Performance of Digital Pheromones for Swarming Vehicle Control

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ABSTRACT

The use of digital pheromones for controlling and coordinating swarms of unmanned vehicles is studied under various conditions to determine their effectiveness in multiple military scenarios. The study demonstrates the effectiveness of these pheromone algorithms for surveillance, target acquisition, and tracking. The algorithms were demonstrated on hardware platforms and the results from the demonstration are reported

Categories and Subject Descriptors

I.2.9 [**Artificial Intelligence**]: Robotics – a*utonomous vehicles.*

General Terms

Algorithms, Performance, Experimentation

Keywords

Swarming, multiagent, autonomous vehicles, pheromone control.

1. INTRODUCTION

The word "swarming" is currently in vogue to describe two different types of systems. Students of biological systems use it to describe decentralized self-organizing behavior in populations of (usually simple) animals [2, 4, 10]. Examples include path formation, nest sorting, food source selection, thermoregulation, task allocation, flocking, nest construction, and hunting behaviors in many species. Military historians use it to describe a battlefield tactic that involves decentralized, pulsed attacks [1, 6, 8].

The link between these two uses of the word is not coincidental. Insect self-organization is robust, adaptive, and persistent, as anyone can attest who has tried to keep ants out of the kitchen, and military commanders understand the advantage of being able to inflict the confusion, frustration, discomfort, and demoralization that a swarm of bees can visit on their victims.

In spite of the military promise of swarming, little attention has been given to how to implement the mechanisms observed in biological communities into military systems. This paper describes the use of digital pheromones to produce swarming behavior in military systems and studies their effectiveness in performing various functions.

The sequence of sections reflects the engineering process of moving from requirements, through mechanism selection, design and implementation, testing, and deployment. Section 2 summarizes the requirements for three applications of swarming derived from specific military scenarios. Section 3 outlines the particular swarming mechanism that we applied to these applications, a computational analog of insect pheromones. Section 4 details how we applied this mechanism to each of the applications. Section 5 outlines specific experiments that were conducted to test the algorithms, and Section 6 describes a physical demonstration of the capabilities. Section 7 concludes.

2. IDENTIFICATION OF REQUIRED FUNCTIONS

This study focused on the analysis of swarming algorithms to support a range of military scenarios. A suite of realistic scenarios was developed by military experts addressing three capability areas: (1) intelligence, surveillance and reconnaissance, (2) communications and (3) battle damage assessment.

Analysis of these swarming scenarios identified three swarm functions that were targeted for this study:

1. **Surveillance and patrol** – a single or continuous sweep of an area by the swarming platforms to look for entities (possibly mobile) of interest.
2. **Target acquisition** – configuring and coordinating the alignment of the right sensors to determine the location, class, and identification of an entity in an area.
3. **Target tracking** – continuously or intermittently maintaining sensor contact with a moving entity to determine its location and heading.

In addition to these three functions, three additional functions were identified but were not included in the study due to time and cost constraints. These were, responding to human commands, maintaining line of sight communications among the swarm entities, and plume monitoring.

Parunak [9] reviews the major classes of swarming algorithms that have been applied to the Command and Control (C2) of multiple robotic entities and compared them to Altarum's pheromone approach. In this paper we report on the results of experiments with digital pheromones under various scenarios.

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3. DIGITAL PHEROMONES

Digital pheromones are a *stigmergic* mechanism for coordinating and controlling swarming vehicles. "Stigmergy" is a term coined in the 1950's by the French biologist Grassé [7] to describe a broad class of multi-agent coordination mechanisms that rely on information exchange through a shared environment. Examples from natural systems show that stigmergic systems can generate robust, complex, intelligent behavior at the system level even when the individual agents are simple and individually non-intelligent. In these systems, intelligence resides not in a single distinguished agent (as in centralized control) nor in each individual agent (the intelligent agent model), but in the interactions among the agents and the shared dynamical environment.

Stigmergic mechanisms have some attractive features.

Simplicity.—The logic for individual agents is much simpler than for an individually intelligent agent. They can easily run on the small platforms envisioned for swarming vehicles. These agents are easier to program and prove correct. They can be trained with genetic algorithms or other weak optimization methods without requiring any knowledge engineering [15].

Scalabilty.—Stigmergic mechanisms scale well to large numbers of entities. In fact, stigmergy *requires* multiple entities, and performance typically improves as the number of entities increases.

Robustness.—Because stigmergic deployments favor large numbers of entities that are continuously organizing themselves, the system's performance is robust against the loss of a few individuals. The simplicity and low expense of each individual means that such losses can be tolerated economically.

Digital pheromones are modeled on the pheromone fields that many social insects use to coordinate their behavior. Digital pheromones support three primary operations, inspired by the dynamics of chemical pheromones.

1. They can be deposited and withdrawn from an area. Deposits of a certain flavor are added to the current amount of that flavor of pheromone located at that place. (*Information fusion and aggregation*).
2. They are evaporated over time. This serves to forget old information that is not refreshed. (*Truth maintenance*).
3. They propagate from a place to its neighboring places. The act of propagation causes pheromone gradients to be formed. (*Information diffusion and dissemination*).

Digital pheromones are modeled as difference equations across a network of "places" at which agents can reside and in which they deposit and sense increments to scalar variables representing the digital pheromones. These equations are provably stable and convergent [3]. They form the basis for a "pheromone infrastructure" that can support swarming for various functions, including path planning [13, 14] and coordination for unpiloted vehicles [5, 16], positioning multi-sensor configurations [11], and maintaining line of sight communications in mobile ad hoc networks [12], several of the functions required by the swarming scenarios.

3.1 Digital Pheromones and Place Agents

A digital pheromone represents information about the system. Different "flavors" of pheromones convey different kinds of information. Digital pheromones exist within in an artificial space called a *pheromone map*. The map is composed of an arbitrary graph of *place* agents. In principle, there are no restrictions on the graph of place agents. In swarming robotics where movement decisions are an important function, it is convenient to have the place agents represent regions of the geographical space. In this study, we tile the physical space with squares, each representing a place agent with eight neighbors.

Several options are available for implementing place agents. Agents can be embedded in the environment using unattended ground sensors (UGS) networked through wireless communications [13]. Place agents can also be distributed on Command and Control (C2) nodes according to area of responsibility. The swarming platforms only need to communicate with the local UGS or C2 node. Alternatively each swarming platform maintains a full or partial version of the pheromone map representing the immediate vicinity around the unit. Pheromone map updates (deposits and withdrawals) need only be communicated locally to maintain each map. Since the information content is low (8 bytes/pheromone) and frequency of map updates is low (on the order of once a second), low bandwidth communications are sufficient to maintain the information flow among place agents.

3.2 Walkers and Avatars

Two classes of agents, called *walkers* and *avatars*, wander through the pheromone map.

A walker agent controls a single platform in the swarm. A walker deposits, withdraws, and reads pheromones in the map and uses that information to make movement and action decisions. The walker can read sensory and other telemetry from the platform and issue commands to control its actions.

Avatars are used to represent the other entities in the environment. These can include friendly (blue), enemy (red), and neutral (green) entities. The avatar receives intelligence about the type, location, heading, speed, and possibly other identifying information that it uses to update its location and make estimates of future locations when sensor information is not available. The avatar can also deposit, withdraw, and read pheromones in the map, which it uses to make estimate about where the unit may move next.

Agents can start and stop what is called a pheromone pump. A pheromone pump resides in a place agent and continuously deposits a pheromone of a particular flavor for a specified time.

An agent uses an *interpreting equation* to weight the pheromones that it senses in the place agents and decide where to move next. Some pheromones may attract the agent, while other pheromones may repel it. The interpreting equation assigns a scalar value ($V(p)$) to the current place agent and each of its neighbor place agents. The agent then makes either a deterministic move (to the place agent with the largest $V(p)$), or a probabilistic move using a roulette wheel weighted by each $V(p)$.

3.3 Pheromone Equations

Each place agent maintains a scalar variable corresponding to each pheromone flavor. It performs the basic functions of aggregation, evaporation, and propagation. The underlying mathematics of the field developed by such a network of places rests on two fundamental equations. The parameters governing the pheromone field are:

- $P = \{p_i\}$ = set of place agents

- $N: P \rightarrow P$ = neighbor relation between place agents. Thus the place agents form an asymmetric multigraph.
- $s(\Phi_f,p,t)$ = strength of pheromone flavor f at place agent p and time t.
- $d(\Phi_f,p,t)$ = sum of external deposits of pheromone flavor f within the interval $(t-1, t]$ at place agent p.
- $g(\Phi_f,p,t)$ = propagated input of pheromone flavor f at time t to place agent p.
- $E_f \in (0,1)$ = evaporation factor for flavor f.
- $G_f \in [0,1)$ = propagation factor for flavor f.
- T_f = threshold below which $s(\Phi_f,p,t)$ is set to zero.

The first equation describes the evolution of the strength of a single pheromone flavor at a given place agent.

$$s(\Phi_f, p, t) = E_f * \left[(1 - G_f) * \left(s(\Phi_f, p, t-1) + d(\Phi_f, p, t)\right) + g(\Phi_f, p, t)\right]$$

E_f models evaporation of pheromone, 1 - G_f calculates the amount remaining after propagation to its neighbors, $s(\Phi_f,p,t-1)$ represents the amount of pheromone from the previous cycle, $d(\Phi_f,p,t)$ represents the total deposits made since the last update cycle (including pump auto-deposits) and $g(\Phi_f,p,t)$ represents the total pheromone propagated in from all the neighbors of p. Each place agent applies this equation to each pheromone flavor once during every update cycle.

The second fundamental equation describes the propagation received from the neighboring place agents:

$$g(\Phi_f, p, t) = \sum_{p' \in N(p)} \frac{G_f}{|N(p')|} \left(s(\Phi_f, p', t-1) + d(\Phi_f, p', t)\right)$$

This equation states that each neighbor place agent p' propagates a portion of its pheromone to p each update cycle, the proportion depending on the parameter G_f and the total number of its neighbors.

4. ALGORITHM DESCRIPTIONS

This section describes in detail the pheromone algorithms that perform the functions identified earlier.

Four pheromone flavors are used in the algorithms: Lawn (Φ_l), Visited (Φ_v), Tracking (Φ_t), and NeedsID (Φ_n). These are described in greater detail below.

Each pheromone flavor has a number of parameters that tune the pheromone to the task. Four different settings are available.

1. Update cycle time – the time interval between propagation, pump auto-deposits, and evaporation for this flavor.
2. Propagation factor (G_f)– The fraction of pheromone in a place that is distributed equally among all the neighbors.
3. Evaporation factor (E_f)– the fraction of the pheromone that remains after the evaporation cycle.
4. Minimum place agent pheromone level (T_f) – If the amount of pheromone in a place falls below this level then the pheromone level is set to zero.

These parameters can be set by systematically experimenting with different values or they can be determined through optimization mechanisms such as genetic algorithms as described in [15]. The specific pheromone settings used for the experiments described below are available in an extended version of this paper available at http://www.altarum.net/~vparunak/AAMAS05SwarmingDemo.pdf

4.1 Surveillance and Patrol Algorithm

The surveillance and patrol algorithm must be able to control Autonomous Surveillance Vehicles (ASV's) surveying one or more Areas of Interest (AOI) with a certain revisit frequency. The algorithm has been nicknamed the "lawn cutting" algorithm as certain features resemble the act of cutting a lawn.

For this algorithm, the place agents within an AOI continually emit an attractive Lawn pheromone that propagates through the other place agents forming an attractive gradient leading to the AOIs (Figure 1). The interpreting equation of the Blue walkers controlling the ASV's (referred to henceforth simply as the "ASV") cause them to probabilistically climb the gradient towards the AOI containing the highest concentration of attractive pheromone. Once an ASV has visited a place agent within the AOI, all the Lawn pheromone is removed (cutting the grass) and the place agent stops emitting any more Lawn pheromone for a time inversely proportional to the desired surveillance frequency. After that time, the Lawn pheromone pump is turned back on and the attractive pheromone gradient forms again (grass re-grows).

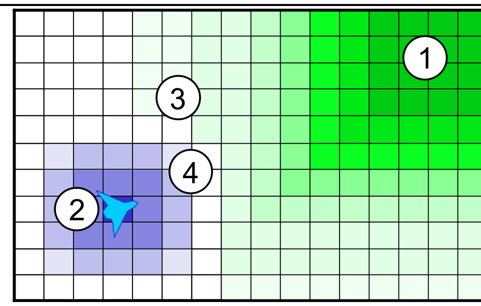

Figure 1. Attractive And Repulsive Pheromones For Surveillance, 1. Surveillance area deposits attractive pheromone, 2. ASV deposits repulsive pheromone, 3. Pheromone infrastructure propagates both attractive and repulsive pheromone to form gradient, 4. ASV climbs net gradient, withdrawing attractive pheromone.

The ASV deposits a repulsive Visited pheromone in the next place agent it plans to move to. This keeps other ASV's away from that same place agent to avoid duplication of effort.

The interpreting equation for surveillance and patrol is:

$$V(p) = s(\Phi_l, p) - s(\Phi_v, p)$$

4.2 Target Acquisition Algorithm

The swarming algorithms for positioning sensors for data acquisition were not included in this study. These algorithms have been studied elsewhere [11]. For this study as long as the swarming entity is within sensor range of the target, then the target is detected with a probability defined by an experimental parameter *Pd*. A dwell time experimental parameter was also used that defined how long the sensor had to remain with the target before it could confirm a target's identification.

The only target acquisition swarming function modeled in this study was the requirement to cue additional sensors to confirm or identify a target. The algorithm is described in Figure 2. There are two kinds of ASVs in this scenario. *ASVdet* has a sensor that can detect, but not identify targets. *ASVid* has a sensor that can both detect and identify targets. If ASVdet detects a target then it creates a Red avatar to represent the target. The Red avatar begins depositing *NeedsID* pheromone.

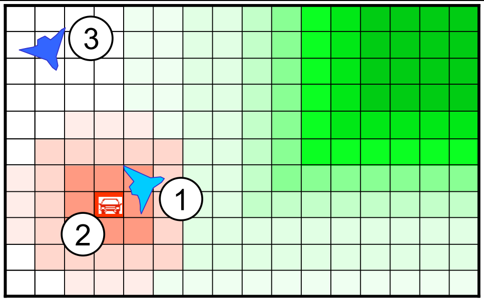

Figure 2. Pheromones Attracting Confirming Sensors – 1. ASVdet detects target and Red avatar is created, 2. Red avatar deposits "NeedsID" pheromone, 3. ASVid is more attracted to NeedsID pheromone than lawn pheromone and climbs gradient to ID target.

ASVid is more attracted to NeedsID pheromone than to Lawn pheromone, so in the presence of NeedsID it will climb the NeedsID gradient and identify the target. Once identified, the Red avatar will stop pumping NeedsID pheromone. ASVid deposits a large amount of Visited pheromone to keep other units from being attracted to the remaining (decaying) NeedsID pheromone in the area. After identification the target is set up for tracking or ignored if it is found to be harmless.

The interpreting equation for ASVid target cueing is:

$$V(p) = s(\Phi_l, p) - s(\Phi_v, p) + 10s(\Phi_t, p) + 2x10^{11} s(\Phi_n, p)$$

The interpreting equation for ASVdet target is:

$$V(p) = s(\Phi_l, p) - s(\Phi_v, p) + 10s(\Phi_t, p)$$

4.3 Target Tracking Algorithm

The target tracking algorithm is designed to allow targets to be tracked continuously or intermittently by the ASVs. A Red avatar estimates the behavior of the Red target in between sensor contacts. The Red avatar continually deposits Tracking pheromone. However the ASV deposits a large amount of Visited pheromone when the Red target is detected (see Figure 3). This "kicker" deposit is designed to cause ASVs to stay away from the Red target after it has been acquired. Once the kicker evaporates, or the Red avatar moves out from under its protective cloud, its Tracking pheromone will again attract ASVs to come and establish another contact to update its track. By varying the amount of the Visited kicker deposit one can vary the revisit frequency for the tracking.

The interpreting equation is:

$$V(p) = s(\Phi_l, p) - s(\Phi_v, p) + 10s(\Phi_t, p)$$

5. EXPERIMENTS AND RESULTS

This section describes a subset of the experiments that were conducted to verify that the swarming algorithm could meet the functional requirements of the military scenarios.

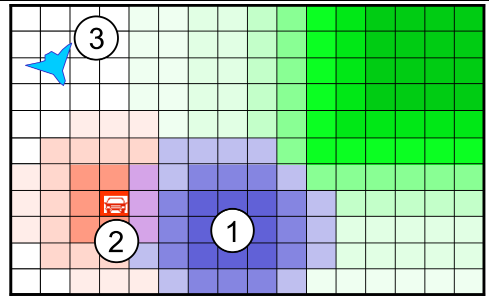

Figure 3. Pheromone Tracking Algorithm – 1. ASV acquires target and deposits Visited pheromone repelling other ASVs, 2. Red avatar estimates movement, deposits Tracking pheromone, 3. As avatar moves away from Visited deposit, nearby ASV is more attracted to its Tracking pheromone than repelled by Visited pheromone and climbs gradient to reacquire the target.

5.1 Surveillance Coverage Performance

Purpose: Determine the performance of Blue ASVs in covering all the places in a surveillance area.

Setup: 30 Blue ASV units operate in a 20 km x 20 km area divided into 200 x 200 place agents. Blue uses the surveillance algorithm described above. A total of 100 runs were executed each with a different random seed.

The coverage results are plotted in Figure 4. The plot of the fixed pattern search shows how a pre-programmed coverage pattern (where each unit is assigned an area to sweep) would perform under the same circumstances. Initially it performs worse than the pheromones as the units move into their starting positions, but eventually it performs better since there is no overlap in their paths. The average time to reach 95% coverage by the swarming algorithm is about 50% longer than a programmed path. A stochastic swarming algorithm will never perform as well as a programmed pattern that can be designed for minimal overlap. But the performance of the swarming algorithm shows some good characteristics:

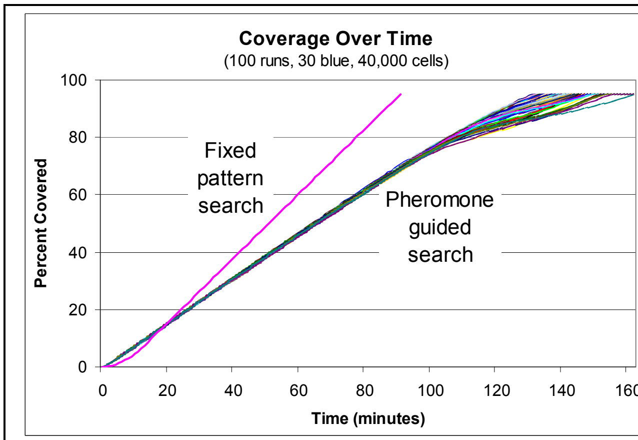

Figure 4. Surveillance Area Covered Over Time - the chart shows 100 runs. The fixed pattern search partitions the area equally the ASVs that then perform a sweep pattern search.

- It has a fairly tight bound on performance (note the narrow bands until coverage reaches 80%) so the algorithm behaves with repeatable performance.

- The performance is linear in most of the region until coverage reaches about 80% so performance does not fall off until most of the area has been surveyed.

It should be noted that when surveying for mobile targets it is not important to visit every point in the surveillance space. In fact a major advantage of a stochastic algorithm over a programmed pattern is that it is unpredictable and an adversary is less likely to be able to determine when to remain hidden.

Figure 5 shows a series of snapshots of the simulation as it progresses. All units begin in the bottom right corner of the grid. They expand out diagonally across the space sweeping back and forth, emergently executing loops and other maneuvers as more of the area is covered.

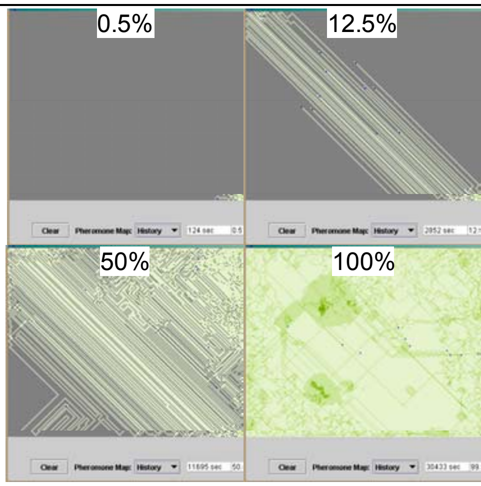

Figure 5. Swarm Surveillance Coverage - 10 ASVs survey a 200 x 200 grid. The swarm begins sweeping diagonally, eventually doing loops and other maneuvers as it seeks out remaining unsurveyed areas. The darker shades in the last panel are areas that have been visited more often. The number on each plot indicates the level of coverage achieved.

5.2 Target Acquisition

Purpose: Determine effectiveness of Blue ASVs in finding mobile Red units.

Setup: A 20 km x 20 km area is divided into 200 x 200 place agents. 10, 20, and 30 Blue ASVs with random start positions move at 90 kph using the surveillance algorithm. When Blue lands in a sector containing a moving Red, the Red is considered detected with probability Pd. 10 Red units start in random locations. Red picks a random point in the area and moves there at 3 kph. When it reaches that point it rests for one hour. While at-rest the unit is undetectable. While moving the detection probability is an experimental parameter set to 0.5, 0.75, or 1.0. 81 total runs were executed representing 9 random seeds for the three Blue swarm sizes and three detection probabilities.

Figure 6 shows the results. Increasing the number of Blue ASVs can have a dramatic improvement in performance. The time to find 10 Red units in a 40,000 cell grid was decreased from 20 hours to 5.5 hours by increasing the number of units from 10 to 30. The improvement is not linear. Eventually adding more ASVs will not significantly reduce the time to detect all the Red units. The effect of varying the probability of detection is roughly linear

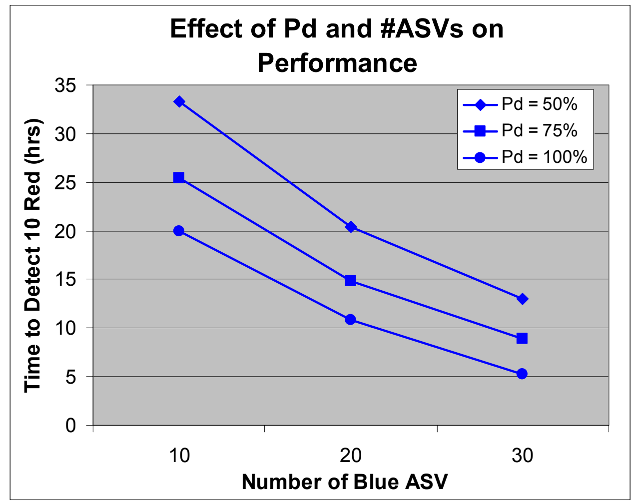

Figure 6. Effect of number of Blue and probability of detection on detecting all 10 mobile Red units – The chart shows the average time to detect all 10 Red mobile units in a 40,000 grid area using different numbers of Blue ASVs. Each plot represents a different probability of detecting Red when Red is not hidden and a Blue ASV occupies the same cell as Red.

as would be expected. Since the average trip made by Red is approximately 10 km taking 3.3 hours and it rests and hides for one hour after each trip, Red is hiding on average 23% of the time. So the effective Pd's for this experiment are 38%, 58%, and 77%.

5.3 Discontiguous Area Surveillance

Purpose: Determine how effective Blue is at distributing assets and covering discontiguous areas of interest (AOIs).

Setup: A 20 km x 20 km area is divided into 200 x 200 place agents. 10 AOIs, each 1 km x 1 km in size are placed randomly in the area. 30 Blue ASVs start in the corner and move at 90 kph using the surveillance algorithm. 13 runs were executed each with a different random seed.

Figure 7 shows the average coverage of the ten AOI's over time. The system converges exponentially to the asymptotic state. The

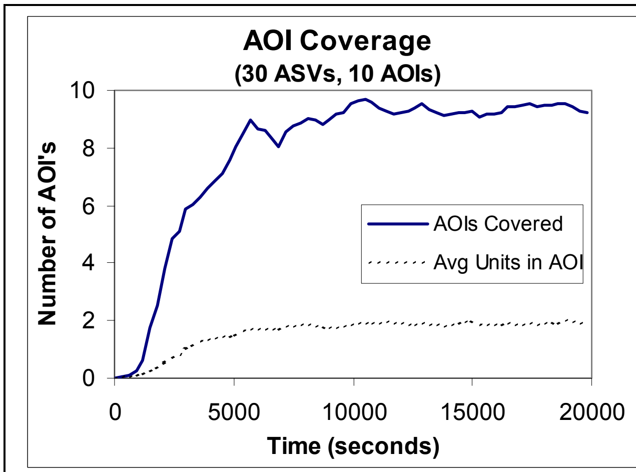

Figure 7. Coverage of the 10 AOIs Over Time (20 point moving average).

asymptote itself is high, maintaining coverage of nine or ten of the AOI's most of the time. On average 2 ± 0.27 ASV's are assigned to each AOI. The low standard deviation shows the effective allocation of ASV's over the AOI's. On average 20 ASVs are within the AOIs and 10 ASVs are surveying either immediately outside or between the AOIs. This provides a population that is able to keep the AOIs covered in the case of failure.

Figure 8 depicts the simulation as it progresses. One can see the units finding and then surveying the different AOIs.

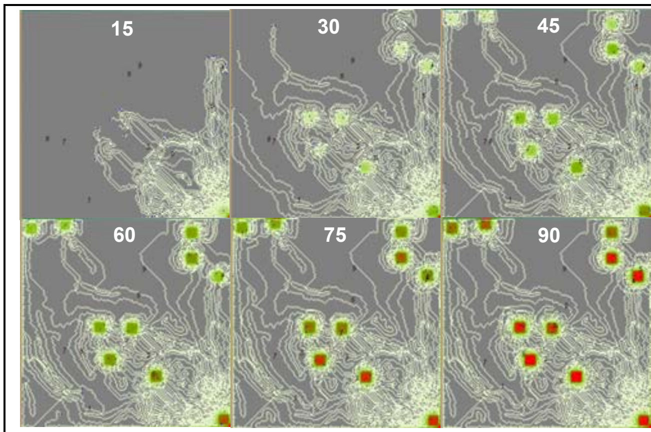

Figure 8. Surveillance of 10 AOIs - The six displays show the history of ASV coverage. The number elapsed minutes is shown. The colors indicate the number of ASV's that have visited that location. By 45 minutes all AOIs are under surveillance

Some of the challenges in this problem include:

- Too many ASVs remaining in AOI where all the units start
- AOIs in upper left are not found or do not attract enough units for surveillance.

The algorithm performed well on a difficult problem: trying to find all the AOIs and then balance the number of ASVs that were allocated to surveying each. None of the swarming units knew the number of AOIs or where they were located. Still they were able to self organize, find the AOIs and distribute their numbers evenly across them to maintain regular surveillance.

5.4 Intermittent Tracking

Purpose: Determine effect of number of Blue on efficiency of tracking Red.

Setup: A 20 km x 20 km area is divided into 200 x 200 place agents. 10, 20, and 30 Blue ASVs starting in the corner move at 90 kph using the tracking algorithm. 20 Red units start in random locations and move and rest randomly as described above. While at-rest the unit is undetectable. While moving the detection probability is 1.0. Blue must be in the same cell as Red to detect it. If the Red unit does not have an avatar Blue requires an additional 600 seconds of sensor processing to identify target and a Red avatar is created to track the Red unit. The Red avatar uses a linear extrapolation to estimate the location of the actual Red unit. If Blue has not revisited the Red unit within 900 seconds the Red avatar is removed. A total of 27 runs were executed using 9 random seeds for each of the three Blue unit sizes.

Figure 9 shows images from the simulation. The left pane shows the tracking pheromone being emitted by the 17 Red units currently being tracked. Units 11, 13, and 16 have not yet been detected by Blue. The other dots are the Blue units. The right pane shows the Red tracks in two colors: dark sections indicate where Blue acquired the target and white indicates periods in between acquisitions. The fairly even spacing of the acquisition points along the track indicates that Blue is maintaining a good track on the vehicles.

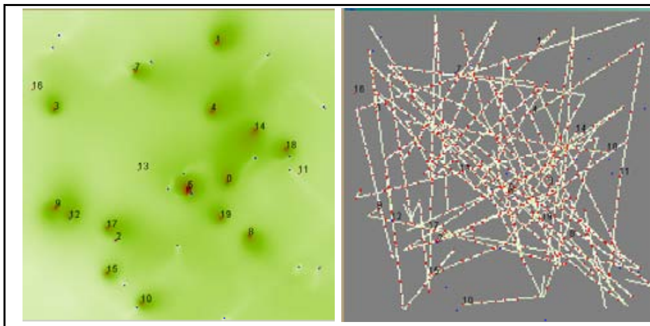

Figure 9. Blue Tracking Result - Left pane shows the tracking pheromone field being emitted by 17 Red units (numbered) being tracked. The right pane shows the Red tracks. Dark sections on the track indicate where the unit was acquired by Blue and white is the interpolated movement in between acquisitions.

Figure 10 shows the percentage of the 20 Red units tracked over time. 30 Blue units were able to find and track 90% of the Red units with only a 0.5% track loss (percentage of times that a reacquisition failed to occur and the track was lost). 20 Blue units trying to find and track 20 Red units is a fairly difficult problem (since the Blue units need to continue surveying when they are not trying to find Red again for another track). But the algorithm performed well, tracking 80% of the Red units with less than 1.2% track loss. When the number of Blue units is reduced to 10, only 40% of Red is tracked with a 3.8% track loss. There appear to be two factors contributing to the 40% figure: Blue is distracted with the tracking task and hence unable to continue surveying to find the other Red units and once they are found, they are more likely to lose the track.

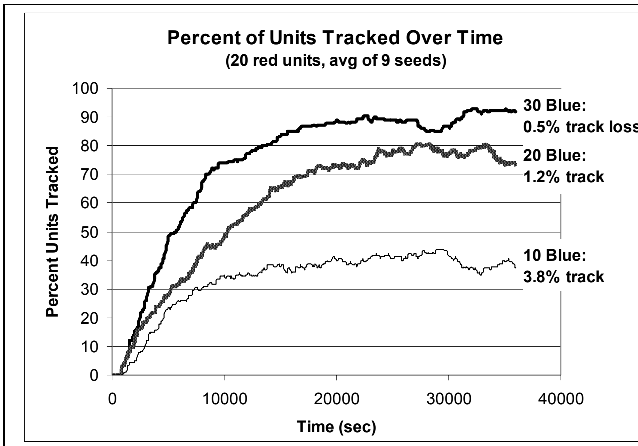

Figure 10. Blue Efficiency in Tracking Red Over Time

Other experiments demonstrated that by varying the amount of the "kicker" deposit made by Blue, one can fairly accurately control the time between re-acquisitions. This allows the frequency of how often a target is revisited to be varied based on how important that target is.

5.5 Target Cueing

Purpose: Evaluate the performance of the cueing algorithms. Some Blue entities need to 'cue' other Blue entities to perform a task. Blue swarm entities are divided into two types. One type has a simpler sensor package that can only detect Red units, the other type can both detect and identify Red units.

Setup: A 20 km x 20 km area is divided into 200 x 200 place agents. 10, 20, and 30 Blue ASVs starting in the corner move at 90 kph using the tracking algorithm. 50% of the ASVs are 'ASVdet' and 50% are 'ASVid'. 20 Red units start in random locations and move and rest randomly as described above. While at-rest the unit is undetectable. While moving the detection probability is 1.0. Blue must be in the same cell as Red to detect it. If Blue detects a Red unit not currently being tracked (no avatar) Blue deposits 'NeedsID' pheromone if the Blue unit is 'ASVdet' otherwise Blue waits 600 seconds to complete identification. The Red avatar behaves as described above for the tracking experiment. A total of 27 runs were executed using 9 random seeds for each of the three Blue unit sizes.

In this experiment only half of the Blue units have the required sensor to identify Red. The other Blue units can detect, but not identify Red. When ASVdet finds a Red unit, an ASVid must come over and positively identify the Red target before it can be placed on the tracking list. Once it has been identified, and as long as the track is not lost, any Blue unit can reacquire the target to update the track (i.e. identification is only required for a new target or an old target whose track was lost).

Figure 11 shows the same information as Figure 10: tracking performance over time. The additional requirement of the second sensor for identification does not appear to affect either the tracking percentage (90%, 80%, and 40% in both experiments) or the track loss percentage. The number of Blue does have a noticeable impact on the number of cueing requests (requests for identifying sensor) that were not fulfilled. With 30 units only 0.8% of the cue requests went unsatisfied, while with 10 Blue units 12.7% of the cue requests went unsatisfied. An unsatisfied cue request does not count as a lost track since the track was never established. But an unsatisfied cue request does mean that a unit previously detected, will now be lost again and have to be reacquired through surveillance before it can be tracked. So a failure in cueing should result in a slightly lower percentage of total Red units being tracked. This effect must be small, since it does not appear in the data as shown.

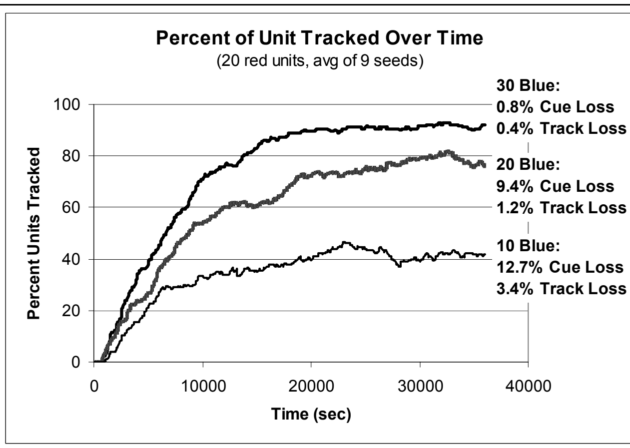

Figure 11. Sensor Cueing - chart shows percentage of Red units tracked over time when initial identification requires a special sensor confirmation. Only half of Blue units have the sensor that can identify Red.

6. DEMONSTRATION

In October 2004 the use of these swarming algorithms to control a heterogeneous population of air and ground unmanned vehicles in an urban combat scenario was demonstrated at Aberdeen Proving Grounds.

The demonstration used four robots controlled by a co-field algorithm, a mock urban area, and two Unmanned Air Vehicles (UAVs) controlled by the digital pheromone algorithms. The demonstration showed how these stigmergic swarming algorithms can control and coordinate the behaviors of a heterogeneous mix of vehicles.

The unmanned ground vehicles were research quality robots made by iRobot, Inc. All four robots used short range fixed acoustic sensors, laser range finders for obstacle detection and avoidance, and commercial GPS receivers for localization.

The air vehicles were modified Mig 117 Bravo target drones with a 6 ft wingspan. The basic airframe was fitted with a modern engine, an autopilot by Micro-Pilot, and low light or infrared camera. The autopilot was taught to take-off, hand launch, fly, and land completely autonomously.

The digital pheromone algorithms controlled and coordinated the flight of the two UAVs as they performed continuous surveillance over an urban area looking for potential adversaries. The two air units worked together to ensure even, thorough, and continuous coverage of all areas in the surveillance region while avoiding any collisions. They also provided patrol coverage of a mock convoy as it moved through the area.

While the UAVs surveyed a broad area over the airfield, the ground robots surveyed and patrolled around some mock buildings set up for the demo. During the demonstration, one of the ground robots failed. The other ground robots were able to dynamically readjust their patrol patterns to accommodate the missing unit without any intervention by the operator. This unplanned event helped to demonstrate the robustness of these algorithms to unexpected events.

The demonstration showed cooperative behavior between the air and ground units when the identity of a potential adversary detected by one of the UAV's was automatically confirmed by one of the ground robots with a special sensor capable of target identification.

The actions of the vehicles were not scripted as evidenced by their adapting to the unplanned failure of one of the ground robots. Rather than specify each vehicle's task, the operator simply gave a high level command to the whole swarm, such as "survey this area and track any identified targets" or "patrol around this convoy". The vehicles autonomously configured themselves to determine which vehicle would perform what task in order to accomplish the overall objective. The operator was free to monitor their behavior, receive their reports, and provide additional guidance as needed when priorities or mission objectives changed. The swarm did not need any special configuration to meet a wide variety of mission requirements, respective of the operating environment or the number and type of vehicles involved.

7. CONCLUSIONS

At the start of this study there was concern about the whether the wide range of scenarios and the requirements they placed on the swarm would result in a large variety of algorithms being required. This study was able to demonstrate that a single pheromone mechanism can be used to perform all the functions required by these scenarios. The surprising versatility arising from such simple mechanisms is one of the more promising aspects of this new class of algorithm.

The mechanism proved to be surprisingly robust to large variations in the parameter settings. Certain parameters (such as the Lawn evaporation and propagation factors), had a greater influence than others, but the mechanism performed well even when those were varied by a factor of 10 or 100.

Adding a new function typically involved at most

- Adding a new pheromone
- Adding a new term to the interpreting equation
- Conducting some experiments to get the right settings

The stigmergic swarming algorithms appear quite promising as a means to control a wide variety of important behaviors for a swarm. They are robust against a wide variety of scenarios, do not require extensive tuning, and are effective in controlling both large and small swarms distributed over large areas. This study has laid the groundwork for future studies and implementation tests.

8. ACKNOWLEDGMENT

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