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The path planning of cleaner robot for coverage region using Genetic Algorithms

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HIGHLIGHTS

- Method for the path planning of cleaner robot for coverage region.
- Genetic Algorithms approach.
- To demonstrate the efficiency and feasibility of our approache and validate the results obtained, we conducted a numerical comparison.

ARTICLE INFO

Article history:
Published online 27 May 2016

Keywords:
Vacuum cleaner robot
Artificial intelligence
Path planning coverage region
Genetic Algorithms

ABSTRACT

The vacuum cleaner robot should have a mechanism such as the artificial intelligence to solve the problem of cleaning the entire environment areas taking into account some factors such as the number of turns and the length of the trajectory. This robot's mechanism or task is known as the path planning of coverage region (PPCR). In this paper, to resolve the problem of PPCR in a room environment, we propose an evolutionary approach. The latter is based on Genetic Algorithms (GA) which, consist of several steps to get the solutions. Each gene represents the robot position and some of chromosomes represent also the mini-path. In addition, this algorithm helps the robot to pass through every part of the environment by avoiding obstacles using different sensors. The results of simulation and comparison studies demonstrate the effectiveness and efficiency of the proposed approach.

1. Introduction

Artificial Intelligence has fully assisted in the use of many robotic applications such as mobile cleaning [1], elderly people [2], underwater [3], aerial vehicles [4] and agricultural robot [5].

Vacuum cleaner robot, for instance, sweeps every accessible area in the entire room environment. This mechanism is known as path planning of coverage region (PPCR) [6].

Several coverage path planning approaches are proposed [4,7,8]. These methods in [4,7,8] are not efficient for the PPCR simply because they neglect the unknown environment.

Hence, map building is an important task for the PPCR [9]. We can get these map building by using the sensory data obtained from the deferent sensors through camera, infrared

Peer review under responsibility of Qassim University.
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http://dx.doi.org/10.1016/j.jides.2016.05.004

sensor and ultrasonic sensor. After that, it is combined with an algorithm to form a PPCR [10–12].

However, the works [10–12] on PPCR did not guarantee the dynamic environment.

Many kinds of algorithms and approaches have been used to accomplish the task of a PPCR with dynamic environments [10,13].

These approaches [10,12,13] have not take into account the optimization of the generated path length, the number of turns and the revisited areas.

The Genetic Algorithms (GA) yielded warrant results in many fields, such as finding the shortest path [14].

Therefore, this paper focuses on PPCR of vacuum cleaner robot in the room environment using a Genetic Algorithms.

The proposed GA model is inspired by John Holland [15]. In the proposed model, the map is built on a disk shape which represents the robot position that are connected to each other with only local lateral connections. The proposed model does not require knowledge of the room environment in advance, so it works in a real time and in a dynamic environment.

This paper is organized as follows. In Section 2 we explain the robot's task and the environment modeling. In Section 3 we give a brief description of the evolutionary approach and its application on the path planning of coverage region. The simulation studies with comparison to a conventional approach are given in Section 4. Finally, conclusion is drawn in Section 5.

2. The vacuum cleaner's task and the environment modeling

2.1. *The vacuum cleaner's task*

To clean an empty room two ways can be used the spiral or the zigzag motion trajectories.

The vacuum cleaner robot has an important mission which is to sweep every accessible area in the entire environment avoiding obstacles. When the robot pass through an area position it will be cleaned and if not yet it remains unclean.

This task is named the path planning of the coverage region (PPCR) in which the robot should sweep each accessible free area and avoid obstacles with an efficient trajectory.

This efficient trajectory should be short in distance and contains a minimum number of both turning angles and revisited cells.

2.2. *The environment modeling*

Before the vacuum cleaner robot starts its task, an important aspect must be guaranteed which is the modeling of the environment.

The environment modeling is depended to the map of the workspace which is built using the sensory data obtained from different sensors through camera, infrared sensor and ultrasonic sensor.

The workspace W is discretized by discs as a shape of cleaning robot instead of rectangles or squares to facilitate the motion of this robot. It is assumed that the diagonal length of a discrete area represented by that disc cell should be equal to a sweeping robot diameter.

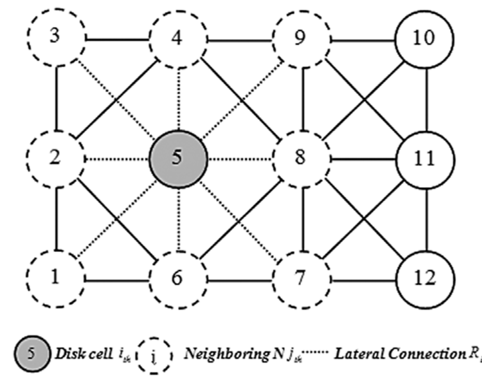

Fig. 1 – The environment modeling.

Each disk ith represents whether an obstacle or a free position for the robot to occupy in the environment. Each connection has a maximum eight of neighboring position jth. The connection R_{ij} between two neighboring disks represents the Euclidean distance between two positions as shown in Fig. 1.

3. The path planning of the coverage region by evolutionary approach

To get an efficient trajectory of the PPCR for the vacuum cleaner robot, we proposed in this paper, an evolutionary approach.

This approach is based on the Genetic Algorithms (GA) which is inspired by evolution via natural selection, to solve optimization problems.

3.1. *The path planning method*

In this paper, the path which is traveled by the robot from a start position $P_S(x, y)$ to an exit position $P_e(x, y)$ with passing over all accessible positions and avoiding obstacles is named the global path planning for the coverage region.

To get this global path, it should be divided into mini-path, the latter must not exceed the range of the sensor as shown in Fig. 2.

The mini-path contains some positions $P(x, y)$ which are occupied by the robot during its displacement. These positions become cleaned but the others remain unclean until they are taken into consideration by the next mini-paths planning.

The aim of our work is to get an efficient global path, for this, the mini-path should be so as automatically efficient and it will have a short distance, a least number of both turns and repeated cleaned positions.

3.2. *The evolutionary approach*

To minimize the number of turns, the multiple visits of cleaned cells and the trajectory distance, we proposed an evolutionary approach which is based on Genetic Algorithms (GA).

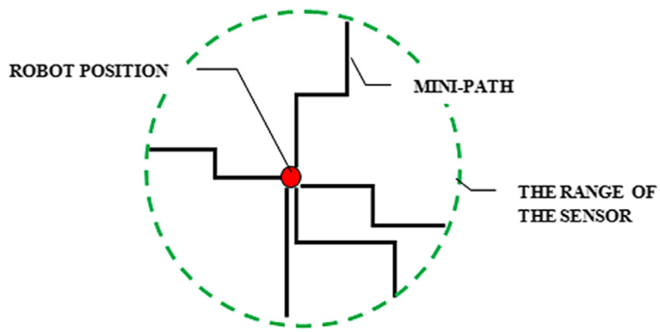

Fig. 2 – The path planning method.

The GA helps the vacuum cleaner robot to find an efficient path and clean all accessible areas from a start position $P_S(x, y)$ to an exit position $P_e(x, y)$.

The GA were invented by John Holland. It consists of several steps in which the first step is initialization of the solutions (genome or chromosome). After that, the evaluation of these population is launched using the fitness functions, from this evaluation we can pass to the following generations which have the higher fitness values. The operators inspired by biologic genetic variation are applied by remplacing the existing chromosomes by the new populations to preserve the constant number of chromosomes.

These operators which that are popular used are selection, crossover and mutation. All of these steps should be passed by the process genetic that is shown in Fig. 3. For more clarification, we described as follows how this process can help the robot to solve the problem of PPCR.

3.2.1. *Encoding and representation*

After the environment modeling is finished. Each disk has an own number. The gene is made of one part which represents this number disk.

In the path planning of the coverage region, the gene corresponds to an elementary movement of the robot. The chromosome consists of genes, so it corresponds to the mini-path which is described in precedent sections.

In this study, The chromosome contains a some of genes, the latter should be belong to the rayon of the sensors. To more clarification an example is illustrated in Fig. 4 in which we notice that any gene which is located between the robot position and the circular area is taken into consideration to form a chromosome. For example if we take the mini-path number 3, the robot should pass over 5 disks or positions (disk 32, 33, 26, 19, 12), this allows to create a new chromosome which should contain 5 genes, so that the encoded of each gene should correspond to one of disks or positions and take its number.

The order of genes in chromosomes should be obligatory because it represents the different positions that take the robot.

3.2.2. *Generation of initial population*

In this phase, the mini-path planning is random by choosing a neighboring positions if possible. Therefore, random chromosomes are generated for each mini-path in which we can get different proposed paths with two standard ways spiral or zigzag motion as shown in Fig. 5.

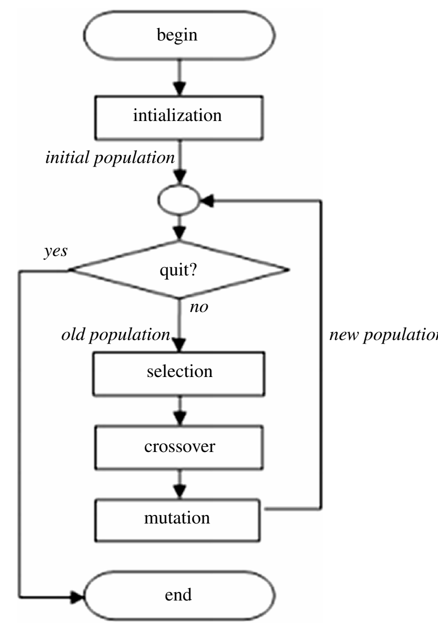

Fig. 3 – The Genetic Algorithm process [16].

3.2.3. *Fitness function and selection*

A fitness function is necessary to know the detailed description and solution of the problem. It is directly related to the constraints of navigation coverage, ie the absence of collisions, reduced road size (battery life).

To evaluate the fitness of individual mini-paths three parameters are taken into consideration: the total distance of the mini-path, the number of consecutive unclean cells and the total distance of each position cell relative to the current robot position. An appropriate fitness function of mini-path (i) is constructed as:

$$F_i = A * Dist(i) + B * \sum Free(i) + C * \sum Dist(x_c - x_j^i) \quad (1)$$

where A, B, C are the constant number and $Dist(i)$, $Free(i)$ and $Dist(x_c - x_j^i)$ are the distance of mini-path, number of free cells and the distance of the free cell relative to the current robot position respectively.

- *The total distance of mini-path*: It is calculated by the sum of each distance between two cells position in which this distance represents the Euclidean distance as shown in Fig. 6.

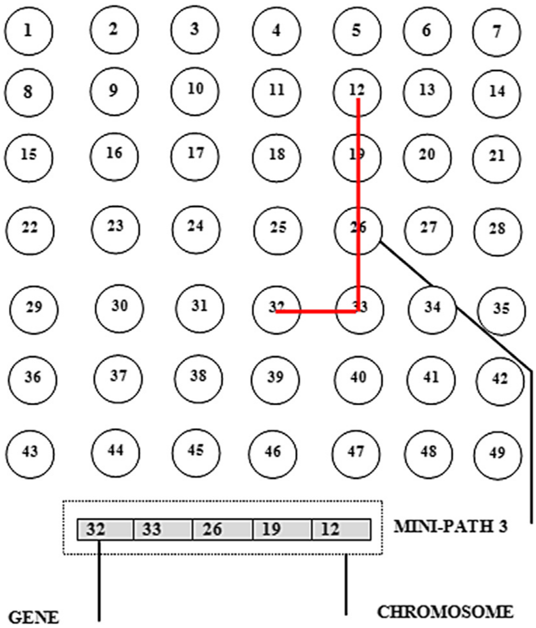

Fig. 4 – The Gene.

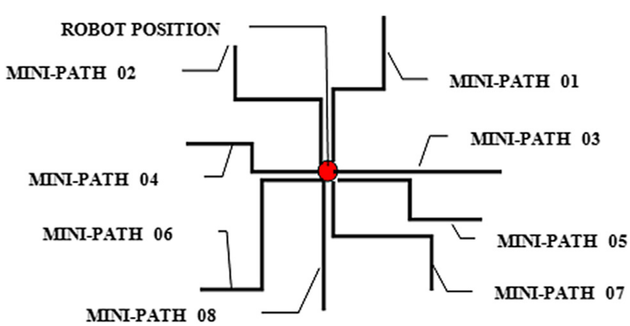

Fig. 5 – Random mini-path with two ways of motion.

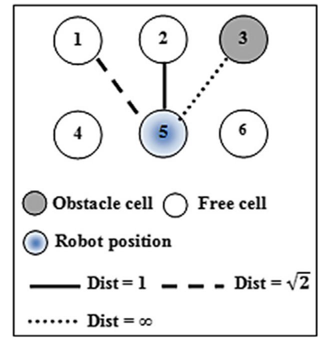

Fig. 6 – The Eucledean distance between two cells positions.

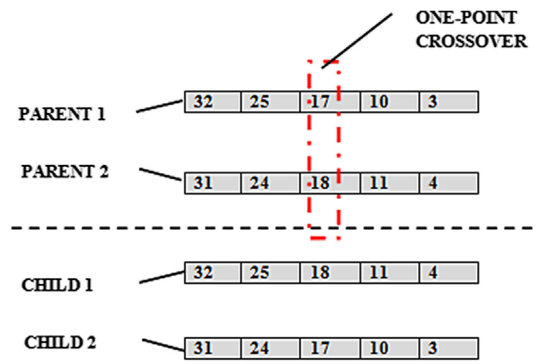

Fig. 7 – The crossover operator.

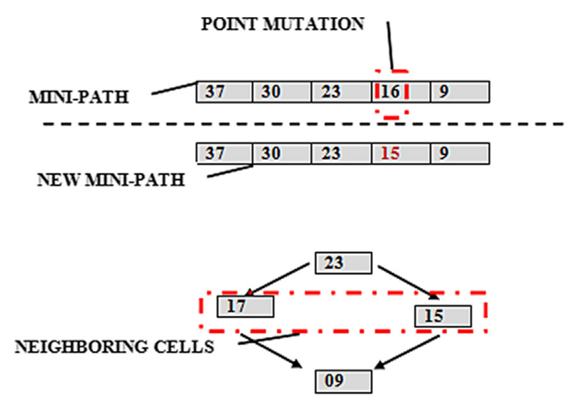

Fig. 8 – The mutation operator.

- *The number of unclean cells*: It is the number of consecutive unclean cells which belong to the mini-path from the current robot position.
- *The total distance of each position cell relative to the current robot position*: It represents the distance on the $X - Axis$ between the current robot position x_c and the unclean cell position x_j which belongs to the mini-path (i).

The ideal fitness is the solution which contains no redundant visited and obstacles cells. Stochastic tournament selection with elitism is applied based on fitness values.

3.2.4. *Genetic operators*

Crossover and mutation are applied and adapted to improve the fitness.

- *Crossover*: After two mini-paths were selected by the selection operator, they will be considered parents. The crossover operator allows the generation of children to inherit the genetic code of the mixture between the father and the mother. We opted for a one-point crossover techniques and the two children are then added to the population. An example of crossover operator is illustrated in Fig. 7 in which we notice that from the point crossover (the third gene), the gene's value of chromosome1 are replaced by the gene's value of chromosome2 and the same case for the chromosome2. Therefore, we obtained a new two mini-paths.
- *Mutation*: It is used to incorporate the exploration impact. The gene's value is modified by one of the neighboring's precedent gene. The selected point of chromosome is random as shown in Fig. 8.

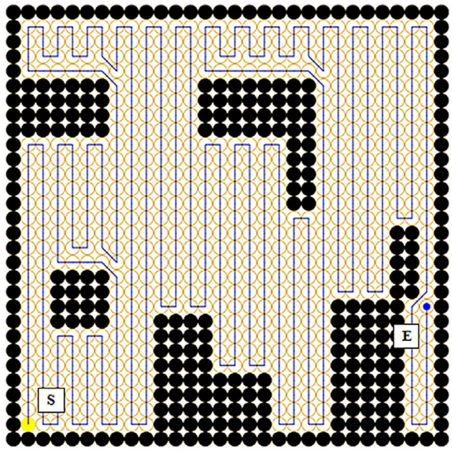

Fig. 9 – Path planning of the vacuum cleaner in a dynamic environment.

4. Simulation results

In this section we present a simulation of the proposed genetic algorithm which are applied to resolve the problem of the path planning of the coverage region (PPCR) for the autonomous cleaning robot in a simulation environment. For this, The environment is modeled with disks cell. The algorithms are examined in different states of this model of the environment and compared with different existing methods also.

The simulations are implemented in C#. The bound wall of the workspace is assumed to be known in the simulation.

4.1. *Tested in an unknown environment*

To verify the effectiveness of GA algorithm, we examined this simulation in an environment which contains obstacles.

This test is applied to a room environment where it is modeled with 28×28 disks as shown in Fig. 9. The obstacles, initial and exit positions of the robot are represented with black, yellow and blue disks respectively. The parameters of the GA algorithm are set as: Population size is 50, crossover probability is 0.85, mutation probability is 0.2, number of iterations is 400.

In this test the robot has not any information in prior about the environment, it depends on its different sensors to obtain the sensory data. We assume that the robot's sensory range is limited with radius of $R = 6$, the robot starts from the position $S(1, 1)$. During its displacement, the robot moves from its current position to another position and the thick line is constructed to show the mini-path which is planned by the GA algorithm. It will follow the same previous step until it meets the last exit position $F(28, 9)$. The robot traveled an ordered zigzag path, from bottom side to top side, then from top side to bottom side, to cover and clean the whole workspace with obstacle avoidance. After certain time, all of these generated mini-paths form the global path planning for the coverage region between the start position to the exit position as shown in Fig. 9.

4.2. *Comparison with ORD and SCD algorithms*

To illustrate the effectiveness and efficiency of the proposed algorithms some experiments are carried out in which we compared this proposed model with existing methods as the combine of scan matching and oriented rectilinear decomposition (ORD) [17] which divides the workspace into cells at each scan simple, these cell boundaries are formed by extended critical edges which are the sensed partial contours of walls and objects, an other method the spatial cell diffusion (SCD) [18] which encodes the target area as groups of Gray codes for grid cells with size of instantaneous robot coverage and extends its sweep area by diffusing occupied cells outwards through continuous spiral movement. For this, these methods are coded in C# and they are tested in the simulation environment which is modeled by 20×20 disk cells. For each simulation, we measured some quantities: the turning direction, the revisited cells and the length distance traveled by the robot.

We assumed that all of these algorithms are the same start position and the same environment which has 20×20 disk cells.

The start position $S(1, 1)$ is designed and some obstacles are placed into a room environment.

In Fig. 10(b) after the cleaning robot uses the SCD algorithm and arrives at position $A(1, 20)$. Then, it will be blocked. After that, the robot moves to another zone that is not cleaned yet by going backwards.

Next, the SCD is applied again to complete the cleaning of all unclean areas of the room.

In Fig. 10(c). The cleaning robot uses the ORD algorithm which is based on the combined of scan matching and oriented rectilinear decomposition.

The proposed algorithm is tested in the same case of environment where the generated path planning for the PPCR using this approach is illustrated in Fig. 10(a).

As seen in Fig. 10(b). The cleaning robot was blocked several times at position A, B and K, this caused to generate a path that contains many cells which the cleaning robot sweeps repeatedly compared with the generated path in Fig. 10(a)–(c).

To better understand, the results of the methods to path planning for PPCR are summarized in Table 1. For each algorithm, we calculated the distance traveled and the number of both revisited cells and the numbers of turns by the cleaner robot.

Table 1 shows that the SCD algorithm has the worst results because it has the greatest length of path planning (365.0 units), the number of turns (124.0) and revisited cells (16.0) than the other algorithms.

The ORD algorithm has the least length of distance traveled by the robot (349.0 units) but the number turns (106.0) is higher than our proposed algorithm.

We cannot decide that the path is efficient from a single best parameter but all of the parameters described above in Table 1 should be taken into consideration.

If we take into account all of these parameters from the Table 1, we notice that our approach has an efficient path for the PPCR by reducing the length of the traveled path, the

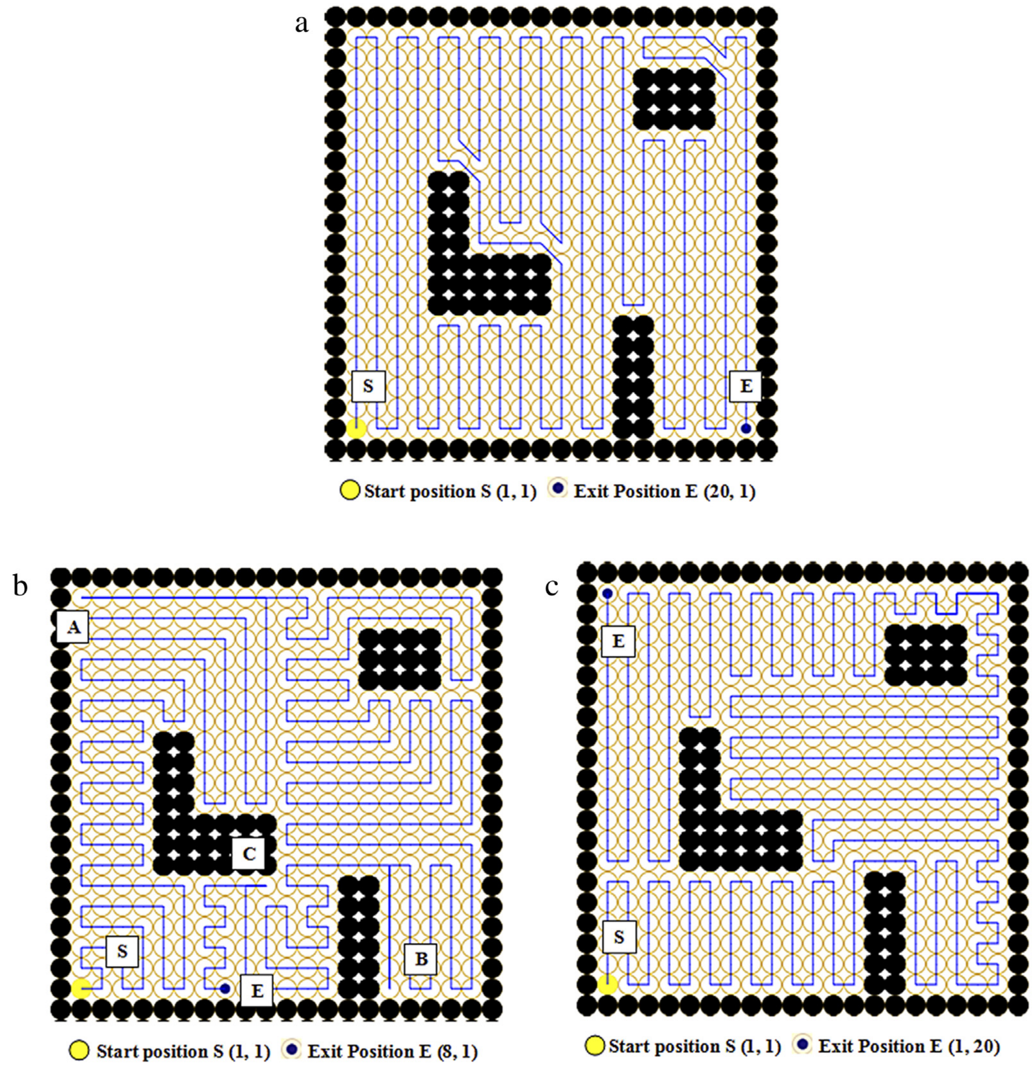

Fig. 10 – The path planning for coverage region using (a) The proposed Genetic Algorithm (b) The SCD algorithm (c) The ORD algorithm.

number of both turns and revisited cells compared to the other algorithms.

Therefore, this parameters have a strong impact on the PPCR in which the robot can sweep and clean all the accessible environment in a fiew time.

Table 1 – Comparison between the ORD, the SCD and the proposed Genetic Algorithm in the PPCR shown in Fig. 10.

Algorithm	Revisited cells	Turns	Length
SCD algorithm	16.0	124.0	365.0
ORD algorithm	0.0	106.0	349.0
Proposed algorithm	0.0	62.0	351.46

5. Conclusion

We presented in this paper the path planning of the coverage region (PPCR) for a vacuum cleaner robot using the genetic algorithms (GA) which generate an efficient path to clean all accessible areas in the room environment. The proposed algorithm uses an evolutionary approach which is based on Genetic Algorithms (GA). In this paper, we described how the steps of the GA can represent the global trajectory and how we divided this global path into mini-paths. We also demonstrated the efficient and robustness of this algorithm to embedded the robot to attain complete coverage in a different case of the environments during the simulation. In addition, we compared this model with some of existing methods in the literature and it proves some advantages by reducing the length of the trajectory, the number of turns and revisited cells.

Therefore, all of this parameters have contributed to clean this room in a few time. But, in the future, it needs to be tested in more complex environment and studied for multiple robots.

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