Game Theory and Biology Inspired Flight Control for Autonomous UAVs Operating in Contested Environments

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***Abstract*—A self-organizing swarm of autonomous unmanned areal vehicles (UAVs) can provide a quick response to cyber-attacks in austere civilian and military environments. However, if a UAV swarm relies on centralized control, synchronization of swarm members, pre-planned actions or rule-based systems, it may not provide adequate and timely response against cyber attacks. We introduce game theory (GT) and biologically inspired flight control algorithms to be run by each autonomous UAV to detect, localize and counteract rogue electromagnetic signal emitters. Each UAV positions itself such that the swarm tracks mobile adversaries while maintaining uniform node distribution and connectivity of the mobile ad-hoc network (MANET). UAVs use only their respective local neighbor information to determine their individual actions. Simulation experiments in OPNET show that our algorithms can provide an adequate area coverage over mobile interference sources. Our solution can be employed for civilian and military applications that require agile responses in dynamic environments.**

***Index Terms*—Autonomous UAV, swarm, MANET, evolutionary computation, game theory, cybersecurity**

I. Introduction

Inexpensive unmanned areal vehicles (UAVs) are capable of operating in hostile environments without risking valuable assets. A swarm of such expendable UAVs can successfully and rapidly be deployed into areas without preexisting infrastructural support. However, for a swarm to accomplish complex mission objectives with high scalability and responsiveness, its UAVs must form and maintain a mobile ad-hoc network (MANET). The features that make MANETs suitable for rapid self-deployment in dynamic environments introduce challenges for autonomous UAVs. Despite advances in UAV swarm systems, current flight control solutions often rely on centralized control, synchronization, or pre-planned actions, hence lack the agility demanded by modern electromagnetic (EM) warfare.

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Game theory (GT) provides a framework for evaluating behavior of rational players in strategic situations, where outcomes depend on actions of all participants. GT has been broadly applied to solve problems with multiple competing goals in such areas as economics, finance and political science. Its wide range of applications in computer communications includes network resource allocation, routing efficiency and intrusion detection systems. For many MANET operations (e.g., topology control of mobile nodes), a GT can be adopted with incentives and deterrents built into mobile node actions to provide desired solutions, while eliminating need for coordination and synchronization among nodes [1], [2].

Biology inspired computation techniques have gained popularity in networking due to their ease of implementation and effectiveness to solve multi-objective and often intractable optimization problems, including MANET topology control [3], routing [4], node collaboration [5] and cybersecurity [6]. Bio-inspired solutions emulate nature, where fitter individuals have greater chance of survival and strive in a given environmental niche. Typically, they are computationally inexpensive in providing optimum or near-optimum results satisfying conflicting objectives faster than traditional techniques.

In this paper, we introduce near real-time flight control algorithms that combine GT and bio-inspired computation techniques to effectively guide autonomous UAVs. These algorithms, run independently in each UAV, use only the information collected from local surroundings of a UAV to position it over a target area. Simulation experiments using realistic models in OPNET suggest that our algorithms, while requiring limited near neighbor communication, provide a satisfactory area coverage and maintain uninterrupted MANET connectivity when tracking a mobile adversarial target.

The rest of this paper is organized as follows. Recent research in UAV decision control techniques, biology inspired and GT based algorithms for MANETs is in Section II. In Section III, our flight control algorithms combining bio-inspired and GT for autonomous UAVs are presented. Results of OPNET simulation experiments to evaluate swarm performance for different configurations are in Section IV.

II. RELATED WORK

Recent UAV flight control algorithms typically rely on a centralized authority controlling a single stand-alone UAV to improve transmission rates and coverage of a target area [7]. In [8], the authors perform a pre-planed 3D distribution of multiple UAVs to optimize power usage. Damaged communication infrastructures can be supported by tactical networks with hybrid aerial and terrestrial communication vehicles providing mission critical communications [9]. Partially autonomous UAVs that need periodic interactions with a centralized (often ground-based) controller to eliminate long-distance communication links [10] or UAVs using costly image processing and coordination procedures in tasks such as topology formation and obstacle avoidance [11] may not be adequate for a swarm of UAVs operating in dynamic environments.

Self-organization of a swarm implies that a swarm possesses an emergent capability to carry out a complex task by its members, which have not been explicitly designed to achieve a mutual goal [12]. The emergent behavior is not preprogrammed but raises from spontaneous responses of members to ongoing environmental changes. There are partially autonomous UAV swarms operating in familiar geographical regions with pre-determined set of actions [13], whereas others rely on *cooperative games* to coordinate actions [14]. Several research results suggest that UAV tasks be administered by centralized mission planners [15] or by global cooperation and target state sharing among swarm members [16], [17].

Coordinating a swarm of UAVs to provide continuous area coverage, an intractable problem [18], can be effectively handled by evolutionary techniques. Our previous work [3] demonstrates that autonomous vehicles can operate as a self-organized swarm accomplishing nontrivial missions in severe environments. Each individual in a swarm makes its own decisions using bio-inspired algorithms to solve multi-objective optimization problems, yet, despite locality of individual mobile node decisions, the swarm can maintain the pace needed for preserving MANET connectivity [19]. This swarm agility is attributed to fast and lightweight bio-inspired algorithms guiding individual vehicle movement decisions to maintain fault tolerance and resilience under dynamically changing conditions [20].

Popular applications of GT in communication networks attempt to design efficient routing protocols with enhanced security and improved spectrum sharing [21]–[23]. GT has been demonstrated to detect attacks on UAVs that augment ground sensor and vehicular networks [24], to allocate tasks in a swarm of drones visiting multiple locations [25] and to provide decentralized coalition formation of UAVs for search and neutralization of targets [26]. In our previous work we demonstrated that GT can provide fault-tolerant topology control for autonomous nodes in MANETs that gracefully recovers from adversarial actions in 2D and 3D tactical situations in theaters with obstacles [2], [27].

III. OUR FLIGHT CONTROL ALGORITHMS

A swarm of autonomous UAVs guided by our flight control algorithms aims to provide a high percentage area coverage over targets located in contested environments. In a typical mission, a swarm may be deployed to neutralize disruptive EM actions of interference emitters (e.g., jammers) while providing ongoing uninterrupted services to dispersed ground and low-altitude friendly entities. This task is especially challenging when the swarm is expected to respond to unpredictable movements of adversarial actors in austere conditions. UAVs running our GT and bio-inspired algorithms promote emergent swarm intelligence and self-organization needed for efficient response to ever-changing conditions. Our goal is to form a swarm of autonomous UAVs tracking a mobile hostile target while keeping a high percentage ground area coverage and MANET connectivity throughout a mission. Our GT and bio-inspired flight control algorithms are designed to only require information from near neighbors of a UAV to determine its actions in near real-time.

An autonomous UAV first finds a set of candidate positions to move using a genetic algorithm (GA) to determine the next improved location in the 3D space around it. The candidate positions are then used as strategies in a realistic self-enforcing competitive game [28] set up among a mobile UAV and its near neighbors, where game payoffs reflect the actions of players. In the game, a UAV selects a next position by anticipating next actions of its neighbors to maximize its payoff.

In our implementation of GA, a chromosome represents a candidate next position for the UAV to move. The GA starts with generating a population of individuals ρ. It then finds the fitness of each candidate position. Fitness F_i of a candidate location for UAV n_i with N_i neighbors is defined as

$$Fi = \begin{cases} F_{max} & \text{if } |N_i| = 0 \\ \sum_{j=1}^{N_i} f(d_{ij}) & \text{otherwise,} \end{cases} \tag{1}$$

where F_{max} is the maximum penalty applied to a location that would result in n_i being disconnected from all its neighbors and $f(d_{ij})$ is the virtual force applied on n_i by its neighbor n_j, which is a function of distance between them. The virtual force between n_i and n_j is defined as $f(d_{ij}) = \big(R_{com} - \sqrt{(x_{n_i} - x_{n_j})^2 + (y_{n_i} - y_{n_j})^2 + (z_{n_i} - z_{n_j})^2}\big)$, where R_{com} is the communication range of node n_i. Smaller fitness values in our GA indicate better positions for a given UAV.

In our experiments, each UAV is equipped with hardware capable of measuring the strength of interfering EM signal. Each UAV shares this information and its own coordinates with its near neighbors in N_i to be included in the fitness calculations. All candidate positions in GA will be weighted with respect to their signal levels such that stronger signal levels are given preferences since they indicate positions closer to the rouge transmitter.

An *elitist* selection mechanism is used to choose the best parents from individuals in the population for *cross-over* and *mutation* operations that generate offspring for the next generation. GA stops after a predetermined number of generations or when a required objective is met. The last generation of offspring, called ρ^{last}, is used by our GT to select a next position that would benefit itself and its neighbors.

UAV u_i determines its next position by setting the game $\Gamma_i = \langle P, S, R \rangle$ with its near neighbors. In Γ_i, we define a set of players $P = \{n_i \cup N_i\}$, a space of strategy profiles $S = \times_{n_j \in P_i} S_j$, where strategy space for each player $S_j = \rho^{last}$, and a tuple R of payoff functions denoting preferences of all players over the game outcomes. For each $n_j \in P$, payoff is its anticipated fitness F_j when strategy profile called $\boldsymbol{s}$, with the next locations of each UAV in P, is realized. UAV u_i computes the best response BR_i to possible actions of its rational neighbors N_i as

$$BR_i = \arg\min_{s_i \in S} f(s_i) = F_i(s_i, \boldsymbol{s}_{-i}), \tag{2}$$

where $\boldsymbol{s} = s_i \cup \boldsymbol{s}_{-i}$, with s_i denoting a next position for u_i and $\boldsymbol{s}_{-i}$ representing a tuple of probable future locations for all UAVs in N_i (i.e., $\boldsymbol{s}_{-i} \in \times_{n_j \in N_i}$). By using Eq. (2), u_i avoids moving along directions that overlap with inevitable choices for other swarm members. Equation (2) also prevents nodes from repetitive movements that could result in disconnected MANET topology, requiring additional corrective actions. It is possible that the best response of u_i can designate more than one best choice to move, where $|BR_i| > 1$ is a set of best u_i responses to possible movements of its near neighbors. In such a case, u_i selects its next position which would be the most beneficial to its neighbors in N_i (e.g., minimizes $\sum_{n_j \in P} F_j$).

Our approach combines GT and GA to obtain a computationally lightweight flight control for each autonomous UAV to determine its movements in near-real time. As the adversarial transmitter moves, EM signal landscape changes, which then triggers UAVs to move toward the positions with stronger levels of rouge signals. Hence, each UAV, using only local information, follows a moving target without a priori knowledge on a target trajectory while maintaining connectivity to its neighbors.

IV. Simulation Experiments

In simulations experiments implemented in OPNET [29], each UAV autonomously determines its position to move by using our GT and GA based flight control algorithms. Autonomous UAV swarms use communication ranges of $R_{com} = 100\,m$, $200\,m$, or $400\,m$ and can fly with the maximum speeds of $10\,m/s$, $20\,m/s$, or $28\,m/s$. Every simulation experiment was repeated 10 times and the results were averaged to reduce noise in the data collected from the 40-minute sessions.

OPNET network radio parameters were set to support desired R_{com} ranges in forming MANETs with neighboring UAVs. Additional OPNET transmission parameters of an individual UAV include the antenna type, transmission power, frequency band, data rate and packet size, which mimic real-life communication devices. Periodically, a UAV broadcasts its own position and sensed EM landscape information. Since each UAV has limited communication range, this transmission is only received by neighbors within its locality.

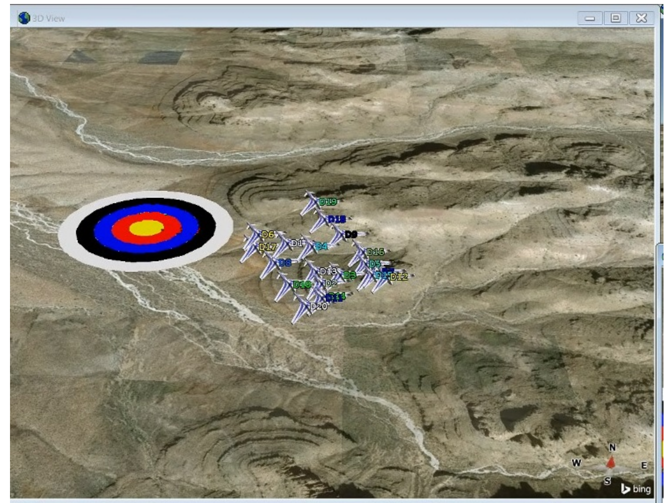


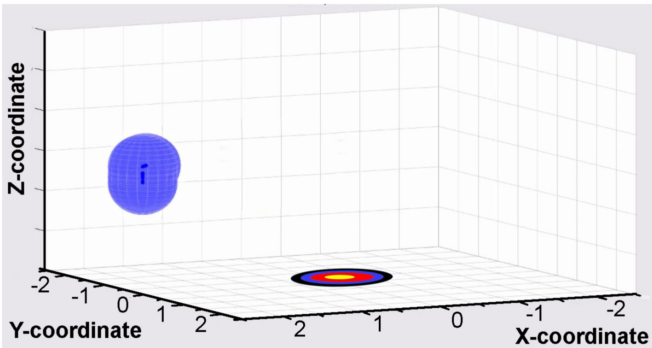
Fig. 1. STK visualization of OPNET simulation for deployment of a MANET of a swarm with 20 UAVs over a realistic terrain

The deployment terrain for our simulation experiments are chosen with real earth latitude, longitude and elevation coordinates. In our experiments, UAVs form a MANET over a mobile interference source located in a contested area. Figure 1 shows a screen capture from STK software [30] used for visualization of UAVs moving over the target area.

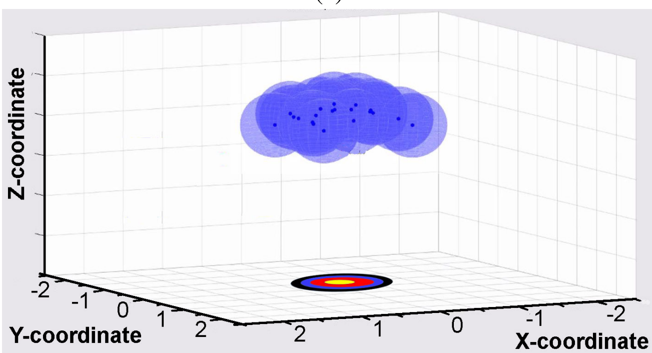
Figure 2 presents a typical 3D distribution of 20 UAVs deployed in a $5\,km \times 5\,km$ area (labels of x and y axes are the distances from the center of the theatre). Each UAV in Figure 2 runs our GT and GA based flight control algorithms with a maximum speed of $10\,m/s$ and $R_{com} = 400\,m$. As a response to hostile activity, the UAV swarm is launched from the ground (depicted at the left corner of Figure 2(a)). This type of deployment imitates realistic situations, where UAVs enter a terrain occupied by hostile forces from a common entry point. Apart from the location of the theatre, marked as a target in Figures 1 and 2, no other geographical information about the target is required by the UAVs when they are launched. Upon arrival at the theatre, each autonomous UAV enables its flight control algorithms to maintain a MANET of uniformly distributed nodes over the target (Figure 2(b)). Swarm of autonomous UAVs maintains a high coverage of the target area, while keeping network connected and tracking the mobile target. Figure 2(c) shows the UAV distribution after they successfully track the mobile adversary throughout an experiment.

One of the important performance metrics for a MANET is its ability to maintain the connectivity among its mobile nodes during an operation. As part of performance evaluation of our flight control algorithms, we monitor the connectivity of MANET throughout experiments. In this study, we compare the performances of swarms guided by only GA with the combination of GA and GT.

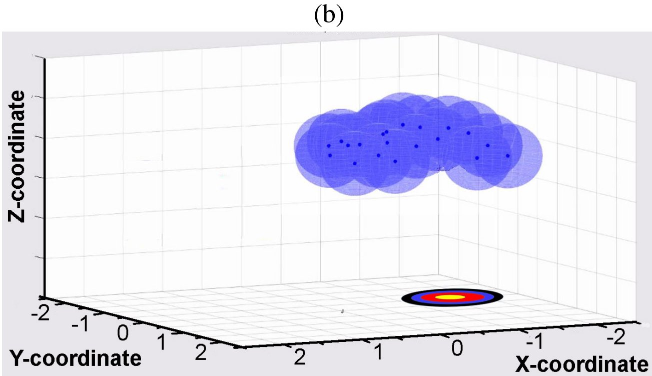
Figure 3 illustrates the number of connected components over time for a typical simulation experiment, where 20 UAVs with $R_{com} = 400\,m$ operating with a maximum speed of



(a)



(b)



(c)

Fig. 2. OPNET simulation of a swarm with 20 autonomous UAVs: (a) at their entry to a mission theatre, (b) after forming a MANET over an initial location of a mobile adversarial entity depicted as a target on the ground, and (c) as the swarm tracks the mobile adversary

$10\,m/s$ follow a mobile adversary (note that the path and the movement parameters of adversary entity are unknown to the swarm members). At time t_1 in Figure 3, swarm arrives at the target and begins spreading over the area of interest. The mobile target starts moving at t_2 and stops its movement at t_4. Network connectivity under GA control (depicted in solid red line in Figure 3) are disrupted starting at t_3, when the swarm detects the movements of mobile target and starts tracking it, without fully recovering until the end of experiment. On the other hand, we observe that GA and GT based flight control (blue dashed line) successfully keeps the MANET connected throughout the experiment. Each UAV detects that mobile entity is moving by recognizing the changes in EM map of the theatre (for simplicity, we do not consider adversaries

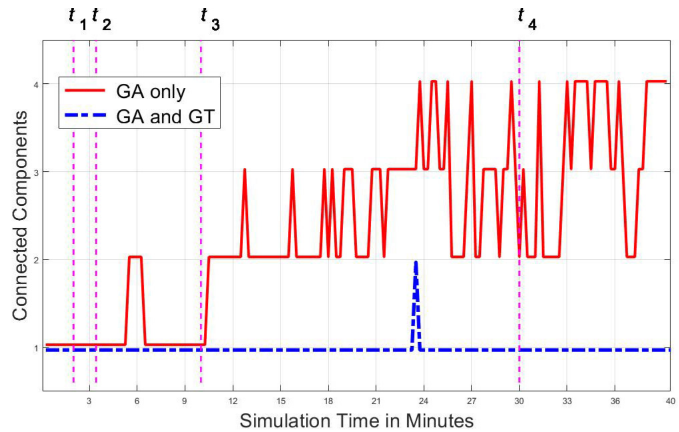


Fig. 3. The number of connected components of UAV swarm over time as it tracks a mobile target during an OPNET simulation experiment using flight control algorithms with only GA and combining GA and GT

changing their EM footprint over time). After repeating this experiment for 10 times, we confirm that, compared to the GA alone, GA and GT together provide a more coherent flight control, where the MANET is kept connected throughout experiments (except for temporary partitions).

In a more detailed analysis of network partitioning problem, we run experiments for various swarm configurations controlled only by GA and by GA and GT combination. In Figure 4(a)-(c), the number of strongly connected components for swarms speeds of $10\,m/s$, $20m\,/s$, and $28\,m/s$ are shown, respectively (for $R_{com} = 100\,m$). We observe that the average results for network partitioning is consistently better when UAVs use GA and GT together to control their movements. When UAVs move faster, it becomes more difficult to maintain MANET connectivity as an experiment progresses, which can be seen by the increased number of connected components over time. For example, in Figure 4(c), with a maximum speed of $28\,m/s$ (which is equivalent to $100\,km/h$), network starts partitioning $10\,min$ after the experiment begins for UAVs controlled by GA, reaching more than 3 partitions on the average at the end. However, UAVs controlled by GA and GT remain fully connected during the first half of the experiments and have on the average less than 2 separate components at the end of experiments.

Figures 4(d)-(f) depict the number of strongly connected components for swarms with the maximum speeds of $10\,m/s$, $20\,m/s$ and $28\,m/s$, respectively (for $R_{com} = 400\,m$). UAV swarms with longer communication ranges running GA and GT outperform swarms that use only GA for movement decisions by maintaining lower number of connected components during the experiments. When comparing MANET connectivity for swarms with $R_{com} = 100\,m$ and $R_{com} = 400\,m$, UAVs running only GA flight control perform noticeably worse at higher speeds (e.g., $20\,m/s$ and $28\,m/s$), especially toward the end of experiments. For example, at 35$^{\text{th}}$ minute of the experiments, swarms running only GA with a maximum speed of $20\,m/s$ and $R_{com} = 100\,m$ have on the average 3

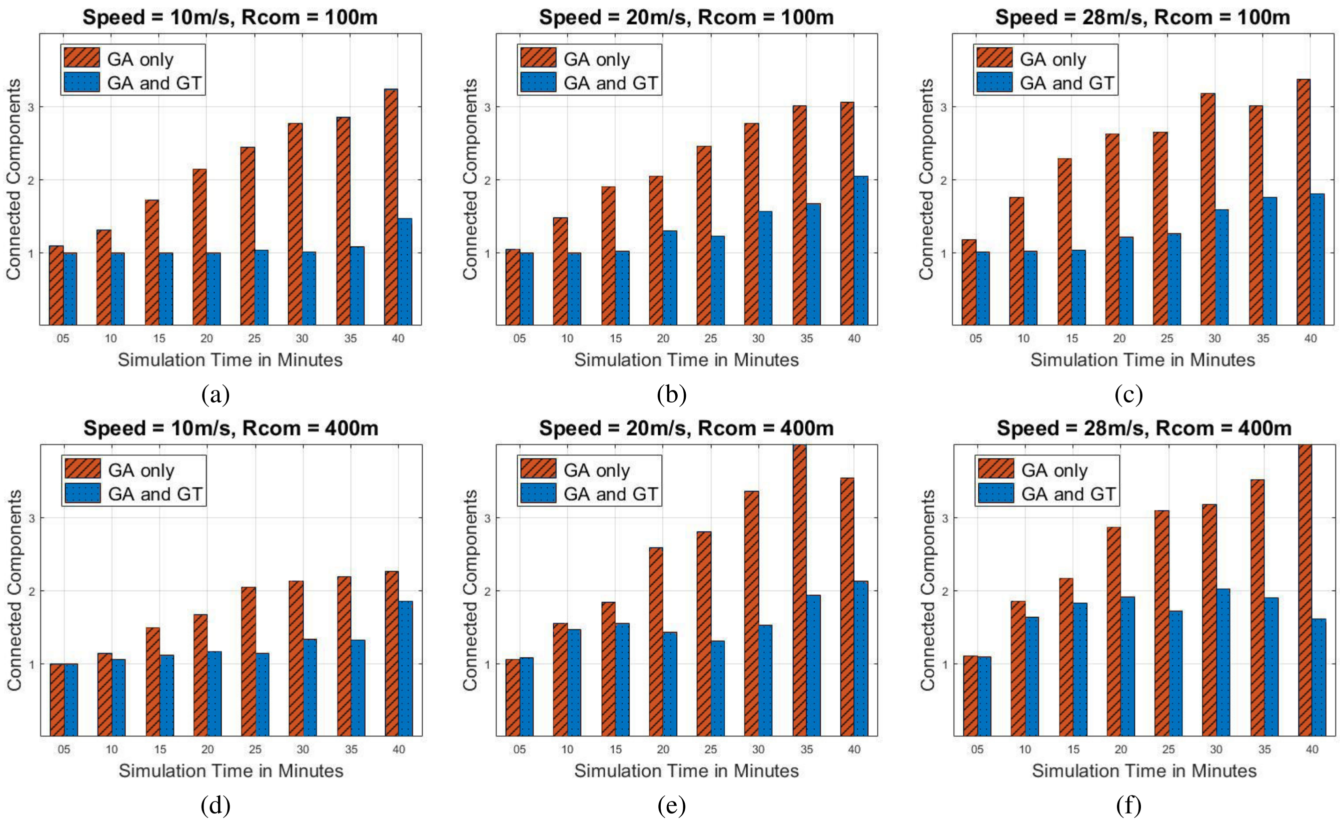


Fig. 4. Number of strongly connected components for swarms guided by GA only and by GA combined with GT flight control algorithms: (a)-(c) $R_{com} = 100\,m$ with speed of $10\,m/s$, $20\,m/s$, and $28\,m/s$, respectively, (d)-(f) $R_{com} = 400\,m$ with speed of $10\,m/s$, $20\,m/s$, and $28\,m/s$, respectively

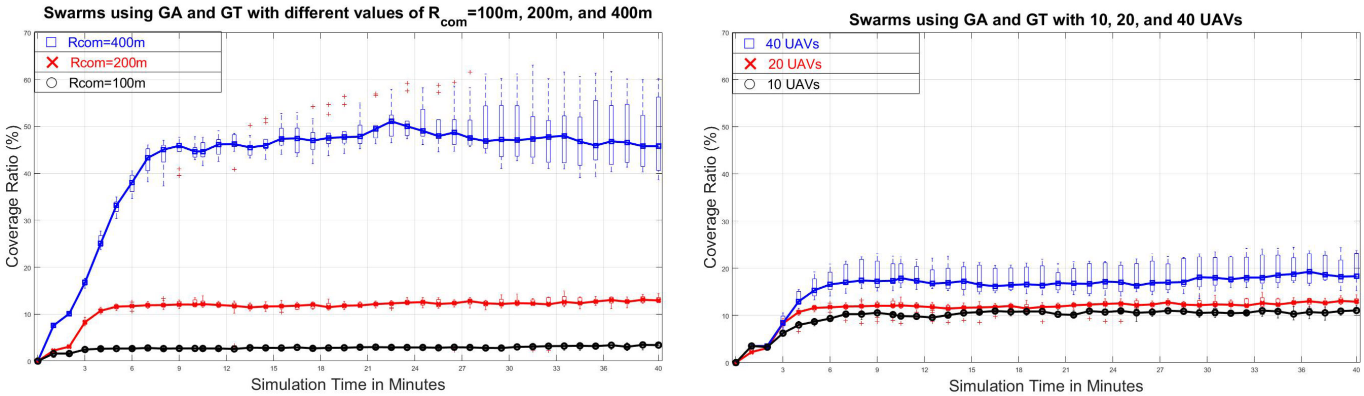
connected components (Figure 4(b)) as opposed to more than 4 by the swarm with $R_{com} = 400\,m$ (Figure 4(e)). We can conclude from the results shown in Figure 4 that when continuous MANET connectivity is important for a mission success, GA and GT combination should be chosen as the flight control strategy.

Figure 5(a) presents the 2D areal coverage obtained by swarms of 20 UAVs running GA and GT over a deployment area for $R_{com} = 100\,m$, $200\,m$ and $400\,m$. As expected, swarms with higher R_{com} values cover proportionately larger areas than the ones with shorter ranges. We observe in Figure 5 that the highest area coverages are obtained approximately at the same time for all three swarm configurations. Although better coverage is obtained by larger communication ranges, network connectivity suffers when UAVs can communicate farther, as discussed earlier with respect to Figure 4. This phenomenon is due to UAVs taking into account more distant positions to move that may put them out of range of their neighbors and, hence, create temporary network partitionings. Swarm configurations shown in Figure 5(b) have the same communication ranges and maximum speeds for different sizes of swarms (with 10, 20 and 40 UAVs). The area coverage for these cases improves proportionally as the number of UVS in a swarm increases.

We observe from our experiments that increasing swarm size does not necessarily increase the time required to reach their respective highest coverages. This significant result means that the number of UAVs can be chosen to accomplish a desired degree of redundancy of UAVs for a given mission without impairing overall swarm performance.

V. Concluding Remarks

We introduce game theory and biologically inspired flight control algorithms for swarms of autonomous UAVs operating in environments contested by rogue electromagnetic signal emitters. In our near real-time flight control techniques UAVs use genetic algorithms to determine a set of improved next positions, from which the best next location is determined by games played among near neighbors. A set of simulation experiments run in OPNET Modeler is used to evaluate the performance of our algorithms with respect to maintaining MANET connectivity and ground area coverage. We observe that biology inspired decision making process for flight control can be improved by incorporating game theoretic mechanisms to provide a high percentage area coverage above an adversarial mobile entity, while keeping the MANET connected throughout missions. Performance of our flight control algorithms make them promising candidates for civilian and military applications that require agile responses in dynamic environments for detection, localization and counteracting adversarial EM sources.



(a)

(b)

Fig. 5. Area coverage for swarms using GA combined with GT: (a) $R_{com} = 100\,m$, $200\,m$, $400\,m$ with speed of $10\,m/s$, $N = 20$, (b) $N = 10$, 20, 40 with a speed of $10\,m/s$ and $R_{com} = 200\,m$

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