6th International Conference on Computer and Knowledge Engineering (ICCKE 2016), October 20-21 2016, Ferdowsi University of Mashhad

An Energy Efficient Metaheuristic Method for Micro Robots Indoor Area Coverage Problem

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***Abstract*—Recently micro robots have become more popular for realizing many indoor area coverage applications. According to the characteristics and limited energy of micro robots, they usually are used as multi-cooperators at covering indoor areas. Hence, researchers proposed some different algorithms for solving indoor area coverage problem. As far as we are aware the existed algorithms for micro robots usually were the same algorithms provided for normal sized robots. At normal sized robots although researchers taking into account the obstacles at the area, most of them did not provide energy efficiency as much as possible. In this paper we propose an Energy efficient Metaheuristic method for Micro Robots Indoor area Coverage problem (EMMRIC). In the proposed method at first we partition area to the number of micro robots through restricted K-mean algorithm and then micro robots cover assigned subareas by utilizing a modified genetic algorithm. The simulation results of EMMRIC prove the correctness of the proposed method in comparison with the state-of-the-art one.**

Keywords*—*Micro robots; Indoor area coverage; Constrained K-means; Genetic algorithm.

I. Introduction

The coverage problem is one of the most challenging issues in different applications. Coverage problem types including area coverage, target coverage and barrier coverage [1-3]. Area coverage problem has indoor area coverage sub-problem [4]. In recent years micro robots have become more popular for realizing many indoor area coverage applications [5-8]. Therefore, indoor area coverage problem with considering different kind of robots always has been one of the most challenging research issue [9]. In addition multiple mobile robots to cover an event through decomposition to a single optimal coverage problem is one of area coverage applications [10]. Robot's energy usually is limited and the problem becomes more complicated when multiple robots involving to achieve indoor area coverage cooperatively [11]. On the other hand when robot's energy is limited, especially in micro robots, it becomes one of the biggest challenges to dedicate suitable subarea of indoor area to be covered by each robot. Hence for proposing area coverage algorithms all cooperative robots' covered points should be considered concurrently. In other words, redundant area covering and also robots collision avoidance are some of the important challenges for achieving efficient indoor area coverage. When obstacles' positions are known in the indoor area, there are some different algorithms for optimum path finding and covering area with different kind of robots [11-13]. Recently proposed algorithms have considered some different variables at multi-robots for indoor area coverage, but these algorithms usually cannot provide energy efficiency as much as possible [9, 11, 14, 15].

In this paper we propose Energy efficient Metaheuristic method for Micro Robots Indoor area Coverage problem (EMMRIC). In EMMRIC we apply micro robots' energy limitations as a main factor and solve the problem at two phases as follows. (i) Utilizing constrained K-means algorithm to partition the indoor area by considering each micro robot's energy to the number of available and suitable robots [16]. In the end of this phase, each of micro robot starts from fixed initial point to reach the start point of its assigned subareas. (ii) Providing optimum full covering path for each micro robot at its assigned subarea in the first phase, through pattern based genetic algorithm. Proposed method provides energy efficiency by minimizing the micro robots travelling path and redundant coverage. The simulation results of EMMRIC prove its superiorities in terms of energy consumptions in comparison with state-of-the-art method.

Rest of the paper is organized as follows: In Section 2 literature review and recently proposed algorithms for area coverage problem are discussed. In Section 3 we provide the assumptions and variables' definitions. In Section 4 we propose EMMRIC and explained its functionality at two phases in details. In Section 5 we compare our method with state of the art and most related method, and finally we conclude the paper in Section 6.

II. Literature Review

Multi-robot systems always have a great deal of attention due to the ability of performing assigned tasks. Specially for path planning problem there are a lot of progress and some laboratories, which work on them continuously [17, 18]. E. U. Acar et al. provided a sensor-based coverage with extended range detectors [19]. They achieved coverage in two steps: The first step considers vast, open spaces, where the robot

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could use the full range of its detector; secondly they considered the narrow or clustered spaces where obstacles lie within detector range, and thus the detector "fills" the surrounding area. M. Ozkan et al. provided a genetic algorithm for task completion time minimization for multi-robot sensor-based coverage in which minimizing the coverage task time is main goal of them [12]. In this study they extended hierarchical oriented genetic algorithm (HOGA) to consider the travel time rather than just the traveled distances at robots. Muzaffer Kapanoglu et al. provided a pattern-based genetic algorithm for multi-robot coverage path planning minimizing completion time [11]. They modeled area with disks representing the range of sensing devices and they calculated travel time of a mobile robot based on the traveled distance and the number of turns. They minimized the maximum travel time of robots. The drawback of this algorithm is missing of calculation dead-ends recovery cost on fitness function. Gustavo et al. presented an algorithm for the problem of minimum time coverage of ground areas using a group of unmanned air vehicles (UAVs) equipped with image sensors [13]. They presented their work at two parts: (i) the task modeling as a graph that a single UAV would cover the area in minimum time; and (ii) the solution of a mixed integer linear programming problem, formulated according to the graph variables defined in the first part, to route the Multi-UAVs over the area. The main drawback of this algorithm is lacking of considering obstacles on robots path. Jeddisaravi et al. proposed an approach for single robot coverage and exploration in an environment with the goal of finding a specific object previously known to the robot [9]. They proposed a multi-objective approach for such search tasks. Chinese Postman Problem to optimize the path followed by the robot in order to visit the computed search disks. As it is clear in this work single robot is a drawback that robots could not considered correlational missions.

III. Assumptions and Variables' Definitions

In EMMRIC we consider micro robots with the ability of moving straight and rotation to both sides. Micro robots move to the start points of the assigned subareas. In the area there are some obstacles which, each micro robot must pass them and move to cover its assigned subarea. The covering area is divided into some grids, which no redundant overlaps are generated and no area is left out of micro robot's coverage. Indeed we assume area as some grids, which micro robots can move in them to cover area (we call each grid of the indoor area as disk except starting point), see [11]. We assume micro robots have homogenies energy at starting time. Micro robots must go to determined start disks (start point) to cover their assigned subareas. An example of the indoor area is illustrated in Fig. 1.

Variables which are used in EMMRIC are listed at Table I with definitions.

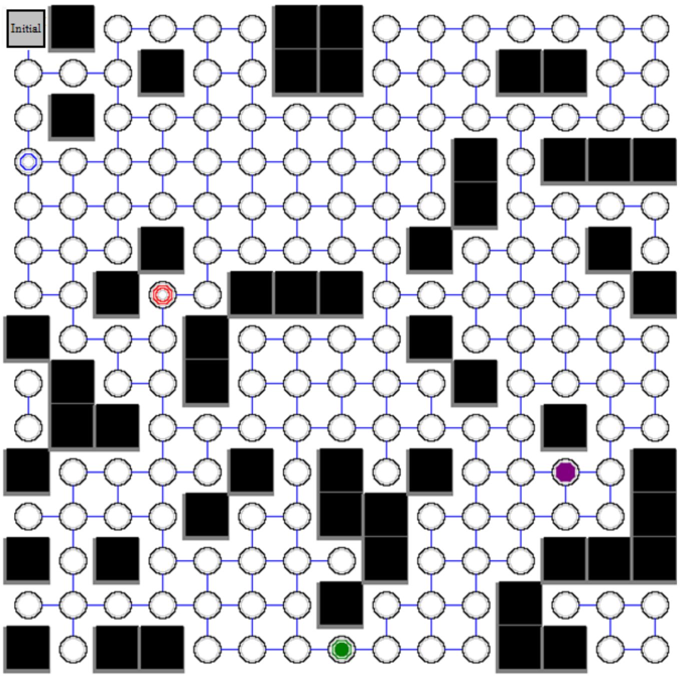

Fig. 1. An example of indoor area with all micro robots Initial point (left-up corner) and their start points.

TABLE I. Definition of the variables used in EMMRIC

	Variable	Definition
1	$S_c(i)$	The i[th] micro robot defined area coverage starting point.
2	N_m	Number of available micro robots.
3	$E_s(i)$	The initial energy of i[th] micro robot.
4	$E_r(i)$	The remained energy of i[th] micro robot.
5	(x, y)	The x and y position of environment disk (grid).
6	(x_H, y_H)	The x and y position of cluster head.
7	(x_{S_a}, y_{S_a})	The x and y position of all micro robots starting point position.
8	$MR_{allocated}(i)$	The i[th] Micro robot allocated point count to cover.
9	P_k	The used robot movement pattern

IV. Proposed EMMRIC

In this section we explain the proposed EMMRIC in details. EMMRIC has two phases organized as follows (see Fig. 2). It is worth mentioning that most of the parameters used in this section are defined in Table I in Section 3.

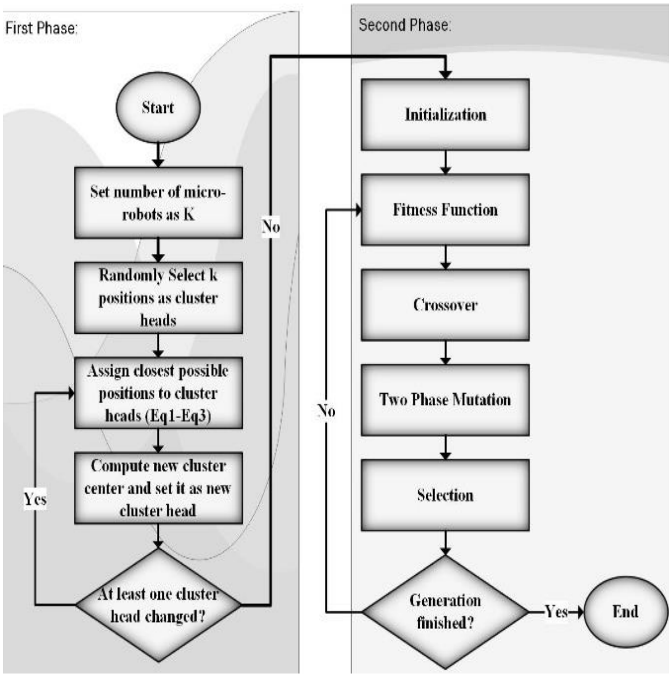

Fig. 2. Two phases of proposed EMMRIC.

A. First Phase

Partitioning the indoor area to the number of available micro robots. In this phase micro robots move from one initial disk named $\left(x_{S_a}, y_{S_a}\right)$ to reach the start point of assigned subarea ($S_c\left(i\right)$), which energy usage of this phase will be considered at portioning. For partitioning area we applied constrained K-means algorithm in which according to $\left(x_{S_a}, y_{S_a}\right)$ the area partitioning to N_m subareas [16].

At first phase we implement constrained K-means algorithm with energy restriction to each subarea (Fig. 2). The constrained K-means algorithm partitions the indoor area to number of micro robots in which each micro robot remained energy $(E_r\left(i\right))$ is considered. In constrained K-means algorithm the number of cluster heads is considered as number of available micro robots $(K = N_m)$ in which each cluster head dedicates one micro robot. In constrained k-means clustering phase each disk assigned to each cluster head through □1).

$$d_{\min} = \min_{p=1}^{N_m} \sqrt{(x_H(p)-x)^2 + (y_H(p)-y)^2}\, iff\ (E_r\left(i\right) > 0) \qquad (1)$$

In the (1), each disk in the area is assigned to one of the cluster heads, which has minimum distance to the disk. For calculation of energy usage of each micro robots from starting point to cluster head location (S_a to $\left(x_H, y_H\right)$), we estimate energy consumption of each micro robot by □2).

$$EstCon(i) = \sqrt{(x_H(p)-x_{S_a})^2 + (y_H(p)-y_{S_a})^2} \qquad (2)$$

After assigning each disk to each cluster head and calculation estimated energy consumption to reach covering subarea the energy of each micro robot will update through □3).

$$E_r\left(i\right) = E_s\left(i\right) - EstCon(i) - MR_{allocated}(i) \qquad (3)$$

If the remained energy of the minimum cluster head was zero, then the next minimum distanced cluster head will selecting with □1). Note that this phase continues until all disk are assigned to cluster heads, but if any of disks because of the energy constraint cannot assigned to one cluster head, this disk remains as un-clustered disk. It usually happens when we do not have enough micro robots with enough energy for covering the whole area. According to first phase constrained K-means algorithm continues until no cluster head changes (Fig. 2). In the Fig. 3 first phase of proposed method is performed and the output illustrated with considering four micro robots.

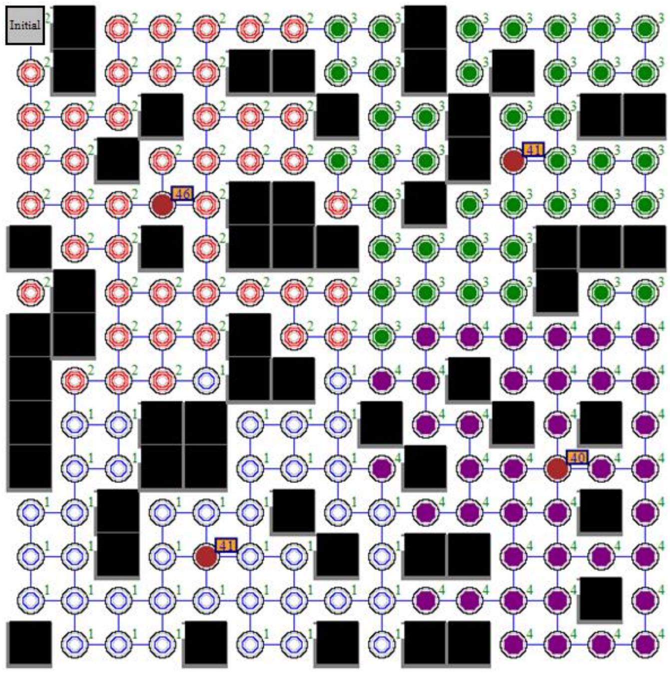

Fig. 3. Proposed constrained K-means algorithm result with 4 micro robots.

As shown in Fig. 3 area is partitioned to four part between four micro robots. Because of energy consumption, for farther micro robot from the initial point less disks are allocated to be covered (see Figure 3).

B. Second Phase

At this phase we describe our improved genetic algorithm shown at Fig. 2, step by step. In this phase the best path is found by Genetic Algorithm (GA) for each micro robot to cover its assigned subarea. Also for achieving best results the assigned subarea may change gradually and dynamically by

GA operators, (Energy limitation considered). In our method compact chromosome structure is used in which the main architecture and 8 movement pattern are according to the proposed movement pattern structure at [11]. In our proposed EMMRIC the chromosome structure is illustrated at Fig. 4.

Ch	Micro Robot 1						...	Micro Robot N_m					
		1	1	...	L	L			1	1	...	L	L
1	Micro robot (i)	Pattern P_k	P_k count	...	Pattern P_k	P_k count		Micro robot $(i+N_m)$	Pattern P_k	P_k count	...	Pattern P_k	P_k count

Fig. 4. Chromosome structure in EMMRIC

In Fig. 4 the chromosome structure shows a compact structure of one chromosome. At this chromosome few micro robots can be defined (i[th] micro robot column), each robot can move by 8 patterns that defined numbers as one to eight (Pattern P_i column). The number of movements at each pattern is characterized in (P_i count column). The GA operators, which are performed at each generation are organized at Table II.

TABLE II. GA operators and their descriptions

GA Operator	Description	Recovery
Crossover	Two point crossover	needed
Mutation	a) Changing patterns and number of movement from each pattern. b) Changing assigned partitioned area on border of areas	needed
Selection Function	20% new population selected by Elitism and 80% selected by roulette wheel.	--

Crossover operation is two point crossover. At mutation operator movement patterns and number of movement from each pattern are changed randomly. In addition, assigned partitioned subarea changes randomly from their borders too. It means this part of mutation operator improves the first phase area partitioning result. Fig. 5 shows border of partitions which can changes to another partition (Energy limitations of micro robots are considered).

At each generation, after running crossover and mutation operators some of chromosomes need to be recovery for avoidance of inconsistent results. Therefore after running crossover and mutation operators, if dedicated movements where bigger than i[th] robot energy, recovery process is applied on the related chromosome (see □4)).

$$\sum_{i=1}^{L} P_k count > R\_Energy(i) \rightarrow recovery \qquad (4)$$

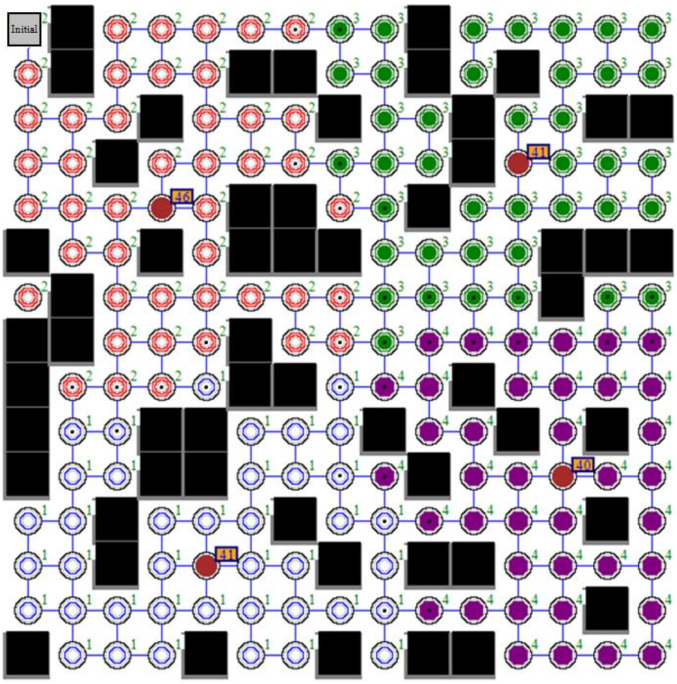

Fig. 5. The border of partitions for mutation at partitions (black pointed disks).

At recovery process after running crossover and mutation operators the additional movement robots are removed by selecting the biggest $P_k count(i)$ and decreasing it to suitable value for related micro robot.

EMMRIC fitness function is shown in (5), at fitness function energy consumptions of micro robots' movements are considered. These energy usages include straight movements and rotations to each sides with considering repeated coverings at area by micro robots.

$$Fitness(i) = \sum_{j=1}^{N_m}((\sum \text{straight moves})*\mathrm{E}_{stright} + (\sum \text{turning})*\mathrm{E}_t)) \qquad (5)$$

$Fitness(i)$ calculates the i[th] chromosome fitness value, $\mathrm{E}_{stright}$ is needed energy to straight movement of robot, E_t is needed energy to each 90° rotation of robot, (for instance at 180° rotation two turning counting). In our method best chromosome is the one with low $Fitness(i)$ value.

In Fig. 6 the result after running proposed EMMRIC is illustrated by considering four micro robots. In this Fig. 6 the path for each robot is shown with numbers at right down corner of each disk. Also each robot start point is colored with black.

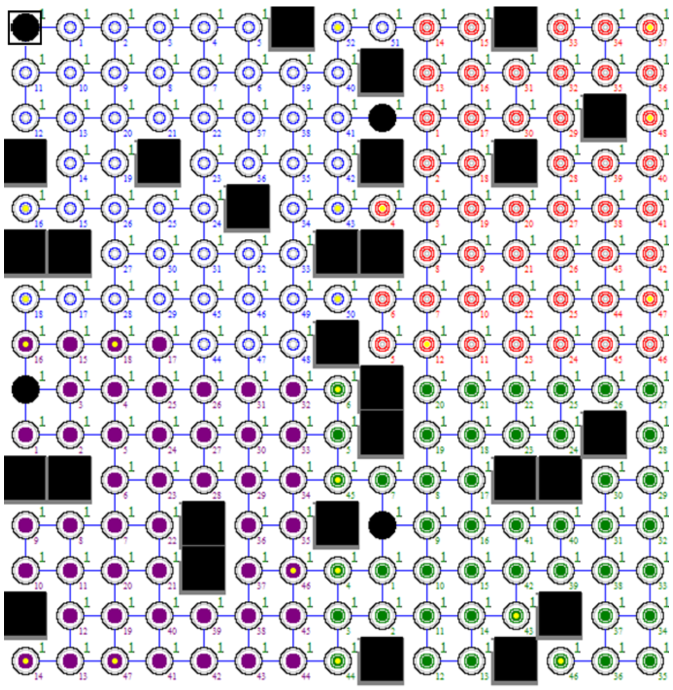

Fig. 6. One sample result of implemented proposed EMMRIC. The black disks are shown for micro robots start points and right-down corner numbers are for following path order of each robot.

V. Simulation Results and Analyses

In this section, the performance of the proposed method is tested in implemented simulator. We compare our proposed EMMRIC against most related state-of-the-art method at [11] in terms of decreasing energy consumption. For decreasing the energy consumption we consider minimizing the robots passed path and redundant area coverage. We named the proposed method in [11] as Pattern-Based Genetic Algorithm (PBGA) all over the Section 5. Assumptions of simulations are as follow: Environment size: $20*20_{disks}$, population size: 500, number of generations: 1000, mutation probability: 0.05, number of micro robots: 8, number of migrated elite: 10% and obstacles distributed randomly in the area. Also we should mention in proposed EMMRIC energy limitation of robots considered enough for 80 movement (include rotations and going straights).

Fig. 7 shows the results of both of the EMMRIC and PBGA on average passed path by micro robots. It is worth mentioning that, energy conservation is very important factor at micro robots. Fig. 7 shows that the proposed EMMRIC decreases average path length of robots, which consequently effects on the energy conservation in micro robots. In EMMRIC the improvement average percentage after 800 number of generation is about 18 percent in comparison with PBGA.

In Fig. 8 we implemented 20*20 disks environment for various number of robots. This figure shows the total redundant number of covered disks by increasing the number of robots. The results show that, proposed EMMRIC at high number of robots obtains lower redundant covered disks (averagely about 25 percent). This reduction proves energy reservation of EMMRIC in comparison with PBGA.

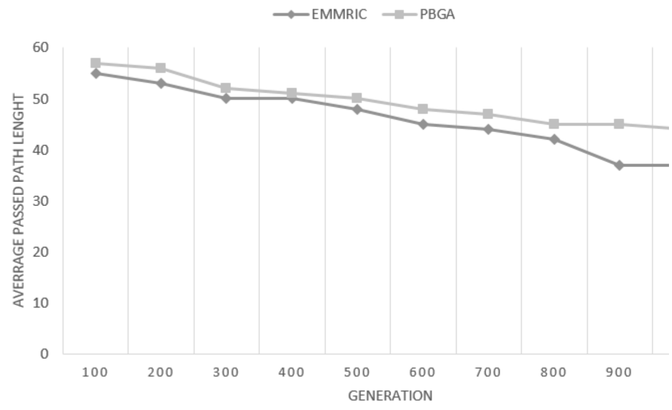

Fig. 7. Average passed path length by robots at different generations.

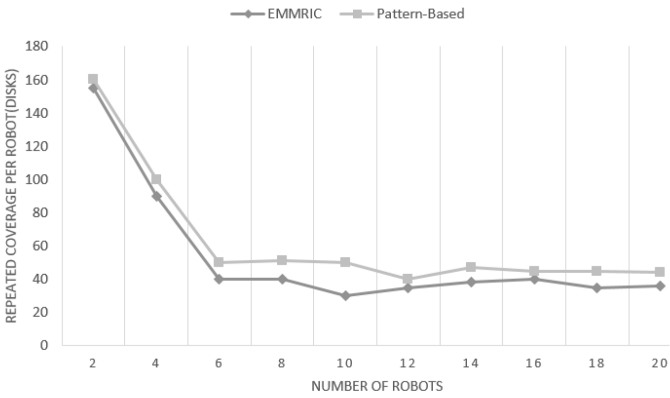

Fig.8. Total redundant number of disks by increasing the number of robots.

VI. Conclusion

In this article an energy efficient metaheuristic method for micro robots indoor area coverage problem (EMMRIC) proposed. According to the characteristics and limited energy of micro robots, EMMRIC aims to minimize the energy consumption with considering robots limited energies. The proposed method had two main phases; partitioning area to subareas with proposed restricted k-means algorithm and finding path for each micro-robot to cover its assigned subarea by proposed pattern based GA. Analyzing performance of the EMMRIC proved the superiority of this method in comparison with state-of-the-art method (PBGA). The obtained results shown that EMMRIC decreased average passed path length for about 18 percent, and redundant covered areas by micro-robots for about 25 percent.

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