Using Differential Evolution to Improve Pheromone-based Coordination of Swarms of Drones for Collaborative Target Detection

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Abstract: In this paper we propose a novel algorithm for adaptive coordination of drones, which performs collaborative target detection in unstructured environments. Coordination is based on digital pheromones released by drones when detecting targets, and maintained in a virtual environment. Adaptation is based on the Differential Evolution (DE) and involves the parametric behaviour of both drones and environment. More precisely, attractive/repulsive pheromones allow indirect communication between drones in a flock, concerning the availability/unavailability of recently found targets. The algorithm is effective if structural parameters are properly tuned. For this purpose DE combines different parametric solutions to increase the swarm performance. We focus first on the study of the principal parameters of the DE, i.e., the crossover rate and the differential weight. Then, we compare the performance of our algorithm with three different strategies on six simulated scenarios. Experimental results show the effectiveness of the approach.

1 INTRODUCTION AND MOTIVATION

The Differential Evolution algorithm (DE) is a stochastic population based algorithm, very suited for numerical and multi-modal optimization problems. Recently, DE has been applied in many research and application areas. Compared with other population-based algorithms, such as genetic algorithm and particle swarm optimization, DE exhibits excellent performance both in unimodal, multimodal, separable, and non-separable problems. Moreover, it is much simpler to use because it has only three parameters (Das, 2011): the population N, the differential weight F, and the crossover rate CR. When managing the DE algorithm, the main effort is to properly set the parameters in order to avoid premature convergence towards a non-optimal solution. As reported by literature, there is no dominant setting, and for each problem a proper study of the behaviour of DE is needed to find the correct parameterization.

In this paper, we adopt DE algorithm to optimize the behaviour of a swarm of aerial drones carrying out collaborative target detection (Cimino, 2015b). In our approach, stigmergy and flocking are exploited to enable self-coordination in the navigation of unstructured environments. Such environments typically contain a number of obstacles such as trees and buildings. Targets are placed according to different patterns. More specifically, stigmergy implies the use of an attractive digital pheromone to locally coordinate drones. When a drone detects a new piece of target, it releases the attractive pheromone. Other drones in the neighbourhood can sense and follow the pheromone gradient to cooperate in detecting the pattern of targets. With respect to (Cimino, 2015b) in this study we sensibly improve the performance of the algorithm, by adopting the parametric DE-based adaptation, by introducing repulsive pheromone and scattering mechanisms. Basically, flocking implies a set of three behavioural rules, named *separate*, *align*, and *scatter*. It maintains the drones in groups enhancing the stigmergy when occurring. In contrast, the repulsive pheromone helps the drones to avoid multiple exploration of the same zone. Indeed, the drone releases a repulsive pheromone whereas it does not sense a target.

Finally, the scattering rule makes a drone to turn by an angle when it tails another drone.

In the literature there are two design methods to develop collective behaviours in swarm systems: behaviour-based design and automatic design (Brambilla, 2013). The former implies the developers to implement, study, and improve the behaviour of each single individual until the desired collective behaviour is achieved. This is the approach adopted in (Cimino, 2015b). The latter is usually used to reduce the effort of the developers. Automatic design methods can be furtherly divided in two categories: reinforcement learning and evolutionary robotics (Brambilla, 2013). The first implies a definition at the individual level of positive and repulsive reinforce to give reward to the individual. In general, it is usually hard for the developer to decompose the collective output of the swarm in individual rewards. Evolutionary robotics implies evolutionary techniques inspired by the Darwinian principle of selection and evolution. Generally in these methods each swarm consists of individuals with the same behaviour. A population of swarms is then computed, where each population member has a particular behaviour. A simulation is made for each member and a fitness function is computed. Then through a mutation and crossover procedure a new generation is computed. This process iteratively repeats improving the performance of the swarm population.

2 RELATED WORK

DE has been used in several domains for optimization and parameterization tasks (Das, 2011). As an example, in (Nikolos, 2005) the authors used a classical DE variant, namely DE/1/rand/bin, to coordinate multiple drones navigating from a known initial position to a predetermined target location. Here, DE is set up with *N*=50, *F*=1.05 and *CR*=0.85. The algorithm was defined to terminate in 200 generations, but it usually converges in 30 iterations. Our problem sensibly differs, because the target position is unknown, and our approach is independent of the initial position.

In (Chakraborty, 2008) the authors confront DE and Particle Swarm Optimization (PSO) for co-operative distributed multi-robot path planning problem. As for (Nikolov, 2005) initial position of the robots and final position are known. Here, both centralized and decentralized formulations are proposed. In the centralized approach, DE minimizes the distance for the next step of each robot. In this case all information of the position of each robot, the next position, and the possible collision are provided to DE. In the decentralized formulation, each robot runs DE for itself considering the information of neighbour robots. Authors conclude that the decentralized approach needs less time in comparison to the centralized one; moreover the performance is comparable to PSO. In our approach, we consider to use DE offline to find a proper and general purpose parameter tuning for the swarms. Moreover, in our formulation drones have a limited computing capability, and then an online execution of DE is not feasible.

In (Cruz-Alvarez, 2013) DE/1/rand/bin is used with *F*=0.7, *CR*=1.0, *N*=120 for 250 generations, and another variant called DE/1/best/bin is used with *F*=0.8, *CR*=1.0, *N*=150 for 200 generations to tune the behaviour of a robot in wall-following task. Here it seems that DE/1/best/bin is able to find a slightly better solution than DE/1/rand/bin. However, authors used different parameters settings (*F*, *N* and number of generations) for each variant, thus a comparative analysis is difficult. In our approach we focus on DE/1/rand/bin variant and evaluate several combinations of *CR* and *F*.

3 SWARM BEHAVIORAL MODEL

In this section we improve the swarm algorithm of (Cimino, 2015b). We refer to the time unit as a *tick*, i.e., an update cycle of both the environment and the drones. Each drone is equipped with: (a) wireless communication device for sending and receiving information from a ground station; (b) self-location capability, e.g. based on global position system (GPS); (c) a sensor to detect a target in proximity of the drone; (d) processor with limited computing capability; (e) a sensor to detect obstacles.

The environment and the pheromone dynamics

We consider a predefined area that contains a set of targets to be identified. The environment is modelled by a digital grid corresponding to the physical area. The grid has C^2 cells, each identified by (x, y) coordinates with x, y ∈ {1,…,C}. The actual size of the area and the granulation of the grid depend on the domain application. Figure 1 shows Pheromone dynamics in an urban scenario. Here, the intensity of the pheromone is represented as a dark colour, and each target is represented by an “X”. A darker gradation means higher pheromone intensity. At the beginning, the pheromone is in one cell at its maximum intensity, and then it diffuses to neighbouring cells. After a certain time the pheromone evaporates, disappearing from the environment. When a drone detects a piece of the overall target, a pheromone of intensity I is released in the cell corresponding to the drone location. Then, at each tick the pheromone diffuses to the neighbouring cells according to a diffusion rate $\delta \in [0,1]$. At the same time the pheromone evaporates decreasing its intensity, by an evaporation rate $\varepsilon \in [0,1]$.

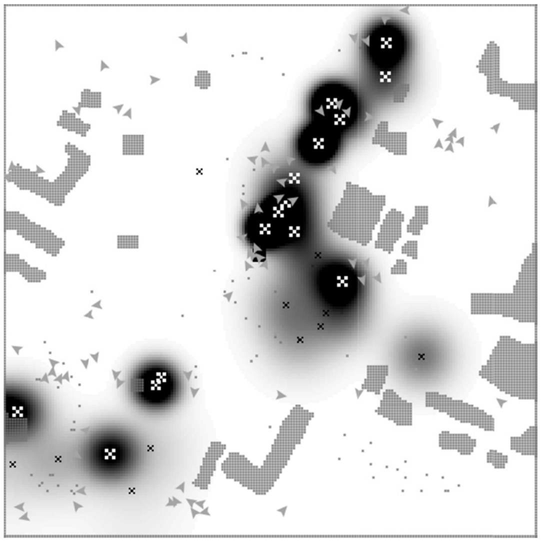


Figure 1: Pheromone dynamics in an urban scenario.

The drone behaviour

The drone behaviour is structured into five-layer logic, where each layer has an increasing level of priority. Starting from the lowest: the random fly behaviour entails the exploration in absence of stimuli/information; the repulsive pheromone-based coordination reduces the redundancy of exploration; the flocking behaviour assembles the flock enabling local pheromone interactions; the positive pheromone-based coordination exploits the digital pheromone and directs the swarm toward potential new targets; finally the highest priority level, the objects/boundary avoidance, which prevents the drone from exiting the area or colliding with obstacles and other drones.

Fig. 2 shows a UML activity diagram of the drone behaviour. Here, a rectangular box represents sensors (left) and actuators (right), a rounded-corner box represents an activity (a procedure), solid and dashed arrows represent control and data flows, respectively.

Every tick period, represented by the hourglass, the drone performs two parallel processes: (a) the target detection, which corresponds to the release of the attractive pheromone on the digital grid or rather of the repulsive pheromone; (b) the movement procedure, which starts with the obstacle and boundary detection. If a close obstacle (i.e., object or drone) is detected (b.1), the drone points toward a free direction. If a free direction is found, it moves forward, otherwise it stays still. If there are no close objects detected (b.2), the drone tries to sense positive pheromone in its neighbouring cells and, if detected, the drone points toward the maximum intensity of it. Differently, if no pheromone is detected (b.3), the drone tries to detect surrounding drones in order to stay with the flock. Then, the drone checks if a repulsive pheromone is in nearby cells (b.4). If there is, the drone moves toward the minimum intensity of it. Finally, if there are no surrounding drones (b.5), it performs a random turn and move forward.

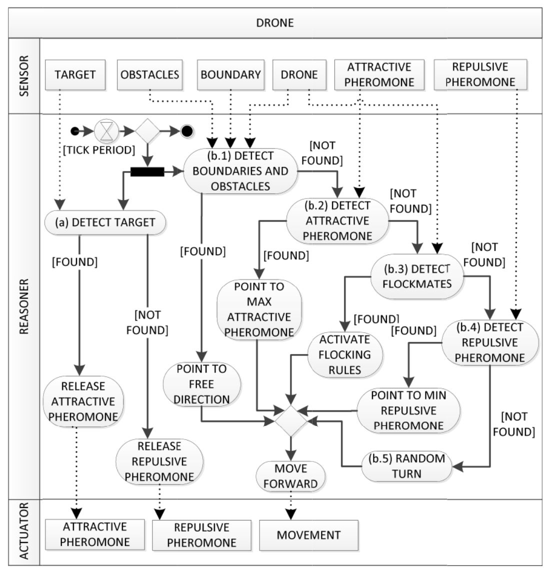


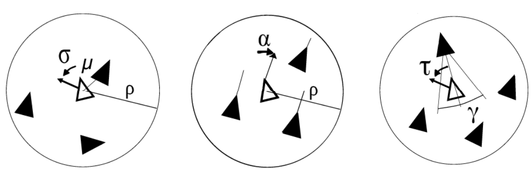
Figure 2: Overall representation of the drone behaviour.

At the highest priority (b.1), the drone has to avoid collision and to exit the search area. For this purpose the drone is able to detect objects (i.e., other drones or obstacle) at the *object sensing distance* (o) on its trajectory. If a potential collision is detected the drone chooses the minimum rotation angle to the left or right to avoid the obstacle. If it finds a free trajectory it moves forward, if there is no free direction within 180 degree it stays still one tick. The boundaries of the area are considered as a "wall" of obstacles.

The second priority is to follow the positive pheromone gradient (b.2), provided by the ground station. Given the drone position (i.e., the cell on the grid), the cell with the maximum intensity of positive pheromone and the minimum intensity of the repulsive pheromone (b.4) in its 8 neighbouring cells is returned to the drone. Then, the drone follows the maximum pheromone intensity.

The flocking behaviour (b.3) consists in three rules, represented by Fig.3. A drone considers as flock mates all drones in a *flock visibility radius* (ρ). The first rule is the *separation*: more specifically, if the drone senses another drone closer than the *flock mobility distance* (μ), it turns away by a *flock separation angle* (σ). The second rule is the *alignment*: the drone computes the average direction of its flock mates and it adapts its direction by a *flock alignment angle* (α). The third rule is the *scatter*: the follower drone considers the closer following drone in front of itself. If the follower is in the tail sector of the following defined by angle *flock tail angle* (γ) the follower turns away the following by a *flock scatter angle* (τ). These three rules determine the structure of the swarm, permitting the drones to navigate in coordinated group, exploring the environment and, most important, sensing pheromone released by flock mates.

The fourth priority (b.4) is to move against the repulsive pheromone gradient. The drone received the information of the lowest cell from the ground station (b.2). Finally, if nothing is detected (b.5) then the drone is in its basic behaviour (random fly). It randomly turns by an angle smaller than the *maximum rand-fly turn angle* (θ).



(a) separation (b) alignment (c) scattering

Figure 3: Flock visibility radius and other parameters in flocking behaviour.

4 ADAPTATION WITH DIFFERENTIAL EVOLUTION

The swarm algorithm presented in Section 3 involves a number of structural parameters to be appropriately set for each given application scenario. Determining such correct parameters is not a simple task since different areas have different topology and different targets distribution. In DE algorithm, a population member is a real n-dimensional vector, where n is the number of parameters to tune. DE starts with a population of N members, injected or randomly generated. In the literature, the population size spreads from a minimum of $2n$ to a maximum of $40n$ (Mallipeddi, 2011). A large population increases the chance of finding an optimal solution but it is very time consuming. To balance speed and reliability we use N=20. At each iteration, and for each population member (target), a mutant vector is created by mutation of selected members and then a trial vector is created by crossover of mutant and target. Finally, the best fitting among trial and target replaces the target.

In addition to DE, other classes of optimization methods, such as Particle Swarm Optimization (PSO) attracted attention in the last decade. The interested reader is referred to (Cimino, 2015a) for further details. Several DE strategies have been designed, by combining different structure and parameterization of mutation and crossover operators (Mezura, 2006 and Zaharie, 2007). As noted by (Das, 2011), practitioners mostly prefer to use a classical DE variant like DE/1/rand/bin. The differential weight $F \in [0,2]$ mediates the generation of the mutant vector. F is usually set in [0.4-1), and a frequently used starting value is 0.8 (Mezura, 2006). There are different crossover methods in DE. A competitive approach is the binomial crossover (Zaharie, 2007). With binomial crossover, a component of a vector is taken with probability CR from the mutant vector and with probability 1-CR from the target vector. A good value for CR is between 0.3 and 0.9, and a frequently used starting value is 0.7 (Mallipeddi, 2011).

The fitness measure to evaluate the effectiveness of a solution is the average time (in ticks), over 5 runs, which the swarm of drones take to find 95% of the targets of the scenario.

5 EXPERIMENTAL RESULTS

We implemented our algorithm using *NetLogo*, a leading simulation platform for swarm intelligence (ccl.northwestern.edu/netlogo), and *MATLAB* for the adaptation algorithm (www.mathworks.com). We evaluated our algorithm by comparing four different strategies: the adaptive stigmergic and flocking behaviour (S+F*) presented in Section 3; the stigmergic and flocking behaviour (S+F) presented in (Cimino, 2015b); the stigmergic behaviour (S), in which the pheromone grid maintains only the positive pheromone intensity information and the drones do not perform flocking behaviour; finally, the random fly behaviour (R), in which drones randomly explore the area with no pheromone nor flocking behaviour. We tested the swarm algorithm on six different scenarios. For each scenario, each of the three strategies has been specifically optimized by the adaptation module. To compare the approaches, 10 trials have been carried out for each considered approach. We also determined that the resulting performance indicator samples are well-modelled by a normal distribution, using a graphical normality test. Hence, we calculated the 95% confidence intervals.

The total number of drones is 80; each drone is represented as a black triangle, arranged in 4 swarms placed in the corners of the map, except for *Illegal Dumps* in which 3 swarms are placed in 3 corners due to the topology. Characteristics of the topology of targets and obstacles are summarised in Table 2.

Figure 4 represents the initial configuration for all scenarios. The three scenarios *Field*, *Forest*, and *Urban* represent respectively an area of 40,000 m^2.

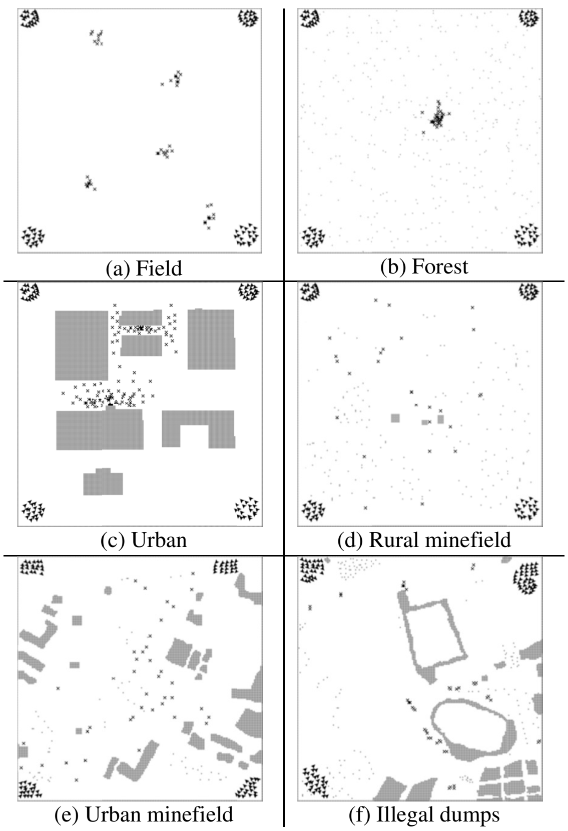


Figure 4: Maps of 3 synthetic and 3 real-world scenarios.

Figure 4 (a) does not contain obstacles at all, but contains 5 clusters of 10 targets each. Figure 4 (b) represents a timber with 1 cluster of 20 targets with tree obstacles. Figure 4 (c) shows an industrial area with 2 clusters of 55 targets, each representing a pollutant lost. The two scenarios *Rural minefield* and *Urban minefield*, represented in Figure 4 (d) and Figure 4 (e), respectively, are two mined areas of 80,000 m^2 derived from real-world maps near Sarajevo, in Bosnia-Herzegovina (www.see-demining.org). The last scenario, *Illegal Dump*, is a real-world example of illegal dumping taken from an area of 80,000 m^2 near the town of Paternò, Italy (www.trashout.me).

Figure 5 shows the evolutions of DE algorithm against generations, with two different values of *CR* and *F*. Here, the best and the mean solution (solid and dashed line, respectively) have been calculated over 5 runs. The optimization is characterized by a very good improvement of the initial solution and by a fast convergence: only 20 generations are needed to reduce the average time by 20%. More precisely, Table 1 shows that the final best performance is achieved with *CR*=0.5 and *F*=0.7.

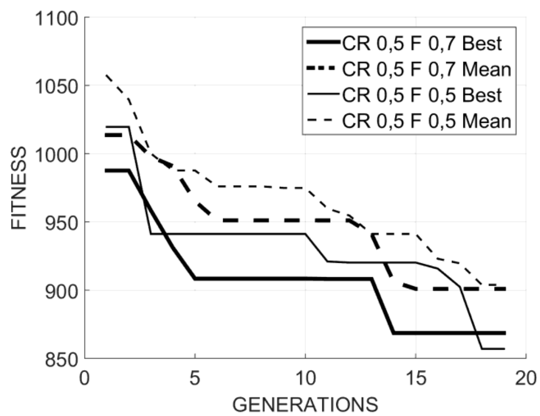


Figure 5: Evolution of the DE algorithm against generations for different DE parameters.

Table 1: Final results of the evolution of Figure 5 in numerical terms.

F\CR	***0.3***	***0.5***	***0.7***
0.5	933,67±14,16	903,85±29,77	950,80±16,36
0.7	966,60±15,53	**900,65±19,06**	907,15±12,96
0.9	951,40±15,67	930,60±22,36	933,73±54,14

Table 2 characterizes each scenario with the results, in the form "mean ± confidence interval". It is worth noting that the proposed adaptive algorithm "S+F*" outperforms the algorithms presented in (Cimino, 2015b) in all scenarios. More specifically, in *Field* and *Forest* scenarios, the two algorithms

"S+F" and "S+F*" are comparable. This is due to the simple layout of both scenarios, which does not allow a good exploitation of the "S+F*" features. Indeed, in the other scenarios, with a more complex topology, the advantages of the "S+F*" strategy are substantial.

Table 2: Features and numerical results of each scenario.

Scenario	*N° of targets / clusters*	*Type / n° of obstacles*	*Completion time (ticks)*	
Field	50 / 5	Trees: 0 Buildings: 0	R	1664±220
			S	656±101
			S+F	589±86
			S+F*	**582±121**
Forest	20 / 1	Trees: 400 Buildings: 0	R	1862±356
			S	615±67
			S+F	602±124
			S+F*	**593±146**
Urban	110 / 2	Trees: 0 Buildings: 7	R	2049±148
			S	998±61
			S+F	890±93
			S+F*	**666±100**
Rural Mines	28 / 28	Trees: 281 Buildings: 3	R	1588±216
			S	1570±158
			S+F	**1530±225**
			S+F*	1123±116
Urban Mines	40 / 40	Trees: 54 Buildings: 28	R	1844±140
			S	1733±169
			S+F	**1704±225**
			S+F*	1025±76
Illegal Dumps	42 / 11	Trees: 140 Buildings:19	R	1548±207
			S	971±160
			S+F	934±216
			S+F*	**757±112**

6 CONCLUSIONS

In this paper, we have presented an algorithm to adapt, via the DE algorithm, the coordination of a swarm of drones performing target detection on the basis of stigmergy and flocking. We first evaluated several combinations of the structural parameters of the DE. Results show that a crossover rate (*CR*) of 0.5 and a differential weight (*F*) of 0.7 produce better solutions. Then, to test the effectiveness and the reliability of the approach, we compared our algorithm with three search strategies over real-world and synthetic scenarios. As a result, our approach resulted dominant in all scenarios. Future work will (i) investigate our approach on additional scenarios, (ii) use other optimization methods for the adaptation, and (iii) include non-functional requirements in the algorithm, such as computing power and endurance of drones.

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