represent a safer, cheaper, faster, and more adaptable solution than traditional methods for capturing aerial shots, to precision agriculture where they are used to monitor and treat a wide variety of crops. This paper examines the challenges associated with using UAVs to provide wide-area mobile communication in place of, or as a complementary system to, fixed network infrastructures such as terrestrial or satellite based systems. The UAVs' ability to be rapidly deployed and their flexibility in adapting to highly dynamic scenarios makes them potentially effective in providing temporary or dynamic networks. For example, shadowing effects from obstructions, or changes in demand that require a quick adaptation of the network infrastructure are phenomena that can be more easily handled by a group of UAVs than by terrestrial or satellite based networks which are limited by the inability to spatially reconfigure the network equipment. The altitude and mobility

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of UAVs can be used to quickly reconfigure the network without having to deploy additional equipment. Moreover, when compared with satellite communication, the reduce slant range of UAV based systems offers improved round trip time signals, and a 50dB to 60dB reduction in free space loss. This can be turned into a series of desirable performance advantages such as power savings, increased bandwidth, or simplified antenna systems.

Thanks to these properties, there is a growing consensus that UAV based systems can complement terrestrial and satellite networks in providing coverage to scenarios such as disaster response or military operations during which a significant amount of network coverage adaptability is required. However, the ability of an UAV system to adaptively reconfigure to changes in demand is strongly associated with the ability of the system to make timely and effective autonomous decisions to generate appropriate flying manoeuvres in response to unpredictable situations. The units of an UAV based system have to operate in a highly coordinated and cooperative way in order to generate group level responses to a multi-objective task (i.e., maximise network coverage, minimise power consumption, avoid collisions, etc.).

The contribution of this study is to describe, evaluate and compare two methods that allow a small group of simulated UAVs to autonomously generate flying manoeuvres that maximise coverage and minimise power consumption. A simulated scenario in which a large number of ground based mobile units is considered. This is seen as a metaphor for a disaster region in which police, military, and first aid units synchronously operate in a coordinated way. The units need full duplex communication links to coordinate the tasks and to share data related to their mission. A small group of UAVs is employed in order to provide the network infrastructure. The UAVs are required to autonomously and dynamically relocate according to the movement of the mobiles on the ground in order to maximise coverage (i.e., number of mobiles covered by the network) and minimise power consumption. It is assumed that the mobiles utilise low-cost omnidirectional antennas and the data rate between mobiles and UAVs is fixed at 2 Mbit/s — a communication that is considered high enough to support stream video, emails with attachments, and transmission of images between mobiles.

The autonomous repositioniong of the UAVs is generated using two different methods. The first one, based on game theory, lets the UAVs participate in a non-cooperative game (NCG) whose outcomes determine the UAVs next flying positions. The second method is based on the use of an evolutionary algorithm (EA) which at regular interval selects the best set of flying manoeuvres (i.e., one for each UAV) based on the maximum coverage and minimum power consumption criteria.

Both the EA and the NCG methods provide UAVs the autonomy to decide where to fly next given the current status of the system (i.e., positions and direction of motion of mobiles, current positions of UAVs). Both approaches allow UAVs to adaptively adjust their locations in an autonomous way based on changes in demand, removing the need for a central planning function that generally comes with an undesired load to the communication network. Both methods offer an effective way to represent, manipulate and ultimately generate efficient flying manoeuvres.

The results of an exhaustive comparison in highly dynamic large-scale environments, as well as a qualitative discussion highlight the differences, strengths and limitations of each methodological approach. It is found that the

EA and the NCG are able to fulfill the coverage objective, with the EA approach performing slightly better that the NCG in scenarios with a larger number of mobiles. The NCG method is seen to be less prone in terms of robustness related to centralisation, and quite competent with small groups of UAVs.

The rest of the paper is structured as follows. Section 2, discuses relevant research works, highlighting similarities and differences with the work in this paper. Section 3, describes the UAVs' kinematics and communication models, followed by section 4, which illustrates how the EA is used to generate the UAVs' flying trajectories, and describes the dynamics of the non-cooperative game. Section 5 presents the results of this study. Section 6, summarises the findings and discusses future work.

2. State of the Art

Coordination of multiple UAVs is an emerging topic of research, mainly in the area of coordinated target surveillance and communications relay for range extension of airborne sensors. A recurring theme for papers in this area is the planning of efficient paths which allow multiple targets to be visited in a region containing forbidden zones such as threats or obstructions. Several path planning techniques have been adopted, for example using Dubins paths to provide shortest routes [1, 2], following the edges of a Voronoi diagram [3, 4], carrot following and A* paths [5] and Pythagorean hodographs [6]. While primarily addressing the problem of timeliness of cover, some of these papers recognize that the coordination process requires some communication between the participating UAVs.

Several researchers, notably Holmberg and Burkadov, have addressed the interconnection of UAVs operating beyond line-of-sight with a ground station [7, 8]. The key aspect of this problem is the optimal positioning of the relay UAVs. This range extension model has included single or multiple UAVs in the relay chain. More recently there has been research into the path planning and networking of multiple UAVs providing area sensor coverage [9, 10].

Although a variety of approaches for the coordination of the actions and paths of multiple UAVs has been proposed, the remainder of this section focuses on those based on the use of EAs and Game Theory. A more comprehensive review of the state of the art in motion planning algorithms and coordination of actions in UAVs can be found in [11] and in [12].

2.1. EAs based algorithms

Path planning algorithms, based on evolutionary algorithms, have been developed for avoiding obstacles [13] or managing performance constraints [14]. Roberge et al showed that genetic algorithms offered better solutions than particle swarm optimization for planning the path of a single UAV [15]. Their analysis considered such factors as fuel consumption and terrain avoidance, demonstrating a new level of complexity in path planning.

The work described in [16] discusses various issues related to the characteristics of the genetic encoding and fitness functions used to generate near-optimal and obstacles-free paths in a dynamic environment. The contribution of the work described in [17] presents the use of parameterised B-Spline curves [18] to represent potentially flyable paths. The results of this work show that the 3D planner algorithm produces an effective flyable path in a variety of 3D terrain that differ with respect to levels of smoothness.

The study described in [19] and in [20] focuses on the use of EAs to generate the most efficient paths for a group of UAVs required to solve a Travelling Salesman Problem like scenario. The contribution of the study described in [19] is in proposing methodological solutions to determine feasible and flyable paths for UAVs required to satisfy several constraints (e.g., the maximum/minimum number of target points that should be controlled by each UAV). In [20], the authors propose the use of multi-objective evolutionary algorithm in order to optmise UAVs paths with respect to UAVs characteristics, properties of the terrain, and other elements of their operating scenario.

In [21], the authors investigate a search method for multi-UAVs missions related to surveillance and searching in unknown areas, using evolutionary algorithms. Their work allows several UAVs to dynamically fly throughout a search space and autonomously navigate by avoiding obstacles, without a priori knowledge of the environment. Although the system assumes perfect communication and central control of UAVs from take-off time to the end of the mission, the authors employ an evolutionary algorithm to make an exhaustive search of the mission area by generating the set of fittest next positions of the UAVs.

Agogino et al [22] look at the coordination of multiple UAVs required to fly over a targeted area in order to provide network communication to ground-based customers. Evolutionary computation techniques are used in their study to optimize network parameters such as power level and antenna orientation in order to maximise area coverage and download effectiveness to the end users. While utilizing the same type of scenario, the work described in this current paper uses evolutionary computation techniques in a different way. While in [22] the UAVs movements are generated with swarm intelligence techniques, and the evolutionary algorithm optimises network related parameters, in our study the evolutionary algorithm generates the UAVs trajectories and most of the network related parameters are predefined.

2.2. Game Theory based algorithms

A survey of game theory in wireless networks by Charilas et al [23] showes that game theory was applicable to all layers of the communications protocol stack. They also observed that some of the implicit assumptions of game theory, particularly rationality willingness to participate, were often absent in real networks where some processes were inherently selfish, with the human users often irrational and selfish. They correctly identified that the choice of utility function directly affected the computational resources required to calculate the payoff.

The use of game theory in path planning was suggested by Shen et al [24]. Their approach was to use Markov games as part of an ensemble of tools for the path planning of UAVs on Intelligence Surveillance and Reconnaissance (ISR) missions. In [25] the authors apply game theory methods to the problem of route planning for teams of UAVs. After defining multiple objectives and constraints that limit the UAVs flying capabilities, a game is designed that involves several players (UAVs), each seeking to optimise its own behaviour with respect to the possible actions of the other players. The UAVs route planning problem is solved looking for the Nash equilibrium (NE) of the game. The results highlight the feasibility of generating routes for teams of UAVs by using game theory methods.

In [26] the authors addresses the problem of obtaining optimal strategies for searching in an unknown environment. The environment is partitioned into a collection of identical cells that can be navigates by two UAVs. The resulting search space is represented as an uncertainty map, where each cell contains a value that represents a probabilistic interpretation of the uncertainty of whether the cell location is occupied by an undefined mass. The objective of the UAVs is to select search routes that visit those cells with large uncertainty values.

The authors assume that the UAVs can communicate with each other and decide upon a global beneficial decision, leading to a cooperative solution. In their method, they adopted a q-step look ahead planning [27], with q determining the depth of the exploratory search environment to obtain optimal strategies. The results show that several mixed-strategy Nash equilibrium can be identified and used in the absence of a pure strategy Nash equilibrium. However, an increase into the computational time is found when increasing the value of q, as well as when using more UAV in the search space.

Algorithms for autonomous UAVs coordination, guidance, and manoeuvrability is still a new research area. The above reviewed research works suggest that both EAs and the Game Theory approach can be effective methods to allow single or groups of UAVs to autonomously move in a mission space, effective both in cases in which the mission requires the generation and use of near-optimal paths among fixed control points, and in cases in which the vehicles are required to operate in an unknown terrain. In this study, the area of applicability of the above mentioned methods is extended by showing that both EA and Game Theory can be effectively used for coordinating UAVs on area communications coverage missions.

3. UAVs' kinematics and communication model

The simulated scenario considered in this study involves a variable number of mobiles moving randomly in a large-scale area ($100km^2$) with the need to exchange data. UAVs are expected to fly over the mission area in order to constantly provide a network infrastructure for the mobiles. It is assumed that UAVs are equipped with two radio antennae: one isotropic able to transmit between UAVs, and one a horn-shaped able to transmit to the ground where the mobiles are operating. Each UAV has limited power for the communication (P_{max}), with which it has to provide as many communication links as possible. UAVs and mobiles are equipped with a Global Positioning System (GPS) and can periodically broadcast information about their current positions.

Simulated UAVs are fixed-wing unmanned flying vehicles modelled as points whose positions are defined by the latitude (ϕ), longitude (λ), and altitude (h) in a geographic coordination system. Each point is associated to a direction vector that corresponds to the vehicle heading (θ). The kinematics that describes the UAVs movements is based on a 6DOF model in which the vehicles' motion consists of unrelated turns of constant speed (default set to 75 knots) in the horizontal and vertical planes, respectively. The model is described in detail in [28]. UAVs can only fly within a pre-defined corridor. This restriction is implemented by forbidding altitude additions or subtractions in cases where the maximum or minimum permitted altitude is reached (default corridor is set to 500–22000 feet).

Within the communication network, the links are treated independently and a transmission is considered successful when the UAV transmitter is able to feed its antenna with enough power to satisfy the quality requirements. No matter which modulation and demodulation scheme is applied at the higher protocol layers, a communication link is considered of a good quality if the ratio of the energy per bit of information E_b to the thermal noise in 1 Hz bandwidth N_0 is maintained. The transmitting power P_t that an UAV is required to feed to its horn-shaped antenna in order to cover a mobile at distance d is expressed by the following version of Friis equation:

$$P_t = p \times (d^2 R_b \frac{E_b}{N_0} \frac{1}{G_r G_t} \Big(\frac{4\pi f}{c}\Big)^2 T_{sys} K); \tag{1}$$

$$\tag{2}$$

where $R_b = 2Mbit/s$ is the desired data, $E_b/N_0 = 10dB$ is the normalised signal to noise ratio, $f = 5GHz$, and $G_r = 1$. The other parameters are computed as follows:

$$G_t = \frac{2\eta}{1 - \cos(\frac{\theta}{2})}; \tag{3}$$

$$\gamma = \sin^{-1} \frac{h}{d}. \tag{4}$$

$$p = \begin{cases} 1, & \alpha < \frac{\theta}{2} \quad \text{and} \quad \gamma \geq \omega; \\ 0, & \alpha \geq \frac{\theta}{2} \quad \text{or} \quad \gamma < \omega; \end{cases} \tag{5}$$

In equation 3, $\theta = 170^\circ$ corresponds to the half-power beamwidth angle of the horn-shape antenna, and the efficiency of the transmitting antenna η is set to 0.95. In equation 4, γ is the elevation angle; d corresponds to the slant range computed with spherical trigonometry, and h is the UAV's altitude (see also [28] for further details).

Figure 1 depicts an UAV providing network coverage to a mobile positioned within the conical footprint of its directional antennae. The higher the UAV flies, the greater its altitude h, the wider its conical footprint on the ground, and thus the greater the area covered. Also, the longer the slant range d between the transmitter and the receiver, the higher the signal power required to support the communication. The slant angle α of the mobile with respect to the UAV is calculated by applying spherical trigonometry on the available GPS data that each network user is expected to broadcast at regular intervals [28]. A mobile needs to lie within the footprint of at least one UAV in order to potentially be covered. However, coverage is granted only if the UAV responsible to provide network has enough power. The existence of obstacles in the terrain is introduced by requiring that the elevation angle $\gamma \geq \omega$, with $\omega = 10^\circ$, for communication link to be operative. If $\gamma < \omega$ then $p = 0$ (see equation 5), therefore no power is dedicated to that specific link, and no network coverage is granted to that mobile. Moreover, the communication link is ultimately considered achievable if and only if P_t is less or equal to the remaining P_{max}, the maximum power available for communications each second. The value of P_{max} in this work is set to 50 Watts.

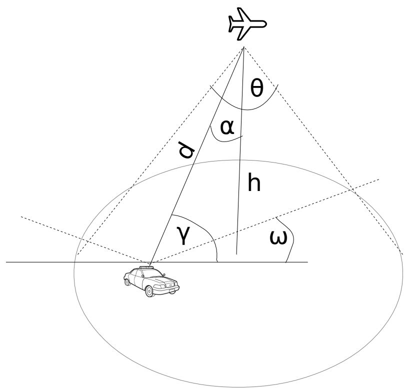


Figure 1: Figure depicting one UAV and one mobile positioned within the UAV's conical footprint. In this picture, d is the slant range; α the angle of the communication link; θ is the beamwidth angle of the horn-shape antenna that defines the area within which links are possible; γ is the elevation angle; ω is the minimum elevation angle below which no communication link can be established, and h is the UAV altitude.

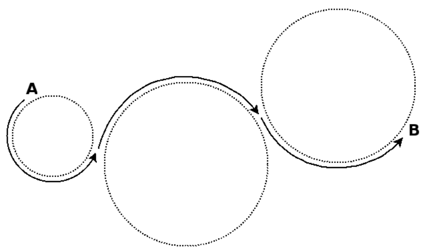


Figure 2: One manoeuvre of three segments of different duration and bank angles between the starting point A and finishing point B. Direction of flying is dictated by the bank angle.

4. Methods used to coordinate the UAVs movements

The EAs and the NCG approach require that the UAVs broadcast data about their own location and the location of mobiles within their footprints. By considering the data, the UAVs can generate their next manoeuvres aiming to maximise the joint coverage of the group. The NCG requires that all the UAVs simultaneously decide on their next moves by solving exactly the same game, and synchronously move to their respective next locations corresponding to the unique NE of the game. With the EA, the system is designed in a centralised way, with a single master UAV that gathers the position data, runs the EA, and broadcasts the next moves to the other UAVs (see Figure 3). Data updates are transmitted every 3 seconds and tagged.

4.1. The Evolutionary Algorithm

In the absence of instructions generated by the EA on the master UAV, the flying vehicles perform clockwise turn circle manoeuvres with the maximum bank angle (48°) in order to keep the current position. Once the EA has generated a new set of manoeuvres (one for each UAV), the master UAV broadcasts the solutions to the team using the network. It is assumed that, during communication, there is no packet loss and that a dynamic routing protocol allows flawless data relaying within the topology.

A flying manoeuvre is described by a Dubins path of 3 parts [29]. Each part can be described by a bank angle and the duration of execution. Each part can be either a straight line, or a left/right turn, depending on the given bank angle (see figure 2). A Dubins path may request a change to the vertical plane, thus requiring an alteration to the UAVs' altitude. Each part of the manoeuvre can vary in duration, but the sum of the duration of the three parts must be equal to a fixed time interval corresponding to the time required to complete a circle with a bank angle of 48°. This time constraint ensures that whatever manoeuvre is executed, the system remains synchronised, with UAVs that start and finish their respective manoeuvres at the same time. The EA has limited time to search and generate the next flying manoeuvres. This time must be shorter than the time it takes to each UAV to perform two turn circle manoeuvres on their respective current positions. Before the end of the second turn, the EA is expected to have found the new best positions, which are immediately transmitted by the master UAV to the other UAVs. At the end of the second turn, each UAV executes the flying manoeuvres transmitted by the master UAV. During the execution of the latest EA generated flying manoeuvres, each UAV gathers fresh GPS data for each of their respective mobiles, and transmit this data to the master UAVs. Figure 3 describes this sequence of events which repeat themselves until the end of the mission.

Flying instructions are encoded into chromosomes of 8 genes, 6 of them defining bank angle β_i and duration δt_i of the manoeuvre i with $i \in \{1, 2, 3\}$. The remaining two genes define variations in altitude δh and whether that variation has to be applied within the duration of the Dubins path (i.e., within the time interval corresponding to $\sum_{i=1}^{3}(\delta t_i)$). Bank angle, duration, and altitude are encoded with real-valued genes chosen uniformly random from the range [0,1]. The gene arbitrating an altitude change is a binary value.

An EA using linear ranking is employed to generate the flying manoeuvres [30]. At generation 0, a population composed of $M \times N$ random chromosomes is generated, with N corresponding to the number of UAVs in the group and $M = 100$ indicating the number of groups or solutions. A solution is made of N chromosomes. For each new generation following the first one, the N chromosomes corresponding to the best performing group/solution ("the elite") are retained unchanged and copied to the new population. Each of the chromosomes for the remaining solutions is formed by first selecting two old solutions using roulette wheel selection. Then, two chromosomes, each randomly

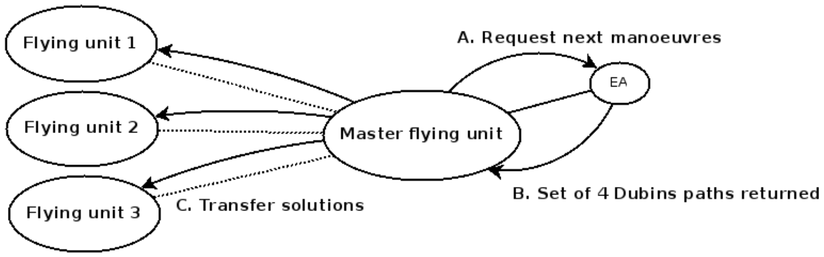


Figure 3: At the completion of a turn circle manoeuvre, the master UAV queries the EA for the next set of manoeuvres. The solution is then communicated to the rest of the team using the network. If the EAs are not ready to generate a solution due to lack of up-to-date information, the returned solution is a set of turn circle manoeuvres, forcing the team to maintain its current position.

selected from among the members of the selected solutions are recombined with a probability of 0.3 to reproduce one new chromosome. Each parameter of the new chromosome is mutated. Mutation entails that a random Gaussian offset is applied to each real-valued genes, with a probability of 0.05. The mean of the Gaussian is 0, and its standard deviation is 0.1. During evolution, all real-valued genes are constrained to remain within the range [0,1]. For binary genes, mutation corresponds to switching the state of the gene. This process is repeated to form $M - 1$ new solutions of N chromosomes each. The EA runs for 200 generations or until an allowed computation time has elapsed.

Algorithm 1 Packing algorithm

let G be a sorted logical map
initialize packing[N] as empty packing arrays for N UAVs
while G is not empty of mobiles **do**
    for each u in logical map G **do**
        let g be the first mobile found in u's sorted list
        let p be the power required to support g
        if $powerbudget(u) - p \geq 0$ **then**
            $packing[u] \leftarrow g$
            $powerbudget(u) = powerbudget(u) - p$
        remove remaining instances of g from G

The fitness of each group/solution is shared by all the chromosomes forming the solution. The group fitness is computed by summing the number of uniquely supported mobiles per UAV, with UAVs assumed to be positioned at their respective next locations. It is important to notice that artificial evolution uses information retrieved from frequent broadcast messages sent by all the vehicles. In order to ensure that the manoeuvres are generated according to valuable positional information, distances between antennae and in-turn power estimation are calculated based on predicted positions. The mobiles are allocated to the UAV following the criteria illustrated in algorithm 1. This algorithm ensures that the number of mobiles allocated to each UAV is maximised while the power consumption is minimised by firstly allocating those mobiles that are predicted to be positioned in the proximity of the centre of each UAV's conical footprint and gradually expanding to its edges. In this way, the least power demanding mobiles are the first to be allocated. Mobiles that are predicted to be positioned within the footprint of more than one UAVs are allocated to the UAV with the smallest slant range, if that UAV has enough power to provide coverage. Otherwise they are allocated to other UAVs.

At the end of each evolutionary process, the manoeuvres corresponding to the best solution of the last generation are communicated to the respective team members for implementation along with the respective mobile-to-UAV allocation table. Each UAV executes the received flying instructions and serves those mobiles that are supposed to be served based on their predicted position. The larger the number of mobiles covered, the fitter that particular solution

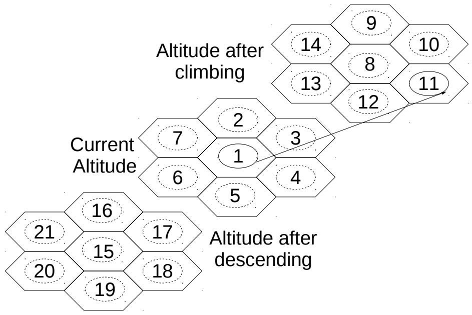


Figure 4: Game strategies for a single UAV. The dotted circles refer to the possible tracks. Continuous line circles refer to the current track.

is when the manoeuvres are executed by the UAVs. This logic allows the EA to generate team solutions that maximise the network coverage by assigning mobiles to those UAVs that are able to spend less power in order to support them.

4.2. The non-cooperative game (NCG)

In this paper, a non-cooperative game (NCG) is used to coordinate the movements of a group of simulated UAVs. Non-cooperative games are games in which the players have a common objective but do not form teams or coalitions to achieve that objectives. In our system, the UAVs are the players, the set of possible locations are their strategies, and the number of ground mobiles for which each UAV provides network coverage are their payoffs. The NCG is the algorithm responsible for generating the UAVs next location based on the current status of the system. Each UAV selects a strategy that maximizes its own pay-off, given the strategies selected by other UAVs. The best response by each UAV to every other UAV leads to an equilibrium state from which there is no incentive for any UAV to deviate from its selected strategy since such a move would reduce that UAV's pay-off. This set of strategies is known as a Nash equilibrium (NE).

With the NCG approach, the airspace over the mission area is configured as a pattern of hexagonal cells as shown in figure 4. At the start of each run of the game each UAV is circling in cell 1. In the simplest case of maintaining a constant altitude, each UAV has the following choices: it can either continue to circle in cell 1, or it can relocate to circle in the adjacent cells 2-7. It could also choose to climb at its maximum climb rate and circle in cells 8-14, or descend to circle in cells 15-21. This gives each UAV a set of 21 pure strategies that can be adopted. Generally speaking, if each of the N UAVs has K possible strategies, the number of combinations of strategies increases as K^N. The size of the payoff matrix must also increase as K^N.

The cellular pattern has a symmetry about the current location that allows all potential locations to be reached in the same time. The time allocated to complete the manoeuvre is sufficient for the UAV to complete one circle at its current altitude, move to the next cell, and complete one circle at its new altitude. The small difference in path length between level flight, climbing and descent are absorbed in the completion of two circuits, giving a manoeuvre time of about five minutes. This ensures that all UAVs have settled into their new altitude before planning the next manoeuvre, and allows the decisions of all UAVs to be synchronised.

Simulation parameters			
Number of UAVs		3	
Terrain size		100 km^2	
Duration		6 hours of flying	
Unmanned aerial vehicles' parameters			
Init altitude		15000 feet	
Init latitude, longitude and heading	#1	52.8636, -2.6373	270°
	#2	52.0512, -1.4219	270°
	#3	52.8605, -1.4219	270°
Ground-based mechanism's parameters			
Number of units		200	
Mobility model		Random WayPoint	
Speed		30 mph	

Table 1: Table of parameters and configuration settings

The payoff matrix of the NCG contains the coverage of all UAVs for all combinations of actions. In other words, the payoff matrix is populated by calculating the number of mobiles that can be supported by each UAVs for all K^N combination of strategies. The mobile-to-UAV allocation is done following the criteria detailed in Algorithm 1 and illustrated in section 4.1. The single NE, usually a mixed-strategy Nash equilibrium[1] (MSNE), of the game is used to define the strategy that should be adopted by each single UAV. The Chatterjee's method is used to solve the game and thus identify the best NE out of all those that can exist. The method starts by assuming a random solution, then progressively refines that solution until the error between successive iterations is less than a given threshold [31]. Contrary to the EA approach, the NCG the system is fully distributed as all UAVs shared the same payoff matrix. Thus they are expected to reach an identical NE solution (see also [32] for further details). Both the EA and the NCG approach require each UAV to access information concerning the positions of all UAVs and the position/direction of motion of all mobiles. In other words, the systems required global information sharing.

5. Results

The performance of the two algorithms for coordinated motion (i.e., the EA and the NCG based algorithm) have been evaluated and compared on various scenarios, in which the number of UAVs (groups of 2 and 3 UAVs), and the number of mobiles (scenarios with 50 and 200 mobiles) were varied. Comparing two different approaches in the same scenarios, with identical initial conditions, has given insight into how the UAVs behave as a team. Here, for both approaches, the results of an exemplar set of simulations in which a group of 3 UAVs are required to provide network coverage to 200 mobilesare illustrated. The similarities as well as the differences between the two approaches are

[1]A mixed-strategy Nash equilibrium is where at least one player in the game randomizes over some or all of their pure strategies, meaning that each player places a probability distribution over alternative strategies.

discussed in terms of flying behaviour and coverage strengths. Statistics are computed over a larger set of simulations that quantitatively describe the behaviour of the group of UAVs for each control policy.

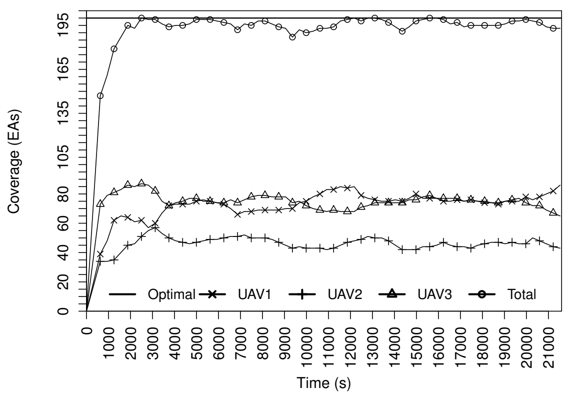
5.1. Exemplar results for the three UAVs and 200 mobiles scenarios

Figure 5 depicts coverage results, the altitude changes, and the relative distance of the UAVs during the course of a flight that lasted 21000 s, with simulation parameters illustrated in Table 1. Looking at Figure 5a and 5b both approaches manage to reposition the UAVs so as to maximise the coverage. The group driven by the NCG is found to equally distribute the covering load amongst its members leading to a power-wise balanced mission. This can offer benefits when managing RF interference between the platforms. By contrast, the EA and in particular the way chromosomes and genes are used to codify flying manoeuvres permit a higher level of manoeuvrability to be demonstrated. The solutions which survive during the artificial evolution are found to fly one UAV as high as possible, enabling the rest of the swarm to constantly fly lower, saving power, thus being able to cover more mobiles (see Figure 5c). This tendency towards specialisation by individual agents, which systematically appear in any re-evaluation of the algorithm, contributes to the imbalance in coverage between the three UAVs (see Figure 5a).

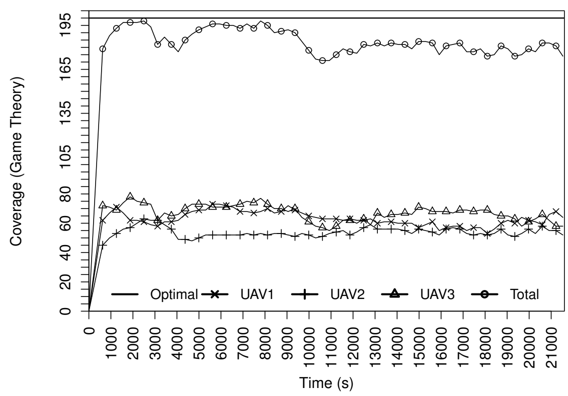
Both approaches exhibit flying behaviours that strongly focus on reaching and maintaining a solution very close to the optimal. The EA approach converges on the optimal solution more quickly than the NCG, and it tends to generate better coverage than the NCG. This is the effect of the strategies employed to generate flying manoeuvres. In the NCG approach, planning for the next move is limited to selecting from a fixed number of positions and thus leads to a more conservative way of flying in terms of flexibility as well as time required towards converge. The UAVs are found to experience frequent changes to their altitudes while attempting to increase their cumulative coverage (see Figure Figure 5d).

By analysing the relative distance between UAVs during mission important characteristics of the emerged swarm behaviour can be identified. In particular, an important feature when seeking to build real-world applications in aviation is demonstrated by both systems. That is, the collision avoidance within the group of UAVs as a result of their flying separation (see Figure 5f). Although this behaviour requires more planning steps, NCG is found to methodically force each UAV to find its own, unique area for covering. By observing the movement of UAVs, it can be observed that each UAV moves around an area following clusters of mobiles and, as the latter dispersed, each UAV actively monitors the formulation of new clusters and follows them. Locating a UAV over a cluster of mobiles reduces the slant range to each mobile, and hence the RF power required to support them. In a power limited system this releases additional power that can be used to support more distant mobiles, improving the overall coverage.

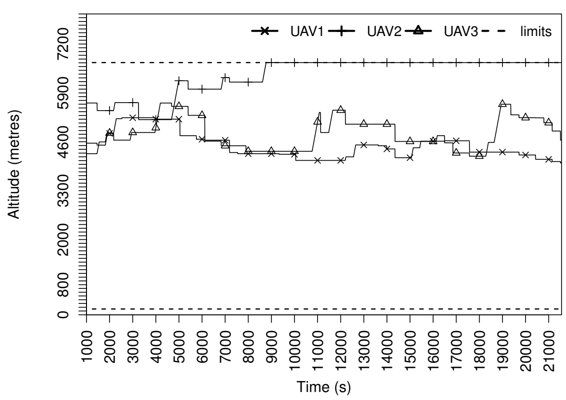
EAs are found to provide flexibility and quick convergence in terms of spreading within the area of interest. Figure 5d shows that EA allows the UAVs to achieve quicker separation during the first flying steps. Once the UAVs have spread enough to provide good solutions, they continue flying by focusing on making changes to their altitudes, managing in that way the power consumption. This aviation feature is undoubtedly very important when deploying real-world applications.



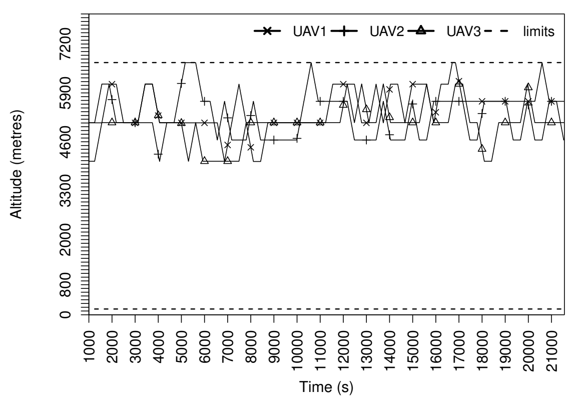
(a) EAs - Coverage with 200 vehicles



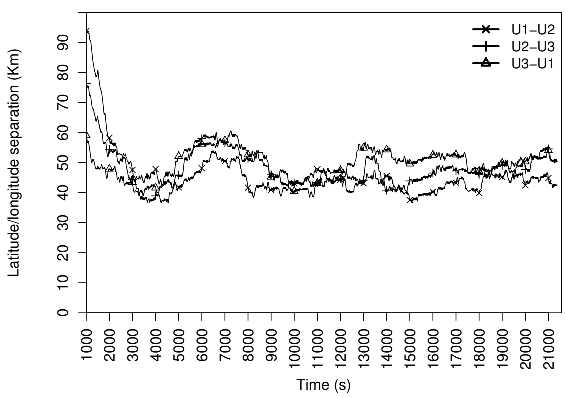
(b) NCG - Coverage with 200 vehicles



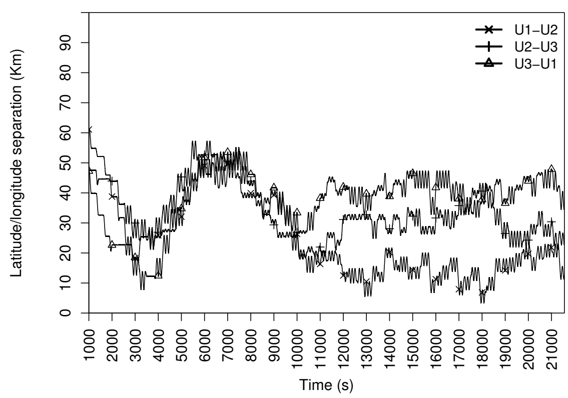
(c) EAs - UAVs' altitude with 200 mobiles



(d) NCG - UAVs' altitude with 200 mobiles



(e) EAs - UAVs' relative distance with 200 mobiles



(f) NCG - UAVs' relative distance with 200 mobiles

Figure 5: Coverage vs time for EAs and Game Theory decision mechanisms of two UAVs supporting 50 (a, b) and 200 (c, d) mobiles.

Another difference in flying behaviours between the two approaches is that in NCG the UAVs tend to behave similarly and in a homogeneous fashion. That is, UAVs follow similar flying patterns making small, conservative changes to their latitude/longitude and mainly concentrate on altitude alterations (see Figure 5d). The UAVs operated by EAs are found to specialise through their flying strategies. Once they achieve a convenient level of separation, one is found to fly as high as possible, allowing others to fly lower and save power.

5.2. *Practical considerations*

One key difference between these approaches results from the way solution are distributed across the group. When a decision is evolved, the EAs require that when a plan for the next set of manoeuvres is evolved at the master agent, it is broadcast to the rest of the UAVs. In the NCG approach, each UAVs is allowed to make its own decision based on the NE of the game. This suggests that a higher level of autonomy is possible for the NCG as all UAVs, given the same data, should arrive at the same plan.

Multiple NE are often found when solving the payoff matrix, leading to the practical problem of deciding on a single strategy from several candidates. A game in which several NE exists is known as a coordination game, and the normal approach is to pick a solution at random. In theory, this could lead to a weaker solution being selected, however it was found that the NE tended to have very similar coverage. Picking one solution at random did not affect the overall performance of the algorithm as small reductions in coverage were usually corrected in the next run of the game.

It was observed that the NCG tended to slightly overestimate the payoff when generating the payoff matrix. Comparing the estimated and actual payoffs at the end of a manoeuvre showed that there was a 1% to 2% overestimate. Further examination showed that this tended to arise from mobiles at the edge of each UAV's footprint moving just outside the edge of cover.

The calculation time for a payoff matrix in an NCG with N players, each having K actions, scaled proportional to K^N. Algorithm execution times for the NCG tended to scale with the size of the payoff matrix. In practice it was found that, in the exemplar experiment, the realistic limit for the algorithm was five UAVs. Beyond this number of UAVs the algorithm took so long to find a solution that the clusters of mobiles had started to disperse. The generation of the payoff matrix took longer as the number of UAVs increased, but the major bottleneck in the algorithm was finding the NE in the payoff matrix.

An algorithm by Chatterjee was used for finding NE [31]. It was chosen because it would always find an MSNE, and was usable for games where $N \geq 2$. Algorithms such as Lemke-Howson [33] are faster than Chatterjee's method for two-player games but cannot be used for games where $N > 2$. There is scope for improvement in the NCG if a method for solving N -player games can be found that combines the speed of the Lemke-Howson algorithm with the flexibility of Chatterjee's method.

If the NCG was run with less than five UAVs it could produce consistent results, even if the data was non-current. Some experiments were run using data that was up to 20 minutes old. It was found that the difference in coverage between runs using current data and runs using old data was very small. This was partly attributed to the relatively slow timescale over which clusters of mobiles formed and dispersed. This is an interesting area for future research.

The EA approach provides more flexibility in its flying manoeuvres and it generates better coverage than the NCG. The algorithm execution times tends to scale with the size of group, and with the population size. While the population size can be kept fixed without seeing a deterioration of the algorithm effectiveness, the group cardinality affects the algorithm execution through the computation of the fitness. The larger the group of UAVs, the more UAVs manoeuvres have to be evaluated, the longer the fitness computation time. Contrary to the NCG which requires a rethinking of the method to solve the game, the EA can potentially cope with larger UAVs groups by efficiently tuning some of the most critical system parameters, such as the length of the time interval within which a new group solution is computed. Contrary to the NCG, the EA is based on a centralised approach in which one UAV first computes the new best locations, and then broadcasts the solution to each group member. The centralised approach is primarily dictated by the fact that with the EA, planning for the next move is not limited to selecting from a fixed number of positions. While this has a positive effect in term of scalability, manoeuvrability of the UAVs, and on group coverage, it also open the possibility of UAVs flying beyond the maximum communication distance. The possibility of generating almost linear and less curved trajectories makes the UAVs able to take longer steps progressively increasing the distance to the other UAVs up to the point in which some of the communication links can broken. In a fully distributed system, in which each UAV is supposed to converge on the same best group solution by running exactly the same evolutionary algorithm, it is impossible to maintain this convergence if some UAVs communication links are broken due to distance, since not all UAVs would have access to the same information. The centralised approach is one way to limit the undesired effects of lost of communication between UAVs, since it finds group solutions only by taking into account UAVs that can communicate with the master UAV.

6. Conclusions

Two approaches in autonomous flying for communications UAVs are discussed in this paper. The first approach employs game theory whereas the second applies EAs in order to generate and evolve flying solutions. Both approaches are designed to maximise the coverage, that is the number of mobiles that can be supported during the mission, considering the limited available power dedicated to communications. Notice that although the problem is concerned with the ability of the systems to increase the number of covered mobiles as well as the efficiency in management of the power, it is treated as a single objective problem by both approaches. This is due to the fact that the employed packing mechanism (discussed in Section 3) does encapsulate the concept of power management when allocating mobiles to their supporting UAVs. Interesting flying behaviours have been observed associated to both approaches, when flying for 6 hours to support the communication need of a large number of mobiles, spread within a 100×100 km unexplored area.

Both approaches are found to fulfil the objective of providing adaptive communication coverage, with EAs being able to maintain a constant, close to optimal, result throughout the duration of the mission. This is due to the flexibility of the flying behaviours offered by the current design of chromosomes in the EAs. The NCG is found to enable the emergence of more conservative flying manoeuvres, a feature that reduces the risk of flying UAVs out of the area of operation. In terms of quickly converging to a sufficient separation, the EAs are found to require less time and be able to specialise the resulting flying behaviours due to their flexibility. The NCG on the other hand requires more time as the UAVs are following a similar trend in traversing shorter distances per flying step, whilst making frequent altitude changes to manage power.

This paper uses coverage as the main criteria for evaluating mission performance and RF power as the primary constraint. Consideration of other performance criteria and constraints will improve the realism of the methods while establishing some interesting possible directions for future research. Two particular factors that need to be addressed are air traffic management and use of radio spectrum.

The most significant challenge in air traffic management is collision avoidance. It can seen that the algorithms, especially the NCG, tend to enforce spatial separation between UAVs so collision avoidance between the UAVs is not seen as a major concern. In reality there are other air users to be avoided, the complex 3D airspace environment to be navigated and no-fly areas to be avoided. The choice of manoeuvre needs to consider the airspace through which a UAV will pass, and whether it is likely to encounter other aircraft. The NCG offers an unsophisticated approach to collision avoidance by allowing temporal constraints to be set on cells. Modifications to the EA would be more complex as the trajectory would need to be inspected to see whether it entered any prohibited airspace at any time, or passed close to another air user. Collision avoidance and airspace management offers some interesting challenges for future research.

The International Telecommunications Union (ITU) has not, currently, allocated any radio spectrum to UAV payloads, so simplifying assumptions have been made about frequency management. When ITU allocations are made, possibly at the 2019 World Radio Conference, these algorithms will need to consider frequency assignment and interference management as part of the solution. Multi variable optimisation is a well established technique for EAs, so interference levels could be introduced as another variable to be optimised by the EA. NCG currently find their NE from a payoff matrix that includes a single parameter, in this case coverage. Developing an NCG that use two parameters will require the combination of both parameters into a single, representative, number. This will provide an interesting challenge for the NCG.

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