COORDINATED FLOCKING OF UAVS FOR IMPROVED CONNECTIVITY OF MOBILE GROUND NODES*

Prithwish Basu
BBN Technologies
10 Moulton St.
Cambridge, MA 02138
pbasu@bbn.com

Jason Redi
BBN Technologies
10 Moulton St.
Cambridge, MA 02138
redi@bbn.com

Vladimir Shurbanov
BBN Technologies
10 Moulton St.
Cambridge, MA 02138
vshurban@bbn.com

Abstract

Unmanned aerial vehicles (UAV) have been used by the military for surveillance and reconnaissance operations for the past few decades. The recent proliferation of wireless networking technologies enables the equipment of UAVs with wireless transceivers, and that can in turn allow them to communicate with the friendly ground nodes as well as other UAVs. Since rugged ground terrain can result in significant signal attenuation, the ground network can be severely partitioned. However the lower propagation loss between ground and airborne nodes can be effectively utilized to connect the islands of connectivity on the ground to form a unified ad hoc network. In this paper, we investigate the UAV placement and navigation strategies with the end goal of improving network connectivity. Since the ground nodes can be mobile, a fixed placement strategy is either inadequate or wasteful; hence, we propose to use local flocking rules that aerial living beings like birds and insects follow, to meet our goals. We show by simulation that a flocking based navigation strategy is adaptive to the motion of ground nodes and can indeed maintain high connectivity in a mobile ground network.

1 Introduction

Traditionally, unmanned aerial vehicles (UAV) have been used by the military for surveillance and reconnaissance operations. However with the advent of robust wireless networking technologies, UAVs equipped with wireless transceivers can thus be enabled to communicate with mobile ground nodes as well as other UAVs resulting in the formation of a mobile ad hoc network. This is particularly useful in scenarios where the terrain is so rugged and mountainous that ground-to-ground communication over large distances is not particularly efficient owing to the heavy signal attenuation; the two-ray ground reflection model predicts the signal power to fall off as the fourth power of distance, and this can be worse if the ground is not flat. But since free space ground-to-air and air-to-air communication suffer only quadratic pathloss, communication can be carried out over greater distances with lower power radios over multiple hops of the ad hoc network comprising of the UAVs which act like mobile base stations for the ground nodes.

In such a setup, the number and placement of UAVs over the ground nodes is of significant importance since they govern the coverage and throughput of the network. We define the optimal UAV placement problem as follows: given a distribution of N points on a plane and free space transmission ranges of UAVs (R) which are flying at a given altitude (H), what is the minimum number of UAVs necessary to cover all ground nodes while forming a connected network, and what is their optimal placement so as to minimize the variance in the number of ground nodes covered by every UAV? Since this problem seems to possess combinatorial complexity, a heuristic approach that works for uniformly (randomly) distributed ground networks is to divide up the ground space into grid cells and place a UAV at the top of each grid cell. The number of grid cells will be determined by the parameters R and H and the fact that the UAVs need to form a connected subgraph. However when ground nodes are mobile and the spatial node distributions are non-uniform, a more adaptive UAV placement scheme is necessary.

We propose to use the biologically inspired metaphor of bird flocking for the continual placement and motion

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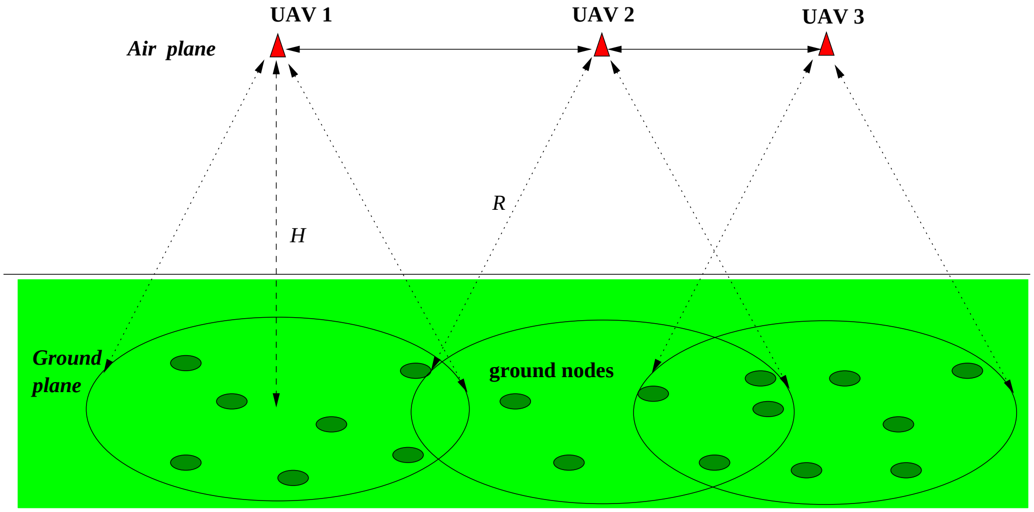


Figure 1: Placing UAVs above ground nodes for connectivity

of UAVs so as to adapt to the mobility of nodes on the ground and achieve good connectivity and load balancing. We propose a set of rules, namely "Move to Point above Ground Centroid", "Repel from UAV", "Attract toward UAV" and "Random Walk", that need to be executed by each UAV depending on the state it is in. The first rule focuses on the tracking aspects of the algorithm. If two UAVs have moved very close to each other then at least one of them will execute the "Repel from UAV" rule. The "Attract toward UAV" rule is utilized to maintain connectivity between two UAVs and also to perform load balancing between them. UAVs enter into the random walk mode when no other rules are applicable.

In this model we assume that only local information is available to a UAV from the ad hoc network before it makes a movement decision; in that sense UAVs execute a flocking algorithm just like birds do. Such local information can be extracted from neighbor heartbeat messages and may include: the positions of neighboring UAVs as well as connected ground nodes, the number of ground nodes connected to a neighboring UAV, etc.

We show by simulations that by the application of the above flocking rules, UAVs can indeed provide good coverage, connectivity, and load balancing to the underlying mobile ground nodes. The performance is very similar to static grid based positioning in scenarios where the mobile nodes are constrained within a pre-defined area. However owing to its adaptive and tracking abilities, flocking outperforms the former scheme when the set of ground nodes, as a whole, moves randomly towards a particular direction, e.g., an army of soldiers ambling forward.

2 The UAV Placement Problem

Although addition of UAVs to a battlefield network can potentially enrich its connectivity significantly, their high cost prohibits large-scale deployment in the current timeframe. Hence, it is cost-effective to minimize the number of UAVs necessary for improving the connectivity of the network. Therefore, we formulate the UAV placement problem as a combinatorial optimization problem as follows:

> Given a distribution of N nodes on the ground plane and the free-space transmission ranges of UAVs (R) which are flying at a given altitude H, what is the minimum number of UAVs necessary such that every ground node can connect to at least one UAV and the UAVs form a connected network. Also, what is their optimal placement so as to minimize the variance in the number of ground nodes connected to each UAV?

Figure 1 illustrates the problem. We assume that H is an input parameter to the optimization problem instead of an optimization variable itself. Since communication between a ground node and an airborne node suffers only r^2 propagation loss (where r is the distance between the transmitter and the receiver), it can be argued that the UAVs should be as close to the ground as possible without actually being on ground, since each UAV can then cover a larger area. However flying closely above ground can render the UAVs highly vulnerable to enemy attack from the ground. Hence the parameter H should be chosen such that the probability of gunfire or

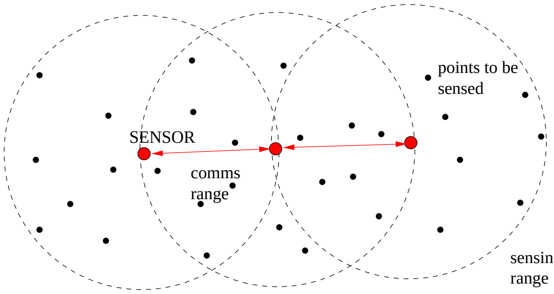


Figure 2: Placing sensors for optimal connectivity and coverage

missile attacks on UAVs from the ground is very low. Potentially, all UAVs need not fly at the same elevation above ground. The optimization problem will increase in complexity if UAV placement is allowed on multiple 2D planes in space.

In this formulation we assume that there is poor or no direct connectivity between ground nodes and only the UAVs are the responsible for connecting the ground nodes. This assumption may seem too restrictive but it is realistic if one represents a connected group of closely located soldiers by a single ground node. If these two groups are separated by a reasonably large distance, then there indeed will not be any connectivity between them owing to the two-ray ground pathloss. We make this assumption for some simplification in modeling and analysis. In future work, we plan to relax this assumption and solve the more general version of the problem.

The UAV placement problem has similar complexity as the sensor point coverage problem (illustrated in Figure 2). In the latter problem, sensors with given sensing and communications ranges (both are assumed to be equal) are to be placed on a 2D plane containing a discrete set of points which correspond to certain "senseable phenomena." The objective is to place a minimum number of sensors such that all the "senseable" points are covered by at least one sensor and the sensor network is connected. Since this problem is NP-complete, approximations algorithms were proposed for this problem in [1]; specifically the approximation factor for the proposed algorithm is $\frac{4\pi}{\sqrt{3}} \approx 7.26$. In other words, the approximation algorithm in [1] will place up to 7.26 times the number of sensors that the optimal algorithm would place to form a connected cover. Note that the UAV placement problem is a more general version of the sensor point coverage problem – they become identical when $H = 0$.

Since each additional UAV results in a substantial increase in total cost (unlike the sensor deployment problem), an approximation algorithm with a high approximation ratio can be indeed very costly. Hence we take a slightly different approach. In our framework, we relax the notion of complete connectivity of the ground nodes, i.e., we allow a small fraction of ground nodes to be disconnected from the rest of the network for a short period of time. Moreover, since the ground nodes are mobile unlike in the sensor coverage problem, the minimum number of UAVs may change rapidly over time. So, we start with a small but fixed number of UAVs and attempt to adjust their movement so that they maintain the best possible connectivity with the ground nodes.

If widespread sharing of location information is available in the system, it may be possible to compute the optimal paths that the UAVs should follow in order to maintain the best possible connectivity among ground nodes. In this paper, instead of taking the aforementioned approach we propose another technique which is influenced by the well known biological metaphor of *flocking* [2]. Flocking is used by aerial life forms such as birds and insects in order to maintain nearness to their group during foraging, but at the same time they prevent colliding with each other. We describe our flocking algorithms in greater detail in the next section.

3 Connectivity and Coverage by UAV Flocking

Flocks of birds and swarms of insects exhibit 3 interesting properties: (1) They always fly in a group; (2) 2 birds in flight do not crash into each other; (3) The overall flight of the entire flock is controlled purely by the local motion of individual birds. Reynolds used the flocking metaphor in his seminal paper on "boids" [2] in the context of computer animation. There he demonstrates that the aggregate motion of the simulated flock is the result of the dense interaction of the relatively simple behaviors of the individual simulated birds.

We utilize the above metaphor for controlling the flight patterns of UAVs in our problem setting. UAVs need to maintain safe distance from each other; they need to maintain connectivity among themselves; and they need to track the motion of ground nodes so that overall network connectivity is maintained. The flight of UAVs is subject to a few constraints:

- They cannot remain absolutely stationary in flight at any point of time.
- A UAV is *not* a point object and therefore has an orientation at any time instant. Hence, the motion

Flocking Rule	**Purpose**
Move to directly above ground centroid	Tracking ground nodes
Move towards neighboring UAV (ATTRACT)	Maintain connectivity and load balancing
Move away from neighboring UAV (REPEL)	Maintain coverage and safe distance
Random walk in vicinity	Heal partitions and do not remain static

Table 1: Flocking rules obeyed by the UAVs

Threshold parameter	**What does it signify?**
D_{max}	Maximum distance between 2 nodes without loss of connectivity
D_{min}	Minimum distance between 2 nodes to maintain good coverage
$D_{centrMAX}$	Maximum distance UAV allowed to remain from ground centroid
D_{safe}	Minimum safe distance between 2 nodes to lower risk of collision
D_{rwalk}	Maximum radius of the loitering zone
θ_{max}	Maximum turn angle allowed for this UAV
α	Averaging bias

Table 2: Threshold parameters used in the flocking rule execution process

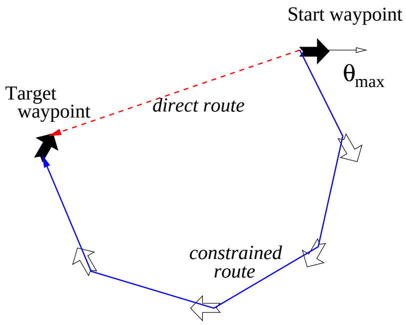


Figure 3: Imposing rotational constraints on UAV movement between source and destination waypoints

between two waypoints depends on the initial orientation of the UAV and the maximum allowed turn angle, θ_{max}. Figure 3 illustrates this constraint.

Since UAVs can form a multihop wireless communication network (unlike birds, which rely on natural instincts), it is possible to share non-local location information of ground nodes as well as UAVs in order to make movement decisions. However, in this paper we restrict ourselves to purely local exchange of information and thus mimic flocking closely. We assume that a neighbor discovery protocol is running on all ground and airborne nodes. Each node sends its neighbor (node within the communication radius) a heartbeat message, periodically. The following information is sent along with the heartbeat message:

1. My current location (e.g., GPS information)
2. Number of ground nodes connected to me

When a heartbeat is received from a ground node, a UAV updates its neighbor table if the former is a new neighbor. Neighbor table entries *time out* automatically in the absence of expected heartbeat messages. When a heartbeat is received by a UAV u_i from another UAV u_j, u_i stores u_j's location information, calculates the separation distance between them, and stores that in a local variable d_{u_i,u_j}. The heartbeat received at time t also contains information on the number of ground nodes connected to the source u_j. UAV u_i stores this in a local variable $N_t^{(u_j)}$. In general, at every UAV node, a variable $N_t^{(u)}$ stores the number of ground nodes connected to the UAV u at time t.

Every UAV continually computes a *cumulative average* of its own N_t values to estimate how well it is tracking the ground nodes. The formula used for this purpose is given by:

$$N_t^{(avg)} = \alpha\, N_{t-1}^{(avg)} + (1-\alpha)\, N_t^{(me)}, \qquad 0 \le \alpha \le 1$$

A low value of parameter α biases the averaging towards current updates and a high value of α results in remembrance of more historical information. The optimal choice of this parameter depends on the degree of mobility of the ground nodes, and should be chosen carefully.

Flocking Rules Table 1 summarizes the various rules that we propose to use for the flocking of UAVs. These may be executed upon the arrival of a heartbeat message from a neighboring UAV. The rule execution sequence

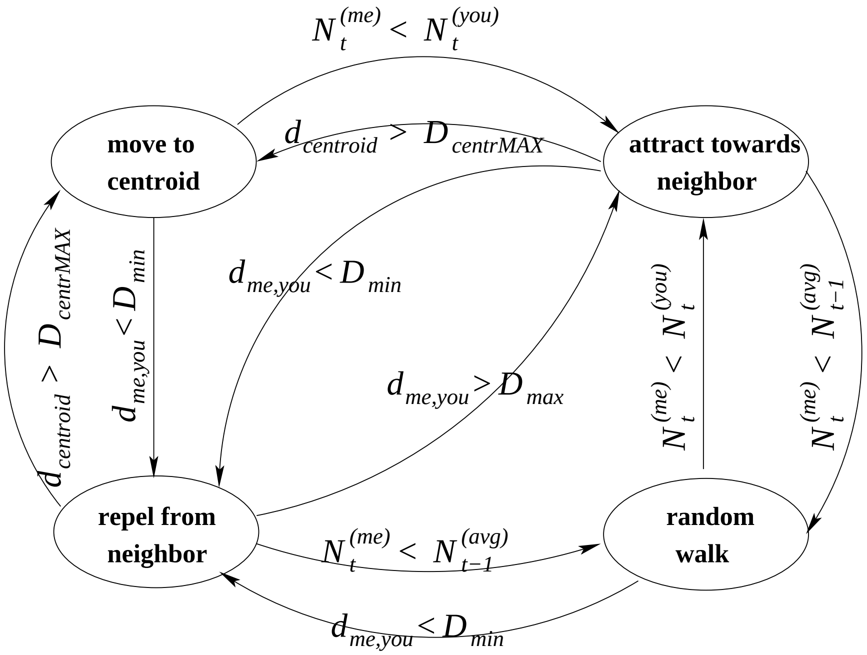
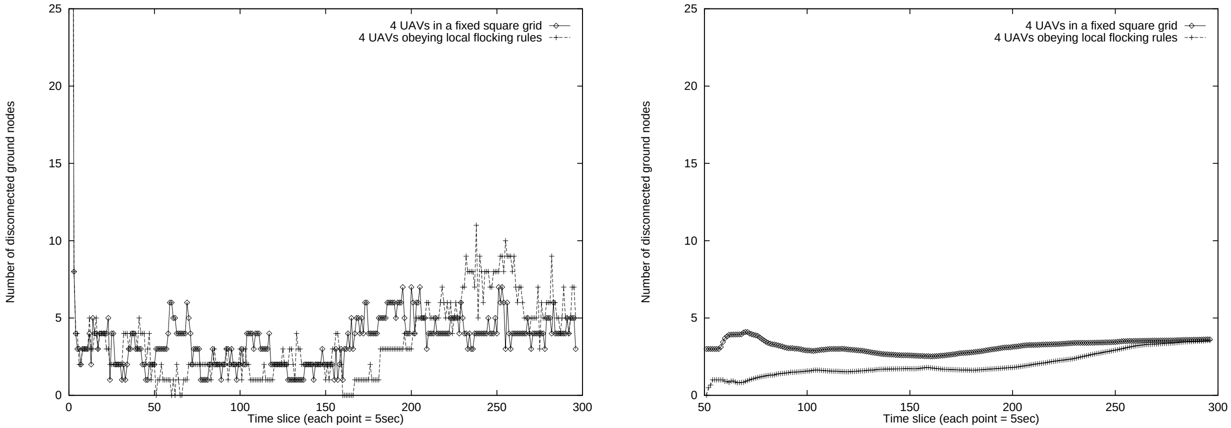


Figure 4: Local rules for flocking of UAVs in a finite state machine format

Parameter	**Value**	**Parameter**	**Value**
$Area(km^2)$	$20 \times 20,\ 20 \times 40$	D_{rwalk}	0.5km
$(N, \#UAV, H)$	$(100, 4, 10km)$	D_{max}	12km
$[v_{min}, v_{max}]$ (in m/s)	$18 + / - 20\%$	D_{min}	10km
Heartbeat period	$5sec$	$D_{centrMAX}$	2.5km
α	0.25	θ_{max}	$\frac{\pi}{6}$

Table 3: Simulation parameters and their values



(a) Snapshot (b) Cumulative

Figure 5: No Marching Scenario: Connectivity Results

is shown in Figure 4 as a finite state machine diagram. The threshold parameters used in that figure play an important role in the execution of the above set of rules. Table 2 enlists the parameters that were used in this work.

Multiple conditions may be valid at each state shown in Figure 4. Hence, there is a state-specific order of testing these conditions. For example, if a UAV is in state "attract", three conditions can be simultaneously true: (1) $d_{centroid} > D_{centrMAX}$; (2) $d_{me,you} < D_{min}$; and (3) $N_t^{(me)} < N_{t-1}^{(avg)}$. The order in which these conditions are tested are (3), (1) and then (2). This is because coverage is considered to be a significant goal in our current framework and the validity of condition (3) alludes to the fact that the UAV under consideration is losing ground neighbors; in this scenario the UAV does a random walk to test whether it can gain more ground neighbors.

The aforementioned order of testing the validity of conditions is not restrictive in any way. The flexibility of this framework allows these rules (as well as their order of execution) to be altered to yield the desired behavior. One point to be noted is that when a UAV is told to move from waypoint A to waypoint B, its path always depends on its orientation when it received the directive because the path has to obey the θ_{max} constraint.

4 Performance Evaluation

In this section we present simulation results of our flocking algorithms and comparisons with a stationary grid based placement scheme. We simulated the flocking rules presented in the previous section over a reasonably long period of time ($T = 1500s$). The parameters used in the simulations are shown in Table 3. We simulated two different scenarios: (1) a $20km \times 20km$ field where all ground nodes follow the random waypoint mobility model; and (2) an elongated $20km \times 40km$ field where all ground nodes are initially randomly distributed in the left half of the field and they randomly move towards the right half of the field. This simulates an example of a group marching in a particular direction rather than randomly moving within a given area. Note that $N = 100$ denotes the number of disconnected components in the network – these could be single nodes or connected groups of nodes.

4.1 Random motion in a constrained area

We divided the simulation time into 5 second epochs and gathered statistics for each such epoch. Each time slice shown on the X-axis of Figures 5-7 corresponds to 5 seconds of simulated time.

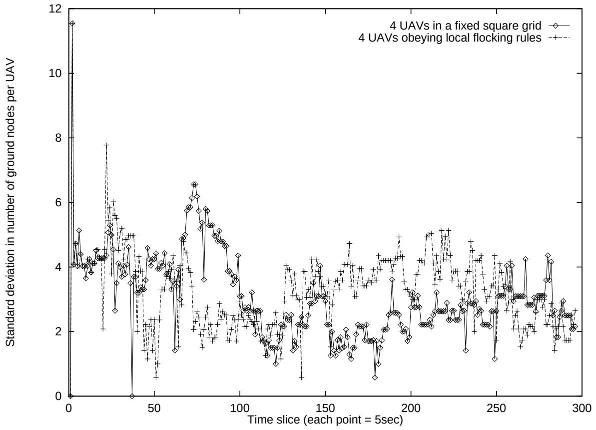
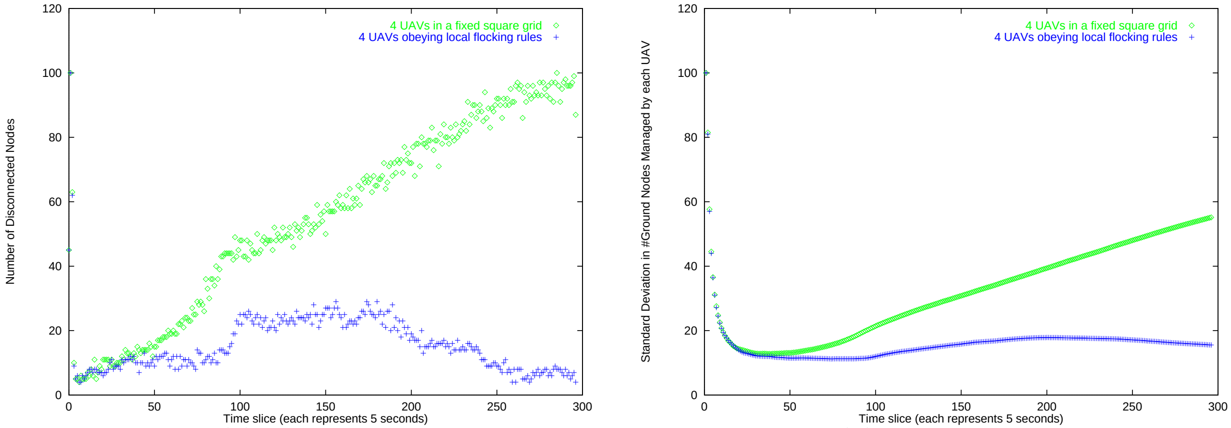


Figure 6: No Marching Scenario: Standard Deviation

We compared the performance of the proposed flocking technique with a fixed UAV placement approach with respect to two metrics: (1) number of disconnected ground nodes; and (2) standard deviation in the number of ground nodes connected to a UAV. In the latter approach, we divided the $20km \times 20km$ area into 4 square cells and placed a UAV at the center of each cell. In this placement, neighboring UAVs are 10km apart and the UAV network is a connected square. Also, these 4 UAVs are enough to cover almost all the 96 ground nodes. The connectivity results are shown in Figure 5. We observe that both flocking and fixed placement exhibit similar performance and each outperforms the other in some regimes. This shows that flocking does not result in the loss of coverage or connectivity in this scenario. The standard deviation curves are plotted for every time slice in Figure 6. We observe that no single technique outperforms the other at all times. These simulations essentially establish, at least for the chosen parameters, that flocking performs as well as grid-like placement in the two chosen metrics.

4.2 Directed group motion (marching)

We now present the results which establish the real benefits of UAV flocking. We simulated an elongated battlefield scenario where ground nodes move from the left half of the field to the right. In order to adequately cover possible areas in the field a grid placement technique will advocate dividing the whole area into 8 square cells and placing a UAV at the center of each cell. This is a wasteful solution especially because each extra UAV is very expensive to deploy. However, if we only place 4 UAVs in the left half of the field and make them flock



(a) Snapshot (b) Cumulative

Figure 7: Random Marching Scenario: Connectivity Results

using the proposed rules, they can effectively track the ground nodes while maintaining connectivity and good coverage.

We can observe from Figure 7 that both schemes perform equally well right in the beginning but as time progresses, ground nodes start moving towards the right side of the field, in the scheme with 4 fixed UAVs, more and more nodes become disconnected from the network. On the contrary, flocking UAVs track the motion of ground nodes and maintain the number of disconnections down to a constant level (see Figure 7(b) for the cumulative plots). Arguably, the flocking rules used in this paper need to be improved further in order to achieve the goals of lowering the number of disconnects (which should theoretically go down to the levels of Figure 5).

5 Conclusions

UAVs are traditionally used by the military for reconnaissance and surveillance. Recent growth in wireless networking technologies has made the use of UAVs for connecting far-flung ground nodes/networks attractive. We proposed a technique based on flocking behaviors of birds to effectively connect a large fraction of the mobile ground nodes. Flocking works as well as static grid placement in a fixed, constrained environment while it expectedly outperforms the latter when there is an overall motion of the nodes towards a particular direction, e.g., marching ground troops. Static placement of UAVs is either inadequate in terms of coverage or wasteful in terms of cost. On the contrary, flocking adapts effectively to the group mobility of the ground nodes and as we showed by simulations, flocking UAVs can provide good coverage, connectivity and load-balance to the underlying mobile ground nodes. Flocking uses local information in making decision about where to move, hence keeping the network control overhead very low. Using multiple-hop information can arguably improve performance of the flocking algorithms and is a subject of future research, e.g., landmark routing [3] can be leveraged to gather more information about the network. Another topic for future research is how flocking can be made to adapt to specific application needs and not just pure connectivity.

NOTE: The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U. S. Government.

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