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Multi-Agent Control Algorithms for Chemical Cloud Detection and Mapping Using Unmanned Air Vehicles

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Abstract

Traditional control approaches fall well short of the necessary flexibility and efficiency needed to meet the commercial and military demands placed upon UAV swarms. Effective coordination of these swarms requires development of control strategies based on emergent behavior. We have developed a rule-based, decentralized control algorithm that relies on constrained randomized behavior and respects UAV restrictions on sensors, computation, and flight envelope. To demonstrate and evaluate the effectiveness of our approach, we have created a simulation of an air vehicle swarm searching for and mapping a chemical cloud within a patrolled region. We then consider several different detection and mapping strategies based on emergent behavior. We then establish an inverse linear relation between the size of the swarm and the time to detect the cloud, regardless of the size of the cloud. Further, we also show the size of the swarm has a linear relation with the successful detection of the cloud.

1. Introduction

Unmanned Air Vehicles, or *UAVs* present an intriguing set of operational and tactical opportunities. A vast array of critical military operations including reconnaissance missions, situational awareness, target identification, surveillance, and battle damage assessment have all been performed with greater efficiency and less risk through the use of unmanned air vehicles [1].

A major goal of this work is to generate control algorithms enabling UAV swarms to achieve **emergent behavior** - the ability to accomplish complex objectives through synergistic interactions of simple reactionary components. Inspired by emergent behavioral strategies observed in insect societies, algorithms have been produced that successfully mirror insects' capacity to solve complex problems through interactions of simple agents. These types of algorithms can control UAV swarms in situations that require a level of flexibility and robustness unattainable by a single, more complex air vehicle. Additionally, achieving effective use of UAVs requires more than just controlling a single vehicle; the larger problem, with a potentially greater payoff, resides in establishing coordinated behavior of many such vehicles [6]. While much work has been done applying emergent behavior and swarms to a wide variety of problems [2,4,7,8,11], there has been a deficiency in simulating realistic air vehicles within swarms. Air vehicles have been modeled as particles [9], as objects that can arbitrarily move within a hexagonal grid [10] or as detailed *individual* representations of actual aircraft [12]. In this paper, we consider both issues: *swarms* of air vehicles that *respect the physical realities of their flight envelopes*. Our model of the flight envelope is both general enough and realistic enough to apply to a wide variety of UAVs. We also define an equivalent of randomized motion within such constraints, and use it to build simulations of UAV missions that exhibit emergent behavior. Several scenarios we have investigated include: multiple-aircraft rendezvous, tracking of enemy aircraft, formation flying, and dynamic target assignment.

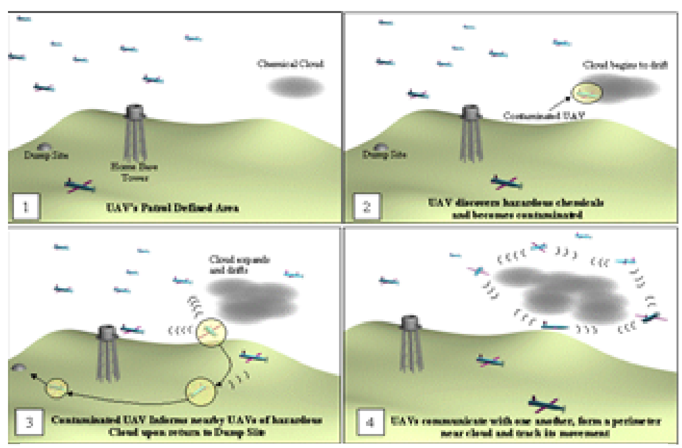

Figure 1: *The various stages of a chemical cloud detection mission: deployment, detection, communication, and mapping*

The main simulation scenario used in the development and evaluation of UAV swarm control strategies was that of a chemical cloud threat (**Figure 1**). In this scenario, a UAV swarm is assigned a region to patrol, with the objective being to detect if a chemical cloud is present. The swarm is deployed from a tower-like structure, which could include the roof of a tall building. Once deployed, the UAV swarm executes various distributed search algorithms. If a cloud is detected, many actions can be taken, such as attempting to map the size and density of the cloud. Also, if a UAV does find the cloud, and subsequently becomes contaminated, it must not return to the home base, but to a predefined decontamination center.

2. Emergent Behavior Overview

In our work, we define emergent behavior as those accomplishments that a swarm of *n* agents can perform in *t* time that a single agent cannot perform in *nt* time [2]. A classic example of this is the formation of an ant bridge. Individually, no ant has the ability to traverse a large gap, but by forming an ant-bridge with their bodies, they can cross by climbing over each other.

The concept is an enticing one: program a few simple agents to react to their limited environment, mechanically replicate the agents into a swarm and gain the ability to realize complex goals. The resulting system is flexible, robust and inexpensive. Flexibility comes about because swarms can invoke or upload new rules and divide tasks among the agents. The system is robust because it provides for the possibility that several agents can be lost while the swarm still achieves its mission goals. In addition, the size and composition of the swarm can change over time in conjunction with evolving mission requirements. Furthermore, this approach is also less expensive because many simple system components consume fewer resources to build and maintain than a single, centralized system.

3. System Overview

In order to aid the development and simulation of emergent behavior strategies for UAVs, we developed an optimal path planner that respects the UAV flight envelope. The optimal path planner uses simple geometric operations to construct the optimal flight path between two points for a UAV traveling at a constant speed. Given the destination and desired final heading, the optimal path planner constructs a control history for the UAV [3].

3.1 Emergent Search and Mapping Strategies

Emergent behavior relies on randomized motion. Due to the flight envelope restrictions imposed on UAV movement, unconstrained randomized motion was not possible. Thus, a main thrust of the work was to develop strategies that allow emergent behavior in the context of UAV motion constraints, an area of emergent behavior with little previous research. Also, limited size of the swarms dramatically reduces the amount of agent interaction and impacts the quality and speed of the emergence. Yet, even within these constraints, we were able to achieve emergent behavior. A majority of the behavior development time was used in the creation of emergent search and mapping strategies. These strategies were specifically developed with chemical cloud detection in mind, but are fully capable of being adapted for general applications with little or no modification to the algorithms themselves.

3.2 Swarm Simulation Package

SWEEP (SWarm Experimentation and Evaluation Platform) is a generic, flexible package to facilitate the design, implementation, and evaluation of swarm intelligence algorithms [2]. SWEEP was used for the simulation of the emergent behavior strategies developed for UAVs.

3.3 Postulated UAV Configuration

In conjunction with Air Force projections and requirements, we defined a set of characteristics for the envisioned UAVs. Swarm intelligence algorithms focus primarily on emerging complex behavior from simple agents. With this in mind, the postulated UAVs are as minimalist as possible. This is done for two reasons: to reduce individual UAV cost, and to make the developed strategies applicable to a broad range of UAVs. The developed algorithms can be easily built upon to leverage the capabilities of more advanced UAVs.

Current military UAVs, such as the Air Force RQ-1B Predator and the Navy FireScout, are much larger than the envisioned UAVs. The postulated UAVs in this work are assumed to be of a size such that a small team of soldiers could transport, assemble, and launch the UAV with speed and ease.

The UAVs are assumed to have a constant velocity of 40 knots. Computing capabilities will be comparable to a 66 Mhz computer. Some form of inter-agent communication is assumed to be present, with no bias towards global communication capabilities. The UAVs will have modular sensor arrays that can accommodate specific mission requirements. The battery or fuel cell for the UAVs should provide at least one hour of operational time and be able to be recharged while detached from the craft.

UAV Flight Model. In this 2D model, the UAV is a point mass with its state specified by (x, y, θ), where (x, y) is the instantaneous position and θ is the heading angle. In addition, ω, which is the time rate of change of heading angle, is a controllable input. It is assumed that the input ω is bounded by $[-\Omega, \Omega]$. Such bounds for the control input are due to the limits on the flight envelop of UAV turning rate and speed. As per the postulated UAV configuration, a constant velocity v_C is assumed.

$$\boxed{\begin{cases} \dot{x} = v_C \cos(\theta) \\ \dot{y} = v_C \sin(\theta) \\ \dot{\theta} = \omega \end{cases}}$$

Optimal Path Planner. Note that since the UAV air speed v_C is assumed constant and the time rate of change of the heading angle is bounded by Ω, the turning radius in a

UAV path must be greater than or equal to the minimum turning radius given by $r_{\min} = v_C / \Omega$. The minimium length path can now be obtained using a geometric method, as follows.

Referring to **Figure 2**, draw two circles (O_1, $r_{\min}$) and (O_2, $r_{\min}$), where O_1 and O_2 are the centers and $r_{\min}$ the radii of two circles, such that they are both tangential to the initial heading line of the UAV at its initial location (x_I, y_I). Similarly, draw two circles (O_3, $r_{\min}$) and (O_4, $r_{\min}$) such that they are both tangential to the final heading line of the UAV at its final location (x_G, y_G). Next, draw tangent lines to connect the two circles (O_1, $r_{\min}$) and (O_2, $r_{\min}$) at the start location of UAV to the two circles (O_3, $r_{\min}$) and (O_4, $r_{\min}$) at the goal location. Considering the UAV dynamics, it is simple to identify the connections that are flyable by the UAV and bring it from the start to goal state. Each of these flyable paths is actually a local optimal path, with the shortest one being the global optimal. In our SWEEP simulation, such a geometric method may be used so that each UAV generates all possible local optimal paths from its current state to the goal state specified by the SWEEP algorithm and identifies the shortest one to be its planned path.

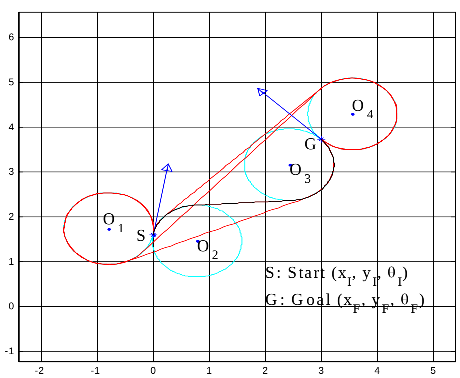

Figure 2: *Geometric construction of an optimal flight path for a UAV.*

4. Applications of Swarm Behavior

4.1 Search Algorithms

UAV swarms are well-suited for tasks involving reconnaissance due to their inherent parallelism and highly robust nature. A monolithic air reconnaissance platform can only observe a single area at a time, and no information can be obtained if the aircraft is disabled. These restrictions do not apply to UAV swarms. The parallel nature of a UAV swarm can allow multiple areas to be observed by a single swarm, but also allows for continued reconnaissance even if multiple members of the swarm are disabled.

Restrictions. The largest obstacle encountered when designing search strategies for UAV swarms is managing the physical restrictions of the UAV. There are four main restrictions when it comes to UAV performance: flight envelope, radar and communication, onboard processing power, and fuel supply.

The flight envelope of a UAV is very restrictive. The cruising speed and turning radius of the UAV are such that even the most basic search strategies need to account for these factors. For example, if the objective is to locate or track a fast moving object, the total area being simultaneously searched may have to be reduced in order to improve the overall accuracy of the swarm due to the low cruising speed of the individual UAVs.

Typically, in reducing the size and cost of a UAV, the communication and radar capabilities of the UAV are comparably diminished. These restrictions greatly impact emergent behavior search strategies attempting to magnify the capabilities of the swarm. For example, a swarm of UAVs with low-resolution sensor footprints could locate an object smaller than their sensor input by merging their individual sensor readings while still only requiring minimal communication overhead [6].

Search strategies for UAV swarms must expect limited onboard computation capabilities, thus complex calculations will be either too slow or impossible to perform in a real-time environment. Therefore, highly computational search strategies will not be very effective.

Perhaps the most severe restriction is battery life. If a UAV can only be operational for one hour before its power supply is completely drained, then one knows how sufficiently efficient and reliable a search strategy must be.

Randomized Search. Randomized searching is the most basic search strategy capable of being implemented on a UAV swarm. Each UAV chooses a random heading and a random amount of time, and then proceeds to fly in that direction for that duration. The operational requirements for randomized searching are minimal. No communication capabilities need be present onboard the UAV. The randomized search is adaptable for any type of flight envelope and sensor array. As can be expected from any distributed, randomized algorithm, results can only be guaranteed in a probabilistic manner. When the number of UAVs is low, emergent behavioral algorithms suffer and perform no better than any other strategy.

Symmetric Sub-region Search. A symmetric sub-region search divides the search area into equally shaped and sized regions, and then assigns one or more agents to each region (**Figure 3**). Symmetric sub-region searching is useful when there is little a-priori information about the target (size, location), and when there are a relatively large number of agents as compared to the size of the region to be searched. For example, if there exists the threat of a chemical or biological cloud, a symmetric sub-region approach could prove effective. Since the only information known is the wind heading and the fact that a threat may exist, symmetric sub-regions allow for a higher probability that a threat will be detected due to all of the simultaneous searches. This search strategy is only effective when each UAV is assigned a search area proportional to its sensor capabilities and physical characteristics, otherwise large, unexamined gaps will remain.

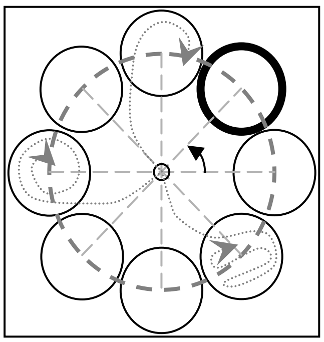

Figure 3: *An example of a symmetrical search.*

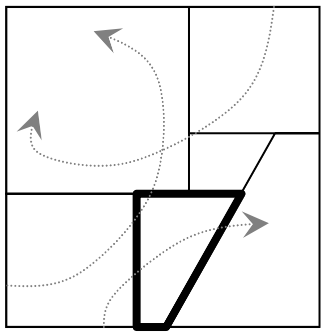

Figure 4: *An example of an asymmetrical search.*

Asymmetric Sub-region Search. An asymmetric sub-region search divides the search area into sub-regions of varying shapes and sizes, and then proceeds to assign one or more agents to each region (**Figure 4**). Asymmetric sub-region searching can be useful when more detailed information about the search area is available. Unlike the symmetric sub-region search, this approach can leverage the power of relatively few UAVs by defining sub-regions according to the probability of finding a target, then assigning agents to those sub-regions. If the possibility of threats exists in any parts of the search area, then fewer agents can be assigned to high probability regions, leaving extra agents to better search low probability areas. This logic may seem counter intuitive, but since the sub-region probabilities are calculated based on a-priori knowledge that targets will be in certain areas, low probabilities really mean that less information is known about that region as compared to other regions, so more agents need to be placed there.

4.2 Cloud Detecting

UAV Restrictions. The chemical cloud scenario imposes many restrictions on UAV swarms. Generally, UAVs are capable of flying at speeds much greater than the average wind speed, thus causing a problem in cloud mapping because a UAV can outpace the cloud. The clouds involved in this scenario generally range from ½ km to 3 km in length. The cloud is relatively small as compared to the 10 km^2 region that must be patrolled. Since our swarms only consisted of 5 to 15 UAVs, detecting clouds of this size reliably made this scenario a good driving problem. Battery life was the largest restriction on the UAVs' capabilities. The UAVs evaluated had ½ hour of operational time, thus making it critical to manage flight time with respect to returning to base or a decontamination center.

Enhancements. Various enhancements to the UAV control schemes and search patterns arose from the restrictions placed upon the scenario. In order to improve the chances that a UAV swarm will successfully detect a chemical cloud, different search strategies were considered with the modification that UAVs would search in manners that crosscut the wind, thus leveraging the wind as much as possible. For example, the symmetric sub-region search would have each UAV search their sub-region using some kind of cross-cutting pattern (**Figure 5**). The random search strategy would have each UAV fly, and then at a randomly chosen moment crosscut the wind for a time, then continue a random flight. An added bonus of crosscutting the wind is that the UAVs can easily adjust to changing wind conditions by simply changing their crosscutting vector.

4.3 Cloud Mapping

Once a chemical cloud is detected by the UAVs, its location and heading are known. By switching to alternative behavioral rules, the swarm can begin to ascertain the cloud's dimensions and density. With all types of mapping algorithms, the data collected must be adjusted with time to take into account for the movement and diffusion of the cloud. Either this can be done at a central location, or if capable, each UAV can manipulate the data itself. When considering algorithms for cloud mapping, the type of sensors that the UAVs are equipped with must be taken into account. Binary sensors, which deliver a *chemical present/absent* signal, were assumed without loss of

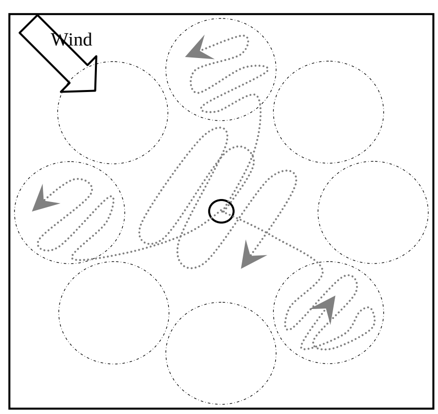

Figure 5: *A symmetrical sub-region search leveraging wind direction.*

generality. There are three types of mapping strategies we considered: inside-outside, outline, and dispersion.

The inside-outside method is very straightforward, as illustrated in **Figure 6**. If an agent is inside a cloud, it chooses a direction and flies until it is outside of the cloud. Once outside of the cloud, the UAV chooses a point randomly offset from the last intersection with the cloud, and then flies back in. The points where the agent exits or enters the cloud, transition points, are then recorded. From this data, a model of the cloud size can be extrapolated.

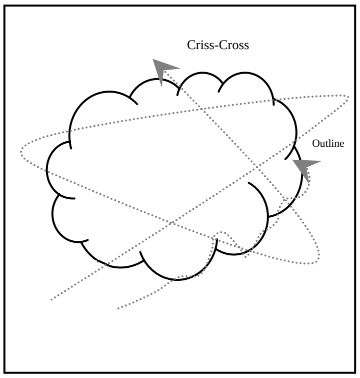

Figure 6: *Examples of inside-outside and outline cloud mapping*

The outline method, as its name implies, attempts to have UAVs from the swarm follow the outline of the cloud (**Figure 6)**. Though more reliable and efficient than the inside-outside method, the outline method is significantly more complex, in terms of UAV control, and thus may not be suitable for all UAV designs.

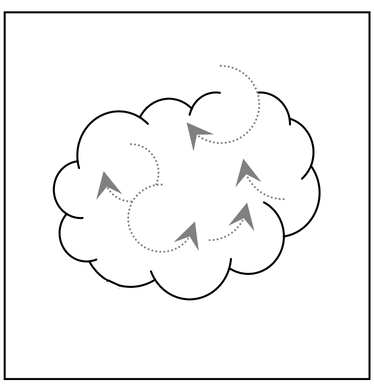

Figure 7: *The dispersion cloud mapping behavior.*

Dispersion algorithms can very effectively be used to map chemical clouds. Essentially, once a UAV detects the cloud, it broadcasts this information to all surrounding UAVs. After rebroadcasting the received message, the UAVs converge to the general area that the cloud was initially located and begin executing a dispersion algorithm. The agents execute the algorithm with only one modification; the UAVs continue to expand the dispersion area until a UAV is out of the cloud. At this time, the UAVs outside the cloud begin moving back into the cloud, as seen in **Figure 7**. Thus, the shape of the cloud emerges.

5. Results and Conclusions

5.1 Chemical Cloud Mapping

In order to demonstrate the capabilities of emergent behavioral strategies, a UAV rule-base was constructed for mapping a chemical cloud. The scenario used 10 UAVs in a bounded 10 km^2 region. Initially, a single UAV was placed in close proximity to the cloud while the rest of the UAVs were randomly distributed throughout the region, thus simulating an end-game situation for cloud searching.

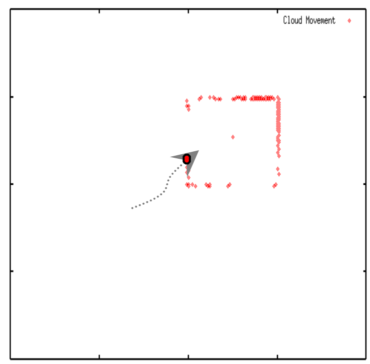

Figure 8: *The outline of a chemical cloud as mapped by a UAV swarm*

Quickly, UAV finds the chemical cloud and broadcasts the location of the cloud. Upon receiving the broadcasts, the UAVs swarm to the general region where the cloud was found and begin the mapping process. For simulation purposes, the inside-outside mapping method, as previously described, was implemented. For purposes of simplicity, the cloud was represented as rectangular and immobile. If implemented with a moving cloud, the data collected by the UAV swarm would have to be processed more rigorously in order to obtain the shape of the cloud. **Figure 8** shows a plotting of the data the UAV swarm collected in approximately 5 minutes of flight time. As can be clearly seen, the UAV swarm was able to approximate the shape of the chemical cloud relatively quickly. The mapping of the cloud is an emergent behavior. In all three mapping strategies, no agent has any knowledge about the cloud's size, shape or rate of diffusion. They simply randomly modify their behavior (change flight direction) whenever they detect an inside/outside transition. By recording the time and location of these transitions the UAVs create a data set that contains all information necessary to accurately depict the cloud's movement over time.

5.2 Chemical Cloud Searching Scenario

The scenario chosen for the trade-off study was the detection of a chemical cloud by a UAV swarm, as previously described for UAV swarms. The purpose of this trade-off study is to empirically determine the best size for a UAV swarm searching a bounded region for a hostile-released chemical cloud. In this scenario, a UAV swarm is deployed from a central tower in a square region. Since the main objective of the swarm is detection of chemical clouds, it is unknown to the swarm whether there previously existed a chemical cloud in the region they patrol. Once released, the UAV swarm executes various emergent behavioral search strategies in order to detect the presence of a chemical cloud. If the cloud is not found before the UAVs' power supplies are depleted, the swarm returns to the tower where a fully-fueled UAV swarm is ready to be deployed to continue the search. When the chemical cloud is observed, the UAV swarm can transition into multiple cloud-mapping behaviors, which report sensor-based information such as cloud size, density, and composition.

The swarm is responsible for patrolling a bounded square region. The intended target is a chemical cloud of unspecified size or type that moves with the wind. The chemical cloud is capable of diffusion, thus there is a fleeting window of time in which the cloud can be detected before the cloud has diffused completely. Also, the cloud diffusion causes the size of the cloud to increase, thus improving the chances of detection, while at the same time causing a decrease in cloud density, which in turn decreases gradient sensor effectiveness.

The UAV swarm used a modified random search to detect the cloud. Since the UAVs are capable of detecting wind direction, a wind crosscutting addition was made to the randomized search. Crosscutting is defined as flying perpendicular to the wind direction. When en route to randomly chosen destination, the UAV can decide to randomly crosscut the wind, thus increasing the chances of finding the cloud. The UAV will crosscut the wind for a non-trivial random amount of time, then resume the randomized search.

5.3 Swarm Trade-off Study: Chemical Cloud Searching

Though there are more structured search algorithms, the nature of the scenario lends itself to the randomized search. As Clough states in [6], "random searches are optimal given no a-priori information." Consider the case where the wind speed is 0 m/s, thus the cloud does not move and has minimal dispersion. In this case, more structured search algorithms will outperform the randomized search. Since the cloud does not move, a previously searched location need not be searched again. Thus, information does not become stale, and the swarm can systematically search the region with confidence. In more reasonable cases, the wind is driving a cloud along a path, and since the UAV swarm has no *a-priori* knowledge about the cloud's location, information is only fresh for a wind-speed dependent amount of time.

Since the UAV swarms being considered are relatively small (typically between 5-15 agents) and more complex algorithms provided no additional benefit, the trade-off study only examined the performance of the randomized search algorithm.

We examined cases of the chemical cloud scenario with UAV swarms of sizes 5 through 15 in a region 10,000 m^2. Cloud size varied from 1km to 3 km in length, and 1 km to 1.5 km in width. The size of the cloud was regulated using diffusion and decay parameters. The cloud was simulated as if there existed a single moving source of the chemical (e.g. a crop duster).

The cloud lengths, beginning at 1 km, were incremented by 0.1 km. For each cloud length, 100 simulations were executed for each discrete swarm size, starting at 5 and incrementing up to 15, for a total of 30,000 simulations. The simulations ran until either the cloud was detected or the swarm ran out of fuel. The time to cloud detection was recorded and presented in **Figure 9**.

As **Figures 9a,b,c,d** indicate, there is a performance increase when the number of agents is increased for the same-sized cloud. **Figure 9a** represents the normalized amount of time taken by a UAV swarm to locate a chemical cloud. The search times were normalized against the total amount of time with which the UAV swarm could have searched. As expected, larger swarms were able to find similarly sized chemical clouds faster than smaller sized swarms.

Figure 9b represents the percentage of times that the UAV swarm was able to successfully detect the chemical cloud. An increase in the number of UAVs in the swarm increases the swarm's chances of finding the chemical cloud because probabilistically speaking, more of the territory is being covered.

Figure 9c illustrates the average hit percentage of a UAV swarm of size *n* for any sized cloud. **Figure 9d** represents the average amount of time taken by a UAV swarm of size *n* to find any sized cloud. As can be seen, even with the maximum number of agents, the chances of a UAV swarm finding a cloud of indeterminate size is 83%. This performance rating may be acceptable for some situations, for example, if the UAV swarm is used as an early detection system. As shown in **Figure 9c** and **Figure 9d,** there exists a linear improvement in the performance of the UAV swarm with the addition of only one agent.

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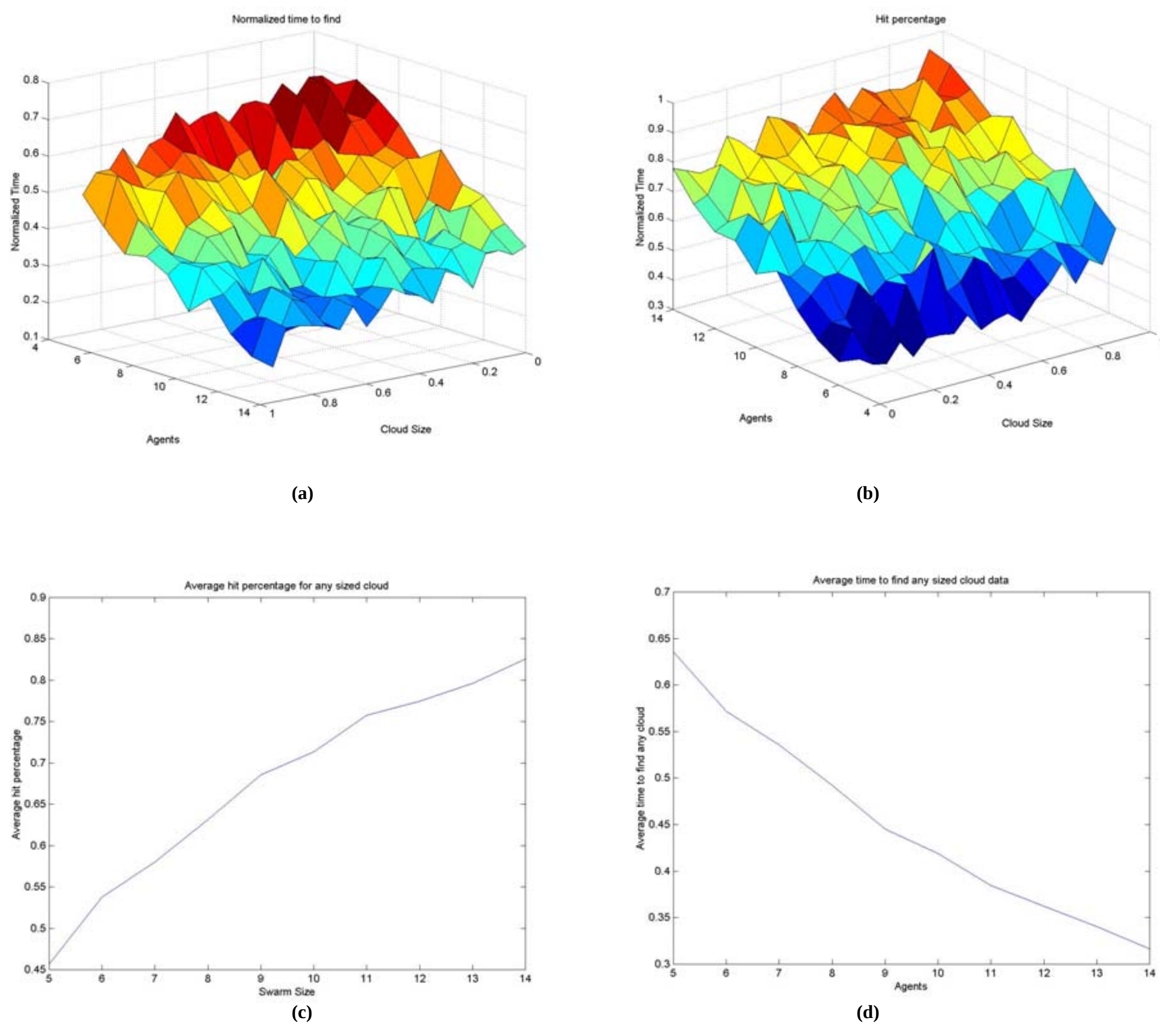

Figure 9: *Results from the chemical cloud searching trade-off study.*