Multi-Robot Cooperative Tasks using Combined Nature-Inspired Techniques

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Abstract: In this paper, two metaheuristics are presented for exploration and mine disarming tasks performed by a swarm of robots. The objective is to explore autonomously an unknown area in order to discover the mines, disseminated in the area, and disarm them in cooperative manner since a mine needs multiple robots to disarm. The problem is bi-objective: distributing in different regions the robots in order to explore the area in a minimum amount of time and recruiting the robots in the same location to disarm the mines. While autonomous exploration has been investigated in the past, we specifically focus on the issue of how the swarm can inform its members about the detected mines, and guide robots to the locations. We propose two bio-inspired strategies to coordinate the swarm: the first is based on the Ant Colony Optimization (ATS-RR) and the other is based on the Firefly Algorithm (FTS-RR). Our experiments were conducted by simulations evaluating the performance in terms of exploring and disarming time and the number of accesses in the operative grid area applying both strategies in comparison with the Particle Swarm Optimization (PSO). The results show that FTS-RR strategy performs better especially when the complexity of the tasks increases.

1 INTRODUCTION

In the robotics field, an important aspect of multiple agents systems is the coordination that allows the system accomplishes efficiently general tasks, such as exploration, coverage and surveillance. Autonomous robots, equipped with proper sensors, are deployed in the environment to find the object of interest, i.e., fire spots in the jungle, mines in unknown area, missing black box from a crashed airplane, or to measure a concentration of hazardous materials. The use of a swarm of robots is utilized in these applications for the expected benefits of reducing risks to humans, lower cost, and improved efficiency (Bellingham and Godin 2007).

Swarm robotics is a new approach to the coordination of a multi robots system, that typically consist of a population of simple agents interaction locally with each other and with the environment. The benefit of cooperation can be significant in situation where global knowledge of the environment does not exist. Individuals within the group interact according to the swarm intelligence algorithms by exchanging information that is useful for performing the tasks collectively.

In our collective construction task, there are some mines randomly distributed in an unknown area. The robots should first search for these mines individually, but for disarming task, multiple robots are needed to work together. The problem is not a pure exploration: on one hand, it is required for robots to cover as much area as possible in the minimum amount of time, avoiding any overlapping area. On the other hand, the problem needs to allocate more robots in the same area to disarm a mine. The problem is a bi-objective optimization problem where robots have to make decisions whether to explore the area or to help other robots to disarm the detected mines.

Because the problem of the unknown lands with the constraint to disarm mine is a NP hard problem, we proposed a combined approach using two bio-inspired meta-heuristic approaches such as Ant Colony Optimization (ACO) and Firefly algorithm (FA) to perform the coordination task among robots.

Basically, each robot consists of two phases during the task: searching and disarming. When there is no detected mine, the robot status should be in the searching phase, where robots are exploring the area and searching for mines, taking into account the quantity of pheromone perceived in the cells. Once

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mine is detected either by the robot itself or by its neighbours, the robot status should be switched to the disarming phase, under specific condition. The strategy for the exploration task is designed according to the main ideas of the ant system (Dorigo et al., 2006). While the robots navigate, they deposit a specific substance, the pheromone (the analogue of the pheromone in biological ant systems), into the environment. At each time/iteration, each robot receives information from the pheromone and makes a navigation decision: it chooses the area in which it perceives a less quantity of pheromone because this area has a greater probability to be unexplored (De Rango and Palmieri, 2012; De Rango et al., 2015).

The algorithm for exploration has been previously validated (De Rango and Palmieri, 2012) and this paper presents the analysis of the recruiting strategies in order to disarm the mines. The first is based on the exploration strategy and uses the pheromone to attract the robots in the area where the mine is placed. The second strategy is based on the new recent bio-inspired technique called Firefly Algorithm (FA) where the robots that detect the mines become the fireflies and try to attract the other robots according with a certain formula (Yang, 2009; Yang, 2010). These strategies were compared to the well known Particle Swarm Optimization in order to evaluate the better coordination mechanism for this problem. This contribution can be effective because the recruiting strategy can affect the exploration task and the overall bi-objective exploring and recruiting tasks.

The paper is organized as follows. Section 2 introduces the related work. Section 3 describes the firefly algorithm. In Section 4 we present the problem statement. In Section 5 we present the distributed cooperative algorithms for a multi-robot disarming task. Section 6 presents the simulation results using a java-based platform and Section 7 analyses the quality of the solutions. To conclude the paper, Section 8 outlines the main research conclusions and discusses topics for future work.

2 RELATED WORK

Multi-robot exploration has received much attention from the research community. Swarm robotic searching algorithm is one of the most concerns of the researchers besides those basic tasks. The swarm intelligence shows great ability in scalable, flexibility and robustness and is suitable for real life applications with the aid of various existing strategies. Within the context of swarm robotics, most work on cooperative exploration is based on biologically behaviour and indirect stigmergic communication (rather than on local information, which can be applied to systems related to GPS, maps, wireless communications). This approach is typically inspired by the behaviour of certain types of animals, like the ants, that use chemical substances known as pheromone to induce behavioural changes in other members of the same species (Russell, 1999; Sugawara et al., 2004; Garnier et al., 2007; Ducatelle et al., 2011, Masàr, 2013).

Other authors experiment with chemical pheromone traces, e.g. using alcohol (Fujisawa et al., 2008) or using a special phosphorescent glowing paint (Mayet, 2010). Another approach is the pheromone robotics where robots spread out over an area and indicate the direction to a goal robot using infrared communication (Payton et al., 2001). In our approach, during the exploration the robots sign/mark the crossed cell through the scent that can be detected by the other robots; the robots choose the cell that has the lowest quantity of substance to allow the exploration of the unvisited cells in order to cover the overall area in less time (De Rango and Palmieri, 2012).

The self-organizing properties of animal swarms such as insects have been studied for better understanding of the underlying concept of decentralized decision-making in nature, but it also gave a new approach in applications to multi-agent systems engineering and robotics. Bio-inspired approaches have been proposed for multi-robot division of labour in applications such as exploration and path formation, or cooperative transport and prey retrieval. Within the context of swarm robotics, most work on cooperative tasks is based on social behaviour like Ant Colony Optimization (Dorigo et al., 2006), Particle Swarm Optimization (Meng and Gan, 2008) Bee Algorithm (Jevtic et al., 2012).

For sharing information and accomplishing the tasks there are, basically, three ways of information sharing in the swarm: direct communication (wireless, GPS), communication through environment (stigmergy) and sensing. More than one type of interaction can be used in one swarm, for instance, each robot senses the environment and communicates with their neighbour. Balch (Balch, 2005) discussed the influences of three types of communications on the swarm performance and Tan (Tan and Zheng, 2013) presents an accurate analysis of the different type of communication and the impact in a behaviour of swarm.

In this paper, we considered the spatial and temporal dispersion of the pheromone to make the scenario more realistic (De Rango and Palmieri, 2012). While walking, the robots leave pheromone, which marks the cells they took. This chemical substance can be detected by other robots. After a while, the concentration of pheromone decreases due to the evaporation and diffusion associated with the distance and with the time; in this way we can allow continuous coverage of an area via implicit coordination. The other robots, through proper sensors, smell the scent in the environment and move in the direction with a minimum amount of pheromone that corresponds to an area less occupied and probably an unexplored area. On the other hand, in order to deactivate the mines, the first robot that detects a mine (recruiter) in a cell, sprays another scent smelled by the robots; in this case the robots move into the cells with a higher concentration of pheromone and reach the area where to deactivate the mines. In this attraction strategy of the recruiter, another recent and novel bio-inspired approach inspired by other insects such as fireflies has been investigated in this work so as to see the effectiveness of the algorithm and potential use of different insect behaviour on the robot coordination task and their performance. The algorithm inspired by fireflies is called Firefly algorithm (FA) and is summarized in the next section.

3 FIREFLY ALGORITHM

The firefly algorithm is a nature-inspired meta-heuristic algorithm developed in 2008 by Xin-She Yang to solve optimization problems (Yang, 2009; Yang, 2010; Yang, 2014). The algorithm is based on the social flashing behavior of fireflies in nature. The key ingredients of the method are the variations of light intensity and formulation of attractiveness. In general, the attractiveness of an individual is assumed to be proportional to their brightness, which in turn is associated with the encoded objective function.

In the firefly algorithm, there are three idealized rules, which are based on some of the major flashing characteristics of real fireflies. They are:

1. All fireflies are unisex, so that one firefly will be attracted to other fireflies regardless of their sex;
2. The degree of attractiveness of a firefly is proportional to its brightness, which decreases as the distance from the other firefly increases due to the fact that the airabsorbs light. For any two flashing fireflies, the less bright one will move towards the brighter one. If there is not a brighter or more attractive firefly than a particular one in the neighborhood, it will then move randomly;
3. The brightness or light intensity of a firefly is determined by the value of the objective function of a given problem.

The distance between any two fireflies i and j, at positions X_i and X_j, respectively, can be defined as the Cartesian or Euclidean distance as follows:

$$r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{D}\left(X_{i,k} - x_{j,k}\right)^2} \tag{1}$$

where $x_{i,k}$ is the k-th component of the spatial coordinate X_i of the i-th firefly and D is the number of dimensions.

In the firefly algorithm, as the attractiveness function of a firefly j, one should select any monotonically decreasing function of the distance to the chosen firefly, e.g., the exponential function:

$$\beta = \beta_0 e^{-\gamma r_{ij}^2} \tag{2}$$

where r_{ij} is the distance defined as in Eq. (1), β_0 is the initial attractiveness at r_0, and γ is an absorption coefficient at the source which controls the decrease of the light intensity.

The movement of a firefly i which is attracted by a more attractive (i.e., brighter) firefly j is governed by the following evolution equation:

$$x_i = x_i + \beta_0 e^{\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha(\sigma - \frac{1}{2}) \tag{3}$$

where the first term on the right-hand side is the current position of the firefly, in our case a mine, the second term is used for considering the attractiveness of the firefly to light intensity seen by adjacent fireflies, and the third term is used for the random movement of a firefly in case there are not any brighter ones. The coefficient α is a randomization parameter determined by the problem of interest, while σ is a random number generator uniformly distributed in the space [0, 1].

Furthermore, we look at equation (3), thus non linear equation provides much richer characteristics. Firstly, if γ is very large, then attractiveness decreases too quickly, this means that the second term in (3) became negligible, leading to the standard simulated annealing (SA). Secondly, if γ is very small (i.e. $\gamma \rightarrow 0$), then the exponential factor $e^{-\gamma r_{ij}^2} \rightarrow 1$ and FA reduces to a variant of particle swarm optimization (PSO). Also, the randomization term can be extended to other distributions such as Lévy flight. Furthermore, FA uses non linear updating equation, which can produce rich behavior and higher convergence than linear updating equation used for example in standard PSO. Regarding the parameters setting, parametric studies suggest that $\beta_0=1$ can be used for most application; γ should related to the scaling L. In general, we can set $\gamma = \frac{1}{L}$ (Yang, 2014).

4 PROBLEM STATEMENT

We consider an environment assuming that it is discretized into equally spaced cells that contains a certain number of mines. Each cell has the potential to consider three states: free, occupied by mine, occupied by robot. Robots can move among cells and they can have just local information about robots (neighbors) or regions to explore (neighbor cells) in order to provide a scalable strategy.

The considered scenario is presented under this assumption:

1) The robots are equipped with proper sensors that are able to deposit and smell the chemical substances (pheromones) leaved by the other robots; for exploration task they make probabilistic decision based on amount of pheromone in the cells. The exploration strategy is the same for the recruiting strategies.
2) The robots are equipped with proper sensor to detect the mines.
3) The robots can move on a cell-by-cell basis to explore new cells or to go towards the mine.

The robots during the exploration spray a scent (pheromone) into the cells to support the navigation of the others. In the algorithm, the robots decide the direction of the movement relying on a probabilistic law inherited by swarm intelligence and swarm robotics techniques. The scent evaporates not only due to diffusion effects in the time, but also in the space according to the distance; this allows a higher concentration of scent in the cell where the robot is moving and a lower concentration depending on the distance.

Let M be the matrix of size mxn representing the coverage area of size mxn. Let $M(i,j)$ be the cell in the matrix with row i and column j. Let z be the number of mines on a set MS to distribute on the grid in a random fashion (e.g., it is applied a uniform distribution on X and Y axes). The MS set is characterized by the coordinates of the mines. For example, $MS = \{(3,4),(5,10),(7,12)\}$ indicates that there are 3 mines in the area with the coordinates (3,4), (5,10) and (7,12). The robots can be placed on the same initial cell or can be randomly distributed on the grid area. It is assumed that each robot in a cell $M(i,j)$ can move just in the neighbor cells through discrete movements. Let t_e be the time necessary for a robot to consider a cell, and let t_d be the time necessary to disarm a mine once it has been detected. It is assumed that a fixed number of robots (rd_{min}) are necessary to disarm a mine; this means that for the exploration task robots can be distributed among the area because each robot can independently explore the cells, whereas for the mine detection, more robots need to be recruited in order to perform the task. $M(i,j)\_a$ is a variable representing the number of robots (accesses) that passed through the cell (i,j).

For the problem we define an bi-objective function as both the time to detect and the disarming the mine through the exploration on the overall grid.

$$\min \sum t_e \text{ and } \min \sum_{i=1}^{z} t_{d,i} \tag{4a}$$

subject to

$$M(i,j)\_a \geq 1 \;\; i = 1 \ldots m;\; j = 1 \ldots n \;/\; (i,j) \in M$$

$$M(i,j)\_a \geq rd_{\min} \text{ with } (i,j) \in MS$$

This is a bi-objective optimization problem and its solutions will result in a Pareto front. However, in order to solve this problem more effectively, for simplicity, we will combine these two objectives to form a single objective optimization problem so as to minimize the overall total time as follows:

$$\min T_{tot} = \min\left(\sum t_e + \sum_{i=1}^{z} t_{d,i} \right) \tag{4b}$$

subject to

$$M(i,j)\_a \geq 1 \;\; \forall\, i = 1,..m; j = 1,\ldots n \;/ (i,j) \in M$$

$$M(i,j)_a \geq rd_{min} \;\; with \; (i,j) \in MS$$

The law used by the robots to choose the cells during the movement is presented below (De Rango and Palmieri 2012).

We consider a robot in a cell s and it will attribute to the set of next cells v_i following a probability as:

$$p(v_i|s) = \frac{[\tau_{v_i,t}]^{\varphi} \cdot [\eta_{v_i,t}]^{\vartheta}}{\sum_{i \in N(s)} [\tau_{v_i,t}]^{\varphi} \cdot [\eta_{v_i,t}]^{\vartheta}}, \forall v_i \in N(s) \tag{5}$$

where ($p(v_i|s)$ represents the probability that the robot, that is in the cell s, chooses the cell v_i; $N(s)$ is the set of neighbors to the cell s, $\tau_{vi,t}$ is the amount of pheromone in the cell v_i; $\eta_{vi,t}$ is the heuristic

parameter introduced to make the model more realistic. In addition, φ and θ are two parameters which affect respectively the pheromone and heuristic values.
Taking into account the spatial dispersion of the scent and the temporal dispersion in the amount of pheromone in the cell v where the robot will move during the exploration is:

$$\tau_{v,t+1}(d) = \tau_{v,t} + \tau_v(d) \tag{6}$$

In order to explore different areas of the environment, the robots choose the cell with a minimum amount of pheromone (MINIMUM_TRACE_FOLLOWER), corresponding to cells that probably are less frequented and therefore not explored cells. The chosen cell will be selected according with eq. (5):

$$v_{next} = \min \left[p\left(v_i \mid s\right)\right] \forall v_i \in N(s) \tag{7}$$

5 BIO-INSPIRED APPROACH FOR THE DISARMING TASK

The purpose of the problem is to discover all mines disseminated in the area and to disarm them. In the first strategy the first robot that detects a mine becomes a recruiter,which on the basis of the recruiting startegy can spray a scent in order to inform the other robots about the presence of a mine and to recruit other robots for the disarming task (indirect communication).
Alternatively, in the second startegy, the robots are equipped by wireless module and the recruiters can send a packet where putting the information about the mine position (this can be useful for the FA based strategy).
We assumed that the robots are not able to communicate in a multi-hop manner but just via a direct message (single-hop) (using for example a wireless radio). Each robot can only communicate with its neighbors. Two robots are defined as neighbours if the distance between them is less than a pre-specified communication range. In the following section, the recruitment issue is formalised in order to apply the proposed combination of the two bio-inspired techniques.

5.1 Ant-based based Team Strategy for Robots Recruitment (ATS-RR)

For this strategy we assume that the robots are equipped by sensor that perceived a pheromone, different by the pheromone used for the exploration. The robots communicate with others through the environment (indirect communication).
We considered that the mine disarming time is equal to the total evaporation time of substance (scent); in this way when the mine is disarmed, the robots involved in this operation will not be affected by scent trails.

We assume t is the time in which the robot r detected a mine and it deposits the substance. The robot r continues to spray until all necessary robots reach its position.
If m is the time needed to disarm the mine, the law for the evaporation of the scent is the following:

$$\xi_{t+1} = \xi_t - \frac{1}{m} \cdot \xi_{t0} \tag{8}$$

where ζ_{t0} is the substance sprayed when the robot detetects a mine. At the beginning $\zeta_t = \zeta_{t0}$.
In this way after m steps ζ should be zeo so the scent will not affect any more the movement of the other robots. This assures that all robots will cover other new space and disarm other mines completing the task in an efficient and distributed manner.

5.2 Firefly based Team Strategy for Robots Recruitment (FTS-RR)

For this task we considered the following assumption:

1) The robots are equipped by wireless module; infact when a robot detects a mine, it becomes a firefly and tries to attract other robots sending messages via broadcast communication to the robots in its wireless range.
2) The robots, that receive messages by different robots (fireflies), evaluate the light of fireflies and choose the best firefly (at minimum distance) and move toward firefly according to a modified Discrete Firefly Algorithm.

When a robot finds a mine, during the exploration task, it applies the FTS-RR and becomes the recruiter of the other robots in order to disarm the mine. For this purpose, in FTS-RR strategy, it becomes a firefly and it tries to attract the other robots on the basis of the mine position. The original version of FA is applied in the continuous space, but in our case we modified the algorithm in order to fit with our problem. In our case, the robots can move in a discrete space because they can go just in the contiguous cells step-by-step. This means that when a robot perceives at a distance the presence of a firefly (the recruiter robot) and it is in a cell with coordinates

x_i and y_i, it can move according with the FA attraction rules such as expressed below:

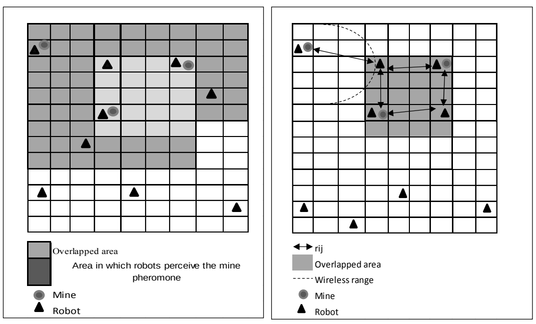
$$\begin{cases} x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha(\sigma - \frac{1}{2}) \\ y_i^{t+1} = y_i^t + \beta_0 e^{-\gamma r_{ij}^2}(y_j - y_i) + \alpha(\sigma - \frac{1}{2}) \end{cases} \quad (9)$$

where x_j and y_j represent the coordinates of detected mine translated in terms of row and column of the matrix area. r_{ij} is the Euclidean distance between mine (or recruiter) and robot that moves towards the mine. The robot movement is conditioned by mine (recruiter) position in the second term of the formula (9) and by a random component in the third term. This last term is useful to avoid that more robots go towards the same mine if more mines are distributed on the land (this avoids the local minimum in order to approach to a global optimum) Fig.1.

In order to modify the FA to a discrete version, the robot movements have been considered through three possible value updates for each coordinates: $\{+1, 0, -1\}$ such as expressed in Eq.(10). A robot r that

$$\begin{cases} x_i^{t+1} = x_i^t + 1 & if\left[\beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha\left(\sigma - \frac{1}{2}\right) > 0\right] \\ x_i^{t+1} = x_i^t - 1 & if\left[\beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha\left(\sigma - \frac{1}{2}\right) < 0\right] \\ x_i^{t+1} = x_i^t + 0 & if\left[\beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha\left(\sigma - \frac{1}{2}\right) = 0\right] \end{cases} \quad (10)$$

$$\begin{cases} y_i^{t+1} = y_i^t + 1 & if\left[\beta_0 e^{-\gamma r_{ij}^2}(y_j - y_i) + \alpha\left(\sigma - \frac{1}{2}\right) > 0\right] \\ y_i^{t+1} = y_i^t - 1 & if\left[\beta_0 e^{-\gamma r_{ij}^2}(y_j - y_i) + \alpha\left(\sigma - \frac{1}{2}\right) < 0\right] \\ y_i^{t+1} = y_i^t + 0 & if\left[\beta_0 e^{-\gamma r_{ij}^2}(y_j - y_i) + \alpha\left(\sigma - \frac{1}{2}\right) = 0\right] \end{cases} \quad (11)$$



a) b)

Figure 1: Robots during the exploration receive two recruiting calls because they are in an overlapped area. a) In ATS-RR strategy the robots will choose the cell where they perceive a greater quantity of pheromone; b) the FTS-RR strategy tries to coordinate better the robots in the disarming task considering the distance from the recruiter.

is in the cell of coordinates x_i and y_i such as depicted in Fig.2 can move in eight possible cells according with the three possible values attributed to x_i and y_i. For example if applying eq.10 and eq.11 and the result is {-1,+1} , the robot will move in the cell with coordinates { x_{i-1}; y_{i+1}} such as depicted in Fig.2

	y_i		
	x_i-1, y_i-1	x_i-1,y_i	x_i-1,y_i+1
x_i	x_i, y_i-1	r	x_i, y_i+1
	x_i+1, y_i-1	x_i+1, y_i	x_i+1, y_i+1

Figure 2: Possible movements for a robot on the basis of the x_i and y_i values.

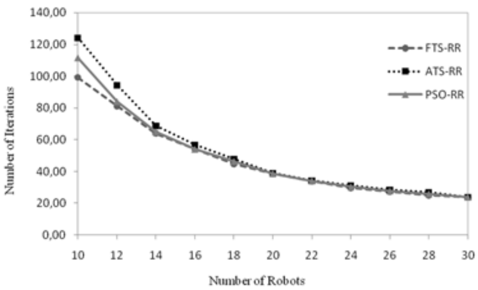
6 PERFORMANCE COMPARISON

In this section, we evaluate the performance of the two proposed algorithms in comparison with the well known Particle Swarm Optimization, focusing on the time to cover all unknown area and disarm all mines and the number of accesses in the cells in order to see the effectiveness of the joint exploration task (space distribution) and disarming task (space concentration).The specific FTS-RR parameters were set as follows: $\beta=1$; $\alpha=0.2$; $\Upsilon=1/L$ where L is max{m, n} where m and n are the number of rows and columns of the matrix M, respectively. For the ATS-RR, the parameter values were set as follow: φ=1, θ=1; ɳ=0.9. We considered different scenarios by varying the minimum number of robots necessary to disarm a mine, the total number of robots in the rescue area, the dimension of grid and the number of mines. To highlight the performance benefits, we use random positions of the mines and the robots in the area by varyng the number of robots so as to investigate the performance of all strategies.

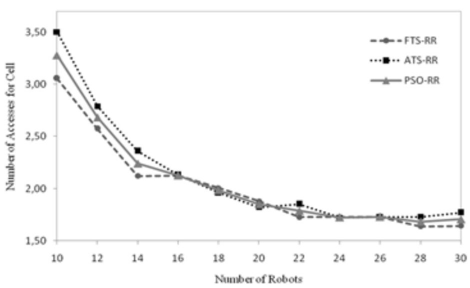
In Figures 3, 4 and 5 the number of mines and the grid area have been fixed, respectively, to 3 and 20x20.

In Fig.3a and 3b, a comparison of the three algorithms is depicted. In particular, it is shown the time to complete both tasks measured as the number of iterations and the number of accesses in the cells. The convergence time and number of accesses in the cells was averaged over 50 independent simulation runs in order to enter in the 5% of confidence interval.

It is possible to see that the FTS-RR strategy performs better mainly when the number of robots is low. This is due to the better robot recruitment when a mine is discovered that is able to balance the robot coordination and movements among all mines. On the other hand, when the number of robots increases and the number of minimum robots to disarm a mine is equal to 2, ATS-RR, FTS-RR and PSO-RR are similar because the high number of robots in comparison to the number of mines allows to complete both tasks in a lower time and no significant difference between the strategies is so evident. The number of accesses in the cells was plotted in Fig.3b. Simulations show that FTS-RR is able to balance better the robots in the recruitment phase considering that the exploration phase is common to all algorithms. This determines that a lower average number of accesses in the cells can be obtained in FTS-RR in comparison with ATS-RR and PSO-RR. The same considerations can be made when the number of robots needed to disarm a mine is 3(Fig. 4). An interesting result is shown in Fig 5. In these cases, FTS-RR performs better for both low and high numbers of robots in the convergence time especially in comparison with the ATS-RR. This is due to the most effective recruitment strategy that is able to better distribute robots when, in the overlapping area, more recruiters can engage robots for disarming. In this case, the use of distance and the firefly algorithm allows robots to spread over different mines avoiding going towards the same mines to disarm. The overall effect is a reduction in the task execution time.

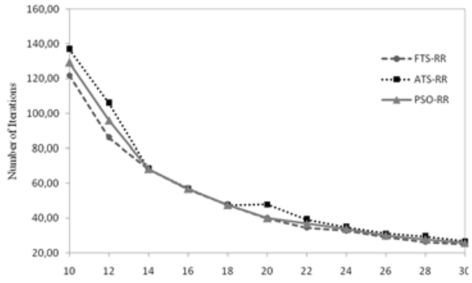


a)

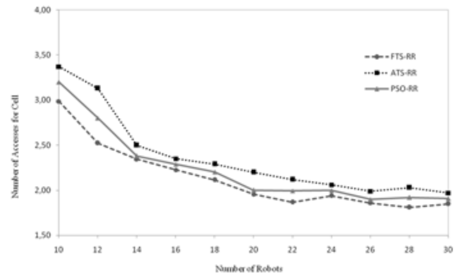


b)

Figure 3: Comparison between ATS-RR, FTS-RR and PSO evaluating with 3 mines and 2 robots per mine to disarm and increasing number of robots: a) number of iterations; b) number of accesses in the cell.

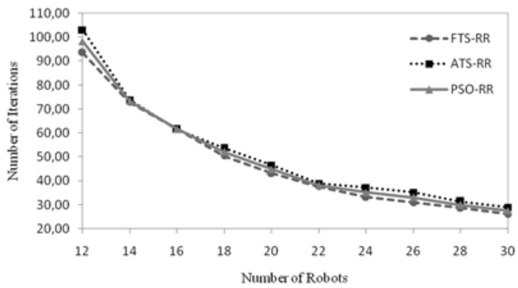


a)

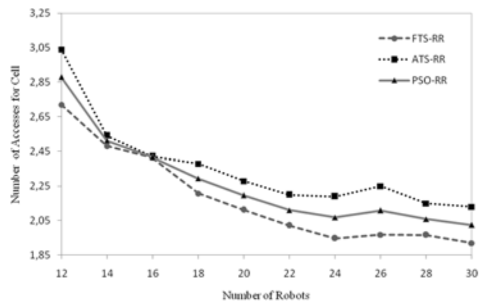


b)

Figure 4: Comparison between ATS-RR, FTS-RR and PSO evaluating with 3 mines and 3 robots per mine to disarm and increasing number of robots: a) number of iterations; b) number of accesses in the cell.



a)



b)

Figure 5: Comparison between ATS-RR, FTS-RR and PSO evaluating with 3 mines and 4 robots per mine to disarm and increasing number of robots: a) number of iterations; b) number of accesses in the cell.

Concerning the number of accesses is much lower in the FTS-RR. Increasing the complexity of the task the difference between the three different algorithms, in terms of overall time to complete the tasks, is greater (Fig.6 and Fig. 7). This means that the best performing of recruiting task can affect indirectly the discovery task leading to a better distribution of robots among mines to disarm and consequently to explore the novel un-explored cells.

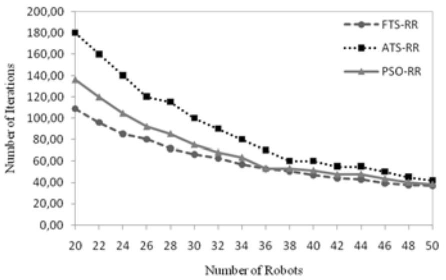


Figure 6: Comparison between ATS-RR, FTS-RR and PSO, evaluating with 5 mines and 4 robots per mine to disarm and increasing number of robots in a 30x30 gird map.

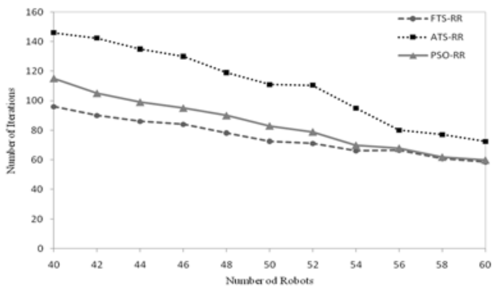


Figure 7: Comparison between ATS-RR, FTS-RR and PSO in terms of overall time, evaluating with 10 mines and 4 robots per mine to disarm and increasing number of robots in a grid 40x40.

7 SOLUTION QUALITY ANALYSIS

To validate the quality of solutions and results of the three metaheuristics we have also considered the *p* values of Student t-tests. The t-tests were used to analyze the relationships between the results obtained from the three metaheuristics. The parameter of interest is the *p*-value.

Table I, Table II and Table III show the p-value obtained from the t-tests using all above simulation results by considering each parameter (the number of interactions and the number of accesses in the cell) for all considered scenario.

Table 1: Results of p values in the t Test for ATS-RR and FTS-RR.

	Scenario 1 (Fig.3a, Fig.3b)		Scenario 2 (Fig. 4a, 4b)		Scenario 3 (Fig. 5a, 5b)		Scenario 4 (Fig. 6)	Scenario 5 (Fig. 7)
	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Iteration
p value	0,0362	0,0261	0,0447	0,00342	0,02976	0,00172	0,001153	1,32E-05

Table 2: Results of p values in the t Test for ATS-RR and PSO-RR.

	ATS-RR VS PSO-RR							
	Scenario 1 (Fig.3a, Fig.3b)		Scenario 2 (Fig. 4a, 4b)		Scenario 3 (Fig. 5a, 5b)		Scenario 4 (Fig. 6)	Scenario 5 (Fig. 7)
	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Iteration
p value	0,0552	0,0328	0,0476	0,00048	0,0347	0,00368	0,003667	0,00030

Table 3: Results of p values in the t Test for FTS-RR and PSO-RR.

	FTS-RR VS PSO-RR							
	Scenario 1 (Fig.3a, Fig.3b)		Scenario 2 (Fig. 4a, 4b)		Scenario 3 (Fig. 5a, 5b)		Scenario 4 (Fig. 6)	Scenario 5 (Fig. 7)
	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Access in the cells	Number of Iteration	Number of Iteration
p value	0,0623	0,0522	0,0524	0,001524	0,0495	0,0045	0,00667	0,00364

By analyzing the experimental results, it can be observed a significant difference between the ATS-RR and FTS-RR and ATS-RR and the PSO-RR. In all considered scenario the p-value < 0.05, so there is a strong statistic evidence of the difference between the strategies. Regarding to the PSO-RR and the FTS-RR analyzing the results (Table III) it can be observed that the p-value <0.05 except for the Scenario 1 and 2. For other Scenario the p-value <0.05. This confirms that the FTS-RR exhibits superior performance when the complexity of tasks, in terms of dimension of operative area, number of mines and number of robots need to disarm a mine, increases.

8 CONCLUSION

Novel bio-inspired self-organizing coordination algorithms are proposed for a distributed multi robot coordination in a mined region.

For this purpose, two different strategies for the mine disarming task combined with an Ant-based space discovery strategy are proposed. The first strategy ATS-RR isbased on Ant Colony optimization, and the other one is based on the Firefly Algorithm (FTS-RR). We compare both startegies with the well known Particle Swarm Optimization. By extensive simulations,we have concluded that the FTS-RR can perform better in terms of the time to complete the task and the number of acccesses in the cell, leading to a better distribution of robots with a better combined time for both mine disarming and exploration tasks expecially when the complexity of the task increases.

Possible directions for future work can be followed. Firstly, it would be very useful to vary the ACO and FFA parameters and then evaluate their performance. Secondly, it will also be fruitful to study the energy consumed by the robots. Finally, mobile targets can be a much better and realistic extension of the current work. It can be expected that this present work can form a basis for further extension and research.

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