AI and Game Theory based Autonomous UAV Swarm for Cybersecurity

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***Abstract*—Uninterrupted communication is crucial for modern electromagnetic (EM) spectrum operations where successes of situational awareness, defensive and offensive missions depend on ongoing control of a wireless spectrum. Preventing an adversary from dominating cyberspace becomes challenging as rapid technological developments allow state and non-state actors to engage in a broad range of destructive cyber electromagnetic activities (CEMA). Digital threats to communication networks can range from eavesdropping and impersonation attempts to various forms of denial-of-service attacks. In this paper, we present bio-inspired and game theory based flight control algorithms for a swarm of autonomous UAVs. Each UAV considers MANET connectivity, overshadowed ground area coverage and signal strength from interfering mobile radio emitters. Our algorithms use 3D Voronoi tessellations and linear interpolation for EM mapping of local neighborhood as a part of decision making process. Simulation experiments in OPNET show that our algorithms can successfully guide autonomous UAVs while requiring limited near neighbor communications to provide a high percentage area coverage with an uninterrupted MANET connectivity. By providing a lightweight solution for rapidly deployable swarm of autonomous UAVs, our flight control algorithms are good candidates for deployment in complex environments in presence of adaptive and mobile sources of EM interference.**

***Index Terms*—Autonomous UAV swarm, MANET, AI, game theory, cybersecurity, EM heatmap, CEMA**

I. Introduction

Defending cyberspace against adversarial entities has become more difficult due to recent technological developments allowing state and non-state actors engage in a broad range of potentially harmful cyber electromagnetic activities (CEMA). Disruption of electromagnetic (EM) spectrum is one of the main concerns that may hinder successful realization of modern cyberspace objectives. Digital threats to positioning, navigation and timing (PNT) systems and communication networks can range from eavesdropping and impersonation attempts to different forms of denial-of-service attacks.

Expendable unmanned areal vehicles (UAVs), operating in near real-time, can eliminate the need for costly equipment or direct engagement, otherwise required to accomplish a set of complex mission objectives with high scalability, resilience and responsiveness in contested and hostile environments. Such a UAV swarm is expected to form and maintain a mobile ad-hoc network (MANET) to accomplish tasks that are for traditional communication infrastructures with centralized control and synchronization. The same characteristics that make MANETs suitable for a rapid self-deployment in dynamic tactical environments also introduce challenges for implementing control of autonomous UAVs. Current flight control solutions often rely on computationally expensive mechanisms such as computer vision, centralized control, preprogrammed decision making algorithms, and hence, lack the agility demanded by modern missions.

Bio-inspired solutions emulate evolution in nature with better organisms having higher chances of enduring in an environmental niche compared to less fit ones. Effective design and implementation of bio-inspired algorithms can provide suitable results for problems with conflicting objectives while requiring only light computational loads. Evolutionary computation gained popularity in addressing complex networking problems due to their effectiveness and speediness in solving difficult and often intractable optimization problems in MANET topology control [1], routing [2], and cybersecurity [3].

Game theory (GT) is an effective tool to solve problems with multiple competing goals, where outcomes depends on actions of all involved entities, so-called players. Its initial application to economics was quickly followed by a broad range of applications in financial, social and political sciences [4], [5]. Recent networking applications of GT include resource allocation, routing and intrusion detection mechanisms [6]. Game-theoretical approaches are shown to facilitate MANET topology control by incorporating incentives and deterrents into autonomous mobile node decision processes while eliminating a need for coordination and synchronization among mobile nodes [7].

We present a flight control mechanism for a swarm of autonomous UAVs making independent movement decisions using only information from near neighbors of each node. Flight control algorithms at each UAV apply bio-inspired AI and GT based techniques to determine the next best position while maintaining MANET connected with a high area coverage overshadowed by the swarm. They use 3D Voronoi

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tessellations and linear interpolation for EM mapping of local area as part of their decision making process to effectively follow a source of rouge EM signal. Simulation experiments run in OPNET modeler [8] and examined in STK [9] modeling environment suggest that our method is suitable to maintain a high percentage of area coverage and uninterrupted MANET connectivity as the swarm shadows a mobile adversarial target.

Section II of this paper presents recent UAV decision control techniques and research results for MANETs using biology inspired and GT based algorithms. Our flight control algorithms for autonomous UAVs are introduced in Section III. Results obtained from OPNET simulation experiments to evaluate swarm performance for different configurations are in Section IV.

II. Existing Research

State of the art flight control systems may not be adequate for a swarm of UAVs operating in hostile and dynamic environments. UAV tasks can be administered by mission planners in a control center [10] or by global cooperation and target state sharing among swarm members [11]. They often require a centralized entity controlling a single UAV [12], or utilize pre-planed 3D distribution of UAVs [13]. Some UAVs that are partially autonomous need periodic interactions with a single control unit to avoid ongoing long-distance communication [14], [15]. Other flight control systems use *cooperative games* to coordinate UAVs [16], as opposed to more realistic and self-enforcing *competitive games* used in our flight control algorithms.

Swarm coordination to provide satisfactory areal coverage by UAVs, which is classified as an intractable problem [17], can be successfully handled by evolutionary techniques. In our previous research [18], using bio-inspired algorithms to solve multi-objective optimization problems, autonomous vehicles are shown to operate as a self-organizing swarm in austere environments. Each swarm member makes its own movement decisions based on local information such that the swarm can preserve MANET connectivity in dynamic environments. Our fast and lightweight bio-inspired algorithms guiding UAVs provide adequate fault tolerance and resilience under rapidly changing conditions [19].

Cyber security systems based on GT can detect attacks on UAVs that augment ground sensor and vehicular networks [20] and provide decentralized coalition formation of UAVs for localization of targets [21]. In our previous research, we successfully combined bio-inspired algorithms and GT to provide fault-tolerance for swarms in 2D and 3D tactical situations in theatres with obstacles and asset losses [1], [7], [22].

III. Our Flight Control Algorithms

Adversarial activities on cyber infrastructures can severely disrupt communication networks and PNT systems by EM interference (i.e., DoS) and rogue radio data transmissions (e.g., MitM). A swarm of UAVs guided by our AI and GT based flight control algorithms can form and maintain a MANET over a mobile adversarial entity, while maintaining network connectivity and high areal coverage influenced by the attacker to, for example, augment communication and PNT services for friendly entities.

Our research results in 3D underwater network topology control [18] indicate that genetic algorithms (GAs) can be adopted into flight control mechanism operating with relatively small time and computational complexity. The fitness function of a GA evaluates next improved locations by considering positions of near-neighbor UAVs and power of the signal from an adversary emitter. We assume that, with modest modifications (e.g., using directional antennas and tagging friendly radios), UAVs can observe EM footprint and power of radio signal that is interfering with PNT services. Without loss of generality, our experiments do not consider adversarial interference of EM band used in MANET communications. Our flight control algorithms presented in this paper use local 3D EM propagation heatmaps generated by Voronoi tessellations and linear interpolation of emittance at neighboring nodes.

The GA starts by generating a population of chromosomes ρ representing candidate next positions for a UAV to move. The fitness F_i of a candidate location for UAV n_i with N_i neighbors is defined as

$$Fi = \begin{cases} \sum_{j=1}^{N_i} \gamma \times D_{ij} & \text{if } |N_i| \geqslant 1 \\ \mathcal{M}_c & \text{otherwise,} \end{cases} \quad (1)$$

where $\mathcal{M}_c$ is the maximum penalty applied to a location that would result in n_i being disconnected from its neighbors. For all practical applications, $\mathcal{M}_c$ should have a greater value than any feasible F_i for n_i if $|N_i| \geqslant 1$ (e.g., $\mathcal{M}_c > (R_{com} \times |N|)$, where $|N|$ is the number of UAVs in the swarm). Smaller fitness values in Eq. (1) indicate preferred positions for a UAV. The weight $\gamma \in (0, 1]$ in Eq. (1) incentivizes locations with stronger interference signal power and, hence, promotes a swarm emergence needed for following the source of an EM interference. All UAVs use γ values that are proportional to the changes in ISR of candidate new locations.

In Eq. (1), D_{ij} denotes the virtual force applied to n_i by its neighbor n_j as a function of Euclidean distance between them $d(n_i, n_j)$. The virtual force D_{ij} between n_i and n_j is

$$D_{ij} = \begin{cases} R_{com} - f(d_{ij}) & \text{if } 0 < d(n_i, n_j) < d_{th} \\ \eta & \text{if } d_{th} \leqslant d(n_i, n_j) \leqslant R_{com}, \end{cases} \quad (2)$$

where R_{com} is the communication range of n_i and d_{th} defines a threshold value for the best node separation with a sufficiently small η.

Each UAV periodically broadcasts its position and ISR measurement to its neighbors in R_{com} distance away. A UAV obtains local 3D EM propagation heatmap by applying either Voronoi tessellation or linear interpolation to the known ISR measurement points in its locality. For any point p_j corresponding to a location of the ISR_j obtained by $n_j \in \{n_i \cup N_i\}$, Voronoi tessellation [23] outlines a Voronoi region V_j such that all locations closer to p_j than to any other p_k from the respective $n_k \in \{N_i \cup n_i\}/\{n_j\}$ are parts of V_j. We define a Voronoi region for a p_j of $n_j \in \{n_i \cup N_i\}$ as

$$V_j = \{\omega \in \Omega : d(p_j, \omega) < d(p_k, \omega), \forall_{p_k \in \{N_i \cup n_i\}/\{n_j\}}\} \quad (3)$$

where Ω represents the set of all points within R_{com} distance from n_i and $d(p_j, \omega)$ stands for the distance between p_j (x_j, y_j, z_j) and a point $(x_\omega, y_\omega, z_\omega)$ in Ω.

Interpolated value of ISR at a given location in 3D space around a UAV is obtained by linear interpolation of the values from its known neighboring grid points. In this study we obtain ISR_i at a candidate position p_i using OPNET and MATLAB. When a rouge transmitter moves, EM signal landscape surrounding each UAV changes, triggering UAVs to move toward stronger ISR, while maintaining MANET connectivity and high area coverage around the area under attack.

We implement a GT based approach to mitigate cohesive movement of neighboring UAVs. After running GA, u_i obtains a final set of candidate next positions ρ^{last} that is used to start a game with near neighbors to determine its most preferred next position while anticipating future actions of its near neighbors. Our game is defined as $\langle P, S, R\rangle$, where $P = \{n_i \cup N_i\}$ represents the players, $S = \times_{n_j \in P} S_j$ is the space of strategy profiles with a set of strategies for each player S_j and the tuple R reflects preferences (payoffs) of all players over the game outcomes. Payoff for n_i is its anticipated fitness F_i when playing strategy $s_i \in S_i$ against deleted mixed strategies of its neighbors $\boldsymbol{s}_{-i} \in \times_{n_j \in N_i} S_j$ (i.e., $F_i(s_i, \boldsymbol{s}_{-i})$). Autonomous UAV u_i finds the best response BR_i to given actions of its set of rational neighbors N_i as

$$BR_i = \underset{s_i \in S}{\arg\min} = F_i(s_i, \boldsymbol{s}_{-i}). \qquad (4)$$

Node u_i selects a point indicated by BR_i against possible deleted strategy profiles $\boldsymbol{s}_{-i}$, where BR_i can be a set of best responses to possible actions of its near neighbors. This way, u_i can avoid moving into areas that overlap with inevitable choices of other swarm members.

In our flight control algorithms, GA facilitates rapid identification of a set of promising locations in dynamic environments, whereas GT promotes adequate next positions that benefit both the moving UAV and the swarm. Since these algorithms are not computationally expensive, each autonomous UAV using our flight control system can respond to changes in environment in near-real time.

IV. Simulation Experiments

We developed simulation experiments in OPNET [8], where each UAV model is implemented to independently make its movement decisions using our flight control with GA and GT algorithms. In evaluating candidate positions to move while considering adversarial emitter movements, GA uses a temporal local 3D EM heatmap created by Voronoi tessellations and linear interpolation of ISR values in its vicinity. For simplicity and without loss of generality, UAVs in our simulation experiments have the same communication range R_{com} and the maximum speed. In each experiment, 20 UAVs were dispatched to form a MANET over an area of interest in a $5km \times 5km$ theatre. Each swarm deployment was simulated as a 40-minute mission and repeated 10 times with results averaged to eliminate noise in the collected data.

OPNET Modeler is capable of simulating realistic signal propagation in dynamically changing environments. Wireless

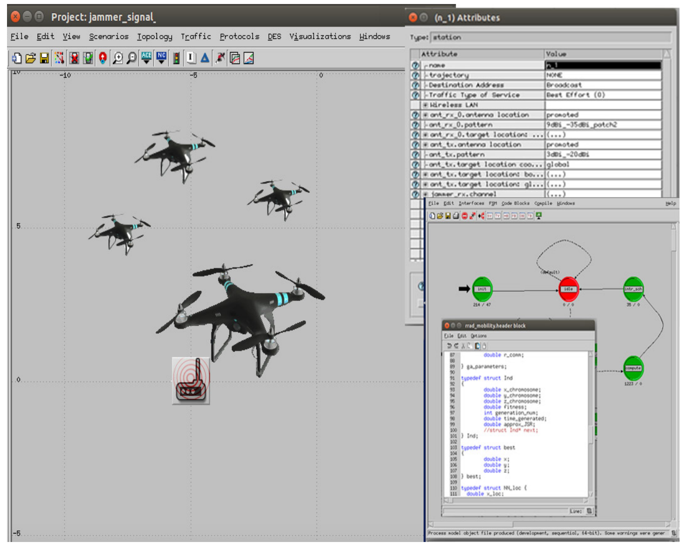


Fig. 1. OPNET Modeler environment simulating MANET of autonomous UAVs

communication parameters (e.g., antenna type and transmission power) were set to facilitate R_{com} ranges required by real-life use-cases. Figure 1 presents a capture of OPNET screen with an autonomous UAV swarm reacting against a mobile source of EM interference. Overlapping windows in Figure 1 show OPNET interfaces for setting transmission parameters and the code for GA and GT algorithms. User can adjust movement capabilities of a UAV by setting its speed and degree of freedom in its movement as needed throughout an experiment.

Figure 2 is a screen capture from STK software [9] for 3D visualization of a swarm operation with real earth coordinates. The left pane shows a perspective view of UAVs forming a

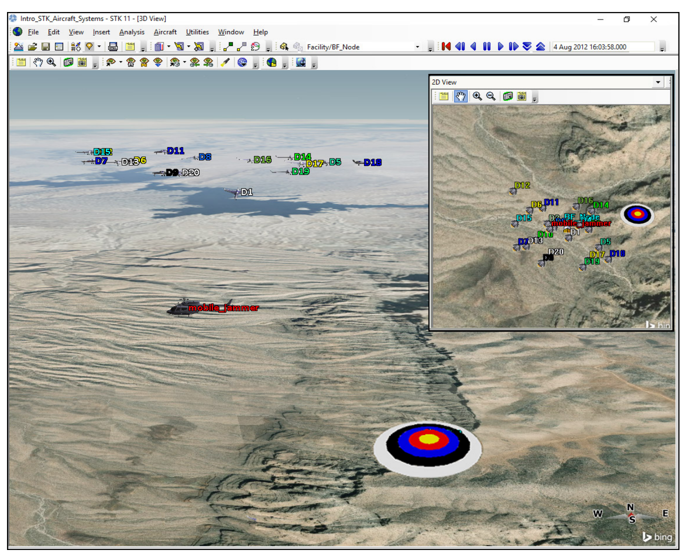
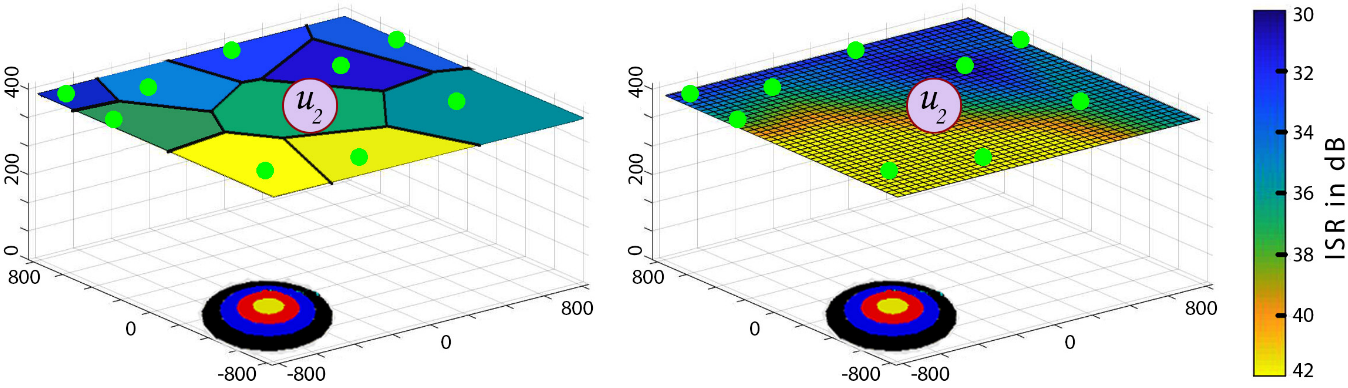


Fig. 2. STK visualization of OPNET simulation for deployment of a MANET form by a swarm over a realistic terrain



(a) (b)

Fig. 3. EM heatmaps obtained from ISR points surrounding u_2 using: (a) Voronoi tessellations and (b) linear interpolation

MANET above an airborne source of EM interference, whereas the top right pane is the bird's-eye view of UAVs. The initial area of interest is depicted in Figure 2 as a target on the ground, which moves as the interference source relocates throughout an experiment.

OPNET allows for simulating hardware components that continuously monitor received radio signal strengths. Each UAV periodically sends a heartbeat message to its neighbors within an R_{com} radius. Our AI algorithms employ Voronoi tessellations and linear interpolation computed based on ISR points located at the vicinity of a UAV. This information is used in evaluating candidate positions for the UAV to move and in estimating the location of a rouge mobile emitter(s).

EM heatmaps of the area around a UAV (called u_2) are shown in Figure 3, where u_2 is located at the center, the locations of its neighbors are represented as green dots and an adversarial radio emitter is marked as a target on the ground. The intensity of ISR in dB are represented by the colored bar placed at the right hand side of Figure 3. For simplicity, only a single cross-section of the 3D EM landscape is included in Figure 3.

The Voronoi tessellation shown in Figure 3(a) is obtained using Eq. (3), where the green dot at the center of each cell represents the location of a neighbor UAV. Our AI flight control algorithms incorporate the anticipated ISR of a candidate position to guide the UAV in its movement decisions. The local EM heatmap in Figure 3(b) is generated using linear interpolation between observed dB values of ISR measurements. We can see in Figure 3(b) that, compared to Voronoi tessellations, the EM landscape generated by linear interpolation is more detailed and, hence, can be more beneficial in maintaining MANET connectivity and following a mobile target. However, we should note that compared to linear interpolation, Voronoi tessellations is computationally cheaper and may be preferred by applications with limited resources.

Figure 4 shows a typical 3D distribution of the UAV swarm tracking a mobile source of radio interference. The swarm is dispatched from the left corner of a theatre (Figure 4(a)) and flies to the area of adversarial activities (depicted as a target

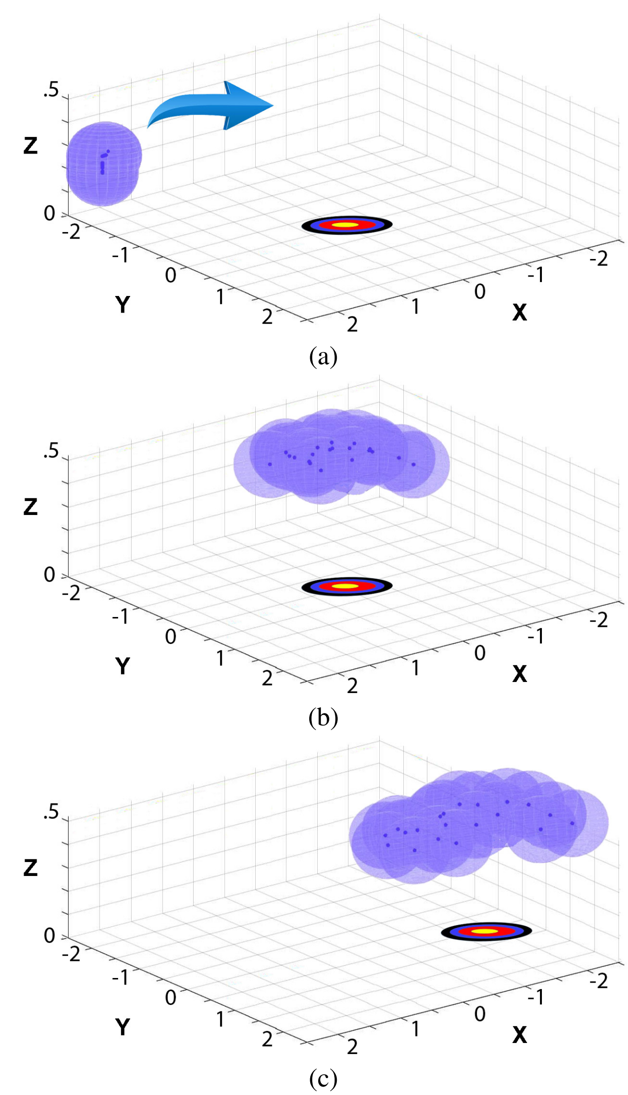


Fig. 4. Deployment of a UAV swarm (generated from a sample OPNET run): (a) shortly after the deployment, (b) when forming an initial MANET over a target on the ground after 4 minutes, and (c) after 40 minutes of simulation

mark). This type of deployment mimics realistic situations where assets are released from a launch platform outside of the theatre. After arriving at the initial destination, UAVs spread to increase ground-area coverage, while maintaining MANET connectivity (Figure 4(b)). At the final stage of the simulation (Figure 4(c)) 20 UAVs successfully track the target moving horizontally during the experiment and maintain appropriate elevations from the source of a rouge EM signal. It should be noted that the UAVs do not have *a priori* knowledge of actions and strategies of an adversarial entity, and they do not rely on a central controller for swarm coordination to continue overshadowing the area of interest.

The ability of a swarm to preserve network connectivity throughout a mission is an important metric to evaluate its capability for fulfilling a coherent operation. We compare the MANET connectivity of our swarm when it utilizes Voronoi tessellation and linear interpolation as part of its flight control algorithms. Figure 5 illustrates the averaged number of connected components over time for UAVs using local EM maps. At time t_1 in Figure 5, swarm arrives at its initial destination

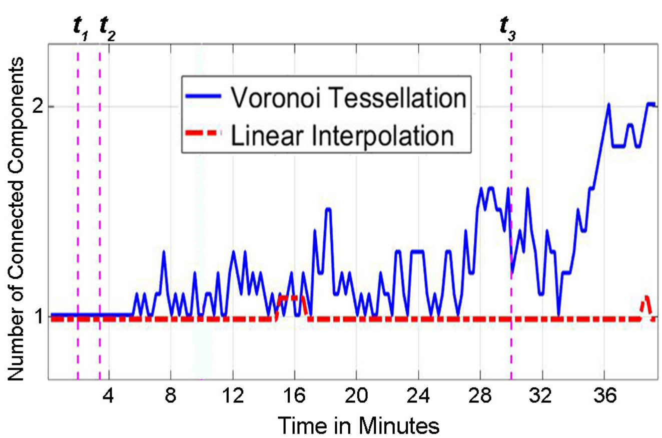


Fig. 5. Number of strongly connected components in a UAV swarm as it follows a mobile target using different EM mapping methods

and begins spreading over an area of interest. The mobile target starts moving horizontally at t_1 (implemented as $3\,min$ for this simulation experiment) and stops at t_3 (at $30\,min$). For the swarm using Voronoi tessellation (depicted in blue solid line in Figure 5), the network splits shortly after the mobile target starts moving (at t_2) and MANET never recovers full connectivity in this experiment. On the other hand, we observe that when UAVs employ linear interpolation into their flight control algorithms (red dashed line), the swarm successfully keeps the MANET connected throughout the experiment.

Figure 6 provides a comparison of the network partitioning problem in discrete time intervals for swarms with UAVs using Voronoi tessellation and linear interpolation. It can be seen that average results for network connectivity are consistently better when UAVs use linear interpolation to obtain local EM maps. With a more coarse but computationally cheaper Voronoi tessellation of the surrounding area, selection of the next position to move may be an inadequate response to the current

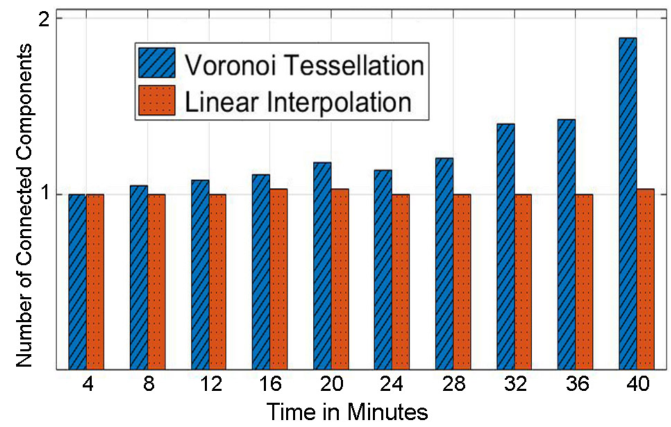


Fig. 6. Number of strongly connected components in a UAVs swarm using Voronoi tessellation and linear interpolation for 3D EM interference maps

EM landscape. Such actions may cause a UAV to cruise away from the swarm and require additional steps to reconnect to the MANET. However, when the more precise method of linear interpolation is used for creating EM maps, UAVs accurately follow a mobile interference source while keeping the MANET connected and avoiding temporary partitions.

We use a metric called network area coverage (NAC) to evaluate effectiveness of a swarm in overshadowing a terrain affected by hostile EM activities. NAC is computed as the ratio of an area of interest covered by UAVs and the area impacted by an adversarial radio signal A_a

$$NAC = \frac{\bigcup_{u_i}^{|N|} A_i}{A_a} \tag{5}$$

where $\bigcup$ represents the union operator and A_i denotes the area covered by R_{com} range of UAV u_i. If a region is covered by more than one UAV, the overlapped area is included in NAC calculations only once. Also, when a part of coverage

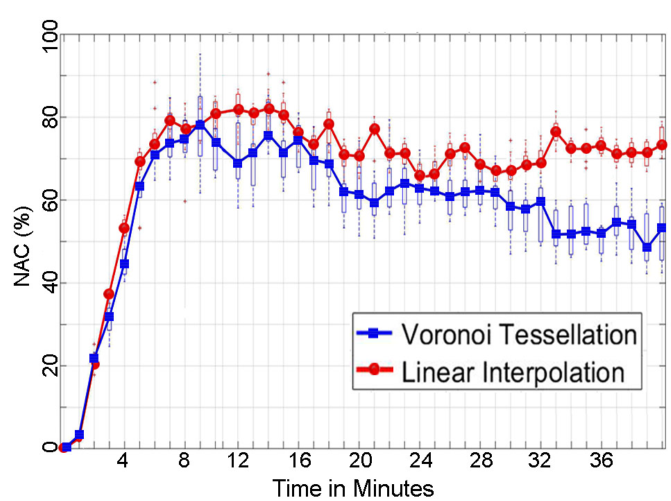


Fig. 7. NAC of UAV swarms employing Voronoi tessellation and linear interpolation to obtain local EM maps used by our flight control algorithms

area falls outside of A_a, only the portions located inside of it is considered for NAC. In our simulation experiments, A_a is defined as a $2km \times 2km$ square with a mobile adversarial EM source at its center.

Figure 7 displays the change in NAC throughout simulation experiments obtained by autonomous UAV swarms using Voronoi tessellation (blue line with squares) and linear interpolation (red line with circles). The outcomes in Figure 7 are presented as boxplots, where the boxes indicate 50% of the results and the whiskers above and below are the minimum and maximum values for that measurement, respectively.

We can see in Figure 7 that as the UAVs approach the center of the initial area of interest (during the first 6 minutes of the experiments), NAC keeps increasing until approximately 80%. Afterwards the mobile EM emitter starts moving, which causes the NAC to decrease since swarm needs time to respond to the changes in EM landscape. Compared to Voronoi tessellations, the swarms using linear interpolation in AI and GT calculations show better agility in adapting to the EM changes and sustain a higher coverage of A_a throughout the experiments. When local EM maps are generated by Voronoi tessellations, we observe a slight lag in responses to target movements in Figure 7 indicated by decreasing NAC values toward the end of the experiments. It should be noted in Figure 7 that swarms using Voronoi tessellations perform less consistently than with linear interpolation, as indicated by the larger deviations of the boxes and whiskers from the average NAC measurements.

V. Concluding Remarks

We introduce AI and GT based flight control algorithms for swarms of autonomous UAVs operating in terrains contested by rogue EM emitters. Each UAV use only local information to make flight control decisions to maintain MANET connectivity while following a moving target. In our flight control techniques, UAVs use Voronoi tessellation and linear interpolation to obtain local EM maps considered by GAs when determining a set of improved next positions from which the best next location is selected by non-cooperative games among near neighbors. We evaluated the performance of our techniques with respect to MANET connectivity and coverage of the area of interest by a set of realistic simulations run in OPNET Modeler. Compared to less complex Voronoi tessellation algorithms, linear interpolation based EM mapping gives better awareness of target locations, resulting in faster reconfiguration needed to preserve the connectivity of a MANET while following a rouge radio transmitter. We show that our flight control algorithms can contribute in preventing an adversary from dominating cyberspace as rapid technological developments allow state and non-state actors to engage in a broad range of destructive cyber electromagnetic activities (CEMA).

Future extensions of this research will include countering activities of multiple heterogeneous adversarial radio emitters moving in unpredictable patterns in complex and realistic military and civilian missions. Applications of our AI and GT based methodology will also be considered for augmenting existing telecommunications infrastructure and services.

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