ANNALS OF THE UNIVERSITY OF ORADEA
Fascicle of Management and Technological Engineering
ISSUE #3, December 2016, http://www.imtuoradea.ro/auo.fmte/

A REVIEW OF SWARMING UNMANNED AERIAL VEHICLES

Mihai CORNEA[1], Vlad Ovidiu MIHALCA[2]
[1] University of Oradea, mihai@techswarm.ro
[2] University of Oradea, ovidiu@vmihalca.ro

***Abstract*—** This paper in if fact an overview of state of the art in mobile multi-robot systems as an initial part of our research in implementing a system based on swarm robotics concepts to be used in natural disaster search and rescue missions. The system is to be composed of a group of drones that can detect survivor mobile cell signals and exhibit some other features as well. This paper surveys the swarm robotics research landscape to provide a theoretical background to the implementation and help determine the techniques available to create the system. The Particle swarm optimization (PSO) and Glowworm swarm optimization (GSO) algorithms are briefly described and there is also insight into Bird flocking behavior and the model behind it.

***Keywords*—**navigation, search and rescue, swarm intelligence, swarm robotics

I. Introduction

THE fascinating world of robotics sits at the confluence of many disciplines, borrowing ideas from many of them to tackle problems in new ways Tarca [1], Tarca [2]. Often the aim is to find a more natural solution, perhaps one that has already been put in practice by biological systems or other systems.

Such is the case with our project - SURFINDER (PN-III-P2-2.1-BG-2016-0296). Its goal is to implement a system of drones that are helpful in assisting rescue operations by providing victim (survivor) search and localization, GSM ad-hoc network establishment for communication availability and relief of standard networks (whose bandwidth may be negatively affected when such events occur and could lead to downtime, thus creating, even more, difficulties) as well as other services, which will be incorporated into the design of the robots at a later stage in the development of the project. While some aspects regarding the flight stability and propeller's thrust were already investigated Kuantama, Craciun, I. Tarca, R. Tarca [3] and Kuantama, R. Tarca [4], the aim of this paper is to approach the problem of field scanning and target localization by means of swarm robotics techniques, which in theory allows for systems of many similar agents to perform intelligent behaviour, in this case, to accomplish the tasks it is meant to do.

As a first step in the project's design, we set out to grasp a general idea of the published theory and research in this area, which will help in determining what techniques are available for us to implement in our system. This paper continues to outline state of the art in mobile multi-robot systems that constitutes an initial part of our research, as well as ideas on how we might use our findings for certain parts of the project.

II. Theoretical Aspects

First of all, it is important to note the classification of multi-robot systems into the swarm and non-swarm types. The important distinction between them lies in homogeneity and features of the individuals: swarm systems are comprised of homogeneous agents who all have the same set of features (usually primitives in action space) that may be too simple to generate meaningful output on their own, but as a group can accomplish objectives and demonstrate intelligent behaviour. Conversely, non-swarm systems are comprised of heterogeneous agents, which exhibit different features and have well-determined roles in the system. Each agent accomplishes part of the objective; however, it is specialized for it and cannot take on other roles (or could hardly do so).

Swarm systems due to their nature also give an economic advantage since robots can be easily replaced. This makes them more fault-tolerant and adapted to hazardous environments. Because all the robots are the same, others can fill in the gap when one agent malfunctions. Because individual robots are simple and have basic features, they are cheap to be built, and mass production is, therefore, more feasible.

In contrast, non-swarm systems feature a smaller number of robots which are more complex and can be different. If one agent has a failure, it may be impossible for others to take its place and the system cannot complete its mission until the defunct robot is repaired or replaced with a similar one. Because they are more complex, it also means the robots are harder to be produced and more expensive.

This is an important factor to consider when designing and building a robot system. If a particular set of objectives can be accomplished by a swarm-like system, then an implementation is more likely to be possible, as a proof of concept or otherwise working, production system.

Concerning this classification, the SURFINDER project can be considered a hybrid swarm-like system. Structurally, the individuals will be similar, like in a swarm system. This will allow swarm techniques to be applied if the drones are abstracted into cells.

The field of robotics benefits from research in other related areas that are of interest. One such area is Distributed Artificial Intelligence. This field sees advances in two major topics: distributed problem solving (DPS) and Multi-agent systems (MAS).

Research in DPS is focused on solving a particular problem using multiple agents. These agents cooperate by independently solving subtasks and periodically exchanging partial solutions.

In DPS it is assumed that agents are willing to cooperate. On the other hand, MAS is concerned with the collective behavior of heterogeneous groups in which individuals may have different goals. The research in DPS builds frameworks for cooperative behavior among willing individuals, instead of frameworks that try to make potentially incompatible individuals converge towards a target.

In cooperative robotics, there is a lot of inspiration from biological systems, especially in swarm systems. The studied, known behavior of eusocial insects such as ants or bees stand as striking evidence that systems composed of simple agents can achieve complex goals in the real world. It is often presumed that these insects have very limited cognitive abilities and complex behavior emerges from individual interactions. Therefore, instead of thinking about robots as rational entities, some researchers used a bottom-up approach in which agents are similar to ants: they abide by simple rules and are highly reactive.

Swarm robotics makes use of many algorithms from the field of Swarm Intelligence (SI). There are a great number of variations on some classical techniques used in this field. Search algorithms that are typical and form the basis for many others are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Glowworm swarm optimization (GSO). As the name suggests, these are all inspired by natural biological systems and demonstrate a particular technique in reaching specific goals.

According to Tan, Zang [5], one of the most widely used algorithms in SI is Particle Swarm Optimization, inspired by the flocking behavior of birds. The purpose of the algorithm is finding an optimum in a multidimensional hypervolume Brownlee [6]. Similar to genetic algorithms, the system is seeded with a random population of solutions. Unlike genetic algorithms, each possible solution is also assigned a velocity and these solutions – called particles – move through hyperspace.

As described in Eberhart, Kennedy [7], each particle retains its best solution so far, together with the value, called Pbest. The system also retains the best position found by any of the particles, Gbest. The optimization concept consists of changing each particle's speed every moment of time, towards Pbest and Gbest. The acceleration is weighted with a random factor, being generated random numbers for Pbest and Gbest.

Swarm intelligence algorithms present scalability, flexibility and robustness and can be used in real applications, alongside other techniques. These algorithms also have drawbacks, such as many random moves, a lot of global interaction and tendency to get trapped in a local optimum.

Massive global interaction can pose a technological disadvantage of the techniques, since this usually relies on broadcast communication which is less efficient and possibly expensive, because of the hardware required to handle it.

Search algorithms in swarm robotics are used in multiple ways: parameter optimization and modeling individual behavior are two examples.

In the first type of applications, search algorithms are used to optimize the parameters of other methods – especially in cases where they are hard to optimize, for example in neural networks or heuristic schemes.

Examples of research effort in this direction include the work of Pugh, Martinoli [8]. They developed an adaptive strategy to localize multiple targets. The search algorithm is inspired by bacteria behavior, and its parameters are optimized using PSO.

An improved version of PSO was used as the foundation of a path planning algorithm by Yang, Li [9]. The concept is based on cubic splines, which are the center of the path and planning is then equivalent to optimization of these cubic splines.

The second way in which swarm intelligence algorithms are used in robotics involves modeling individual behavior. Algorithms of this type model each robot as a particle (agent) and the search environment as fitness values. These values are used by the swarm to search the target.

Pugh and Martinoli studied how PSO algorithms can be applied directly in swarm robotics searching problems. They presented in [10] an algorithm for robot cooperation in finding targets. The technique is similar to PSO but adapted to swarm robotics search processes.

Another algorithm inspired by PSO was presented by Marques, Nunes and de Almeida in [11]. It seeks odor sources in a search space. In order to improve swarm performance, the robots will repulse each other in the absence of a chemical cue.

In the experiment of Hereford, Siebold and Nichols [12], a swarm of robots used PSO to search for light spots in a room with obstacles. Individual robots are considered particles and broadcast information to the entire swarm. His experiment has the aforementioned downside of requiring a lot of communication, to maintain the global pest position of the swarm.

A modified technique of glowworm swarm optimization (GSO) was presented by Zhang, Ma, and Miao [13], used for multiple odor source localization. It uses a global random search and a local search based on GSO. Once discovered, a source is marked as forbidden area so that it won't be located again.

In nature, ant colonies are known for their pheromone-based navigation and migration techniques. Swarm robotics researchers used similar methods by simulating pheromones with the help of specific robot parts as emitters.

Sperati, Triann, and Nolfi [14] made a study in which a robot swarm managed to explore the environment and create a navigational path between two key areas which were too far apart to be perceived by any one agent alone. The robots would continuously move along the path, interacting with their neighbors. The robots' behavior was controlled by a neural net. Therefore the swarm evolved to optimize the path, converging on the shortest distance.

The third algorithm mentioned, glowworm swarm optimization (GSO), represents an optimization technique meant to simultaneously detect several optimum values from multimodal functions, which exhibit many local maximums. Initially, agents are randomly spread according to a uniform distribution, in the target function's space. Every agent carries a luminescence quantity called luciferin that encodes information about the function at his current location. Agents are metaphorically viewed as glowworms (firefly larvae) that glow with light, whose intensity is proportional to the associated luciferin. A worm sees as neighbors other worms situated in the local decision domain which has a greater luciferin value. The decision domain is adaptable and has an upper bound given by the circular distance of the sensor. Every worm selects a neighbor using a probabilistic mechanism and goes towards it. This results in every worm being attracted by the most powerful glow of its neighbors. These individual moves, based only on local information, allow the swarm to divide into disjoint subgroups and then gather at multiple optimums of multimodal functions.

As described in Liu, Wang, Tan [15], a worm that has maximum luciferin value in a given iteration will be stationary. This property will ideally mean that the system will be in a deadlock if the maximum point is outside the convex hull of the glowworm positions. This results in the glowworms moving away from peaks. However, because the movement updates in steps of discrete values, each glowworm will move with a distance s towards its neighbor. When it gets close enough so that the distance between them is less than s, it will overtake the neighbor and swap the leader-follower positions. This particular feature is called the leapfrogging effect and is what allows the glowworms to actually reach the peak points on a gradient, even if the maximum lies outside the convex hull of their positions. Multiple glowworms will use this principle to perform an improved local search and converge on a maximum.

Aside from the search issue, which is important in tracking objectives, another feature of major significance to swarm systems are formation and navigation. For the SURFINDER project, inspiration was drawn from the technique of boid flocking, presented by Craig Reynolds in 1987. Boids stand for birdoid objects – an abstract metaphor of birds. Initially, it was designed as a simulation and later a paper was presented at the SIGGRAPH 1987 computer graphics conference. The concept was described by Craig [16]. The motivation for the paper arose from avoiding manual and crude techniques to animate a group of bird-like elements with scripted paths. The premise is that a flock is the result of individual interactions. A resemblance to swarm methods can be noticed, where the fundamental idea is the same.

The behavioral model that controls flight and flocking is based on the distributed self-organized systems model. Individual agents possess state and behavior, which can be encapsulated in objects (a useful construct for practical implementations in object-oriented languages). Every instance of these objects requires a computational process to be able to run the behavioral program on the internal state. Objects along with necessary processes are known as actors. The actors represent virtual computers that communicate by exchanging messages.

A fundamental part of the proposed model was the geometric capability of flying. The motion happens along a 3D curve. Although movement is rigid, the geometric model of the object could change shape during an animation, within its flight coordinates.

In order to model the flock, there are three behaviors that need to be taken into account: avoiding collisions between neighboring members, matching the speed with neighboring members and centering the flock – the individuals' effort to keep proximity to neighboring members. Avoiding collisions and dynamic velocity adjustment are complementary influences: they allow simulated flock members to fly freely inside the flock without running into each other. Static collision avoidance is based on member's relative position and ignores velocity. On the other hand, velocity matching is based on speed only and ignores position.

Flock centering determines the boid's tendency towards its center. Given that every member has a local perception of the world, the center is defined as the centroid of neighboring members. If the individual is located in the center of the flock, population density is homogenous in the neighborhood, therefore almost constant in all directions. In this case, the centroid of the neighboring members is identical to the center of the neighborhood, so flocking tendency towards the center is small. However, if the agent is situated at the edge of the flock, there will be neighboring members only on one side of him. The centroid of neighboring members is translated from neighborhood center to the body of the flock. This makes the flocking tendency higher, and the movement trajectory will be changed towards the flock center.

The above three behaviors allow group separation, which can be a method of obstacle avoidance. The motion will be adapted to close members. Force field model assumes a repulsion force field which is generated by the obstacle in the space and members are pushed away from the more they get closer to the obstacle. This model can produce good results, but it also has disadvantages: if a member comes from a direction which is the exact opposite of his motion, it will not turn, but will merely be slowed down.

The robot control technique that is envisioned for the SURFINDER project is a variant of the flocking method described above. Each robot (agent) of the group will be coordinated by a resultant vector, calculated as the vector sum of all influence forces acting upon it. These forces of influence will determine the behavior of the member towards the group and the group as a whole. The forces will be weighted with dynamically adjustable parameters during the mission. Because the technique is modeled after the concepts presented by Reynolds in his work regarding flocking, there will be cohesion forces and repulsion forces, which will constitute the foundation of drone group movement without collision among members and keeping a steady minimum distance between each other. At the system level, drones can be controlled by setting goals or through a multi-phase strategy. In case a multi-phase strategy is used. Initially, there can be placed target position in perimeter search space, towards which the drones could maintain direction, and after acquiring signals from nearby, those initial positions could lose importance to new objectives, set by the drones. Initial points could be randomly uniform distributed inside the perimeter or sub-zones. If there are sub-zones involved, a suitable partition strategy needs to be used. After closing in on initial targets, drones could enter a secondary phase during which they make a zone surveillance so as to cover the whole region of interest in their search for signals. In this case, a strategy for surveillance behavior is needed. As signals are acquired, drones could move on to a new phase with a behavior suited for a more detailed search, or assistance with setting up an ad-hoc GSM network or other tasks.

As an alternative to or in conjunction with a multi-phase strategy, the drone swarm can be controlled by modifying the weights of the influence forces on the individuals. There can also be influences on the whole system. A proposed method is that of a food sources metaphor. Initially, some food sources can be set up by a human operator and drones can be pointed towards these virtual food sources. These targets decay and are replaced by new ones in surrounding area, creating a renewed interest in visiting other zones. Acquired signals can become virtual food sources that don't get depleted, to stabilize the drones around them.

A fundamental principle, regardless of the techniques implemented, is controlling the system by means of influences acting upon it and not direct control of the drones. This will facilitate guiding the swarm and will abstract all the particular navigation details which could overwhelm a small number of human operators.

III. Conclusion

The purpose of the drones in the SURFINDER project is not limited to reconnaissance and victim localization. The system should be useful in as many moments of a rescue operation as possible. Therefore, on a higher level, there will be behaviors defined for multiple situations and goals. The generic capabilities of drones will be established, such as GSM network setup, survivor detection based on mobile phone signal, informing the base of environment status and other planned operations. On a lower level, simple and practical mechanisms need to be established in order to communicate between agents as well as with the operation headquarters, to sense the environment, to move to a target and other necessary mechanical actions.

Acknowledgment

This work is supported by PNCDI III Programme P2 - Transfer of knowledge to the economic operator (Bridge Grant PN-III-P2-2.1-BG-2016-0296) funded by UEFISCDI, Romania.

References

[1] R Tarca, Advanced Mechatronics, *Publisher: University of Debrecen*, Hungary, HU ISBN 978-963-473-508-3.
[2] R. Tarca, Introduction in Robotics (Introducere in Robotica}, *Editura Universitatii din Oradea*, ISBN 973-613-456-3
[3] E. Kuantama, D. Craciun, I. Tarca, R. Tarca Quadcopter Propeller Design and Performance Analysis, *Mechanical Transmissions and Robotics* Vol. 46 pp 269-277.
[4] E. Kuantama, R. Tarca – Quadcopter Attitude and Thrust Simulation Based on Simulink Platform, *Robotica & Management*, 20-2 / 2015, pp. 40-44.
[5] Y. Tan, Z.Y. Zheng, Research Advance in Swarm Robotics, *Defence Technology*, Vol. 9, Iss. 1, 2013, pp. 18-39.
[6] J. Brownlee, Particle Swarm Optimization http://www.cleveralgorithms.com/nature-inspired/swarm/pso.html
[7] R. C. Eberhart, J. Kennedy, A New Optimizer Using Particle Swarm Theory *Proceedings of the sixth international symposium on micro machine and human science*, 1995. Pp.39-45.
[8] J. Pugh, A. Martinoli, Distributed adaptation in multi-robot search using particle swarm optimization., 2008, pp. 393-402
[9] M. Yang, CZ. Li, Path planning, and tracking for a multi-robot system based on improved PSO algorithm. In: *International conference on mechatronic science, electric engineering, and computer. IEEE*; 2011. p. 1667e70.
[10] J. Pugh, A. Martinoli, Inspiring and modeling multi-robot search with particle swarm optimization In *Proceedings 2007 IEEE swarm intelligence symposium. IEEE*; 2007, pp. 332-339.
[11] L. Marques, U. Nunes, AT. de Almeida, Particle swarm-based olfactory guided search *Autonomous Robots* 2006;20(3):277-287.
[12] MJ Hereford, M Siebold, S. Nichols, Using the particle swarm optimization algorithm for robotic search applications. In: *Proceedings 2007 swarm intelligence symposium. IEEE*; 2007. p. 53-59.
[13] YL Zhang, XP Ma, YZ Miao. Localization of multiple odor sources using modified glowworm swarm optimization with collective robots. In: *30th Chinese control conference. IEEE*; 2011. p. 1899-1904.
[14] V. Sperat, V. Triann, S. Nolfi, Evolution of self-organised path formation in a swarm of robots, 2010, pp. 155-166
[15] D. Liu, L. Wang, K. C. Tan, Design and Control of Intelligent Robot Systems, 2009 *Springer-Verlag Berlin Heidelberg*, ed. I, vol. 177.
[16] W. R. Craig, Flocks, Herds, and Schools: A Distributed Behavioral Model, 1987, *ACM*, pp.25-34