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"Nearest Zero-Point" Algorithm for Cooperative Robotic Search Missions

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Abstract

Four path planning and data exchange algorithms for cooperative search and coverage robotic missions are proposed and modified. The introduced methods are simulated using C++ programming environment and the results are discussed in detail for environments with static obstacles. It has been shown that using the ***"nearest zero-point"*** *algorithm can greatly optimize the mission duration and also overlapping of the search trajectories. Finally, the results are compared with several existing algorithms.*

Keywords*: Cooperative Search, Artificial Intelligence, Robotic search, Grid-based Algorithm, Optimization*

1. Introduction

Recent years have witnessed the development of robots for carrying out different missions, such as hazardous missions for human beings. Search and coverage missions are among the important missions, in which robots are employed for searching an environment that is unsafe for human presence. The first issue to address, while searching an environment using cooperative robots, is to prevent them colliding with one other or obstacles in the environment [1]. Secondly, in order to save energy and time, it is of prime importance to minimize the duration of cooperative search mission. The main objective of path planning is to find an appropriate path for the movement of robots in an environment, in order to avoid collisions between them, reducing the mass of the data calculations for finding the right path and also minimizing the search mission duration and energy consumption [2]. Consequently, the chosen search trajectories should be optimized to account for the mentioned factors. To this aim, robots must cooperate with one another, mainly by sharing their individual search data base, to guarantee a safe and efficient search and coverage mission.

This paper applies a grid-based method for defining the search environment. Grid-based methods utilize geographically distributed locations data sources in order to provide users with the access to a scattered large database. Such techniques make use of the grid resources to perform the search tasks and also to improve the search performance. The following research intends to address both aforementioned issues in the first paragraph, by proposing four grid-based cooperative search and coverage algorithms. The efficiency of each algorithm is then evaluated in terms of mission duration and overlapping search trajectories by simulating the search mission in C++ environment and finally, a

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comparison between the studied algorithms and several existing search algorithms is provided.

The next section introduces the related search and path planning algorithms and their demerits. After that, the problem statement is mentioned in order to identify the gap in current literature following by the intended contribution of the presented research to the field of knowledge. Finally, the efficiency of the proposed algorithms is measured and results are discussed.

2. Related Works

Overall, the problem of cooperative path planning can be divided into four sub-problems; expression of the search environment, path calculation, path execution and also communication between the agents. Most of path planning algorithms available in the literature are based upon the theory of visibility graphs [3], Voronoi diagram [4], grid-based [5] and artificial intelligence-based [6] methods each having its own advantages and shortcomings. For instance, Voronoi diagrams methods are one-dimensional in nature that may lead to an inaccurate representation of the search environment which eventually degrades the path planning efficiency [7]. On the other hand, artificial intelligent-based methods, *i.e*. genetic algorithm methods, are proven to be suitable mostly for handling small-scale problems because of their huge computational burden [8].

Among the introduced methods previously, grid-based methods are of interest to this research, since such methods are easy to set-up, as well as fast and reliable in comparison with the other mentioned techniques. Koceski and Panov applied the method successfully to a gridded environment consisted of obstacle occupied and empty cells [9]. To find the optimum path Dijkstra algorithm has been used; however, the method has its own disadvantages. In this algorithm the processing of the data of individual cells of the environment takes too long which in turn degrades the overall efficiency of the algorithm. To overcome this problem, a quadtree method has been deployed in [12]. A different approach to Dijkstra algorithm, known as A* algorithm, has been used in parallel with the Dijkstra by Zhang and Zhao [10]. Although, the process flow of the algorithm is complex, so that efficient application of A* algorithm requires deep knowledge of mathematics. The combination of hormone-inspired path planning methods, a kind of grid cell marking *i.e*. by numerical value *etc.*, and the gird based methods can provide an optimum search algorithm [11]. The marking of map cells enable the robots for updating a section of the map that may contain different sorts of information and data, such as compulsory operations, hazard warnings and also number of times each robot searches that particular area. The overall efficiency of this method becomes better as the number of searching robots increases; however, the increase in number of searching agents raise the computation burden for path planning.

Generally speaking, the current literature still demands comprehensive researches for considering majority of the parameters involved in a real search mission altogether. This paper presents a novel research, since it covers issues such as search duration minimization, search trajectory overlapping minimization, efficient data transferring among agents, alongside implementation of a real-time search mission simulation of a static environment in C++ environment. Consequently, the proposed research provides solution for all of four sub-problems mentioned earlier in this section.

3. Problem Statement

Before implementing a robotic search mission, it is important to simulate the whole mission using computers. As a consequence, general shortcomings of a search scheme are identified and probable failures like damages to robots due to collision can be prevented. It is however, important to note the limitations of a robotic search mission simulation,

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which hinder the realistic evaluation of the mission. An efficient robotic search simulation must consider the real search scenarios such as presence of obstacles in search environment, limitations in communication range of search agents in cooperative search missions, energy consumption management, *etc.*

The following research intends to provide a realistic cooperative search simulation algorithm called "digital environment marking", by addressing most of aforementioned limitations. In this research search environment is represented by grid of identical digitally marked cells, each contains number of times the cell was being searched. Robots can move between adjacent cells including diagonally placed cells; while, they have limited information about the other agents surveying the area. During the search mission, information can be exchanged if robots are close enough to each other. Four search algorithms based on digital environment marking concept are proposed. Finally, the goal is that each cell is visited at least once by any of the robots as soon as possible. The novelty of the presented research can be concluded in the following lines:

1. In the proposed method, the obstacles can be defined accurately, whereas the polygon division of the environment method [13] lacks such a characteristic. This helps in producing a realistic simulation of the mission.
2. Since the number of times a cell in the environment is searched is specified, the robots can easily detect the cells those have been searched less. This approach eventually reduces the overlapping of the search trajectories and also mission duration.
3. In the introduced methods, each robot saves and processes the recorded search data (cells' information) independently and updates its own data-base only when it approaches other robots; therefore, in case of the malfunctioning of one or more robots, the rest of the properly functioning robots can carry out the search mission to the end without any limitation. This kind of encounter with possible accidents has not been dealt with in the other similar methods such as the methods based on the centralized learning methods [15].
4. The algorithms do not require the robots to be in touch with each other all the time, or even with the central operator. Therefore, the optimum use of the communicational receivers and transmitters can greatly improve the energy consumption. Lack of a central operator, or in other word, this autonomously functioning method minimizes the human intervention.
5. Using an innovative data exchange technique, called "nearest-zero" algorithm, greatly improves the cooperation efficiency between robots which results in an optimized computation burden of the algorithm and also a short search mission.

The following section explains the general methodology of the research. Four grid-based cooperative search algorithms are then introduced and comparison is made between them in terms of search trajectory overlapping and also mission duration time-step.

4. Research Method

This section contains explanations on representing the search environment, introducing the structure of the algorithms, path planning of search agents, and the way they interact and cooperate with each other. The whole search mission has been simulated using C++ programming environment and artificial intelligence programming techniques, which includes simulation of the robots' path planning, the environment, the sensors' range, and the way robots cooperate. In this research, it has been assumed that:

1. The obstacles in the environment are all static.
2. Obstacles have been considered as a collection of square cells. If the obstacle size is smaller the cell size, then the whole cell is considered as an obstacle.
3. The search trajectory of each robot consists of segments.

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4. The communication range of the robots is limited. Each robot informs the other robots of its decisions only when it is in the communicational range of them.
5. The decision making and obstacle sensing delay time has been ignored; therefore it does not affect the calculation time of a path.

5. Algorithm Design

When addressing for mathematical modeling of the obstacles, before starting the simulation, it suffices to assign a high value to the cells with obstacles (Namely 999 or 9999, *etc.*) and "0" to the cells without obstacles in the numerical field map of the environment. After the simulation starts, each time that a cell is being searched by robots, its value increases by one unit. Therefore, the numerical value of a cell at a given iteration indicates the number of times that the cell has been searched until that iteration.

In general, dividing the environment into cells and the necessity of cooperation between the agents requires that each agent to deal with 9 cells simultaneously. The algorithm starts with the robots situated at their initial positions. As the search mission starts, each robot searches its 8 neighboring cells and then moves to cell with minimum value (Figure 1).

	*	*	*	
	*	A	*	
	*	*	*	

Figure 1. Eight Different Choices (Cells Indicated by "*") for the Movement of the Robot A

If the minimum values of several neighboring cells are the same, algorithm chooses one of them at random. As the robots come approach each other so that their position becomes within the sensing range of the other robots, they exchange their recorded search data and update their own maps of the environment so that they all become identical. As it will be seen later, the way a robot combines its own data with those that it receives from the others significantly affects the performance of the algorithm.

The search algorithm continues until all the cells have been searched and finally when each robot searches the last "0" value cell, the mission terminates and the number of search iterations (search duration) and the final map including final the numerical values of the cells are sent to the printer as the output. The pseudo-code of the digital marking method is as follows:

```
voidsearchMap{
        Let time to 0
                for all robots do{
                if all the cells have been searched
                        return number of iterations
                Let Around[8] to the value of the eight neighboring cells of
                                thisRobot
                Let Minimums[] to the minimums of the Around array
                Target = choosing a random block in the Minimum's array
                                move the robot position to Target
                                value(robot.position) = value(robot. position) + 1
                for i from 0 to the number of robots
                        if thisRobot and robot[i] are close to each other
```

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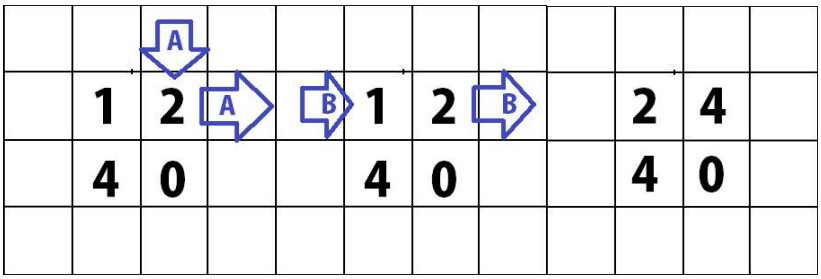
```
                changeData(thisRobot, robot[i])
        time = time + 1
                }
        }
```

5.1. Z Data Exchange Algorithm

A similar approach to the digital marking method called "Z data exchange" algorithm is introduced in this section. The difference between the algorithm and the digital marking method is in the way robots update their maps when they exchange their recorded search data-base. For the sake of clarity, suppose that the agent A and B, without getting close to one another, search certain parts of the map within different time intervals (Figure 2a and b). According to the criteria of the Z data exchange method, when the agents A and B approach each other, their maps will look like as the one in Figure 2c, where the numerical value of each cell indicates the total number of times the robots have searched it. The pseudo-code for the Z data exchange method reads as follows:

```
voidchangeData (robota,robot b) {
        Let t* to time
        Let t0 to last time robots have seen each other
        Let h(i,j,t) to the value of (i,j) cell in the map at time t
        Let finalValue[][]
                for i from 0 to row
                for j from 0 to column
                        finalValue = a.h(i,j,t*) + b.h(i,j,t*) - b.h(i,j,t0)

                a.value = finalValue
                b.value = finalValue
return
}
```



(a) (b) (c)

Figure 2. (a) and (b) are the Way that Robot A and B Search the Shown Part of the Map. (c) The Same Map after the Robots Met

5.2. Z* Data Exchange Algorithm

The second data exchange algorithm, called the "Z* data exchange", follows the same procedure as the previous algorithm; however, the only difference between them is that when the robots meet and compare their maps with each other, the maximum value of each cell is recorded on the final map (Figure 3). Therefore, in this method the numerical value of the cells at a given iteration of the mission is not the number of times that the cells have been searched anymore. As we shall see later on, this method is more efficient

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than the previous one. The pseudo-code for the Z* data exchange method reads as follows:

```
voidchangeData(robota,robot b){
        Let finalValue[][] = 0
                for i from 0  to row
                        for j from 0 to column
                                finalValue[i][j] = maximum of a.value(i,j) and
                                                        b.value(i,j)
                        a.value = finalvalue
                        b.value = finalValue
return
```

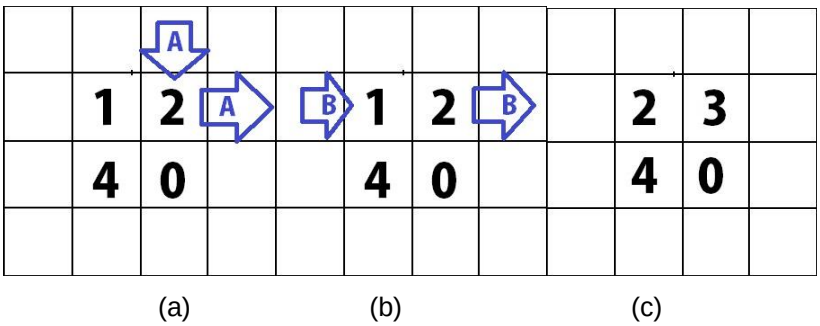

Figure 3. (a) and (b) are the Way that Robot A and B Search the Shown Part of the Map. (c) The Same Map after the Robots Met

5.3. Double-Layer Search Algorithm

The two previously mentioned algorithms were intended to alter the data exchange criteria of digital marking method. Additionally, the following two algorithms are expected to change the path planning algorithm of the digital marking method. In the first algorithm called "double-layer search", each robot not only searches its nearest 8 neighboring cells but it also searches its 16 second nearest neighbors. Therefore, when the minimum numerical values of more than one of first nearest 8 cells are equal, then the robots' next destination cell is not chosen at random. In this case, for each cell the numerical values of its 3 nearest neighbors are also taken into account and minimum of the sum of numerical values of these 3 neighboring cells is chosen as the destination for the robot. For example, in Figure 4, if the numerical values of the cells 0* and 5* are equal and also minimum among 8 first neighboring cells of robot A, then the robot A calculates both the sum of the numerical values of the cells 8, 9, and 10, and the sum of the numerical values of the cells 11, 12, and 13. Therefore, regard to which one of them is minimal, the robot moves either to cell 0 or cell 5.The pseudo-code for the double-layer search method is as follows:

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```
voidsearchMap{
        Let time to 0
                for all robots do{
                        if all the cells in the map have been searched
                                return number of iterations
                                Let Around[8] to the value of the eight
neighboring cells                                                       thisRobot
                        forI from 0 to 8
                                Around[i] = Around[i] +
aroundValus(Around[i].position)
                                Let Minimums[] to the minimums of the Around
array
                                target = choosing a random block in the
Minimums array
                                move the robot position to target
                                value(robot.position) = value(robot.position) + 1
                        for i from 0 to number of robot
                                if thisRobot and robot[i] are close
                                changeData(thisRobot, robot[i])
                        time = time + 1
        }
}
```

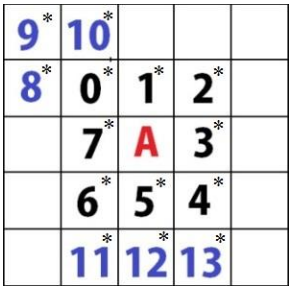

Figure 4. Double-layer Search Using Robot a (Each Number with "*" Identifies a Specific Cell and should not Confused with the Numerical Value of the Cell)

5.4. Nearest Zero-Point Search Algorithm

A novel path planning method, called the "nearest zero-point" search algorithm is presented herein. In this algorithm, each robot, not only searches the numerical values of its neighboring cells, but also, if it necessitates, it searches every cells in the environment and moves through the direction to the nearest cell that has not yet been searched. In fact, each agent measures the distance of its 8 neighboring cells from the nearest cell yet to be searched and chooses a neighboring cell as the origin of its next move that has the least distance from the nearest cell with zero value. If on its way to this cell, the agent encounters other agents, they start exchanging their stored data and if it finds that one of these robots is going to search a cell that it had already intended to search, changes its path and moves towards the nearest cell that has not yet been searched. In case the next destination of the robot is occupied by obstacles, the neighboring cell with minimum value that is still in nearest distance to a zero cell will be selected. The pseudo-code for the "Nearest-Zero Point" Algorithm reads as follows:

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```
float distToNearestZeroPlace(position a){
        Let Mine to 10000
        for i from 0 to row
                for j from 0 to column
                if min < (i - a.x) ^ 2 + (j-a.y)^2
                min = (i - a.x) ^ 2 + (j - a.y) ^ 2
        return mine
}
void searchMap{
        Let time to 0
        Let mines[]
                for all Robot do
                        if all the cells in the map are searched
                        return number of iterations;
Let Around[8] to the distToNearestZeroPlace of the eight cells around thisRobot
                        Let Minimums[] to the minimums of the Around array
                        target = choosing a random block in the Minimums array
                        move the robot position to target
                        value(robot.position) = value(robot.position) + 1
                        for i from to number of Robot
                        if thisRobot and Robot[i] are close
                                changeData(thisRobot, robot[i])
                time = time + 1

}
```

6. Mission Simulation

In this section the functionality and efficiency of aforementioned algorithms is evaluated. To this end, four simulation environments have been defined. The dimensions of the environments are all equal to 10×15 and they differ only in the number and distribution of the obstacles. In the first simulation experiment, the environment is considered with no obstacles (Figure 5a). Such an environment provides a possibility to examine the efficiency of cooperation among agents using each algorithm. In the second simulation experiment, a slab covering three cells, a local maximum or, in other words, a potential barrier [15], has been created (Figure 5b). In the third simulation experiment, a second slab has also been added, so the efficiencies of the algorithms could be studied in the presence of obstacles having no corner (Figure 5c). Adding the second obstacle has decreased the search area and, on the other hand, has increased the number of the local maxima. Therefore, the encounter of the algorithms with these two factors could be checked. In the fourth simulation experiment, more complicated obstacles are introduced and therefore the study of the efficiencies of the algorithms in dealing with the cells bounded from three sides becomes possible (Figure 5d).

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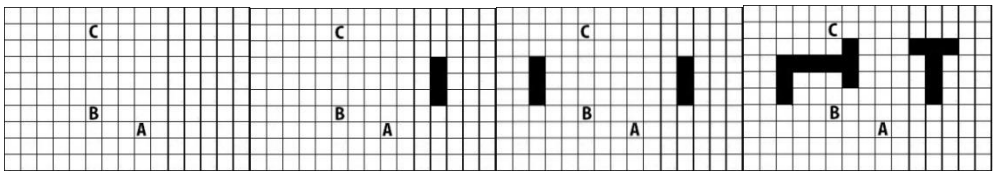

(a) (b) (c) (d)

Figure 5. The Simulation Environments and the Initial Positions of the Robots a, b, and c, at the Onset of the Search Mission

7. Results and Discussion

The results of the simulations in different environments are presented in this section. Table 1 shows the number of iterations takes for each one of mentioned algorithms to completely search the environments A to D (Figure 5) using three robots. The results reveal that when the number of obstacles increases, the Two-layer data exchange algorithm is more efficient than the Z data exchange algorithm which is due the structural difference between these two algorithms. This is a little improvement and does not show a difference more than 9 search iteration in whole of the search mission. In addition, Table 1 shows that when number of obstacles and corners of the environment increases, the Z* data exchange algorithm reduces the number of the search iterations by 21 iteration, and in comparison with the Two-layer data exchange algorithm, does a superior improvement. As is evident, "Nearest zero-point" algorithm has the least search iterations among four studied methods; it can reduce the search iterations of the mission by up to 20, 30 and 38 iteration compare with Z* data exchange, Two-layer data exchange and Z data exchange algorithm respectively.

In order to investigate the effect of the number of robots on the number of mission completion iterations using the presented algorithms, another simulation experiment has been conducted. For this simulation, the third environment in Figure 5 has been selected and different numbers of robots have been employed. The reason behind choosing the environment is its simple structure that allows for checking the data exchange parts of the algorithms. The results of the simulation are given in Table 2.

Table 1. Simulation Results for the Environments with Different Number of Obstacles being searched by Three Robots. The Total Number of the Cells in All these Environments is 150

Environment Type	(1)[1]	(2)[2]	(3)[3]	(4)[4]	(5)[5]
A	0	77.8	73.2	63.7	57.2
B	3	85.2	80.8	72.2	52.4
C	6	88.8	79.8	70.5	50.8
D	15	80.3	76.9	55.3	46.2

[1]Number of obstacles, [2]Number of search iterations in the Z data exchange Algorithm, [3]Number of search iterations in the two-layer data exchange Algorithm, [4]Number of search iterations in the Z* data exchange Algorithm, and [5]Number of search iterations in the "Nearest zero-point" data exchange Algorithm

Although it may seem obvious that the increase in the number of robots would cause decreasing the search iterations, it should be noted that the rate of the decrease in the search iterations is not the same for different algorithms and, as we shall see later, this indicates that some algorithms have a better cooperative functionality than the others. Table 2 shows that, considering Z* and "Nearest zero-point" algorithms, not only the

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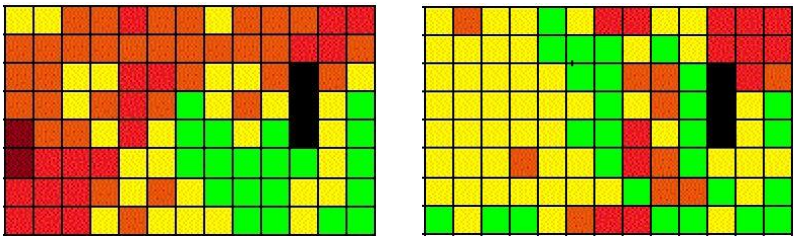
effect of the number of searching robots on the decreasing of the iterations of the search mission is much better than the other two algorithms, but also when one robot is employed in the search mission, the obtained results are comparable to the results of more complex data exchange algorithms [16] which is explained later in this section.

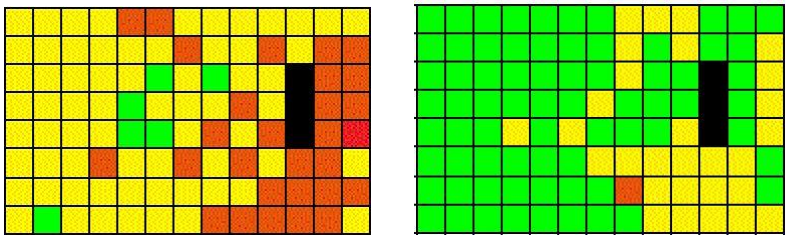
Table 2. Effect of Number of the Agents on the Number of Mission Iterations

Algorithm	Number of iterations for one agent	Number of iterations for two agents	Number of iterations for three agents
The Z data exchange	175	110	85
Two-layer data exchange	162	92	80
The Z* data exchange	156	88	72
"Nearest Zero-point" data exchange	121	77	52

In the second simulation experiment, the overlapping of the search trajectories has been studied. One of the criteria for measuring the optimality of a search algorithm is that the robots must search the environment uniformly, so that the number of the overlapping trajectories has been kept at minimum. It is clear that if the mission is performed with lesser iterations, then the overlapping of the search trajectories will decreased. However, in the simulation of some of the search algorithms, although the number of the search iterations is low, it is observed that the environment has been searched irregularly and non-uniformly and therefore some of the cells have been searched repeatedly. This, in turn, degrades the efficiency of the algorithm. In this experiment, by assigning different colors to different number of times each cell has been searched, a visual map of the overlapping searches has been prepared. The results of this experiment performed using the aforementioned algorithms considering different number of agents and search environments are depicted in Figure 6, 7 and 8.



(a) The Z Data Exchange Algorithm (b) Two-layer Data Exchange Algorithm



(c) The Z* Data Exchange Algorithm (d) "Nearest Zero-point" Data Exchange Algorithm

Figure 6. The Overlapping of the Search Paths, Using Different Search Algorithms in the Second Environment (Figure 5b) by Three Agents, where Green, Yellow, Orange, and Red Cells are the Cells that have been Searched Once, Twice, Three to Eight, and Eight Times or more, Respectively

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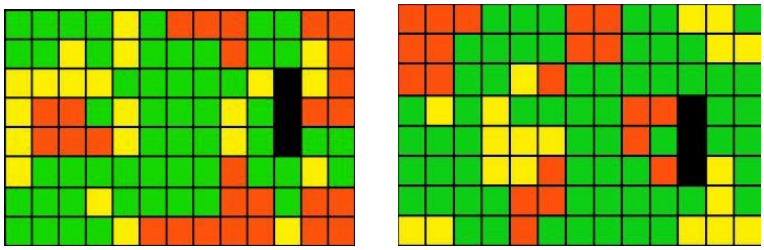
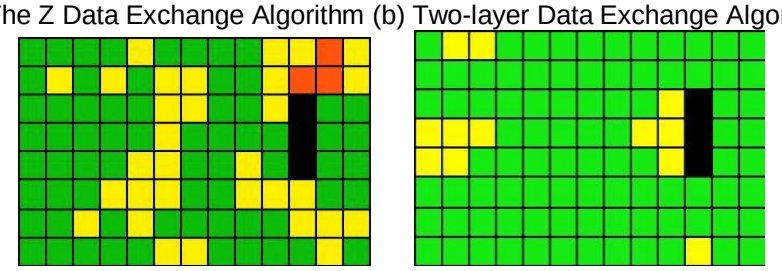


(a) The Z Data Exchange Algorithm (b) Two-layer Data Exchange Algorithm



(c) The Z* Data Exchange Algorithm (d) “Nearest Zero-point” Data Exchange Algorithm

Figure 7. The Overlapping of the Search Paths, Using Different Search Algorithms in the Second Environment (Figure 5b) by Five Agents, where Green, Yellow, Orange, and Red Cells are the Cells that have been Searched Once, Twice, Three to Eight, and Eight Times or more, Respectively

Figure 6a and 6b, 7a and 7b, and also 8a and 8b show that, compared to the Z data algorithm, the overlapping of the search paths is much lesser for the Two-layer data exchange algorithm. As a matter of fact, some of the simulations done with the Z data exchange algorithm revealed that some environment cells were searched more than 14 times, while this did not occur when using the Two-layer data exchange algorithm.

Z* data exchange algorithm, where the data exchange pattern has been altered, yielded much better results than the Z and Two-layer data exchange algorithms (Figure 6c, 7c and 8c). The numerical value of the environment cells indicates that when the Z* algorithm exchanges the data, the numerical values of the cells in the resultant maps are uniformly distributed over the search map, which therefore avoids generation of the large localized numerical values that is considered as a local maxima. This, in turn, provides a better search efficiency, especially for searching cells around the obstacles during the search mission. As is evident from Figures 6c, 7c and 8c, no cell has been searched more than 4 times while using Z* data exchange algorithm.

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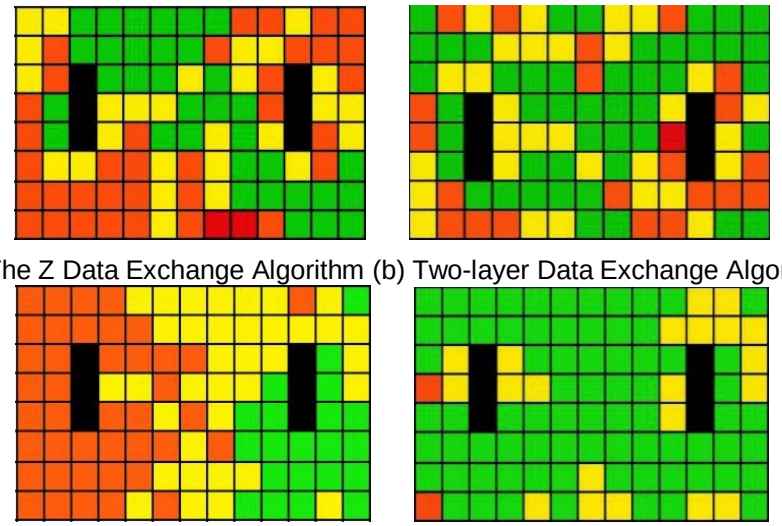

(a) The Z Data Exchange Algorithm (b) Two-layer Data Exchange Algorithm

(c) The Z* Data Exchange Algorithm (d) “Nearest Zero-point” Data Exchange Algorithm

Figure 8. The Overlapping of the Search Paths, Using Different Search Algorithms in the Third Environment (Figure 5c) by Three Agents, where Green, Yellow, Orange, and Red Cells are the Cells that have been Searched Once, Twice, Three to Eight, and Eight Times or more, Respectively

In general, considering the overlapping of the search trajectories indicates that the more uniform are the colors of the cells, the closer are the numerical values of the cells and therefore the search process is performed more smoothly. For example, the colors are more scattered in Figure 6a than in Figure 6d. Since the concept of the gradient has been used in this research to search the neighboring cells, it is clear that the “nearest zero-point” algorithm is more efficient than the other three algorithms. This is because when there is a cell that has a numerical value much larger than the numerical value of its adjacent cells then it produces a greater gradient in that region and the robot searching the region gets confused and as a result the number of the search iterations increases.

In the “nearest zero-point” algorithm, a different method of path planning is used in all of the simulation experiments. This algorithm reduces the number of iterations in the search mission. In an identical environmental conditions, when the effect of the number of the searching robots is considered, the efficiency of this algorithm and also Z* data exchange algorithm are approximately up to 10% better than that of given in [16]. When number of robots increases from one to two robot, the number of search iterations drops approximately 43% and 37% using “Nearest zero-point” and Z* data exchange algorithm respectively, while this rate is 33% for the given algorithm in [16]. Although the efficiency of the “nearest zero-point” algorithm in comparison to that of the Depth-first [17] is up to 30% better (Considering identical search environments) while using one robot (61 iteration in comparison with 86 iteration of the Depth-first), when the number of the robots is increased the situation is reversed and the Depth-first based algorithm shows up to 25% better performance while using three robots. On the other hand, Figures 6d, 7d and 8d show that the number of the overlapping trajectories is a minimum in the “nearest zero-point” and most of the cells have not been searched more than twice. However, the “nearest zero-point” algorithm is superior to the rest of algorithms studied in this research, it searches every points on a given map and therefore its computational load is much more than that of the other studied algorithms and it is expected to degrade the efficiency of the search when the simulation of the missions carried out by real robots.

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8. Conclusion

Several search algorithms have been utilised in this research. The final algorithm, “nearest zero-point”, shows an effective performance in comparison with previously used methods. The results of the simulations have also been comparable, and even show greater significance in such aspects as search iteration and data transfer, with existing algorithms introduced in [16, 17]. However, when the number of robots increases, the performance of Modified Depth First Method shows an improvement in comparison to “nearest zero-point”. The number of overlapping of search paths in “nearest zero-point” was also the lowest amongst other four methods studied in this paper. That is to say, no cell was searched more than twice. Although the “nearest zero-point” method performs better than other methods and provides more realistic simulation of the robotic missions, it requires a much heavier computational load than simple algorithms, such as Z* data exchange; as every point of the search environment is taken into consideration in this approach. For future research, the proposed algorithms must be simulated using real robots as software simulations cannot reflect the real characteristics of a search mission.

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