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Robots/mines ratio effect on multi-robots mines detection system based on modified ACO algorithms

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***Abstract*— Abandoned minefields represented main causes of injured and killed persons in conflicts zone. This article described an automated approach for demining operations based on heuristic algorithm. For this aim, we chose a multi-robotics system to operate in unknown landmines. This article focused on effects of minefields configuration variation on temporal performances for mine detection purpose. In This case, different mine distribution strategy was tested on a multi-robotic system to ensure optimal time for detection. In This article we presented a comparative study about use of ACO algorithm for mine detection purpose. Especially we presented effect of various robot organizations on timing system performance and multi-robotic demining systems was simulated for different mine land distributions.**

Keywords*— *multi-robotic; ACO algorithms; minefields distributions; robots/mines rate; temporal performances

I. Introduction

Demining operations represent an important development in the humanitarian area. Mines random dispersion and the long duration of mine activity into un-known areas make difficult demining operations. Each year and referring to [1], 15 000–25 000 people are maimed or killed by landmines. In other hand, the single landmine cost is about $3-$10 and device deactivation cost is about $300-$1000 per mine at removal rate of 100,000 per year [2]. Mines can exist in various environments especially in unstructured environment field. The nature mine field complicates demining operations. In general, mine clearance cost depends on various criteria which include: first the country budget resources, in the case of poor countries. Second the safety operations degree, if we consider that demining operations are performing manually in unsafe circumstances, and third the operation demining delay. Use of robotic demining system represent a secure solution replacing dangerous human mine manipulation in unavailable mine field. The existing robot systems designed for demining operations have limited performances if we consider that these systems should explore unknown configuration field [3]. In addition, demining robots are equipped with high sophisticated technology instruments for mine detection and processing [4] rise mine clearance cost. Time optimization of demining operations becomes an important humanitarian objective if we consider the number of abandoned mines fields [5]. This optimization must respect security constraints attached to demining operator and enhance efficiency of demining tasks in time proceeding and energy consummation. According to [4, 5],various assistant tools were designed and tested to help automation demining process, limit risk of human error, and rise estimation of risk zone. Substitution of human operators by robotic agent participates with appropriate strategy in the realization of this goal [6]. However, the sophisticated robots agents and the distributions variety of mines field, enhance the demining operations cost. This cost includes time demining operation, energy management, equipment, and security considerations. In this article, we explore the possible applications of multi-robot systems in time detection optimization of Mx% (maximum mine portion detected.) mines in particular case of field mine configuration. Adaptation of multi-robot systems for demining operations, induce the choice of an adaptable coordination algorithm. Demining operations are complex problems and they need meta-heuristic algorithms as coordination algorithms. Search and optimization algorithms have risen their exploration capabilities by including basic heuristic [7]. Many evolutionary 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. In Sect. 2, we present works related to multi-robots application on demining operations. In particular these works include configuration constraints in the case of mine distribution and size of robotic set, type of collaboration algorithms and performances metrics. Sect. 3 presents field mine distribution and collaboration models used in demining operations. Sect. 4 describes simulation considerations for performed experiences. Sect. 5 lists and analyzes the simulations results.

II. Related works

Multi-robots application in demining operations for humanitarian purposes represents an evaluation example of coordination strategy performance. Many researches such as [8-10] use specific coordination strategy in order to evaluate some criteria performances. General research organization starts with definition of collaboration Algorithms used in order to perform specific task. In our case we choose demining operations. Demining process includes many constraints related to the nature of minefield distribution and performance evaluation criteria. Some researches as in [8, 10, 11] 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 can't be defined easily with deterministic clustering approaches. Landmine variety induces different mine distribution patterns. Different mines distribution 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 mine field map, would allow the consideration of environmental and social conditions [5].

Simulation example given in [3] tests real case minefield distributions in order to realize an automatic estimator to mines localization. Mines distribution configuration represents limitation if we work in unknown environment. But in several cases, mines distribution can be modeled by stochastic model like in [4, 5, 11]. In other part efficiency of demining operations depend of scenario followed for each robotic agent.

In other part, the choice of collaboration strategy represents other constraint. In fact, demining operations with multi-robots systems raises complexity of collaboration interactions [8, 12]. In this case application of suitable meta-heuristic algorithms for multi-robot demining operations was performed in research such as [13-16]. 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 [17] define evaluation metrics to quantify collaboration performance cost. Localization and distribution robotic agents' configuration was taken as evaluation criteria. These criteria de-pend on applications constraints like possible robot agents interference [18]. 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. In the rest of experimentations we will focus on temporal performance optimization using modified meta-heuristic algorithms. In particular, configuration parameters for minefield and multi-robots systems as type of mine distributions and effects of robotic group size were treated in experimentations. Other performance metrics like: robotic agents displacements which represents aggregation of the distances inter-agent position during demining operations (consumed energy), Robotic Agents proportion of agents which ensure demining operations, and communication flow exchanged between agents during robots interactions; represent other optimization objectives and they will be treated in further works.

III. Methods and hypothesis

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

A. Field mine configuration

Measurement of demining operations time was performed at different values of configuration parameters. In first stage and in concordance with [19], we con-sider robotic set size as influential parameter. In fact, we vary robots/mines ratio (RM %) and note detection mines time for different minefield proportion (Mx %). Tested mines proportion was been fixed to 60%, 70%, 80% and 90% for a total number of 50 mines [4].

In other part, mine spatial distribution has possible effect in mine detection time [4, 5]. We try different spatial distributions which include:

- 1st case: (random distribution) mines are placed randomly with uniform density of probability.
- 2nd case: (fixed spatial distribution) second distribution is destined for fixed mine position. We try two different dispositions with limited mined zone. These two tests are indicated in Fig 1 and Fig 2. In Fig 1 we divide mine field into two parts relatively to a vertical symmetry axe. P1 represents mined area zone. In figure 2 we divide mine field 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 [20], in the case of environment symmetry, 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 3) 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

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errors mainly due to navigation and drop timing errors. Random lines are assumed to have random orientation and mine spacing. But in this experimentations random mine lines are parallel [3].

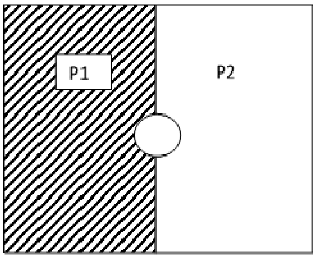

Fig. 1. Fixed spatial distribution 1.

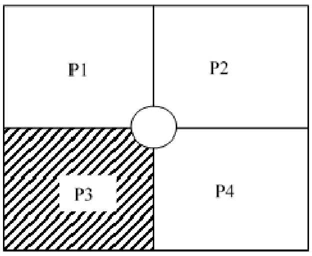

Fig. 2. Fixed spatial distribution 2.

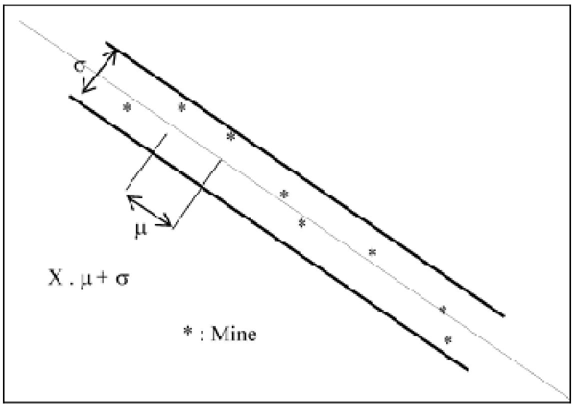

Fig. 3. Random line distribution (s=1,μ=3 and areas dimensions=16x16).

B. Navigation and research methods

In this part, we will present 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 with any constraints except some particular rule listed in fallow:
  - R1: when robot agent finds a mine. It must return to the base for deactivation 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 (Ant Colony Optimization) algorithm to find optimum demining operation. We save the same rules adopted in model BASE (R1 R2 R3). Used robot agents path is fixed by pheromone rate τ deposed by other searching agents. In this test we fixe evaporation pheromone rate ρ (static evaporation pheromone rate) and we calculate pheromone rate as fallow [21]:

$$\tau(k) = \tau(k-1)(1-\rho) \qquad (1)$$

- 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:

$$P_x(k)=(P_x(k\text{-}1)+R_{ix}(k\text{-}1)) / 2 \qquad (2)$$

$$P_y(k)=(P_y(k\text{-}1)+R_{iy}(k\text{-}1)) / 2 \qquad (3)$$

The ($R_{ix}(k)$, $R_{iy}(k)$) couple represent coordinates of recent detected mine$_i$. The idea presented was inspired from intensification and diversification [7, 22]. Diversification for robotic agent represents ability to demining many and different mine land regions. Intensification summarized in the ability of base guides demining operation in specific zones with high mine concentration. At this stage we can reserve robot agents for mine research and the base as a new agent for deactivating operations.

IV. SIMULATION PROTOCOL

In this section, we introduce general simulations protocols followed in collaborative algorithms efficiency validation. All simulations are performed with NetLogo [23, 24]. NetLogo is used as 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 were modeled in simple design without consideration of collision avoidance. As given in Table 1 experience design was performed by variation of robots/mines 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 con-

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figuration results. Each collaborative model was tested for various robots/mines rates and specific distributions.

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 up and come 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 4 shows the state diagram for demining operations scenario. Robotic agents detect, collect mines and bring them to a mine neutralizing base.

TABLE I. SIMULATION PARAMETERS

Model	RM%	Distributions
Base	10%-100%	Random, fixed 1, fixed 2 and random line
ACO	10%-100%	Random, fixed 1, fixed 2 and random line
Modified ACO	10%-100%	Random, fixed 1, fixed 2 and random line

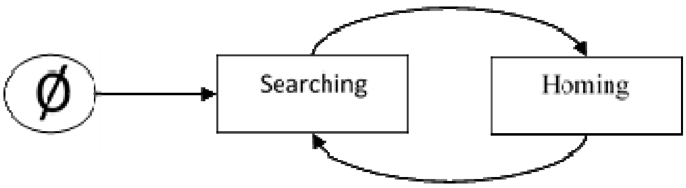

Fig. 4. State diagram of a multi-robot demining system with base return (homing).

V. RESULT AND INTERPRETATION

Experimental studies in this article were performed for various mines/robots rate in order to test robotic set size influence on time demining optimization. Application of various mines/robots 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) haven't influence on system timing performances. In fact, rising robots/mines ratio (RM %) beyond 50% don't affect time detection and this time was stabilized. Table 2 summarized 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.

TABLE II. MEANS AND DEVIATIONS LIST OF MINE DETECTION TIME VALUES (RM% = 50%)

Model		Base	ACO	Modified ACO	Mean time for all models
Time for Mx%=90%	mean	129.13	149.92	118.67	132.57
	deviation	9.31	10.68	22.37	
Time for Mx%=80%	mean	100.88	117.25	93.04	103.72
	deviation	9.63	12.25	14.94	
Time for Mx%=70%	mean	83.42	97.25	76.71	85.79
	deviation	9.85	11.81	9.78	
Time for Mx%=60%	mean	70.17	80.54	64.79	71.83
	deviation	9.19	10.84	6.33	

TABLE III. TIME CORRELATION VALUES TAKEN FOR MX%=90% AND RM% = 10%

Model	Correlation time results for different robots/mines ratio		
	RM%=20%	*RM%=30%*	*RM%=40%*
Base model	0,2072	-0,0045	0,9247
ACO model	0,9972	0,9062	0,9893
Modified ACO model	0,9617	0,5755	0,9162

Table 3 summarizes investigations about RM% effect on detection time results. It presents correlation values between detection times taken for RM%= 10% and other time values taken for increasing RM% (20%-40%). These experimentations were performed separately for each collaboration models with different mine distributions consideration. Correlations results between given tests in the case of RM%=10% and other RM% (20%, 30% and 40%) indicate high level of relation intensity between temporal system performances and RM%. This relation intensity is deteriorated in the case of base model. Best results are noted for ACO and modified ACO models (correlation values = 0.9, except correlation value between RM%: 10%-30% = 0.5755).

Time detection variations are noted for RM% lower than 50%. If we choose base model collaboration; best timing results are noted for random distributions (600 < time < 700 simulation steps (s.t) for 90% mines detected). Demining operations take more time in the fixed distributions (= 800 s.t for 90% mines detected) due that in base model collaboration, robots agents perform random movements with uniform density. Variations of mine detection time appear for RM% equal to 10%.

TABLE IV. MODELS TIMING PERFORMANCES FOR MX%=90%

model	distribution	Time (RM% =10%)	Time (RM% =20%)	Time (RM% =30%)	Time (RM% =40%)
base	Random	649	404	281	194
	Fixed1	777	400	271	206
	Fixed2	927	377	252	210
	Random line	631	338	233	186
ACO	Random	727	389	266	213
	Fixed1	820	440	320	242
	Fixed2	854	450	299	258
	Random line	686	368	243	207
Modified ACO	Random	715	353	239	215
	Fixed1	538	264	216	162
	Fixed2	592	282	184	155
	Random line	626	326	235	185

This result can be explained by mine dispersion. In normal case robotic agents are guided by pheromone trace toward the food source which represents in our case mines. In real minefield mines are dispersed and robots are

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occupied in following trail with high pheromone concentration to demine one mine. This allocation of many robots whose demining one mine, overcrowds robots agents by unsuccessful demining tasks and amplify interference [18] effects in robots collaboration. Mine detection time is reduced in spatial fixed distributions (fixed distribution 2) in witch mined area was reduced to limited zone in order to group robotic efforts in the same area with higher mine concentration. If we consider low RM% reduced to 10% with fixed distribution 2, mine detection time (90% of mine detected) in base model (=927 s.t) was reduced in ACO model to ˜ 854 s.t. This improvement is degraded with higher RM%. (Table 4)

If we consider 20%-40% range of RM%, use of modified ACO model enhance temporal system performances for fixed spatial mine field distributions in comparison with random distributions (random and line random distribution). In fact, time detection mine values, taken at RM%=40%, is 185 s.t for line random distribution and ˜ 162 s.t for fixed distributions (Table 4).

In the case of distribution fixed 2, modified ACO model use reduces time detection results given with BASE and ACO models (detection time of modified ACO model = 592s.t: Table 4). This observation is extended to other RM% in which we find better results than BASE and ACO models (Mx%=90%).

Table 5 reports timing performances variations for different range variations Mx%, minefield distributions and using three simulation models: BASE, ACO and Modified ACO models. This prospection help to detect variations in demining acceleration for proportion detected mines between 60% and 90%. Time variation in mine detection ΔMx% reflects acceleration in demining operations for remaining mines. If we consider BASE and ACO models, demining time decreases are noted in fixed distribution 2 under RM% equal to 10%. Time variations are reduced from 498 (s.t) in BASE model to 415 (s.t) in ACO model.

TABLE V. MODELS TIMING PERFORMANCES FOR RM% =10 %

distributions	ΔMx%	Base model (s.t)	ACO model (s.t)	Modified ACO model (s.t)
Random	60%-70%	82	110	73
	60%-80%	175	206	183
	60%-90%	336	416	405
Fixed 1	60%-70%	110	100	58
	60%-80%	210	232	146
	60%-90%	370	417	286
Fixed 2	60%-70%	87	90	70
	60%-80%	235	207	151
	60%-90%	498	415	355
Random line	60%-70%	72	87	87
	60%-80%	168	219	200
	60%-90%	326	376	373

In the case of fixed distribution 2, demining detection time are extended for other RM% values (20%, 30%, and 40%). At this stage, we remark that ACO algorithms applied as cooperative strategy for multi-robots systems reduce time demining operations for fixed type of mine field distribution and at lower RM%. In fact, Table 6 reports reduced time value for RM%=10% with fixed distribution 2 (498 (s.t) in BASE model, 415 (s.t) in ACO model). For the same ΔMx% variation (60%-90%), detection time rise in the case of ACO model with RM%=20% (from 196 (s.t) to 216 (s.t)), 30% (from 122 (s.t) to 134 (s.t)) and 40% (from 98 (s.t) to 132 (s.t)).

TABLE VI. ACO AND BASE MODEL TIMING PERFORMANCES (FIXED DISTRIBUTION 2)

RM%	ΔMx%	Base model (s.t)	ACO model (s.t)
10%	60%-70%	87	90
	60%-80%	235	207
	60%-90%	498	415
20%	60%-70%	39	49
	60%-80%	111	114
	60%-90%	196	216
30%	60%-70%	39	30
	60%-80%	77	75
	60%-90%	122	134
40%	60%-70%	29	25
	60%-80%	57	64
	60%-90%	98	132

This observation (Table 6) can be explained by the nature of stigmergy [25-27] used in ACO algorithms. Coordination strategy is based on random pheromone dispersion and robots displacements are conditioned by pheromone density. In real applications like demining operations, objectives can't be concentrated in one food nest. In addition, raising the number of robots raises pheromones concentration and results are deteriorated if RM% rises. A possible solution for the ACO algorithms temporal performance improvement is the change in the pheromone dispersion strategy in order to make hybrid systems with other meta-heuristic algorithms types. Another type of performance improvement is related to the environment constraints and robotic agent management rules. In fact, robotic agents take more processing time to achieve coming back demining operations to the base. The selected base has fixed coordinates. One possible solution is to allow more freedom degree to the base and take a mobile base. In this case, ACO algorithms modifications touch only behavioral aspects. New mobile base coordinates are calculated in relation of successful demining robotic agent coverage.

Experimental results of base modified ACO algorithm model are presented in Table 5 in comparison with other models. For ΔMx%=60%-90%, demining time performances enhances are detected for fixed distributions compared to BASE and ACO models (fixed 1 distribution: [modified ACO model: 286 s.t] < [BASE model: 370 s.t] < [ACO model: 417 s.t], fixed 2 distribution: [modified ACO model: 355 s.t] < [ACO model: 415 s.t] < [BASE model: 498 s.t]). Results are taken under low RM% (10%). Also time enhances take place for random and line random distribution. Times results are better compared to ACO model and approach results noted for BASE model (random distribution: [BASE model: 336 s.t] < [modified ACO model: 405 s.t] < [ACO model: 416 s.t], random line distribution: [BASE model: 326 s.t] < [modified ACO model: 373 s.t] < [ACO model: 376 s.t]). More results are presented in Table 7 in order to detect effect of RM% variations to perform time demining operations with modified ACO model for random distribution.

TABLE VII. MODELS TIMING PERFORMANCES COMPARISON (RANDOM DISTRIBUTION)

RM%	ΔMx%	Base model (s.t)	ACO model (s.t)	Modified ACO model (s.t)
10%	60%-70%	82	100	73
	60%-80%	175	206	183
	60%-90%	336	416	405
20%	60%-70%	52	50	33
	60%-80%	108	124	95
	60%-90%	239	222	191
30%	60%-70%	30	35	37
	60%-80%	87	79	68
	60%-90%	169	150	124
40%	60%-70%	24	24	30
	60%-80%	55	57	70
	60%-90%	108	114	118

In the case of random distribution (Table 7), RM% has an impact on demining time acceleration enhance. For RM% equals to 20% and 30%, demining time variations associated to range of detected mines proportions (ΔMx%=60%-90%) are reduced ([modified ACO model: from 191 s.t to 124 s.t] < [ACO model: from 222 s.t to 150 s.t] < [BASE model: from 239 s.t to 169 s.t]). But the same results was affected if RM% rise to 40% ([modified ACO model: 118 s.t] > [ACO model: 114 s.t] > [BASE model: 108 s.t]).

VI. CONCLUSION

Experimentations performed with different collaboration models, including ACO based models and free motion robotic agents, led to some ascertainments:

- Time performances stabilized for robots/mines rates = 50%.
- Evaluation of time detection amelioration using base model for robots/mines rates < 50%: 10%, 20%, 30%, and 40%. Time amelioration was noted for random distribution of robots agents in search mode. Bad results were noted for spatial fixed distribution. Random collaboration algorithm (in base model) present bad performance with spatial fixed distribution. ACO collaboration algorithm (in ACO model) present bad temporal performance with random and line random distribution. But it presents better results with static distribution (fixed 1 and fixed 2 distributions).
- In the case of ACO model, use of lower robots/mines rate (10%) has better time processing results with static distribution.
- Variation range of detected mines (ΔMx %) between 60% and 90% presents better temporal result with fixed distribution in the case of ACO model. The variation range study of detected mines was introduced as performance indicator if we consider that demining operations take more time in higher detected mine proportion (Mx%). Use of lower robots/mines rate (10%) have also better time processing results with static distribution for ΔMx %=60%-90%.
- Modification of ACO algorithms with mobile base introduces time processing ameliorations for spatial fixed distribution. Temporal results for other random distributions were reduced in comparison with ACO model but still higher than the results presented in base model.
- If we consider variation range of detected mines (ΔMx %) between 60% and 90%; Modified ACO model present better results in comparison with base and ACO model.

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