Effect of Evaporation Pheromone Rate of ACO-based Coordination Strategy on Multirobot-based Mine Detection System

SAAIDIA RIADH
Computer Laboratory for Industrial Systems (LISI)
National Institute of Applied Sciences and Technology
University of Carthage
INSAT, centre urbain nord BP 676 Tunis, Tunisia 1080, TN
TUNISIA
Riadh.saaidia@insat.rnu.tn

MOHAMED SAHBI BELLAMINE
Computer Laboratory for Industrial Systems (LISI)
National Institute of Applied Sciences and Technology
University of Carthage
INSAT, centre urbain nord BP 676 Tunis, Tunisia 1080, TN
TUNISIA
aroussia@insat.rnu.tn

ABDESSATTAR BEN AMOR
Computer Laboratory for Industrial Systems (LISI)
National Institute of Applied Sciences and Technology
University of Carthage
INSAT, centre urbain nord BP 676 Tunis, Tunisia 1080, TN
TUNISIA
mrdssrst@yahoo.fr

Abstract: - The sphere of conflict zones is extended each year all over the world, and the remain of war and the explosive devises increase the percentage of death and causalities. This critical situation needs the built of a new strategy for demining operation. This paper adopts the ant colony optimization (ACO) algorithms to coordinate a demining multi robot system. In general, demining operations have humanitarian purposes and the operator security is the most focused criteria in demining systems. Otherwise, other criteria are considered for militaries applications. In fact, time demining operation should be optimized in the case of large-scale minefield area. In this paper, two modifications were performed on ACO algorithm related to ant nest position and evaporation pheromone rate. We perform for each situation different experimentations for three types of minefield distributions.

Key-Words: - ACO algorithms (Ant colony optimization algorithms), Demining operation, Evaporation pheromone rate, Landmine, Multi-robotic systems (MRSs), Meta-heuristic, Temporal performances

1 Introduction

According to [1], the number of death and casualties caused by mine, improvised explosive device (IED) and explosive remains of war (ERW) has been decreasing since 1999 (year of mine ban treaty validation). These recorded cases are the estimations of real casualties number then many armed conflicts are still existing or initiated. Consequently, the recorded results of mine accidents given by landmine report is still significant. For instance, between 2011 and 2012, the civilian casualties percentage, compared with military one rose from 73% in 2011 to 78% in 2012. Compared to 2011, casualties percentages of both children and female have increased slightly in 2012. In 2012, the landmine report recorded a total number of 3,628 mine/ERW/IED casualties. In addition, landmine report recorded more than 1,066 killed people and 2,552 injured. Less than 1% of total casualties represent an unknown survival result for injured persons. The record process of casualties' events leaves accident cases and this generates a considerable number of unrecorded data. As a result, the real number of casualties is still unknown and depends on world conflict situations. In 2012, the recorded number of casualties represents a decrease of 19% in comparison to 2011 results (4,474 casualties); but these results have a 14% decrease in comparison to 2009 results (4,224 casualties). Landmines were localized in 62 states (2012) in which 2,367 casualties occur in 30 states; however, Landmine clearance represents a recurrent problem in itself. In fact, a surface area greater than 281 km2 was cleared by 40 mine action-programs (2012). Nevertheless, this surface is extended every year and needs adaptable methods to ensure clearance efficiency. At least, Standard demining clearance model operations (UNDHA standard) must ensure 99.6% rate of successful mine detection, and a 100% of the same rate according to International Mine Action Standards (IMAS) [2-4]. Timing demining process performances are less important than personal safety, reliability and accuracy of the demining process. For this reason, replacing manual methods as primary procedure for humanitarian demining by robotized solutions should increase productivity by speeding up reliably and safely the demining process. Therefore, various demining treatments exist, due to the use of different types of sensors and equipment to detect and neutralize landmines. In addition to this difficulty, the nature of landmines and the characterizations of any demining instrument, which should be 100% reliable, must be taken into consideration. The application of robotics research to demining operations purposes requires the integration of various technologies, including demining-oriented functions like the adaptability to field mines distributions, type of control architecture, integration of heterogeneous sensors, autonomous navigation , coordination in the case of multi-robots system, communication implementation, Machine intelligence and signal processing algorithms [2].

Considering that these systems should explore unknown configuration field, the exiting robotic systems designed for demining operations have limited performances [5]. In addition, demining robots are equipped with highly sophisticated technology instruments for mine detection and processing [6] resulting in high mine clearance cost. Time optimization of demining operations has become an important humanitarian objective in considering the number of abandoned mines fields [7]. This optimization must respect security constraints attached to demining operator and enhance efficiency of demining tasks in time proceeding and energy consumption. According to [6, 7],various assistant tools were designed and tested to help automation demining process, limit the risk of human error, and rise the estimation of risk zone. The Substitution of human operators by robotic agents participates with appropriate strategy in the fulfillment of this goal [8]. However, the sophisticated robot agents and the mines distributions variety enhance the demining operations cost. This cost includes time demining operation, energy management, equipment, and security considerations. In this paper, the possible applications of multi-robot systems were explored for time detection optimization of Mx% (maximum mine portion detected.) mines (in particular case of Minefield configuration). For this reason, the adaptation of multi-robot systems for demining operations should induce the choice of an adaptable coordination algorithm. Due to the complexity of demining operations problems, the meta-heuristic algorithms are considered the most useful coordination algorithm. So research and optimization algorithms have risen their exploration capabilities by including basic heuristic [9]. Many meta-heuristic algorithms like ant colony optimization, genetic algorithms etc. solve difficult optimization problems in a reduced amount of time with approximate solution. At this stage, ACO algorithms represent a coordination algorithm used to optimize demining operations time with adaptable considerations as an example for solving foraging robots problem.

This paper is organized as follows. Sect. 2 introduces the works related to multi-robots application on demining operations. In particular, these works include the configuration constraints in the case of mine distribution, type of meta-heuristics used for collaboration algorithms and performances metrics. Sect. 3 gives formulation approach of ant colony optimization algorithms. Sect. 4 presents the field mine distribution and collaboration models used in demining operations. Sect. 5 describes the simulation considerations for performed experiences. Sect. 6 lists and analyzes the simulations results. Sect. 7 is reserved for results discussion.

2 Related works

Multi-robots application in demining operations for humanitarian purposes represents an evaluation example of coordination strategy performance. Many researches such as [10-12] use specific coordination strategy in order to evaluate some criteria performances. General research organization starts with the definition of collaboration algorithms used in order to perform specific task. Demining process, which is highlighted in this research, includes many constraints related to the nature of minefield distribution and performance evaluation criteria. Some researches as in [10, 12, 13] give statistical studies on variety of spatial mine distribution in minefield. In fact, mines field spatial distributions in conflict zones are highly complex and varied. Landmine descriptions cannot be defined easily with deterministic clustering approaches. Landmine variety induces different mine distribution patterns, that one can be used to test hypotheses for demining operations. However, other assumptions have influence on performances evaluation systems. Combining the different parameters (incidents, populations, roads, agriculture field, etc.) for defining minefield map, would allow the consideration of environmental and social conditions [7].

Simulation example given in [5] tests real case minefield distributions in order to realize an automatic estimator to mines localization. Mines distribution configuration represents limitation in the case of unknown mined environment. Nevertheless, in several cases, mines distribution can be modeled by stochastic model like in [6, 7, 13]. Moreover, the efficiency of demining operations depends on the scenario followed for each robotic agent.

On the other hand, the choice of collaboration strategy represents other constraints. In fact, demining operations with multi-robots systems raise complexity of collaboration interactions [10, 14]. In this case, the application of suitable meta-heuristic algorithms for multi-robot demining operations was performed in research such as [15-18]. Research studies focus on combined and modified heuristic (as is the case for Genetic algorithms, ACO algorithms, etc.) to enhance general performances of multi-robots systems. As a result, studies as [19] define some evaluation metrics to quantify collaboration performance cost. Localization and distribution robotic agents configuration were taken as evaluation criteria. These criteria depend on the application of constraints like possible robot agents interference [20]. A set of generic performance metrics was employed to evaluate each aspect of robotic demining systems. These performance metrics include demining processing speed to measure time elapsed until demining operations can be totally or partially achieved. The rest of experimentations focus on temporal performance optimization by using modified meta-heuristic algorithms. In particular, configuration parameters for minefield and coordination algorithm heuristic, as type of mine distributions and effects of evaporation pheromone rate, were treated in experimentations. Other performance metrics like: robotic agents displacements which represents aggregation of the distances inter-agent position during the demining operations (consumed energy), robotic Agents proportion of agents which ensure demining operations, robotic group size effect and communication flow exchanged between agents during robots interactions; represent other optimization objectives and they will be treated in further works.

3 Ant colony optimization

The choice of combinatorial methods for optimization instead of deterministic ones was determined by the nature of the treated problem. The case of demining problem is a difficult combinatorial optimization problem where demining operations should be performed with optimization of some criteria like operation time, energy, communication, etc. In this section, an example of Meta-heuristic algorithm based on Ant colony optimization (ACO) was presented. This algorithm is inspired by the ant behavior. With ACO algorithms, each ant is represented by an artificial agent that searches randomly a solution for the selected problem. In every iteration, exploration of solutions was made by agents displacements on a graph presenting the problem model. For every iteration, agents graph configurations define tested node which should be added to the optimal solution. Displacement through the problem graph is guided by a probabilistic decision model associated to the graph edges. As a result, the agents decisions were made in respect to edges probabilistic density. The edges probabilistic density is updated directly by the agents during graph exploration. Every individual agent choice influences the edges probabilistic density in order to construct optimal solutions.

Many researchers focusing on bio-inspired algorithm studied the foraging behavior of ant colony. Especially, [21] performs experimentations using ant behavior to find optimal path from nest to food source. By the application of collective processing based on deposit pheromone model used in food ant foraging, this research demonstrates that ants are able to find the shortest path to food source. The artificial agents using ACO algorithms deposit artificial pheromone on the graph edges of the considered problem. The pheromone rate is determined by each artificial agent and it is related to the solution quality constructed by agents set. In fact, the probabilistic decision model is based on the amount of artificial pheromone deposited during solution construction. In the following iterations, other artificial agents use pheromone rate to select optimal edges.

The demining problem can be modeled by a graph built with the quantification of landmine area. However, the ACO algorithm application to continuous domains is not simple. An easy approach would divide the landmine area into a subzone area. The displacement of demining agent is performed through the overlapping boundaries (see Fig. 1). Considering that mines dimensions are covered by acceptable accuracy intervals, landmines can be modeled in this configuration. Other researches as in [22-24] focus on the adaptation of ACO based algorithms to the continuous domain for applications which need more accuracy.

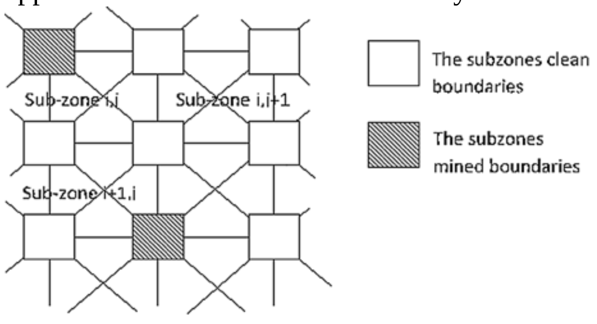


Fig.1. Landmine quantification

The optimization demining problem is presented by (M, f_0) (where M is the feasible solutions set and f_0 is the objective function allowing to each solution m $\in$ M a cost value $f_0(m)$.The demining problem resolution is obtained by an optimal solution m^* which represents minimum demining time. M^* represents the set of optimal solutions. The minimization problem resolution performed by Ant colony optimization consists of iteration of the following steps:

- Construction of feasible solutions is ensured by probabilistic decision model
- Realized feasible solutions participate in the modification of nodes selection.

The given combinatorial optimization problem (M, f_0) is characterized as follows:

- A finite set E = $\{e_1, e_2, \ldots, e_{N\upsilon}\}$ of decision elements, where Nυ is the number of these elements.
- A finite set S of the problem states, where a state is a sequence s = $<e_i, e_j, \ldots, e_k, \ldots>$ over the elements of E. The elements number of a sequence s is expressed by |s|. The maximum length of a sequence has a positive constant limit: n < +∞.
- A solution set M, which is a subset of S (i.e., M ⊆ S).
- A feasible states set $S^{\sim}$, with $S^{\sim} \subseteq S$ representing the constraints set Ω.
- A set of optimal solutions M^* ($M^* \neq \emptyset$), with $M^* \subseteq M$ and $M^* \subseteq S^{\sim}$.

At this stage, the above formulation of minimization problem could be presented by a weighted graph G = (E, L, T). The nodes of this graph are given by the elements in E set. The L set grouped the full connected node in E set. The T set is a vector of pheromone trails τ. Thus, the artificial agents build feasible solutions by performing random exploration on the connection edge of graph nodes. In general situation, pheromone trails can be deposited on nodes, edges or both. In demining problem formulation, only the case where pheromone trails are deposited on edges connections was considered. The pheromone trail noted by τ(i, j) represents the pheromone rate deposited on the edge connection between node i and j. The graph G represents the selected solution, which is under construction. The construction solution process is ensured by artificial agent that realizes a random selection of graph nodes. In the next step, these agents perform a random exploration of selected nodes. The selection of appropriate node was made stochastically in respect of pheromone rate importance, which is detected on the connection edges. During the node exploration of the graph G, a constraints set **Ω** should be verified by agents to prevent infeasible solutions. In the case of demining problems, artificial agents should avoid collision (in the treated experimentations, the consideration of these constraints is avoided for simplification purposes). Algorithmic Formulation of the solution construction behavior is given as follows:

SOLUTION_CONSTRUCTION

For each artificial agent:

- Select a start node e_1 in respect to the given problem constraints.
- Set k = 1 and $s_k = <e_1>$

While $s_k = <e_1, e_2, \ldots, e_k> \in S^{\sim}$, $s_k \notin S$, and the set J_{sk} of elements that can be connected to s_k exist ($J_{sk} \neq \emptyset$), select the next node e_{k+1} randomly according to:

If $(e_k, e) \in J_{sk}$ Then $PT(e_{k+1} = e \mid s_k) =$

$$\frac{F(e_k, e)(\tau(e_k, e))}{\Sigma_{(e_k, w)\in J_{sk}} F(e_k, w)(\tau(e_k, w))}$$

(1)

Else

$$PT\ (e_{k+1} = e \mid s_k)\ =\ 0 \qquad (2)$$

A connection (e_k, w) belongs to J_{sk}, if and only if, the sequence $s_{k+1} = <e_1, e_2, \ldots, e_k, w>$ satisfies the constraints Ω (i.e. $s_{k+1} \in S^{\sim}$). $F_{(i,j)}(x)$ is a monotonic function which generally takes this form: $x^{\alpha}\,\eta(i, j)^{\beta}$ (α, β > 0 and η(i, j) are heuristic function corresponding to selection desirability of element j after i). If $s_k \notin M$ and $J_{sk} = \emptyset$, i.e., the solutions construction process must be stopped, the current state s_k is abandoned. To prevent this situation, artificial agents should have the ability to construct infeasible solutions. Thus, an infeasibility penalty function is usually integrated to the cost function. However, in the majority of coordination based on ACO algorithms, the blocked situation cited before does not occur. The used function F(i,j) in calculation of decision probability integrates the pheromone rate values. The complexity of this function depends on the type of selected problem, which many researches propose an adaptable formulation to it. The random proportional rule scheme represents an example. This scheme affects to η(i, j) function the traveled distance inverse by artificial agent. In addition, [25] use alternative

selection scheme called the pseudo-random-proportional rule (random variable uniformly distributed between 0 and 1).
The Application of ACO algorithms needs the definition of pheromone rate update scheme. Various schemes have been adopted to establish the pheromone update. In general cases, the pheromone updates are following this generic scheme:

ACO_ALGORITHM_PHEROMONE_UPDATE

$\forall m \in M^{+}_{t}$, $\forall (i, j) \in m$:

$$\tau(i, j) \leftarrow \tau(i, j) + Q_f(m \mid M_1, \ldots, M_t), \tag{3}$$

$\forall (i, j)$:

$$\tau(i, j) \leftarrow (1-\rho)\ \tau(i, j), \tag{4}$$

M_i is the i^{th} iteration solution sample, ρ ($0 \leq \rho < 1$), represents the evaporation rate, and $Q_f(m|M_1, \ldots, M_t)$ is the quality function. The quality function Q_f is a non-increasing function and its interval of definition recovers the solutions reference set: M^{+}_{t}. Different schemes of quality functions and reference sets were adopted in ACO algorithms implementations try. Considering the first ACO algorithm developed by [26], the selected quality function was $1/f_0$ (m) and the reference set $M^{+}_{t}=M_t$. In a later pheromone update scheme, called iteration best update [25], the solution reference set groups the best solution within the last best iteration. Another version called global-best update [27] defines the solution reference set by the best solution among of all the iteration-best solutions. A combination between the two approaches was introduced by [28]. At the same time, [29] proposes a formulation of quality function reserved for the case where a prior knowledge of lower bound for the optimal solution cost is available. This formulation is given as follows:

$$\begin{aligned} Q_f(m \mid M_1, \ldots, M_t) &= \tau_0 \left(1 - \frac{f(m) - LB}{f - LB}\right) \\ &= \tau_0 \frac{f - f(m)}{f - LB} \end{aligned} \tag{5}$$

f is the average cost of the last p solutions and LB is the lower bound for the optimal solution cost.
In the proposed quality function, the evaluation of solutions is made by the correlation of generated cost with the cost main value of the other last solutions instead of using the absolute cost values. [25] describe a generic pheromone update based on online evaporation by artificial agents (ant colony system: ACS). During the solution construction, only the pheromone rate used in this construction is evaporated by an artificial agent. Another version of the generic pheromone update was adopted in MAX–MIN Ant System [30]. This version uses maximum and minimum pheromone trail limits. As a result, the generating solution probability is maintained to a positive level. Thus, the convergence to sub-optimal solutions and search stagnations is avoided.

4 Methods and hypotheses

This part represents general configuration parameters for tested environment. These parameters include minefield distribution and adaptation of ACO algorithms for collaborative demining robotic foraging.

4.1 Minefield configuration

The measurement of demining operations time was performed at different values of configuration parameters. In concordance with [31], evaporation pheromone model is studied as influential parameter. In fact, robots/mines ratio is fixed, the evaporation pheromone rate is increased gradually and detection mines time is noted for different minefield proportion (Mx %). Tested mines proportion has been fixed to 60%, 70%, 80% and 90% for a total number of 50 mines [6].
In addition, mine spatial distribution has possible effect in mine detection time [6, 7]. Different spatial distributions are experimented. These distributions include:

- 1st case: (random distribution) mines are placed randomly with uniform density of probability.
- 2nd case: (fixed spatial distribution) second distributions are destined for fixed mine position. Two different dispositions with limited mined zone are evaluated. These two tests are indicated in Fig. 2 and Fig. 3. In Fig. 2, the minefield is subdivided into two parts relatively to a vertical symmetry axis. P1 represents mined area zone. In Fig. 3, the minefield is subdivided into four parts relatively to a vertical and horizontal symmetry axes and P3 represents mined area zone. Other parts are mine free. As presented in [32], and in the case of environment symmetry the localization represents a complicated task. This complexity is due to correctness of robot position and orientation estimation (unknown

mine land without specific information). Collaborative algorithms as for ACO algorithms can reduce elapsed time in mines research operations.

- 3rd case: (random line distribution: Fig. 4) Mine lines are randomly placed along the line or dropped with a constant spacing. The random lines are given a very broad margin of placement error. The random spacing lines are assumed to represent positioning errors mainly due to navigation and drop timing errors. Random lines are assumed to have random orientation and mine spacing. But in these experimentations; random mine lines are parallel [5].

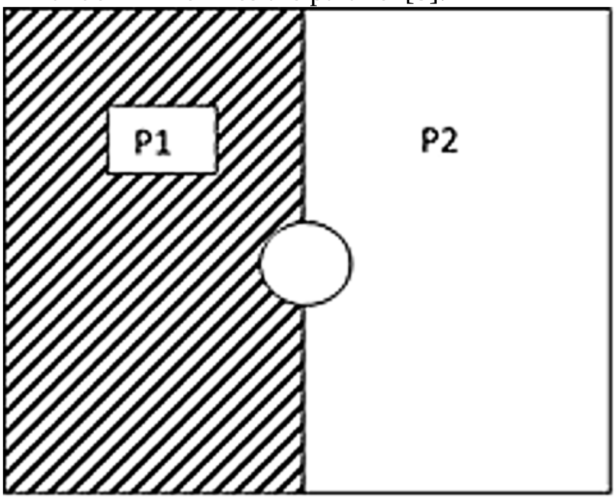


Fig. 2. Fixed spatial distribution 1.

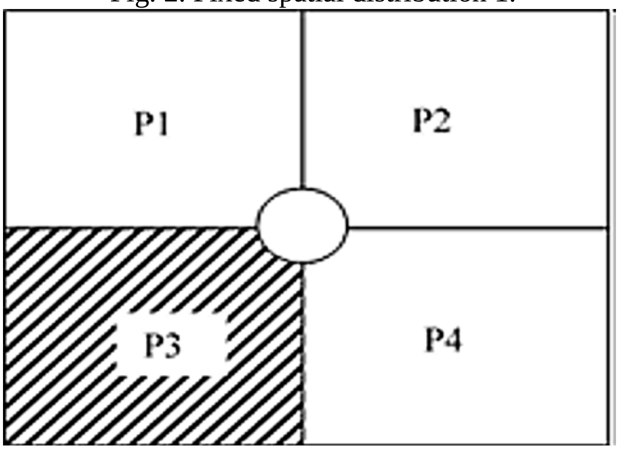


Fig. 3. Fixed spatial distribution 2.

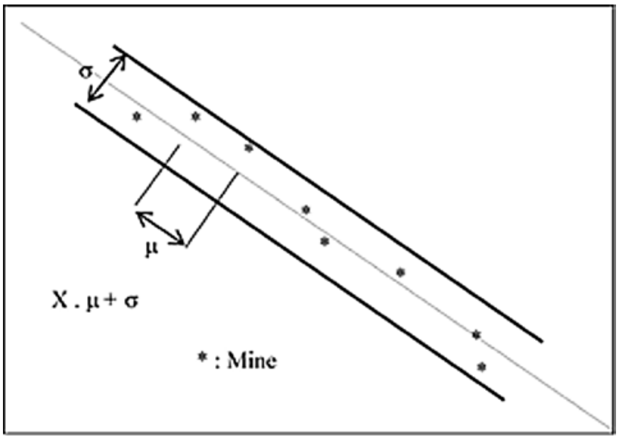


Fig. 4. Random line distribution (s=1,μ=3 and areas dimensions=16x16).

4.2 Navigation and research methods

This part includes the presentation of mine research methods adopted by different robot agents. The evaluation of this methods effect is based on the time detection mines quality. In this experimentation, three main collaborative navigation algorithms were performed:

- Method1: (model BASE) in this model, robot agents do not adopt a particular logic for mine research. So robot agents are not restricted to any constraint except some particular rules listed as fallows:
  - R1: when a robot agent finds a mine. It must return to the base for the deactivation of mine operation.
  - R2: used base is fixed.
  - R3: all robot agents are placed in the base at the demining operations beginning.
- Method2: (model ACO) in this part, robot agents adopt a mine research strategy based on ACO algorithm to find optimum demining operation. The same rules adopted in model BASE (R1 R2 R3) are retained. The Used robot agents path is fixed by pheromone rate τ deposited by other searching agents. Three main methods are adopted for pheromone rate calculation:
  - 1st case: In this test, the evaporation pheromone rate ρ (static evaporation pheromone rate) is fixed and the pheromone rate calculation is given as follows [33]:

$$\tau(k)=\tau(k-1)(1-\rho) \tag{6}$$

  - 2nd case(dynamic evaporation pheromone rate): this ACO algorithm configuration adopts a programmable evaporation pheromone rate to calculate pheromone rate as follows:

$$\tau(k)=\tau(k-1)(1-\rho)+(1-\frac{1}{1+Q})\tau(k-1) \quad (7)$$

$$\rho=\frac{1}{1+\frac{(\tau-\alpha)^4}{\sqrt{2\alpha}}} \quad ,\text{where } \alpha = 0.5 \quad (8)$$

This equation is introduced as a heuristic Q factor, which represents an algorithm quality factor [31]. The α factor used in programmable evaporation pheromone rate was fixed to 0.3 and Q factor represents an algorithm appreciation for method research rule [10] ($Q=\frac{TP}{TP+FN} * \frac{TN}{FP+TN}$). Two main rules for demining research operations are considered:

- Dynamic rule 1= mine research operation (TP=find mine when trying to research mine, FP = robot does not find mine when trying to research mine)
- Dynamic rule 2= base return (TN = robot already charging mine in return when trying to return to base, FN = mine discharged into the base)

- 3rd case (timed evaporation pheromone rate) this case adopts also a programmable evaporation pheromone rate. But, evaporation pheromone rate is defined by the determination of wasted time elapsed between two successive mine detections as follows:

$$\tau(k)=\tau(k-1)(1-\rho)+(1-\frac{1}{1+Q})\tau(k-1) \quad (9)$$

$$\rho=\frac{\Delta t}{1+tM1} \quad (10)$$

$$\Delta t=tM1-tM2+1 \quad (11)$$

tM1=detection time for $mine_i$
tM2= detection time for $mine_{i-1}$

- Method3: (model modified ACO) the method adopted in this part is based on an ACO algorithm but with considering a mobile base in order to minimize base-mine displacement. Base coordinates are defined by P_x and P_y:

$$P_x(k) = \frac{P_x(k-1)+R_{ix}(k)}{2} \quad (12)$$

$$P_y(k) = \frac{P_y(k-1)+R_{iy}(k)}{2} \quad (13)$$

The ($R_{ix}(k)$, $R_{iy}(k)$) couple represents the coordinates of recent detected minei. The idea presented was inspired by the intensification and diversification [9, 34]. The diversification for robotic agent represents the ability to demine many and different mine land regions. Intensification is summarized in the ability of base guides demining operation in specific zones with high mine concentration. At this stage, the robot agents are reserved for mine research and the deactivating operations are assigned to the base as a new agent type.

5 Simulation protocol

This section introduces general simulation protocols followed in collaborative algorithms efficiency validation. All simulations are performed with NetLogo [35, 36]. NetLogo is used as a software platform to simulate robotic agents and landmine map. In fact, NetLogo supports advanced modeling of complex systems using a library of java programming primitives. In NetLogo simulation environment, robotic agents are modeled in simple design without the consideration of collision avoidance. As given in Table 1the experience design was performed by variation of the evaporation pheromone rate and kind of landmine distributions. Each experience is repeated ten times using NetLogo API control. Mine detection time values was reported to MATLAB software platform in order to compare different configuration results.

A simplified foraging scenario was taken to describe demining operations. Robots states include the searching and homing state. When a robot detects a mine, it picks it up and comes back toward neutralizing base. Execution demining time is accounted while a robot is either in searching mode or homing. Time of other robots avoidance is not considered in demining scenario. Fig. 5 shows the state diagram for demining operations scenario. Robotic agents detect, collect mines and bring them to a mine neutralizing base.

TABLE 1 SIMULATION PARAMETERS

Model	Evaporation pheromone rate %	Distributions
ACO	0%-100%	Random, fixed 1, fixed 2 and random line
Modified ACO	0%-100%	Random, fixed 1, fixed 2 and random line

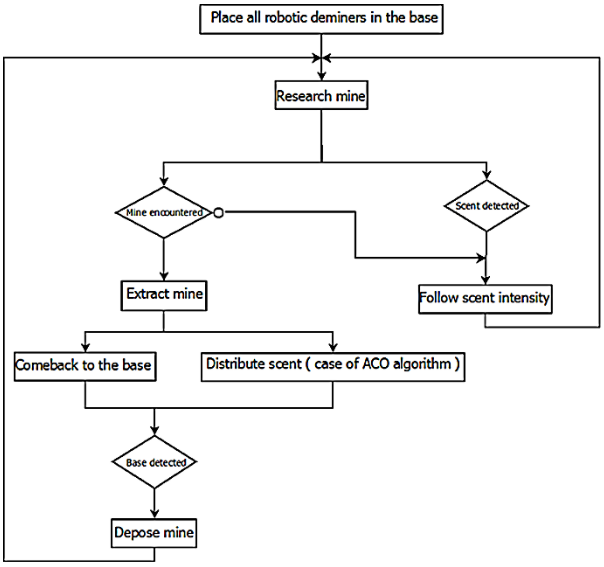


Fig. 5. Behavior diagram of a multi-robot demining system.

6 Result

Experimental studies in this manuscript were performed for fixed mines/robots ratio. According to [20], rising robots/mines ratio beyond some limits do not affect time detection because of the interference of robotic agents, which stabilizes the time result. In order to test evaporation pheromone rate influence on time demining optimization; some tests are performed with different robots/mines ratio. These tests identify limits that do not modify temporal performances. The application of various mines/robot rate on presented mines distributions and collaboration models based on ACO algorithms, attest that rising robotic agents number (in order to minimize mine detection time) has no influence on system timing performances. Fig. 7 gives an example of time detection mine stabilization for base demining model with random distribution (robots/mines ratio = 50%, mean time values=129.17). Fig. 6 summarizes means and deviation values of other stabilized time detection mine for different demining models (base, ACO and Modified ACO models) and detected mines proportion (60%-90%) ranges. Variation effects of distributions study cases are considered with mean values.

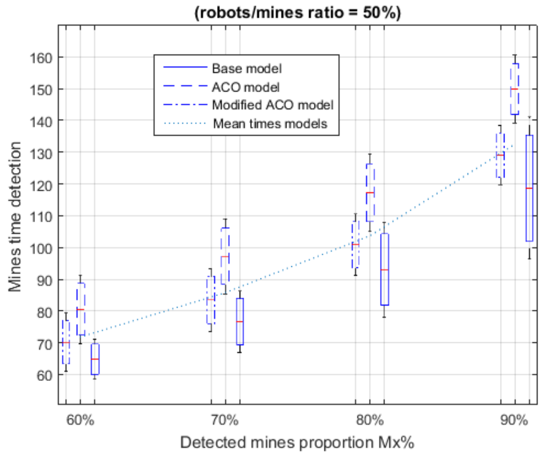


Fig. 6. Means and deviations list of mine detection time values

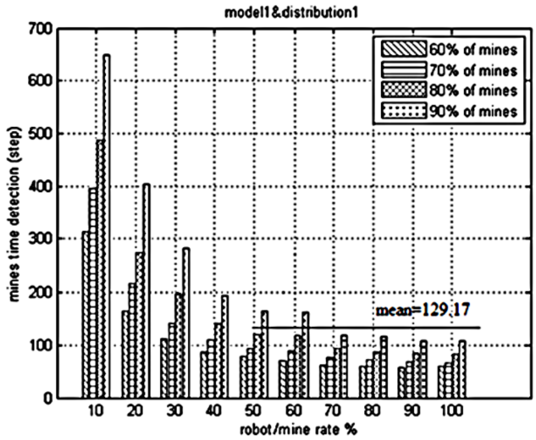


Figure. 7. Time detection mine using model BASE and random distribution.

This part presents the possible effect of evaporation pheromone rate variation on demining time performances for both ACO and modified ACO algorithms (Mx%=90%). In each experimentation, pheromone evaporation rate is increased regularly by 10%.

Fig.8 and 9 represent the detection time variation relating to the minefield distribution type for both ACO and Modified ACO models. For lower pheromone evaporation rate, higher values of detection time results are taken with random distribution. Rising pheromone evaporation rate ameliorates temporal performances. However, this decrease of mine detection-time is stabilized for high evaporation. In fact, detection time results are limited to a range of 200 s.t for evaporation pheromone rate > 60% in the case of ACO model and for evaporation pheromone rate > 30% in the case of modified ACO model.

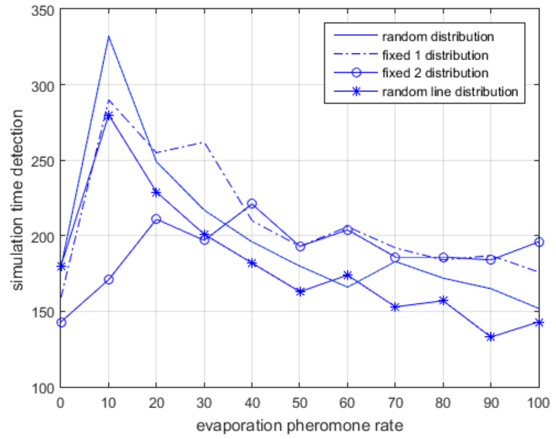


Fig. 8. Time detection results for the ACO model

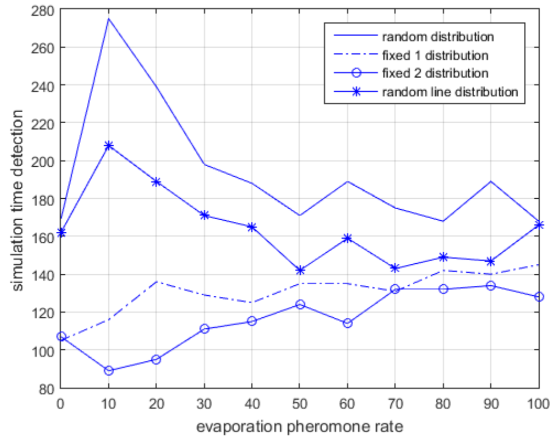


Fig. 9. Time detection results for the modified ACO model

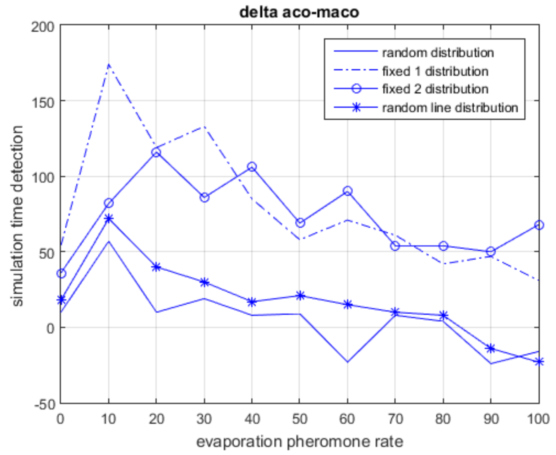


Fig. 10. Time detection comparison between ACO and modified ACO models

Fig. 10 indicates the time variation between ACO and modified ACO models. Considering the effect of minefield distribution type separately, modified ACO model presents better timing results than ACO model with lower pheromone evaporation rate. ACO model presents better timing results than modified ACO model only in the case of fixed spatial distributions with high pheromone evaporation rate (>80%).

The impact of pheromone evaporation rate on time system performances is noted at the beginning of the solutions construction. Adopting a programmable pheromone evaporation rate which induces new solution explorations should reduce time demining. Researches of [31, 37, 38], use different models of programmable evaporation rate based on a mathematical formulation. Dealing with the evaporation pheromone example given by [31], this model is taken as a reference to evaluate our evaporation pheromone rate model. Simplifying evaporation pheromone model is the principal motivation of selection of a timed algorithm model.

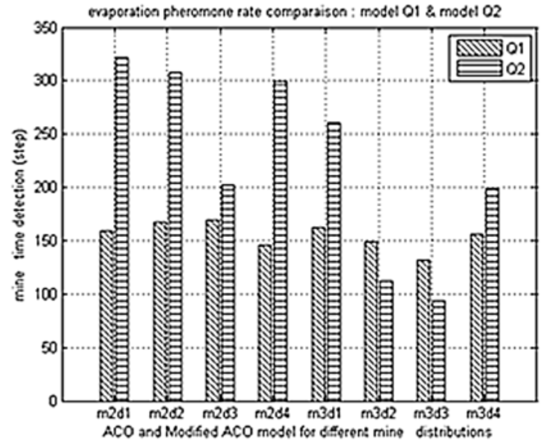


Fig. 11. Evaporation pheromone rate model comparison

Fig. 11 reports the temporal result difference between different evaporation pheromone models for ACO and Modified ACO collaborative algorithms. Mathematical evaporation pheromone rate model [31] is represented by Q1 model. Our evaporation pheromone rate model is represented by Q2 model. In the case of ACO model (m2d1, m2d2, m2d3 and m2d4); temporal results obtained with Q1 model are better than with Q2 model except the result in fixed 2 distribution (m2d1). In fact, the system equipped with Q2 evaporation pheromone model takes double time to detect 90% of mines compared to Q1 model. This different change in the case of Modified ACO model and better temporal performances is detected with Q2 model in the case of fixed distributions. Multi-robot system experimentations are performed on the software simulation platform. In real implementation, the application of mathematical complex model for evaporation pheromone rate should require more hardware resources and reduce temporal performances.

7 Discussion

The realized experimentations use a fixed setting of robot/mine rate. Generally, rising robot/mine rate is higher than 50% does not enhance cooperation impact on demining time optimization. These results were confirmed in the previous researches, like that of [20] and verified in our previous work. The principal aim of research in this paper is the connection between evaporation pheromone rate and timing performance. In fact, as given in Fig. 7, 8 and 9 better timing results are detected for modified ACO model (in most studied cases: Table 2).

TABLE 2 :SUMMARY OF TIME RESULT VARIATION BETWEEN ACO AND MODIFIED ACO MODELS

Distribution	0% to 50%	50% to 70%	70% to 80%	80% to 100%
Random	+	-	+	-
Fixed 1	+	+	+	+
Fixed 2	+	+	+	+
Random line	+	+	-	-

(+/-) Sign of time result variation between ACO and modified ACO models for different static evaporation pheromone rates ($time_{ACO} - time_{modified\ ACO}$)

In general, ACO algorithms are made from ant foraging behavior. ACO optimization gives a short path solution to one source of food. In the case of demining problems, the mines are distributed in various positions. The best initial situation ACO algorithm consists of a limited zone mine concentration. This situation is given by fixed1 and fixed2 distributions. For these two mine distributions and at a lower evaporation pheromone rate, better timing results are obtained in comparison to the base model. However, with random distributions (random and random line distributions), time demining results are degraded with ACO model in favor of the base or modified ACO model. The Amelioration of the ACO model results is given by the raising evaporation pheromone rate. In fact, this action helps robotic agents to forget the previous detected mine positions and forces the agents to explore new zones. Time result experimentations are reduced for the evaporation pheromone rate, which are higher than 60% in the case of ACO model, and 30% rate in the case of modified ACO model. The solution is ensured by modified ACO model presents flexibility toward different mine distributions.

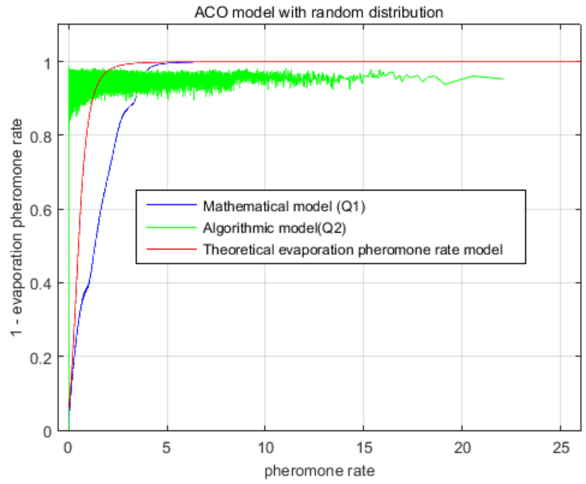
The variation of the evaporation pheromone rate has an impact on timing results. With this interpretation, some researchers [31, 39] applied a specific function to define the evaporation pheromone rate. In general, this function is bounded between 0 and 1. It rises exponentially with the pheromone rate. Table 4 summarizes the demining time results for the two types of evaporation pheromone rates (Q1 and Q2) and for the cooperative robotic models (ACO and modified ACO models). Our proposed evaporation pheromone rate Q2 gives lower timing performances for demining operations in the case of the ACO model. The worst timing results are detected for random mine distribution (55% of time result reduction). However, the Q2 model gives better timing results in the case of the modified ACO model with fixed mine distributions. The best results are detected for fixed 2 mine distribution. The evaporation pheromone Q1 model still has better results in random distributions (with modified ACO model) but the timing performance differences between Q1 and Q2 models are reduced in comparison to ACO model.

TABLE 3: COMPARISON TIME RESULT BETWEEN Q1 AND Q2 MODELS

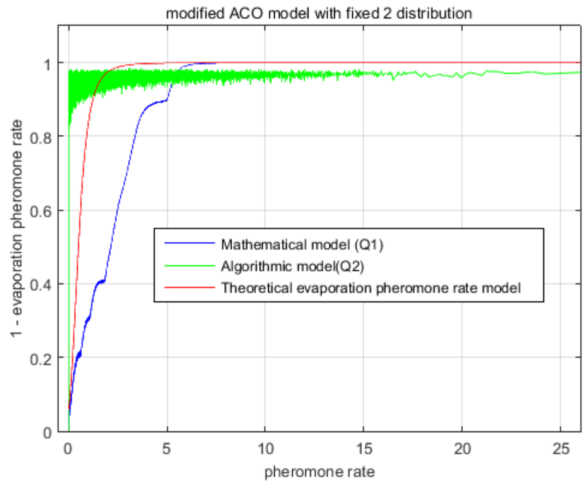
Distribution	ACO model	Modified ACO model
Random	55%	32%
Fixed 1	46%	-8%
Fixed 2	12%	-27%
Random line	42%	28%

(*) $\% = (time_{Q2} - time_{Q1}) / time_{Q2}$

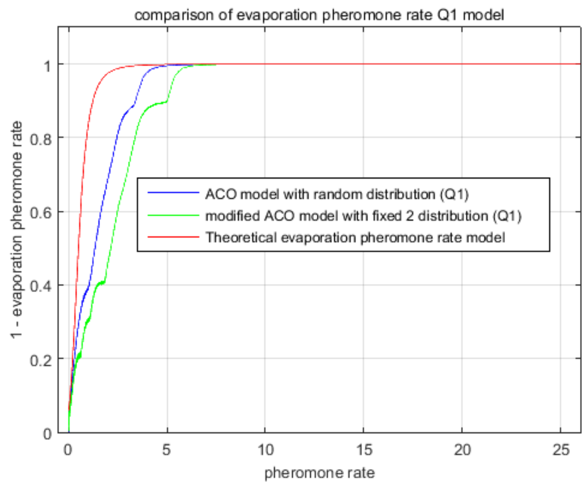
To explain the results given by Table 3, the worst and the best result for Q2 model are selected. The worst time result corresponds to the ACO cooperative model with random distribution. The best time result corresponds to the modified ACO cooperative model associated with fixed 2 mine distribution. Fig. 12 reports the variation of the evaporation pheromone rate models in the worst time result (Fig. 12.a) and the best time result (Fig. 12.b). The recorded evaporation pheromone rate from Q1 model simulations differs from theoretical evaporation pheromone rate formulation ($\rho = \frac{1}{1+\frac{(\tau-\alpha)^4}{\sqrt{2\alpha}}}$). This difference is amplified for the modified ACO model. In addition, the model guided by Q2 approaches the theoretical model but it presents higher sensitivity of the pheromone rate variation and saturates fast bounded limit. Fig. 12.c gives a comparison between Q1 model in the ACO and modified ACO model. Evaporation pheromone model converges to the theoretical model with additional delay in the modified ACO model. In Fig. 12.d, the Q2 model preserves the same pattern and therefore gives better time results for fixed distributions.



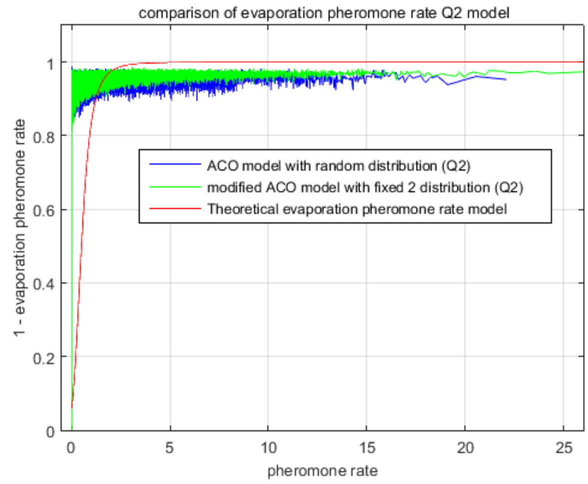
(a) ACO model with random distribution



(b) Modified ACO model with fixed 2 distribution



(c) Comparison of evaporation pheromone rate Q1 model



(d) Comparison of evaporation pheromone rate Q2 model

Fig. 12. Evaluation of the evaporation pheromone rate model (Q1 and Q2 models) for ACO and modified ACO model

Fig. 13 presents the time demining results for the reduction of evaporation pheromone rate sensitivity to variation of the pheromone rate. These attempts of Q2 model amelioration are based on the introduction of delay in the iterations of evaporation pheromone rate calculation. Some increasing values of delays (10 s.t, 40 s.t, 70 s.t and 200 s.t) are experimented. The general time performances of the demining system is degraded for the ACO and modified ACO models and there is no modification of evaporation pheromone rate pattern in the function of pheromone rate.

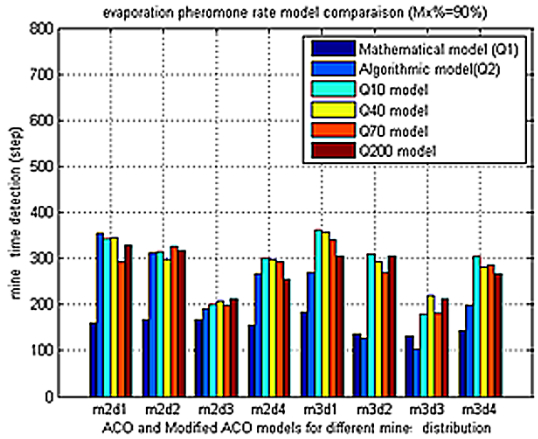


Fig. 13. Time results for different models of evaporation pheromone rate

8 Conclusion

This paper presents the experimentations of the pheromone evaporation rate on the multi-robotic demining system. The Effects of the pheromone evaporation rate are noted for particular rates and better results are obtained with modified ACO algorithms. The temporal performance of demining multi-robot systems is obtained by modifying the ACO algorithms. However, results are still depending on the environment configurations and on the other modifications can be performed on ACO algorithms especially by studying the pheromone evaporation rate. The application of programmable evaporation pheromone rate helps to improve temporal performances. The improvement of temporal performances is set up with the evaporation pheromone rate pulse (instead of high evaporation pheromone rate maintain). The choice of the model of evaporation pheromone rate modifies temporal performances of the demining system. The proposed evaporation pheromone rate Q2 enhances temporal performances of the demining operations for a particular configuration mainly with the modified ACO collaborative model and fixed mine distribution. The studied Q1 model is an example of programmable evaporation pheromone rate. Other functional models can be tested. The aim of the algorithmic evaporation pheromone model is to simplify the implementation of this system. In our case, the additional experimentations on real implementation of multi-robot controller must be performed to evaluate the algorithmic model of evaporation pheromone rate. A collaborative model based on Ant Colony Optimization is selected. In addition, other meta-heuristic algorithms can be applied in the same case. In particular, hybrid meta-heuristic algorithms should be experimented on multi-robotic controllers.

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