AI based Flight Control for Autonomous UAV Swarms

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***Abstract*—Artificial intelligence (AI) based flight control algorithms can be successfully utilized to deploy a swarm of autonomous Unmanned Areal Vehicles (UAVs). In a swarm of autonomous UAVs operating as a mobile ad-hoc network (MANET), use of centralized control, pre-planned missions, synchronization of nodes and reliance on conditional procedures are not feasible We introduce near real-time AI based flight control algorithms for autonomous UAVs to position themselves over an area of interest. Each UAV uses only local neighbor information to advance the swarm toward a desired MANET topology. Simulation experiments in OPNET show that our algorithms can provide high percentage area coverage over a target, while requiring limited near neighbor communication. They are lightweight and power-efficient, hence well-suited for military applications.**

***Index Terms*—AI, MANET, autonomous UAV, swarm, bio-inspired computation**

FULL RESEARCH PAPER FOR CSCI-ISAI

I. INTRODUCTION

Mobile ad-hoc networks (MANETs) are infrastructureless wireless networks formed by nodes that may dynamically and independently change their positions over time. Their decentralized structure supports high scalability and responsiveness and makes them particularly suitable for rapid deployments in many civilian and military applications that, otherwise, would be difficult to accomplish with traditional computer networks. MANETs are increasingly used to operate in austere three-dimensional (3D) tactical situations, where self-deployment of autonomous mobile nodes is critical for maintaining dynamic network topology.

Typically mobile nodes of a MANET use wireless multi-hop communication, participate in non-hierarchical topologies, continuously and unpredictably reposition themselves and have limited power and computational resources. However, these intrinsic features of MANETs that are desirable for many applications also introduce challenges for implementing autonomous flight control of UAVs, including maintaining an expected level of topology control and cyber security.

Bio-inspired computation techniques are excellent candidates to bring effective solutions for MANET topology control [1], routing [2], node collaboration [3] and cybersecurity mechanisms [4]. These techniques can find desired optimum or near optimum solutions to satisfy conflicting objectives in prohibitively large domains. They emulate evolutionary processes found in nature, where better adapted individuals have greater chances of survival in an environmental niche.

We have shown that autonomous UAVs can operate as a self-organized swarm demonstrating an emergent behavior needed to accomplish complex missions in severe military environments [1]. Each autonomous UAV in a swarm can make its own decisions using bio-inspired algorithms to obtain adequate solutions for multi-objective optimization problems. Despite locality of individual mobile node decisions, a swarm of UAVs can exhibit the responsiveness needed for, for example, maintaining MANET connectivity in dynamically changing environments [5]. This agility can only be achieved by fast and lightweight bio-inspired algorithms guiding each UAV's flight control decisions.

In this paper, we introduce near real-time AI based flight control algorithms for each autonomous UAV to position itself over a tactical military theatre. With these algorithms, a UAV uses only the information collected from its local surroundings yet moving the swarm toward a near optimal MANET topology that attempts to maximize overshadowed ground terrain coverage while maintaining network connectivity. Since our AI based flight control algorithms are computationally inexpensive, they are power-efficient, agile and, hence, good candidates for military missions. Simulation experiments in OPNET [6] show that a swarm of autonomous UAVs employing our algorithms provides a high percentage of area coverage over a given target while utilizing a limited near neighbor communication.

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The rest of this paper is organized as follows. Section II presents recent research in flight control and biologically inspired algorithms for governing MANET topologies. Section III introduces our bio-inspired flight control algorithms for UAV swarms. Results of OPNET simulation experiments to evaluate their performance for different swarm configurations are presented in Section IV.

II. Related work

Most flight control algorithms reported in literature use a centralized authority or pre-planned missions where, for example, deployed UAVs provide connectivity services for ground-level wireless nodes. In such settings, coverage and rate performances of a stand-alone UAV may be improved by controlling its movement over a target area [7], while an optimal pre-planed 3D placement of UAVs can maximize the number of served users and minimize power usage [8]. Tactical networks can be arranged as hybrid aerial and terrestrial communication systems to facilitate public safety connectivity if communication infrastructure becomes damaged [9], [10].

Recent advances in biomimetic design and implementation of swarms increase the expectations for the capabilities demanded by modern warfare and similar austere environments. Typically, autonomous UAVs cannot be controlled by predetermined flight mission directives or rule based procedural mechanisms. Although they have limited communication ranges and energy resources, they should make their flight control decisions using their own computational capabilities. Self-governed UAVs should use local neighborhood information rather than centralized control or a swarm synchronization which would otherwise debilitate their rapid response to changes in a dynamic environment.

Many existing solutions for UAV deployment fall short of providing features needed to accomplish military missions in realistic challenging theaters. For example, in a partially autonomous UAV with an embedded computer performing calculations to eliminate long-distance communication links, periodic interactions between a centralized ground based controller and the UAV are needed [11]. In another example, a proposed UAV topology formation and obstacle avoidance mechanism requires costly image processing and coordination procedures, which may not be adequate for a swarm of UAVs operating in dynamic environments [12].

Artificial swarm intelligence has been considered as a potential technique to analyze self-organizing decentralized autonomous systems, where individual agents interact only with their nearest neighbors and local environment to accomplish, as a whole, a complex objective [13]. Since providing continuous area coverage by a swarm of UAVs is an intractable problem [14], evolutionary techniques can be utilized for efficient distribution of UAVs.

Some semi-autonomous swarms are designed with a predetermined set of UAV actions to operate in known territories [15], while others rely on coordination of a swarm using cooperative games [16]. Several studies suggest either the use of centralized mission planners to distribute tasks to UAVs [17], or global coordination among swarm members [18]. Similarly, in [19], the UAVs require coordination procedures and target state sharing in their ant colony based task allocation mechanism.

III. Bio-inspired Flight Control Algorithms

In our approach, a bio-inspired algorithm controls the movements of each autonomous UAV. Based on our previous research results on MANET topology control algorithms [20], we selected a genetic algorithm (GA) for making the movement decisions. Each UAV runs GA when it needs to move to a new position. When the local environment of a UAV changes (e.g., a new UAV moves into vicinity), it considers the positions of its local neighbors to select the next location to move.

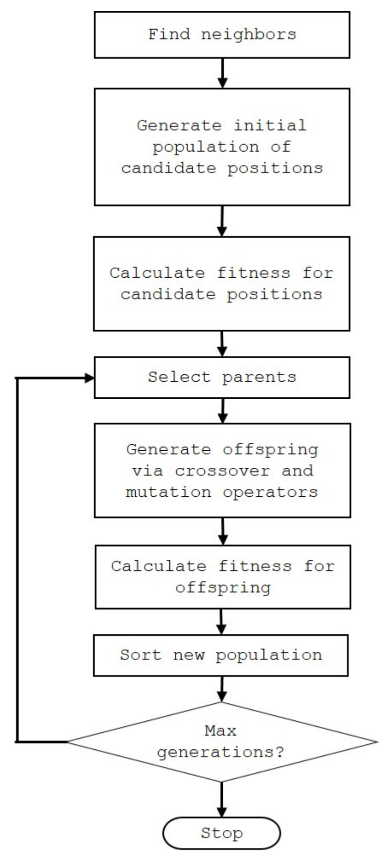
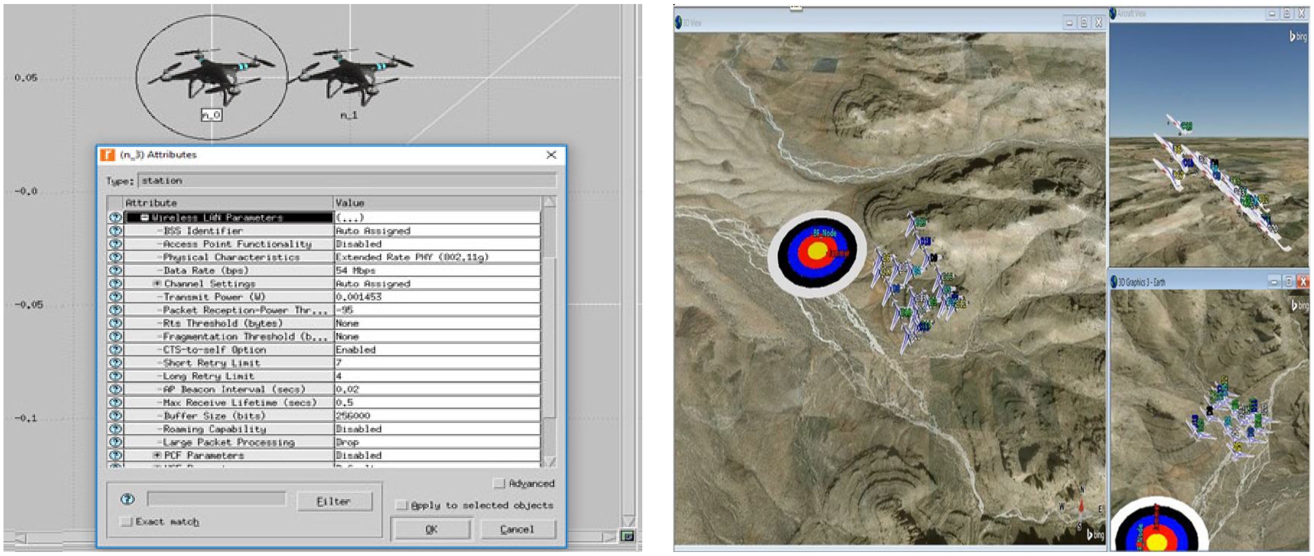


Fig. 1: Flow chart for simple GA employed in UAVs

A flow chart describing the operation of the GA is given in Figure 1. In this implementation, a chromosome represents the next position into which the UAV can move. The GA starts with generating a population of N individuals (i.e., candidate positions). It then finds the fitness of each candidate position. The fitness F_i for a candidate solution for a node N_i with σ_i neighbors is defined as follows:

$$Fi = \begin{cases} F_{max} & \text{if } \sigma_i = 0, \\ min[F_{max}, \sum_{j=1}^{\sigma_i} f(d_{ij})], & \text{otherwise,} \end{cases}$$



(a) (b)

Fig. 2: Simulation software for UAV swarm deployment: (a) OPNET management environment for MANET of autonomous UAVs, (b) STK visualization for deployment of UAV swarm over a realistic terrain

where F_{max} is the maximum penalty applied to any location that causes a node N_i to disconnect itself from all its neighbors, and $f(d_{ij})$ is the virtual force applied on N_i by its neighbor N_j as a function of distance between them. The virtual force between i and j is defined as $f(d_{ij}) = \big(R_{com} - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}\big)$, where R_{com} is the communication range of node N_i.

In our implementation of GA, smaller fitness values indicate fitter positions for a given node. Virtual force values applied to a node by its neighbors are adjusted depending on the class of tasks that the UAVs will be performing. After calculation of fitness, the individuals in the population are sorted based on their fitness values. Using a selection mechanism, parents are chosen, giving a preference to the fitter individuals (i.e., an *elitist* selection mechanism). Then using one point cross-over and a single low-probability mutation operators, GA generates offspring from the parents. It calculates the fitness of the offspring and includes them into the population such that only the top N individuals are kept for the next generation. After a pre-determined number of generations (or no fitness improvement is detected for a few generations), the algorithm stops. The best individual in the population is selected as the next position to move for the UAV. With its linear complexity, our implementation of GA as outlined in Figure 1 is computationally inexpensive.

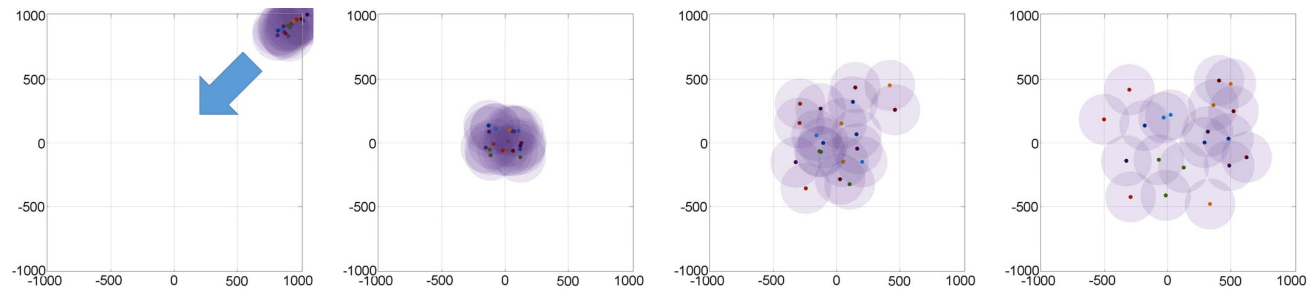
In our previous work, we formally proved that bio-inspired algorithms and game theory can provide fault-tolerance in MANETs in 2D and 3D tactical situations, resembling rescue, military and rescue theaters with obstacles, various node loss situations and adversarial attacks [1], [20]. Our near real-time autonomous solutions, formulated as lightweight, fault-tolerant and power-efficient systems, are shown to be suitable for military missions [21]. Using a homogeneous Markov chain model, we proved that a fitness function inspired by molecular distribution in physics can guide autonomous nodes to desirable geometric configurations with a high probability [22]. We also proved that the transition matrix in our network topology control algorithms is irreducible and aperiodic, hence ergodic and converges to a stable solution [5]. For underwater autonomous vehicles, 3D particle swarm optimization can be effective in achieving desirable spatial node distributions [23], where every vehicle in a uniform volumetric distribution increases its distance from neighbors, resulting in an improved topology.

When running our bio-inspired flight control algorithms to determine its actions in near real-time, each UAV considers only its near neighbor information (e.g., distance, position). Periodically, each UAV broadcasts its own position to its near neighbors. Since each UAV has limited communication range (R_{com}), this broadcast is received only by the nodes within its locality. This way, every UAV maintains a list of its current near neighbors.

IV. Analysis of Simulation Experiments

We designed a set of simulation experiments to demonstrate that our AI based algorithms can provide an agile flight control mechanism. In the experiments presented in this paper, the parameters for GA are set as follows. The population size is $N = 64$, the number of generations is 32, the number of offspring selected at each generation of GA is 16, and the mutation probability is 0.05%. An elitist selection mechanism is chosen to determine the parents at each generation.

For simplicity, without loss of generality, we assumed that all UAVs in a MANET have the same communication radius



(a) (b) (c) (d)

Fig. 3: Top view of 2D areal coverage of 20 autonomous UAVs at their entry to the theatre (a), and 2 (b), 3 (c) and 10 (d) minutes after launching the swarm

(i.e., R_{com}). To avoid statistical noise in observed outputs, each experiment reported in this paper was repeated 10 times. To simplify the initial simulation model, no intrusion of adversarial forces were considered in this study. Each autonomous UAV has the target area coordinates, but has no *a priori* knowledge of the underlining terrain and locations of other UAVs.

The experiments were run in OPNET network management environment [6] to ensure a realistic simulation of UAV near neighbor communication channels in dynamically changing MANET topology. Our flight control algorithms were implemented in each simulated UAV to determine its own position, movement speed and flight direction as a simulation experiment progresses. All wireless communication parameters (e.g., antenna type and transmission power) were set to resemble realistic wireless communication. Transmission power of each UAV was set to facilitate the range of communication R_{com}.

Figure 2(a) shows a screenshot captured from OPNET environment simulating our dynamic MANET topology. The OPNET GUI, shown as the overlapping window in Figure 2(a), allows for setting transmission parameters for each UAV. The inputs that can be specified by this GUI include the antenna type, transmission power, frequency band, data rate and packet size. A user can also adjust movement parameters for a UAV by its maximum speed in meters per second (mps) and degree of freedom.

Figure 2(b) presents screen captures by STK software [24] used for 3D visualization of UAV movements in real terrain. The top right pane represents the view-point of one of the UAVs, which displays the altitude differences among UAV positions. The bottom right pane is the view observed from directly above the target area, which also depicts the area coverage of the UAVs. The left pane is the combination of the side and top views and provides an angled perspective view for the UAV positions.

During all experiments, the UAVs initially fly to the operation theatre for the first 200 seconds of the experiment (the center of the operation area is marked as a target in Figure 2(b)). Upon arrival at the theatre, each UAV raises to a higher altitude and enables its bio-inspired flight control to obtain a uniform distribution of swarm members over the target area. For the remainder of each experiment, autonomous UAVs continuously adjust their positions to maintain a uniform spread over the target area.

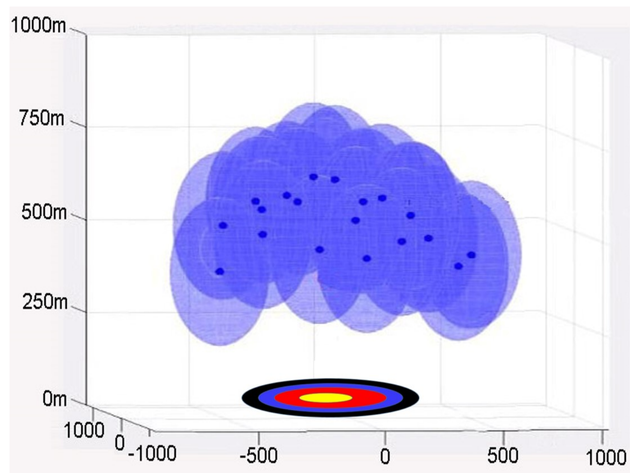
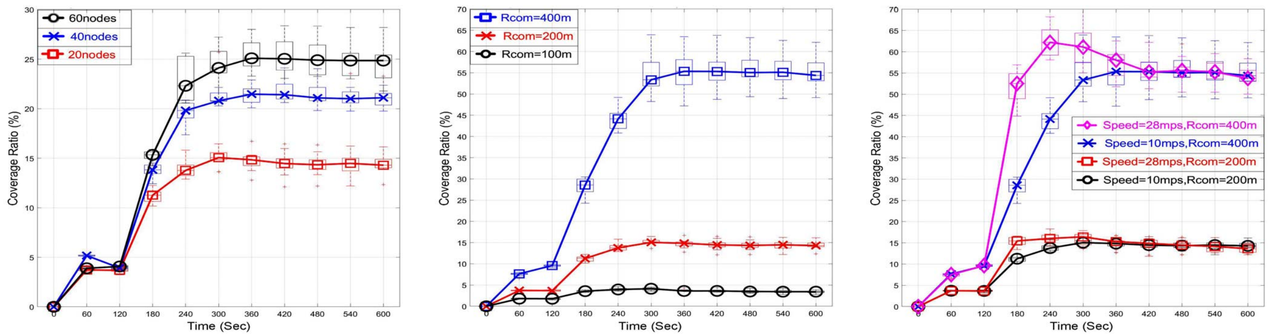


Fig. 4: 3D view of UAV positions after a swarm deployed over a target area in one of the simulation experiments

We demonstrate through our simulation experiments that the movement speed and the communication range for each UAV are the most dominant parameters determining the performance of the swarm. As the speed of a UAV increases, a faster convergence to a uniform distribution is expected. In addition, the areal coverage of the swarm is directly proportional to both the communication range of each UAV and the total number of UAVs in a MANET.

Figure 3 presents 2D areal coverage obtained by 20 UAVs, each with $R_{com} = 200m$, deployed over a 3×3 km^2 area. UAVs are launched from the upper right corner of the deployment area (Figure 3(a)) and initially fly directly to the military theater, which is located at the center (Figure 3(b)). This type of deployment imitates realistic situations, where UAVs enter a terrain occupied by hostile forces from a common entry point (compared to random or other initial allocation schemes often seen in the literature). The central location of



(a) (b) (c)

Fig. 5: 2D areal coverage for different configurations of autonomous UAV swarms: (a) 20, 40 and 60 UAVs with $R_{com} = 200m$, (b) 20 UAVs with $R_{com} = 100m,\ 200m,$ and $400m$, (c) 20 UAVs with $R_{com} = 200m$ and $400m$ and maximum speeds of $10mps$ and $28mps$, respectively

the military theater is the only information known to the UAVs when they are launched. Once they are within R_{com} distance of the center, they start spreading as can be seen in 3(c). Figure 3(d) shows the area covered by 20 UAVs after the simulation experiment is run for 10 minutes.

Figure 4 shows a 3D view of a 20-UAV swarm at the end of a simulation experiment, where our flight control algorithm aims to maintain a uniform distribution of UAVs over a target area while preserving MANET connectivity. This type of topological formation by autonomous mobile nodes are desirable in many civilian and military missions. Note that, without loss of generality, our AI based flight control algorithms can operate over the targets that are defined above the ground level.

Figure 5 shows 2D convergence toward a uniform distribution achieved by different configurations of autonomous UAV swarms operating over a target area. The results are presented as boxplots, where boxes indicate 50% of the results and the *whiskers* above and below show the minimum and maximum values for that measurement, respectively. The area coverage is defined as the ratio of the coverage achieved by the communication areas of all UAVs to the target deployment area. If the same area is covered by more than one UAV, overlapped area is included in coverage calculations only once.

Figure 5(a) shows the convergence for swarms with 20, 40, and 60 UAVs using $R_{com} = 200m$. As expected, we observe that when R_{com} is kept constant, larger swarms with more nodes can provide increased areal coverage. It can also be seen in Figure 5(a) that the respective areal coverage for each different swarm is reached approximately at the same time (approximately 6 minutes after launching). Therefore, as the target area increases, larger size swarms can be dispatched without causing extra delays due to increased swarm size in achieving needed areal coverage. This promising outcome can be mostly attributed to our GA implementation that does not require close coordination among UAVs.

Areal coverage obtained by three swarms comprising 20 autonomous UAVs with communication radii of $R_{com} = 100m,\ 200m,$ and $400m$, and each with a maximum speed of $10mps$, are plotted in Figure 5(b). We observe that an increase in UAV communication range results in a proportional increase in the area covered by a swarm. However, we also note that a swarm with shorter R_{com} values reaches its highest areal coverage sooner compared to the swarms with longer communication ranges. For example, the swarm with $R_{com} = 100m$ requires $200s$, whereas the one with $R_{com} = 400m$ takes close to $400s$ to reach its top areal coverage. This outcome is expected since the UAVs with shorter ranges can only cover comparatively smaller areas and, therefore, have to travel less than the ones with longer ranges. It should also be stated that UAV swarms with longer R_{com} ranges consume more power to transmit and deplete the limited energy resources faster.

Figure 5(c) demonstrates boxplots for swarms with $R_{com} = 200m$ and $400m$. The top two curves in Figure 5(c) show the coverage obtained by 20-node swarms with $R_{com} = 400m$ and the top speeds of $10mps$ and $28mps$. The lower two curves are for swarms with 20 nodes with $R_{com} = 200m$ and maximum speeds of $10mps$ and $28mps$. It can be seen in Figure 5(c) that increasing speed shortens the time needed for a swarm to converge toward a uniform areal coverage, which is an indication of low overhead in our algorithm implementation (i.e., the speed increase is directly reflected on convergence speed of the swarm).

In Figure 5(c), we observe a spike in areal coverage formed by the fastest moving swarms with the longest ranges (i.e., maximum speed of $28mps$ and $R_{com} = 400m$) at the early steps (this increase is observed in all of the repeated simulation experiments for this configuration). In such a swarm, each UAV can move faster and farther, which results in a temporary increase in area coverage but with a risk of being disconnected from the swarm due to moving too fast and too far. However, flight control algorithm corrects itself and brings the UAVs closer together as a uniformly distributed MANET, and hence reduces the areal coverage after the temporary peak. We do not observe such spikes in areal coverage in slower and shorter ranged swarms, because UAVs can re-evaluate and correct their positions before traveling too far.

V. Concluding remarks

In this paper, we introduce near real-time AI based flight control algorithms for a swarm of autonomous UAVs operating as a MANET to position themselves over an area of interest. Implementing a genetic algorithm, each UAV uses only local information to advance the swarm toward a MANET topology with higher coverage over a target terrain. These flight control algorithms are computationally inexpensive and power-efficient, hence well-suited for military missions without central control, node coordination or global network knowledge.

We designed simulation experiments to demonstrate that our algorithms provide an agile flight control for swarms of autonomous UAVs. The experiments were run in OPNET to ensure realistic simulation of UAV near neighbor communication channels in a dynamically changing MANET topology. We used STK for 3D visualization of UAV movements over real earth coordinates. Simulation results show that swarms with shorter communication ranges and faster speeds obtain their aerial coverages sooner compared to slower and farther communicating swarms. We observe that the number of UAVs in a swarm does not affect the time it takes to obtain acceptable level of coverage, which is an indication of low computational overhead in our algorithms. Also, as expected, communication range and the number of UAVs in a swarm are directly proportional to the resulting areal coverage.

Extensions of this work will address different types of missions carried out by swarm of autonomous UAVs, including cyber attacks, target acquisition and tracking, and adaptation to unpredictable terrain obstacles. We also plan to incorporate game theory into our bio-inspired flight control to further improve its performance.

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