ULTRA-LOW COMPLEXITY CONTROL FOR ADHOC MOBILE SENSOR NETWORKS

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ABSTRACT

We introduce an ultra-low complexity decentralized control scheme for adhoc mobile sensor networks that can be used for a great variety of sensing tasks. Sensor networks using this control scheme are easy to configure, can operate completely autonomously without supervision, and automatically adapt to various environmental changes. Moreover, they are robust to individual sensor failure as well as other disturbances and scale very well. Finally, they allow for simple dynamic adhoc networks that can route data based on available sensor connectivity. We demonstrate the versatility and effectiveness of sensor homogeneous and heterogeneous sensor networks using the proposed control scheme in simulations of unmanned aerial vehicles performing target detection, tracking, and reporting tasks.

KEYWORDS

Ultra-low complexity control, mobile sensors, dynamic sensor networks, sensor swarms

1 INTRODUCTION

Mobile sensor networks are situated in the intersection of *stationary wireless sensor networks* and *(autonomous) vehicle networks*, combining the communication infrastructure of sensor networks with the mobility and autonomy of vehicles (e.g., [1,2]). While most (stationary) sensor networks consist of relatively simple nodes with limited power and computational resources, vehicle networks focus on more complex mobile units, which include one or several processors, wireless communication equipment, sensor suites of various complexity, and positioning systems such as GPS. The increased computational and communication resources allow for the implementation of sophisticated communication and navigation algorithms (e.g., [3,4,5]), and, usually, units in such mobile sensor networks inherit this complexity (e.g., [1,6,7,8]).

Various centralized and distributed control approaches have been proposed to control multi-agent systems such as mobile sensor networks (e.g., [9,10,11,12,13,14,15]), ranging from using only local rules (e.g., [16]), to “digital pheromones” (e.g., [17,18]), to sensor fusion (e.g., [19]) and the self-deployment of sensors (e.g., [20]), to forming formation (e.g., [21,22]), to chemical plume detection and tracking (e.g., [23,24]), and many others. Recently, decentralized distributed control approaches (e.g., swarm intelligence [25,26]) have become an interesting alternative to these standard centralized and distributed control schemes. Different from centralized control where a very small number of complex agents determines all actions that the other agents have to perform, distributed decentralized control schemes do not have centralized sources of behavior coordination. Rather, global behavior emerges from the interaction of many agents, whose behavior is usually governed by simple rules. These rules typically use information about an agent’s immediate neighbors (e.g., Reynold’s three rules “flock centering”, “obstacle avoidance”, and “velocity matching” [27], see also [28]). Based on assumptions about such simple interactions, several important theoretical results have been proved about properties like collision avoidance or stability in such systems (e.g, [29,30,31,32,33]).

In this paper, we take the distributed decentralized control scheme to its extreme, introducing an ultra-low complexity control scheme that is sufficient for many types of sensing tasks, while being easy to realize in hardware and thus available to even the simplest of mobile sensors (e.g., [34]). The scheme divides sensing among many very simple, autonomous, expendable individual agents, which not only guarantees the reliability of individual agents, but also a high level of fault tolerance of the overall system. Most importantly, the overall system behavior "emerges" from the interactions of the individual agents and is accomplished in a distributed, collaborative fashion. For the proposed scheme, each agent carries two types of beacons: an *attractive beacon* for resource allocation (moving agents to where they are needed) and a *repulsive beacon* to control agent distribution and density in order to avoid collisions and control sampling density (cp. to [35]). In the most general framework, all agents carrying these two beacons are assumed to be mobile, even though the case of some beacons being stationary also generates interesting applications. We next provide a detailed description of the control scheme and discuss some of its properties. Then we apply the scheme to a target detection, tracking and reporting tasks and present results from simulations studies with homogeneous and heterogeneous networks.

2 ULTRA-LOW COMPLEXITY NAVIGATION CONTROL

As mentioned above, each mobile unit (called "agent") carries two beacons: an "target attraction" beacon *tar* for resource allocation moving autonomous agents to where they are needed and a (repulsive) "collision avoidance" beacon *col* to control agent distribution and density in order to avoid collisions and control sampling density. Target attraction beacons are typically only activated when agents detect a relevant target, while collision avoidance beacons are always on. Each agent is equipped with two receivers (e.g., two stereo antenna/receiver pairs) to detect target attraction and collision avoidance beacons from other agents (and their direction). Note that target attraction beacons effectively translate a signal from a target (regardless of how it was detected) into a different modality (i.e., an on/off radio beacon) to extend the range of its detectability. In contrast to target beacon receivers, the collision avoidance receivers can extract the approximate distance of the source using the received signal strength. This allows the collision avoidance algorithm to react only to agents within a certain circle of radius ϱ (the "repulsion radius") in free space. ϱ effectively is an agent's collision avoidance range and represents the distance an agent must keep between itself and its neighbors to leave enough space to turn. Therefore, ϱ is dependent on the agent's *minimal turning radius* τ, which, in turn, is typically dependent on the agent's speed.

For the control algorithm, we define

$$I_{y,i} = \sum_{j=1}^{n} A_y / (\| \underline{x_j} - \underline{x_i} \|_2^2)$$

where $I_{y,i}$ is a measure proportional to the received strength ("power") of beacon type y at agent i at location x_i with $y \in \{col, tar\}$, and A_y is the transmit power of type y beacons. (There are a total of n agents, and all beacons of the same type have the same power.) Using the directional sensitivity of two sideways looking directional antennas, we can find the following signal intensity for left and right looking antennas of each of the two modalities:

$$R_{y,i} = \sum_{j \in \Gamma_y} A_y f(\underline{x_j} - \underline{x_i}, \underline{\eta_i}) / (\| \underline{x_j} - \underline{x_i} \|_2^2)$$

$$L_{y,i} = \sum_{j \in \Gamma_y} A_y f(\underline{x_j} - \underline{x_i}, -\underline{\eta_i}) / (\| \underline{x_j} - \underline{x_i} \|_2^2)$$

with $\Gamma_{col} = \{j | \|\underline{x_j} - \underline{x_i}\|_2 < \varrho\}$, $\Gamma_{tar} = \{1,...,n\}$, $\underline{\eta}_i$ being the right normal vector to the speed vector of agent i in the plane of operation (i.e., either on the ground or in the flight plane), and $f(x,\eta)$ being the directional sensitivity function of the antenna, where x is the vector from receiver to source and $\underline{\eta}$ is the direction of highest sensitivity of the antenna.

In the case of y=*col*, the summation for the left and right antenna signal intensity L_i and R_i

respectively are taken only over those agents j that satisfy $\|x_j - x_i\|_2 < \varrho$. This requires certain provisions in the modulation scheme that allow the agent to distinguish each collision beacon.

The decision for the turn direction requires two directional antennas on each side of the agent facing in opposite directions ($\underline{\eta}$, and $-\underline{\eta}$), perpendicular to the agent speed vector. Since the turning radius of the agent is assumed independent of the direction (left and right), a simple intensity comparison between left and right directional antenna will allow to derive the new heading of the agents, which is either “turn left” or “turn right”. Define the intensity sum and difference between the antenna pairs as: $L_{y,i} + R_{y,i} = S_{y,i}$, $L_{y,i} - R_{y,i} = D_{y,i}$, $y \in \{col, tar\}, i = 1, \cdots, n$, where $S_{y,i}$ and $D_{y,i}$ denote sum and difference of left and right antenna signal strength of modality y at agent i. The agent control algorithm is thus as follows:

```
while true do
        if Scol,i > 0 then
                if Dcol,i > 0 then
                        turn right
                else
                        turn left
                end if
        else if Star,i > threshold then
                if Dtar,i > 0 then
                        turn left
                else
                        turn right
                end if
        else
                go straight
        end if
end while
```

Note that it is possible to simplify the above algorithm even more if the assumption is dropped that the repulsive beacons of all agents be distinguishable. Then the same summation can be done for the repulsive beacons as is done for the attractive beacons, without the need to use n different repulsive beacons. The downside of this simplification is that it is now possible that an agent will sporadically make wrong decisions about where to turn. Suppose there are two agents to left of agent A at a distance of 100 that have their repulsive beacon on and A’s repulsion range is ϱ=80. Then the intensity reading on A’s antenna will (wrongly) suggest that there is an agent within repulsion range and A will turn to the right even though there was not impending collision. This situation can be problematic, at least in principle, when there are lots of agents on one side whose summed repulsive beacon intensity make A turn in the opposite direction right into the trajectory of another agent whose is also within collision range, but whose beacon intensity is lower than that of the group of agents on the left. While this situation can lead to collisions in principle, it is practically much less problematic, for two reasons: first, because agents are normally separated by a distance of at least ϱ and beacon intensities falls of with the at least the square of the distance, the influence of far away agents is negligible and only a small number of close agents will determine A’s behavior. And second, agents do not have to have their repulsive beacon on all the time, but can rather send pulses at a certain frequency (possibly with a slight random component added). Then the probability that two or more pulses will occur at the same time can be kept very low, and even if they should co-occur, a short period of time later they will be spaced again and the agent can make the right decision (note that in this case we need to add a memory component in the control system that for a short period of time stores the last beacon intensity).

3 SYSTEM PROPERTIES AND EXTENSIONS

The proposed control system allows for a large number of mobile sensor units to self-organize and jointly achieve tasks that involve navigation for positioning, detecting, and tracking. We will now briefly discuss several system properties that are of interest: (1) *dense hex-grid coverage and formation*, (2) *collision-free navigation*, (3) *scalability and reliability*, (4) *adhoc sensor network and routing of information*, and (5) *mechanisms for deployment and recollection of agents*.

3.1 Dense Hex-Grid Coverage and Formations

For efficient sensing and sampling, agents such as *Unmanned Aerial Vehicles* (UGVs) at the same altitude and *Unmanned Ground Vehicles* (UGVs), must form a dense cover of subregions of the 2D plane, the density of which is determined by the agents' *repulsion range* ϱ (top in Fig.1; the dashed circles depict this radius ϱ). Given one attractive beacon in the center of an area, for example, agents will automatically arrange (and continuously re-arrange) themselves in the vicinity of the beacon such that agents are outside each other's repulsion ranges. Specifically, since agents within each other's repulsion ranges move away from each other, while being attracted to the center of the region when they are not within each other's repulsion ranges, we will get a stable oscillation (i.e., a pattern of agents moving in and out of each other's repulsion ranges while staying in the same overall area). Simulations demonstrate that this behavior of agents leads to an emergent arrangement of agents on a hexagonal grid of approximately ϱ grid length (i.e., the shortest distance between two agents before they ignore the attractive beacon and turn away from each other based on their navigation control system, see bottom in Fig.1). Note that this is the tightest possible packing of circles in the plane, and thus the optimal arrangement of agents with circular non-overlapping repulsion regions. Note that because agents are constantly moving, they will be in an out of each others repulsion range, hence the hexagonal formation will be necessarily dynamic and approximate. Yet, for small τ compared to ϱ, we expect the pattern to be sufficiently stable.

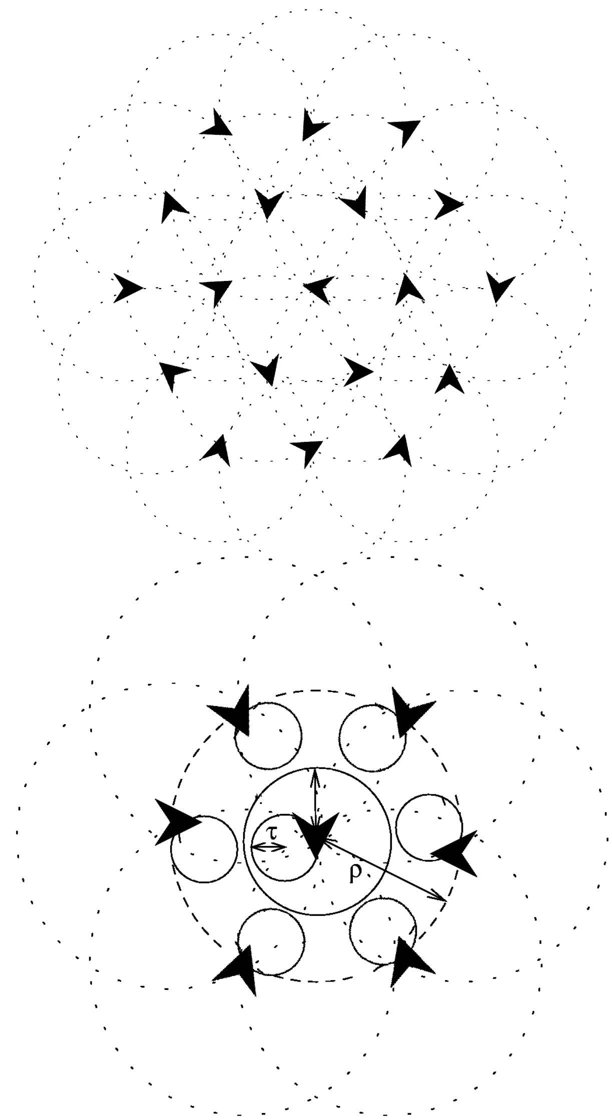

Figure 1: Coverage of area by agents (top) and collision-avoidance (bottom). Dashed circles depict the repulsion range ϱ. τ is the minimal turning radius.

3.2 Homogeneous vs Heterogeneous Agent Systems

The proposed control scheme naturally allows for homogeneous and heterogeneous agent systems, where the difference in agents comes from differences in ϱ (possibly based on differences in τ). In heterogeneous agent systems, interesting patterns of coordination can emerge based on the frequency with which attractive beacons. Figure 2, for example, shows a system consisting of three kinds of agents ("brown", "green", and "blue") with three different repulsion ranges (brown being largest and blue smallest, green in between). The agents are attracted to a cloud of particles, because agents will turn on their attractive beacons whenever they encounter a particle. The top row shows the agent shortly after they encountered the particle cloud with mostly green agents being in the center (the left column shows an overview of the environment, the right column shows a zoomed version of a subarea indicated with a square on the left). Very quickly, the blue agents start to move towards the center, with the green agents grouping around them, and the new incoming brown agents (moving in from the left) forming a ring around the green agents. The results is a dynamically stable pattern of concentric circles (bottom row). This pattern is very robust and emerges due to the asymmetric interactions between agents with different repulsion ranges. Specifically, agents with a smaller repulsion range (e.g., blue agents) encountering agents with a larger repulsion range (e.g., green agents) will cause the agents with the larger repulsion range (i.e., green agents) to turn away without themselves having to turn away (because even though they are within the repulsion range of the other agents, the other agents are not within their repulsion range). This asymmetric penetration of the agents' repulsion ranges thus allows agents with smaller repulsion ranges to move towards the target location, while agents with larger repulsion ranges will have to remain at a distance. Ultimately, this asymmetry gives rise to the emergence of the agent distribution forming concentric circle around the source of the attraction.

3.3 Collision-free Navigation

We conjecture that if repulsion ranges are chosen carefully such that the minimal turning radius $\tau<\varrho/4-\delta$, where δ is some safety distance, then it is always possible for agents to avoid collisions. In the worst case, they will be able to repeat a circular pattern of radius τ in a region within their repulsion range ϱ. Specifically, as shown on the right in Fig.1, a complete enclosed agent can still safely turn away from a set of six surrounding agents, all of which have penetrated the repulsion range of the enclosed agent (note that these agents also have a safe place to turn within the enclosed agent's repulsion range).

Formally establishing collision-free avoidance is currently an interesting, open problem for the proposed agent system. Specifically, it would be interesting to isolation conditions for ϱ and τ such that for given a fixed minimum speed v_0 of all agents it is guaranteed that collisions cannot occur for an arbitrary number of agents as long as all agents start out from a "safe" position with non-overlapping repulsion ranges.

3.4 Scalability and Reliability

One of the interesting properties of most agent systems is that they tend to "scale up", i.e., new agents can be simply added to a system without usually negatively impacting the performance of other agents. For example, if a system S consisting of k agents has achieved insufficient coverage of an area A (i.e., only $p\cdot A$ for $0<p<1$ is covered), then perfect coverage of A can be achieved by adding at least $p\cdot A\pi\cdot\varrho 2$ new agents of the same type. Similarly, if a system S consisting of k agents has achieved coverage of an area A by covering $A+d$ (where d is the excess area covered), then removing an agent (e.g., because it ran out of fuel or was destroyed) will either still cover A (if $d\pi\cdot\varrho 2$, i.e., the area covered by one agent) or A will occasionally not be entirely covered.

3.5 Adhoc Sensor Network and Routing of Information

If agents are equipped with wireless communication devices, they can automatically form an adhoc wireless network as soon as they come sufficiently close to each other, assuming that the communication range $\gamma>\varrho$ (otherwise they could only communicate when they are performing evasive maneuvers).

3.6 Mechanisms for Deployment and Recollection of Agents

Mechanisms for automatically deploying and recollecting agents are an important part of an agent system. For deployment, agents will generally have to be oriented in the expected target direction. E.g., it is possible to make agents follow particular trajectories along "nav points" based on a sequence of attractive beacons that are subsequently ignored. For example, suppose agents have to patrol k areas A_{1A2Ak} in sequence, then by deploying different attractive beacons B_{1B2Bk} in each area (e.g., "shooting" a beacon in the area or dropping it by aircraft), the agents control system can be modified such that after having encountered beacon B_i (at sufficient strength), B_i will be ignored, and B_{i+1} (for i<k) will become attractive (in this case, only one beacon is attractive at any time). As a consequence, agents will visit each area A_i in sequence until they

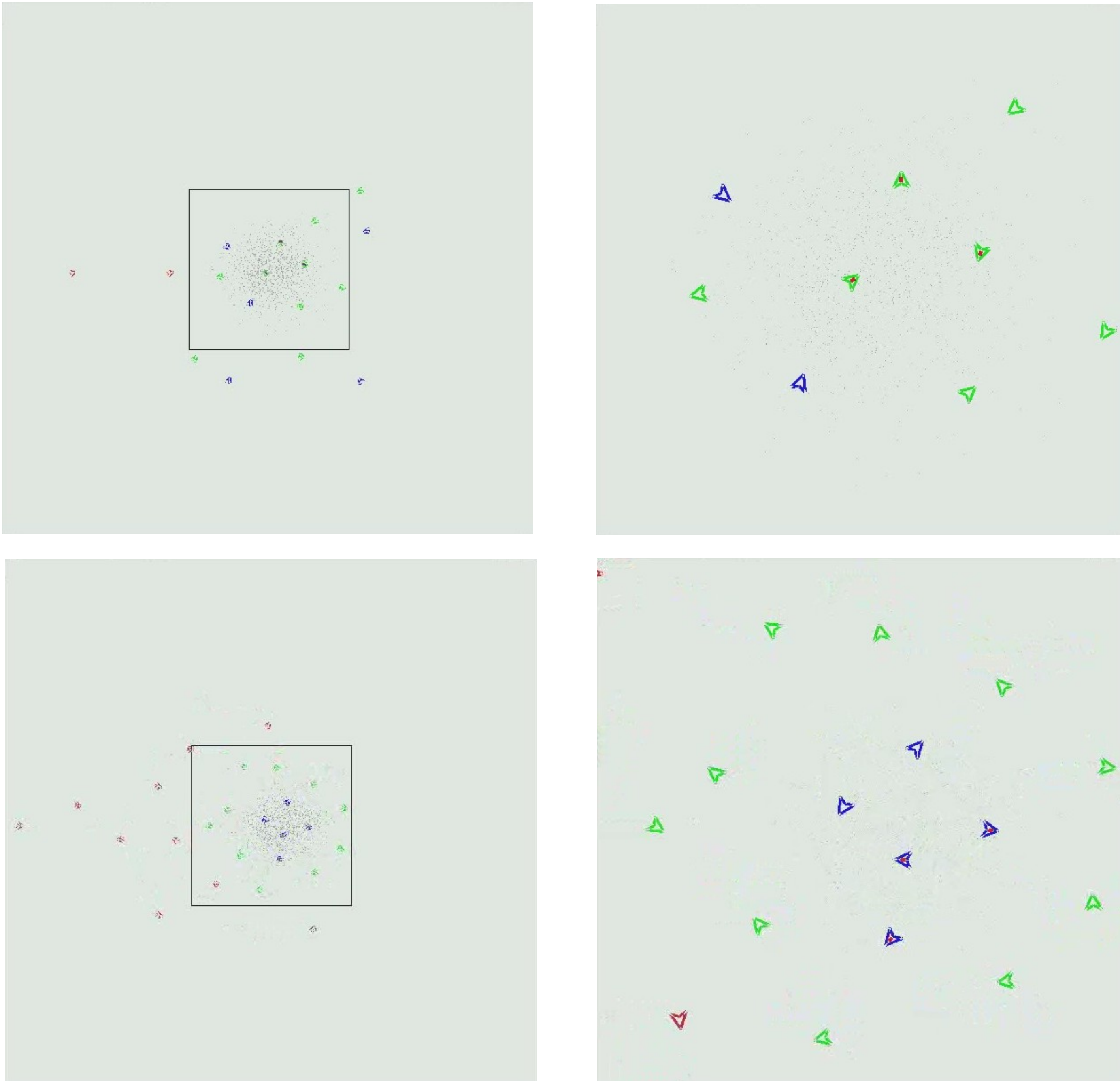

Figure 2: Agents coming to the target area (top) and forming concentric circles based on their collision avoidance range (bottom), see text for more details. The screen shots in the right column show zoomed versions of the quadratic area indicated in the screen shots in the left column.

detect a target, whose attractive beacon temporarily supersedes any attractions from beacons B_i. For recollection, a similar mechanism is possible: a special “recollection beacon” R is activated, which causes agents to ignore all other beacons and return to the home base.

A simple mechanism using different types of beacons can be used for automatically deploying and recollecting agents such that human operators can easily influence the overall behavior of the agent system (e.g., by selectively activating beacons of subsets of agents) without having to

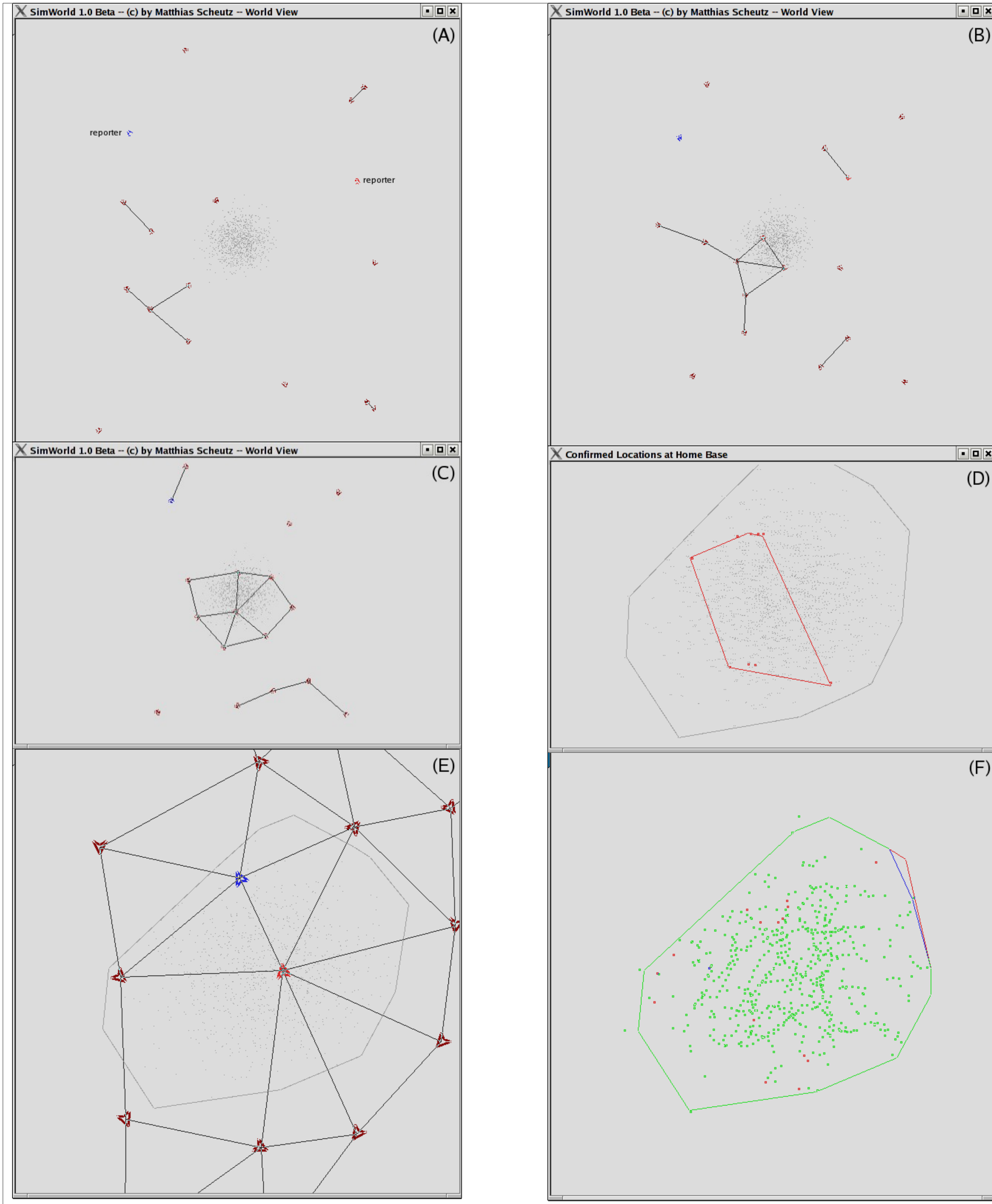

Figure 3: Different phases in the target sensing and location reporting task (see text for an explanation).

worry about the details of navigation. The same idea can also be used for route programming and executing branching operations along the way point trajectory.

4 DYNAMIC MOBILE SENSOR NETWORKS FOR TARGET DETECTION, TRACKING, AND REPORTING TASKS

We now consider a class of applications of the proposed mobile sensor network where mobile units have to detect ground or airborne objects or substances, report their position and track them (in case they are moving). Tasks in this class can take many different forms depending on what the objects and substances are. For example, UGVs could track and locate communication signals, or detect and track chemical substances in the air. Similarly, UAVs could locate and track moving targets on the ground, or detect radioactive substances in a chemical cloud and determine its extension. Here, we focus on a UAV system that can determine the boundaries of the distribution of a large number of target objects or substances (e.g., chemicals or radioactive substances in the air, individuals on the ground, etc.), which *cannot be sensed or identified at a distance* (hence, local sensing is required) (cp. to [11,36,37]).

Fig.3 **(A)** through **(F)** shows various phases and states of this information gathering task as simulated in our distributed parallel agent-based simulation and experimentation environment SWAGES [39,40]. The targets are indicated by gray points – **(D)** through **(F)** depict a magnified view of the targets and their boundary indicated by the polygon. The agent system here consists of two kinds of UAVs, those with large-range communication ("red" and "blue") , call them "reporters", and those without ("brown"), call them "workers". Both kinds have short-range communication links (e.g., Zigbee), GPS, and sensors to detect the targets (e.g., soldiers or vehicles on the ground). Initially, a certain number of UAVs of each kind is sent in the direction in which targets are expected **(A)** (2 reporters and 15 workers here). Lines between two UAVs depict established wireless links (which are established whenever the UAVs come within wireless communication range). As soon as one UAV detects a target, it turns on its attractive beacon and attracts the others to the area **(B)** for further inspection (and possibly corroboration of the detected information). Note that no information has been transmitted to the home base yet, as the adhoc network is still forming and no "reporter" is part of the network yet. **(C)** shows the state shortly after the "red" reporter joined the adhoc network of workers forming in the target area, and starts sending information about detected targets back to the home base. Note that other workers can as part of the network forwarding process integrate their sensory data to corroborate the information (e.g., using Bayesian belief updates or simply by keeping previously routed packets with information about close-by locations in a cache to which current sensory information can be compared). The red circles in **(D)** depict the reported locations of sensed targets and the red polygon indicates the extension of the targets based on the reported measurements (for ease of comparison, the actual locations of the targets are superimposed as gray dots and their extension is indicated by the gray polygon). As can be seen, the center of the target area has been already determined and communicated by the system. **(E)** then shows the state of the system after about 500 simulation cycles. A dense, dynamically changing adhoc network has formed with reporters in the center to increase throughput (this is a robust emergent effect of the proposed navigation mechanism). **(F)** shows again the reported target locations superimposed on the actual ones. Green circles (in addition to red and blue ones) show locations confirmed by both reporters. As can be seen, many individual targets and their overall extension has been determined at this point. Note that none of the demonstrations require central supervisory control to instruct individual UAVs where to move to. Rather, UAVs organize themselves around the targets and will follow them regardless of whether they are stationary or move. Coverage depends solely on the number and distribution of targets, the number of available agents, and the parameters set for the repulsive beacons, which determine the distance

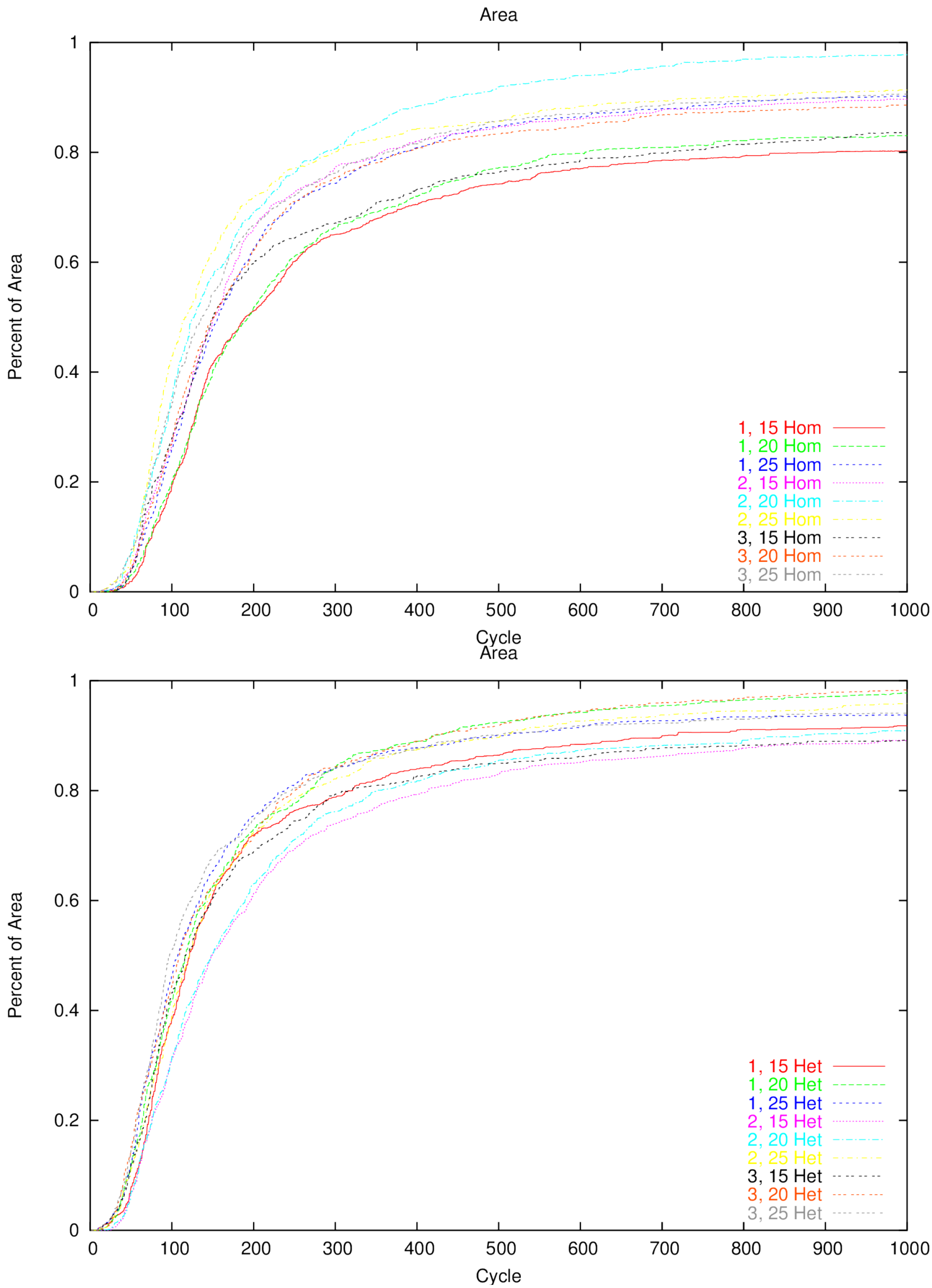

Figure 4: The percentage of the actual target area reported by the sensor network as function of simulation cycles for homogeneous (top) and heterogeneous (bottom) units (1=100%).

agents keep from each other. Some results of our investigations to date are reported in [23].

Note that the dynamic nature of the UAV network and the potentially high rate of changes in positions of UAVs present challenges for networking topologies, protocols, and algorithms. Given the limited communication range of UAVs, any route between any two points can change frequently and unpredictably, and may thus not be available at all from one moment to the next. This means that existing routes have to be periodically checked and new routes have to be discovered if established routes have ceased to exist, possibly requiring agents temporarily to store packets to minimize information loss. Critically, the nature of the connectivity of the network over time will essentially depend on the motion of the agents given that the wireless communication range is limited. Hence, networking tasks (such as establishing communication between agents, discovering and using routes, etc.) cannot be investigated in isolation of the control mechanisms that establish the agents' navigation strategies.

The simulations demonstrate key results similar to results we have obtained previously [23]: (1) the system is capable of finding and tracking targets, (2) the number of required agents will depend on the extension of the target cluster and the repulsion range ϱ, and (3) the average network connectivity is sufficient for fast detection and determination of the extension of the target area.

We would also like to point briefly to the utility of using heterogeneous agent systems for these kinds of detection, tracking, and reporting tasks. As mentioned before, heterogeneous agent systems consist of agents with different repulsion ranges ϱ. To compare a homogeneous and an heterogeneous agent system for the above task, we let homogeneous agents have $\varrho=150$ and agents in heterogeneous agent system have $\varrho=170$ and $\varrho=130$. Both homogeneous and heterogeneous agent system are capable of finding and tracking targets. Fig.4 shows the percentage of the actual target area reported by each agent system as a function of simulation cycles for homogeneous (top) and heterogeneous (bottom) units for nine different combinations of reporters (1 to 3) and workers (15, 20, and 25). As can be seen the heterogeneous configurations do generally better than the homogeneous configurations. The advantage of different ϱ values is that units with smaller ϱ values can "penetrate" tight arrangements of units with larger ϱ values and thus move from the outside into the center of a network (this is useful for reporters as most information accumulates in the center). In general, heterogeneous agent systems will form concentric arrangements of agents based on increasing ϱ values, so that a tighter coverage will be obtained in the center and a looser coverage at the perimeter of the target area. This allows for coverage of large areas with fewer agents than in the homogeneous case. On the other hand, due to the larger separation of some agents, the distance requirements for wireless communication might be more difficult to meet.

5 CONCLUSION

In this paper, we proposed an ultra-low complexity versatile resource allocation and navigation principle for mobile sensor networks that is extremely simple and only involves local beacon-based interactions. The underlying beacon-based mechanisms make the entire system extremely robust to individual agent failure and scalable, and system performance degrades gracefully with a decreasing number of agents. Moreover, the principle provides simple and coarse performance prediction of the entire system in a stochastic sense (rather than each individual agent) even in cases of heterogeneous networks with different types of agents. Future work will develop a mathematical framework for obtaining formal results about the system properties.

Compared to other proposed solutions, the simplicity of the proposed system is its main strength. Because the principle is about as simple as it can get without losing important properties (e.g., collision-avoidance or control of network density), it can be implemented in possibly very small sensors and used to build large mobile sensor networks, where each sensor is cheap and expendable. We demonstrated the viability of the proposed control mechanisms for a class of applications, where targets need to be detected, tracked, and their location needs to be communicated to a base station. Future work will continue to investigate other possible application areas of the principle, obtaining more detailed performance measures for specific applications (e.g., see [23,34,40,41,42,43,44] for a start).

6 REFERENCES

1. J.M. Kahn, R.H. Katz and K.S.J. Pister. "Next century challenges: Mobile networking for smart dust", MOBICOM 1999, Seattle, Washington, August 1999.
2. M. Jakobsson and S. Wetzel and B. Yener. "Stealth Attacks on Ad-Hoc Wireless Networks", IEEE VTC '03
3. D. Shim, H.J. Kim and S. Sastry. " Decentralized nonlinear model predictive control of multiple flying robots" CDC 2003, pp. 3621-3626, Maui, Hawaii, 2003.
4. H. Wong and V. Kapila. "Adaptive learning control based periodic trajectory tracking for spacecraft formations", CDC 2003, pp. 3597- 3602, Maui, Hawaii, 2003.
5. P. Chandler and M. Pachter. "Research Issues in Autonomous Control in Tactical UAVs", Proceedings of the American Control Conference, 394-398 (1998)
6. A. Chohra, A. Farah and C. Benmehrez. " Neural Navigation Approach for Intelligent Autonomous Vehicles (IAV) in Partially structured Environments", Applied Intelligence, Vol. 8, Issue 3, pp. 219-233, 1998.
7. S. Meguerdichian, F. Koushanfar, M. Potkonjak amd M. Srivastava. "Coverage problems in ad-hoc sensor networks", IEEE INFOCOM 2001, Vol. 3, pp. 1380-1387, April 2001.
8. K. Chakrabarty, S. Iyengar, H. Qi, and E. Cho. "Grid coverage for surveillance and target location in distributed sensor networks", IEEE Transactions on Computers, 51,(12), pp. 1448-1453, Dec. 2002
9. Y. Yang and A.A. Minai and M.M. Polycarpou "Decentralized Cooperative Search in UAVs Using Opportunistic Learning" AIAA GNC Conf. 2002, pp. 2002-4590, 2002.
10. M. Flint and M. Polycarpou and E. Fernandez-Gaucherand "Cooperative Path-planning for Autonomous Vehicles using Dynamic Programming" 15th Trienal World Congress, IFAC, 2002.
11. M. Flint and M. Polycarpou and E. Fernandez-Gaucherand "Cooperative control for multiple autonomous UAV's searching for targets" Proceedings of 42nd IEEE Conference on Decision and Control, 3, 2823 - 2828, 2002.
12. L. Jiecai "Some new optimal control problems in UAV cooperative control with information flow constraints" Proceedings of the American Control Conference, 3, pp. 2181 - 2186, 2003.
13. P.R. Chandler and M. Pachter and D. Swaroop and J.M. Fowler and J.K. Howlett and S. Rasmussen and C. Schumacher and K. Nygard "Complexity in UAV cooperative control" Proceedings of 42nd IEEE Conference on Decision and Control, 3, pp. 1831 - 1836, 2002.
14. J.S. Bellingham and M. Tillerson and M. Alighanbari and J.P. How "Cooperative path planning for multiple UAVs in dynamic and uncertain environments" Proceedings of 42nd IEEE Conference on Decision and Control, 3, pp. 2816 - 2822, 2002.
15. A. Ryan, M. Zennaro, A. Howell, R. Sengupta, and J. Hedrick. "An overview of emerging results in co-operative UAV control", CDC 2004, Nassau, Bahamas, 2004.
16. A. Jadbabaie, J. Lin and A.S. Morse. "Coordination of Groups of Mobile Autonomous Agents Using Nearest Neighbor Rules", IEEE Trans. on Automatic Control, Vol. 48, No. 6, 988-1002, 2003.
17. J.A. Sauter and R. Matthews and H.V.D. Parunak and S.A. Brueckner "Performance of Digital Pheromones for Swarming Vehicle Control" Proceedings of Fourth International Joint Conference on Autonomous Agents and Multi-Agent Systems, 2005.
18. H.V.D. Parunak and S. Brueckner. "Swarming Coordination of Multiple UAVs for Collaborative Sensing" Proceedings of Second AIAA Unmanned Unlimited Systems, Technologies,and Operations Conference, AIAA, 2003.
19. R.W. Deming and L.I. Perlovsky "Sensor fusion for swarms of small unmanned aerial vehicles" Proceedings of IEEE Swarm Intelligence Symposium, pp. 302- 308, 2005.
20. A. Howard, M.J. Mataric, and G.S. Sukhatme. "An Incremental Self-Deployment Algorithm for Mobile Sensor Networks", Autonomous Robots, Special Issue on Intelligent Embedded Systems, G. Sukhatme, ed., pp. 113-126, 2002.
21. T. Balch and R.C. Arkin. " Behavior based formation control for multi robot teams", IEEE Trans. on Robot. Autom., Vol. 14, pp. 926-939, Dec. 1998.
22. J. Fredslund and M.J. Mataric. "A General, Local Algorithm for Robot Formations", IEEE Transactions on Robotics and Automation, Special Issue on Advances in Multi-Robot Systems, 18(5), pp. 837-846, Oct 2002.
23. M. Scheutz and P. Schermerhorn and P. Bauer "The utility of heterogeneous swarms of simple UAVs with limited sensory capacity in detection and tracking tasks" Proceedings of IEEE Swarm Intelligence Symposium, pp. 257- 264, 2005.

24. D. Zarzhitsky and D.F. Spears and W.M. Spears, W.M. "Swarms for chemical plume tracing" Proceedings of IEEE Swarm Intelligence Symposium, pp. 249- 256, 2005.
25. E. Bonabeau and M. Dorigo and G. Theraulaz Swarm Intelligence: From Natural to Artificial Systems Swarm Intelligence Oxford University Press, 1999.
26. V. Trianni and M. Dorigo "Emergent collective decisions in a swarm of robots" Proceedings of IEEE Swarm Intelligence Symposium, pp. 241- 248, 2005.
27. C.W. Reynolds. "Flocks, herds, and schools: a distributed behavioral model", Computer Graphics ACM SIGGRAPH 87 Conference Proceedings, 21(4):25–34, July 1987.
28. "Evolving behaviors for a swarm of unmanned air vehicles" Proceedings of IEEE Swarm Intelligence Symposium, pp. 317- 324, 2005.
29. Y. Liu and K.M. Passino "Stability analysis of swarms in a noisy environment" Proceedings of IEEE Conference on Decision and Control, 4, pp. 3573 - 3578, 2003.
30. H.G. Tanner. "Flocking with Obstacle Avoidance in Switching Networks of Interconnected Vehicles", IEEE International Conference on Robotics and Automation, New Orleans LA, April 26-May 1, pp. 3006-3011, 2004. Gaudiano, P.; Bonabeau, E.; Shargel, B.
31. H.G. Tanner, A. Jadbabaie and G.J. Pappas. "Stable Flocking of Mobile Agents, Part I: Fixed Topology", 42nd IEEE Conference on Decision and Control, Maui Hawaii, pp. 2010-2015, December 2003.
32. Y. Liu and K. Passino. "Stable social foraging swarms in a noisy environment", IEEE Trans. on Autom. control, Vol. 49, No. 1, pp. 30-44, January 2004.
33. V. Gazi and K. Passino "Stability analysis of swarms", IEEE Trans. on Autom. Control, Vol 48, pp. 692-697, April 2003.
34. M. Scheutz and P. Bauer "A Scalable, Robust, Ultra-Low Complexity Agent Swarm for Area Coverage and Interception Tasks" Proceedings of ISIC06, pp. 1258–1263, 2006.
35. V. Gazi and K. Passino. "A class of attraction/repulsion functions for stable swarm aggregations", CDC 2002, Las Vegas, pp. 2842-2847, 2002.
36. R.W. Beard and T.W. McLain "Multiple UAV cooperative search under collision avoidance and limited range communication constraints" Proceedings of 42nd IEEE Conference on Decision and Control, 1, pp. 25 - 30, 2003.
37. M.A. Kovacina and D. Palmer and G. Yang and R. Vaidyanathan "Multi-agent control algorithms for chemical cloud detection and mapping using unmanned air vehicles" IEEE/RSJ International Conference on Intelligent Robots and System, 3, pp. 2782 - 2788, 2002.
38. M. Scheutz and P. Schermerhorn. "Adaptive Algorithms for the Dynamic Distribution and Parallel Execution of Agent-Based Models". Journal of Parallel and Distributed Computing, 2006
39. SWAGES. http://hrilab.tufts.edu/software/
40. R. Connaughton and P. Schermerhorn and M. Scheutz "Physical Parameter Optimization in Swarms of Ultra-Low Complexity Agents" Proceedings of Autonomous Agents and Multi-Agent Systems AAMAS 2008, pp. 1631–1634, 2008
41. D.A. Dewasurendra and P. Bauer and M. Scheutz and K. Premaratne "Evidence Based Navigation in Swarms" Proceedings of CDC 2006, pp. 5078–5083, 2006.
42. C. Middendorff and M. Scheutz "Real-time Evolving Swarms for Rapid Pattern Detection and Tracking" Proceedings of Artificial Life X, pp. 419–426, 2006
43. M. Scheutz "Real-time Hierarchical Swarms for Rapid Adaptive Multi-Level Pattern Detection and Tracking" Proceedings of the 2007 IEEE Swarm Intelligence Symposium,Honolulu, Hawaii, 234–241, 2007.
44. Connaughton, R., Schermerhorn, P. and Scheutz, M. (2008). "Physical Parameter Optimization in Swarms of Ultra-Low Complexity Agents". Proceedings of Autonomous Agents and Multi-Agent Systems AAMAS 2008, 1631–1634.