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Fast Method for the Mobile Robot Path Planning Problem: The DM-SPP Method

Souhail Dhouib*

OLID Laboratory, Higher Institute of Industrial Management, University of Sfax, TUNISIA

Abstract The main objective of the Mobile Robot Path Planning Problem is to find a high-quality waypoints for a mobile robot with obstacles collision-free. This is a very complicated and needed task in robotic. Basically, planning rapidly the optimal task will increase the performance of the robot by increasing the speed to reach the target position and reducing energy conception. In this research work, the innovative technique namely Dhouib-Matrix-SPP (DM-SPP) is studied with eight movement directions as well as four. DM-SPP is a very rapid method built on the contingency matrix navigation and needing only n iterations to create shortest path (where n is the number of nodes). The simulation results on several complicated case studies (varying from (20 x 20) grid map to (80 x 80) grid map) prove that DM-SPP can rapidly create an accurate trajectory with obstacles collision-free. Moreover, the proposed technique is compared with the very recently designed artificial intelligence approaches. The results of this comparison proved that the novel DM-SPP is the fastest approach: For example, it is (289.325) times rapider than the A* algorithm, (156.769) times faster than the Improved A* method, (127.901) times speedier than the Bidirectional A* technique, (69.586) times quicker than the Improved Bidirectional A* algorithm and (45.671) times rapider than the Variable Neighborhood Search BA* metaheuristic. These findings underline the speed of the proposed DM-SPP optimization technique and emerge the applicability of DM-SPP as a reliable option for the trajectory optimization.

Keywords Artificial Intelligence, Mobile Robot, Intelligent robots, Optimization, Shortest path problem, Metaheuristic, Operations Research.

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1. Introduction

In the cognitive mobile robot, the crucial task is to automatically plan the optimal trajectory with obstacles collision-free from the current to the destination positions. Usually, several cameras and sensors are used to represent the environment as a grid map and an optimization method is used to design the shortest path. This problem is known as the mobile robot path planning problem which is a very complicated problem where the recent developed artificial intelligence optimization methods have the weakness of slow convergence with the ability to easily falling into a local and not an optimal solution. For the above reasons, the deterministic Dhouib-Matrix-SPP (DM-SPP) method is enhanced for this problem thanks to its speed convergence. Originally, DM-SPP is designed in [1] to unravel the standard shortest path problem in a graph with its three variants: Single-Pair, Single-Source and Single-Destination. In addition, the All-Pairs shortest path problem can be solved via DM-SPP by a simple iteration with changing the source and destination labels. To overcome the limitations of existing methods, DM-SPP is proposed as a novel deterministic method. DM-SPP requires no parameters (Parameter-Free) and repeated n iterations (where n is the number of nodes). It is adapted to solve the autonomous mobile robot path planning problem with eight movement directions in [2, 3]. Also, DM-SPP is advanced for four movement directions (namely DM-SPP-4) in [4] and

*Correspondence to: Souhail Dhouib (Email: souhail.dhouib@gmail.com). OLID Laboratory, Higher Institute of Industrial Management, University of Sfax, TUNISIA.

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investigated with twenty-four movement directions in [5]. In other research works, DM-SPP is adapted to develop the secured trajectory path (by adding virtual obstacles) and also to ensure a hierarchical resolution for a multi-objective trajectory planning. In this research work, the real-world domain of the mobile robot is converted as a grid model and the DM-SPP method is studied (using both four and eight movement directions) with a focus on its rapidity to develop the path with obstacles collision-free. Basically, DM-SPP begins by transforming the grid map model of the mobile robot as a sparse graph, then a navigation through rows and columns will be applied. Figure 1 illustrates the generated solution using DM-SPP for a (60 x 60) grid map where the red squares describe the obstacles and the open spaces to move are represented with white areas (this grid map is composed of 3600 small squares). The blue waypoints depict the trajectory of the mobile robot: Figure 1.a represents the solution obtained by the means of DM-SPP-4 and Figure 1.b illustrates the solution generated via DM-SPP (after only (0.895) second). Obviously, the planned path created via DM-SPP (using eight movement directions) is smoothed than the trajectory planned by DM-SPP-4 (using four movement directions) but both of the methods (DM-SPP and DM-SPP-4) are very rapid (less than one second to solve a complicated grid map composed of 3600 cell areas).

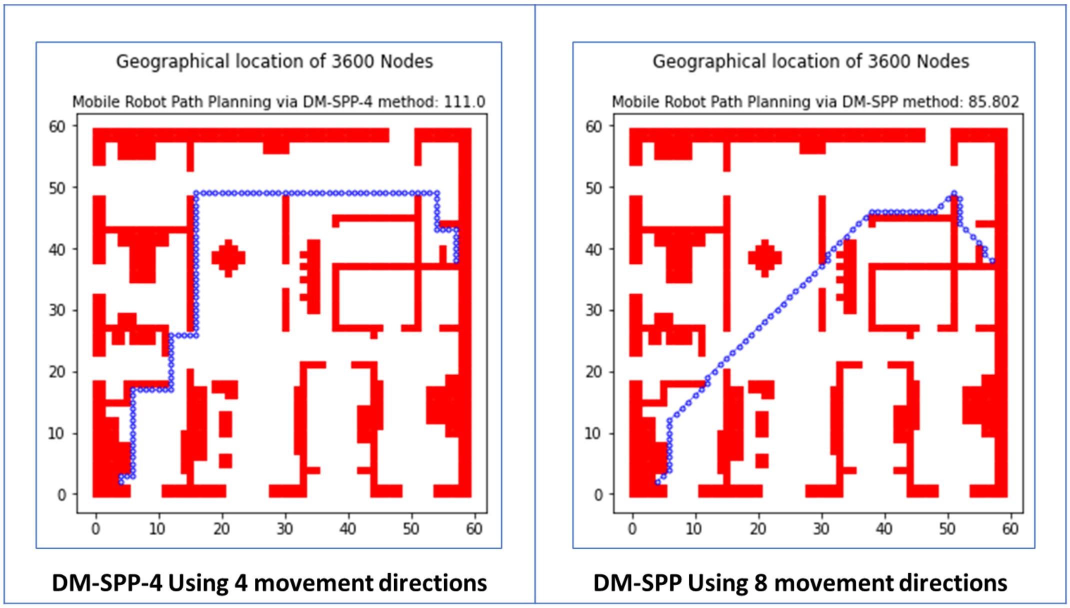

Figure 1. DM-SPP Navigation a) DM-SPP-4 using four movement directions b) DM-SPP using eight movement directions.

By applying DM-SPP, our purpose is to rapidly find efficient and smooth trajectory for mobile robot with obstacles collision-free. The aim of this paper is to study the rapidity of DM-SPP, for that, it is tested on different case studies (ranging from (20 x 20) grid map to (80 x 80) grid map) and compared to several optimization methods. Besides, the simulation results confirm that DM-SPP highly outperforms the recently developed artificial intelligence methods. The exploited DM-SPP approach can indeed be used to rapidly find the shortest trajectory for a mobile robot in various scenarios (disinfection in disease, restaurant delivery, tracked lawnmowers in orchards, Windows cleaning robots, . . . , etc.). It will enhance the efficiency and performance by optimizing the trajectory of the mobile robot and reducing its energy consumption. DM-SPP can be applied on a grid map with different movement directions (four, eight, twenty-four or more). The text in this paper is structured as follows; Section 2 introduce a literature review. Section 3 describes the innovative DM-SPP method and its application to unravel the mobile robot path problem (grid maps, obstacles, path, . . . , etc.). Section 4 studies the application of DM-SPP on four complicated case studies and the simulation results prove its rapidity (DM-SPP highly outperforms the last developed methods in the literature). Finally, Section 5 summarizes this research work with a recommendation for next research steps.

2. Related works

Planning the trajectory for a mobile robot is a complicated task and several optimization methods are developed such as: In [6], the Genetic Algorithm, the Particle Swarm Optimization and the Pattern Search methods are studied to plan the shortest path for an automated guided industrial vehicle. In [7], a modified Sparrow Search Algorithm is developed to obtain collision-free trajectories for a mobile robot. A Rapidly Exploring Random Trees* technique is proposed with Kinematic Constraints in [8] to plan the shortest trajectory. In [9], the Whale Optimization Algorithm is integrated with the Firefly Algorithm in order to create the shortest path for a mobile robot using eight movement directions. The A* algorithm is used to plan the path for a mobile robot in [10], at medical testing laboratories in [11] and for tracked lawnmowers at orchards in [12].

Several hybrid metaheuristics are designed in order to increase the convergence speed towards the optimal path. For example, a hybrid algorithm joining the Variable Neighborhood Search to the A* Algorithm is developed in [13]. Moreover, an Ant Colony Optimization metaheuristic is enhanced with the asymmetric strategy network for dynamic environments in [14]. The Whale Optimization Algorithm is combined with the Tent Chaos Theory to optimize the global path planning problem for a mobile robot in [15]. The Spider-Wasp Optimizer metaheuristic is integrated with the Dual-Median-Point guidance strategy in [16].

A smoothed path is generated using an improved A* algorithm with child nodes and a bidirectional technique in [17]. The Reinforcement Learning method and Lyapunov candidate function are designed in [18] and symmetric pseudo-multi-scroll attractors are adapted in [19]. Besides, the NSGA-II algorithm is combined with a local search method in [20], a rapidly-exploring random tree star is enriched with three procedures to create new nodes in [21] and a vision-based method with optical flow are used to detect and avoid obstacles for Unmanned Aerial Vehicles in [22].

2.1. Optimization methodology

DM-SPP is proposed for the mobile robot path planning problem with no parameters and high search stability and rapidity. In this paper, the grid map is used to represent the real-world environment of the mobile robot and the innovative DM-SPP approach is enhanced for planning the trajectory. Indeed, the grid map subdivides the workspace in several squares with representing the physical obstacles (impassable area) by a red color whereas the permitted spaces are embodied with white squares. Each small square (area cell represented by x and y positions) is labeled (by a serial number z) in a sequential way (starting from 0) from the top corner to the bottom corner and from the left corner to the right corner with a step size of one. Besides, the grid position can easily be converted from the serial number using Eq. (1) where l denotes the length of the grid map.

$$\begin{cases} x_i = Mod(z, l) \\ y_i = Int(z/l) \end{cases} \tag{1}$$

For example, let us consider a (4,4) grid map. The serial number 3 will correspond to the square cell at the position x = Mod (3, 4) = 3 and y = Int (3, 4) = 0. Besides, the serial number 6 will denote the square area at the position x = Mod (6, 4) = 2 and y = Int (6, 4) = 1. And the serial number 15 will denote the square area at the position x = Mod (15, 4) = 3 and y = Int (15, 4) = 3. Figure 2.a illustrates the environment of a bidirectional grid map where eight movement directions (top, down, right, left, top right, top left, down right, down left) are allowed for the mobile robot. Also, a diagonal movement near one obstacle is allowed (Figure 2.b). However, crossing two diagonal obstacles is forbidden for path security (Figure 2.c).

DM-SPP is a column-row technique (see Figure 3) using a distance matrix, with two intermediate matrices (the Path-Memory and the Cumulative-Cost) with a list (Sum-Cost). A step-by-step application of DM-SPP is presented in details in [1]. DM-SPP starts by converting the grid map environment to a graph in order to construct the distance matrix between all the nodes (for the horizontal and vertical movements the distance is affected to (1) and for the diagonal movement the distance is allowed to ($\sqrt{2}$)).

DM-SPP can work with any movement direction. At first, the grid map is converted as a sparse graph, where the number of cells (small squares) represent the vertices and the movement directions describe the neighbors (edges)

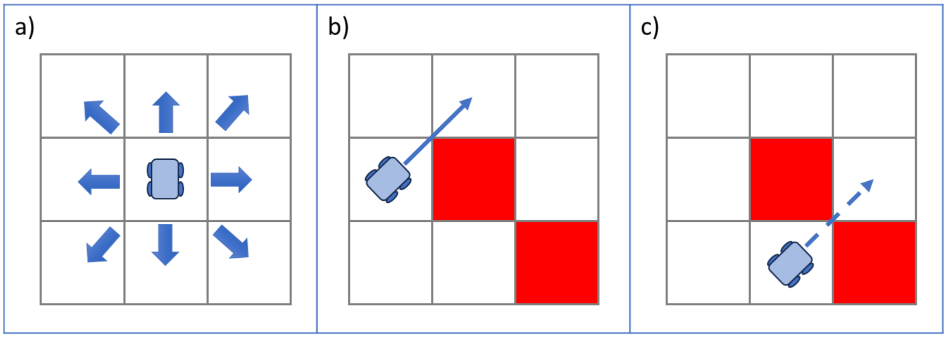

Figure 2. The mobile robot motion direction a) eight node search directions b) authorized diagonal movement c) not allowed diagonal movement.

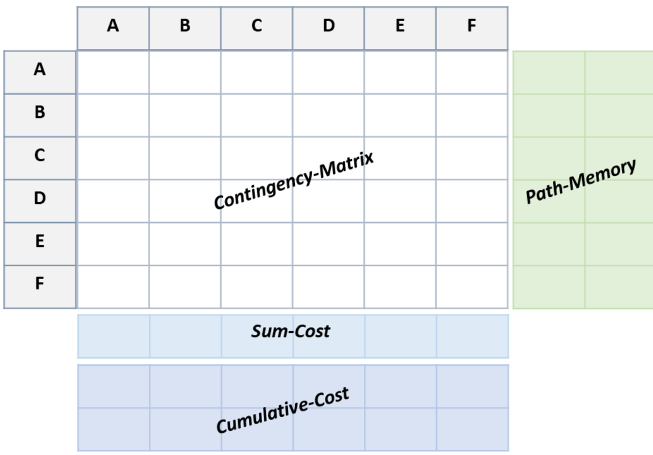

Figure 3. The graphical representation of DM-SPP.

for each cell: For example, for a (30x30) grid map, there are (900) vertices and if eight movement directions are used (7200) edges will be created. In this paper, two versions (DM-SPP-4 and DM-SPP) are considered with respectively four and eight movement directions. Noticeably, increasing the number of movement directions will improve the quality of the solution but this is related to the structure of the mobile robot (see the next section for more clarification). Basically, the DM-SPP method is developed under the general optimization concept of artificial intelligence namely Dhouib-Matrix where several methods are developed: The optimal DM-MSTP technique to solve the minimum spanning tree problem in [23], the DM-TP1 heuristic for the Transportation Problem in [24], the DM-AP1 greedy method for the Assignment Problem in [25, 26, 27], the constructive DM-TSP1 method for the Travelling Salesmen Problem in [28, 29], the optimal method DM-ALL-SPP for All-Pairs Shortest Path Problem in [30], the DM3 metaheuristics in [31, 32, 33] and the multi-start DM4 metaheuristic in [34, 35, 36, 37, 38, 39].

3. Computational results

This section presents practical experimental studies to test the performance of DM-SPP. All simulations are implemented on Python programming language and run on an intel I7-1255U at 1.70 GHz with 16 GB of RAM under Windows 10.

DM-SPP is tested and compared to different workspaces (recently developed in [13]) with different sizes (the grid maps are ranging from (20 x 20) to (80 x 80)). DM-SPP is characterized by its deterministic structure with no parameters (there is no required for sensibility test) and the use of eight movement directions. DM-SPP will be compared to: The A* algorithm (A*) developed in [13], The Improved A* method (IA*) designed in [40], The Bidirectional A* algorithm (BA*) create in [13], The Improved BA* technique (IBA*) developed in [14], The hybrid Variable Neighborhood Search Bidirectional A* metaheuristic (VNS-BA*) designed in [13], And the Dhouib-Matrix-SPP-4 method (DM-SPP-4) using four movement directions developed in [4]. For the comparative study, two criteria (the distance accuracy and the run speed) are used. The distance accuracy (Path-Deviation) of all the methods is computed (on percentage, see Eq. (2)) depending to the solution generated by the DM-SPP method (more the accuracy is higher, more DM-SPP is better).

$$\text{Path-Deviation} = \left(\frac{\text{Path}_{\text{Method}} - \text{Path}_{\text{DM-SPP}}}{\text{Path}_{\text{DM-SPP}}} \right) \times 100 \tag{2}$$

Another criterion (namely Speed-deviation) is used (see Eq. (3)) to compare the run speed of all the methods related to the DM-SPP method (more the criterion Speed-Deviation is higher, more DM-SPP is rapider than the compared method).

$$\text{Speed-Deviation} = \frac{\text{CPU}_{\text{Method}}}{\text{CPU}_{\text{DM-SPP}}} \tag{3}$$

Applying DM-SPP to unravel the path planning problem for a mobile robot not only proves the accuracy of DM-SPP to design the shortest trajectory with obstacles avoidance, but also, it validates that DM-SPP is the fastest approach to solve this kind of problems. This fact represents a practical and valuable advance in the fields of artificial intelligence, robotics and operations research.

3.1. Case study 1

This first case study is based on a (20 x 20) grid map taken from [13]. The current position of the mobile robot (starting point) is at (0,0) and the ending point is at (19,19). At first, this problem is converted as a sparse graph with (20 * 20 = 400) vertices. Concerning the DM-SPP-4 method (using four movement directions), four neighbors will be visited for each vertex (except the cell at the border, the number of the neighbors will be equal to two or three) and the maximum number of edges will be then (400 * 4 = 1600). Regarding the DM-SPP method (using eight movement directions), the maximum number of edges will be then (400 * 8 = 3200). Figure 4.a depicts the trajectory proposed by DM-SPP-4 generated after just (0.031) second. Whereas, DM-SPP plans the high-quality path (28.624) in (0.032) second (see Figure 4.b).

The data in Table 1 shows the simulation results for all the recent developed methods in the literature. Obviously, DM-SPP is the fastest method with a significative gap: DM-SPP is (135.938) times rapider than the A* algorithm, (112.406) times faster than the IA* technique, (67.344) times speedier than the BA* method, (101.469) times quicker than the IBA* algorithm and (79.781) times faster than the VNS-BA* metaheuristic.

Table 1. Comparing the experimental results for several methods applied on a (20 x 20) grid map.

	A*	**IA***	**BA***	**IBA***	**VNS-BA***	**DM-SPP-4**	**DM-SPP**
Path Length	28.627	28.627	28.627	29.213	27.476	38.000	28.624
Path-deviation	0.010	0.010	0.010	2.058	-4.011	32.756	0.000
Path Time (s)	4.35	3.597	2.155	3.247	2.553	0.031	0.032
Speed-Deviation	135.938	112.406	67.344	101.469	79.781	0.969	1.000

It is clear from observing Figure 5 that DM-SPP presents the top Speed-Deviation ratio (compared to all the other methods, except the DM-SPP-4 (which uses four movement directions instead of eight as DM-SPP does)). Commonly, this result can be explicated by the deterministic application of DM-SPP without any parameter.

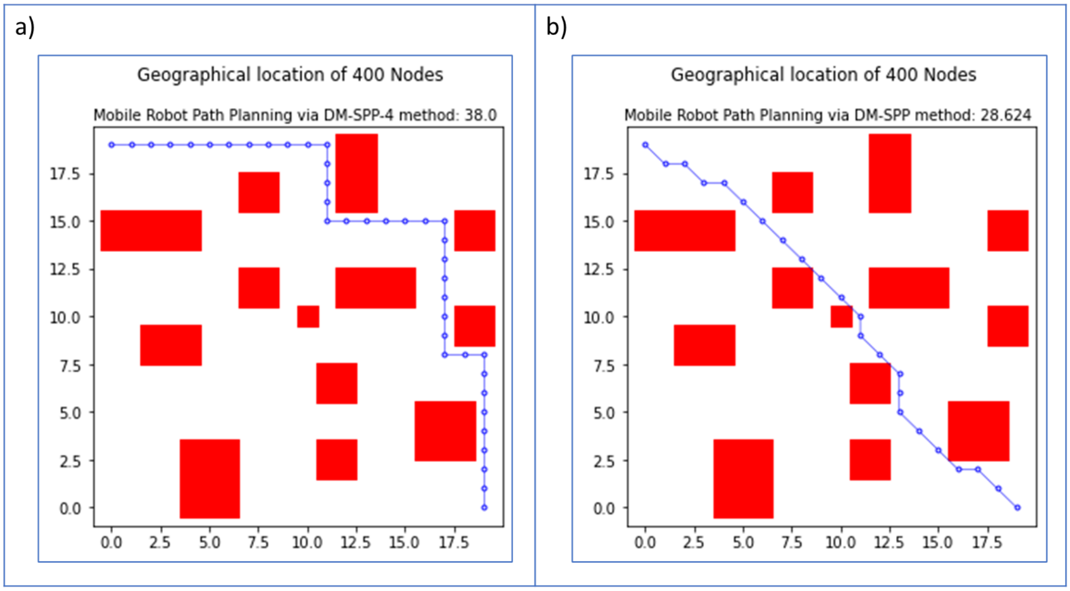

Figure 4. DM-SPP Navigation for a (20 x 20) grid map.

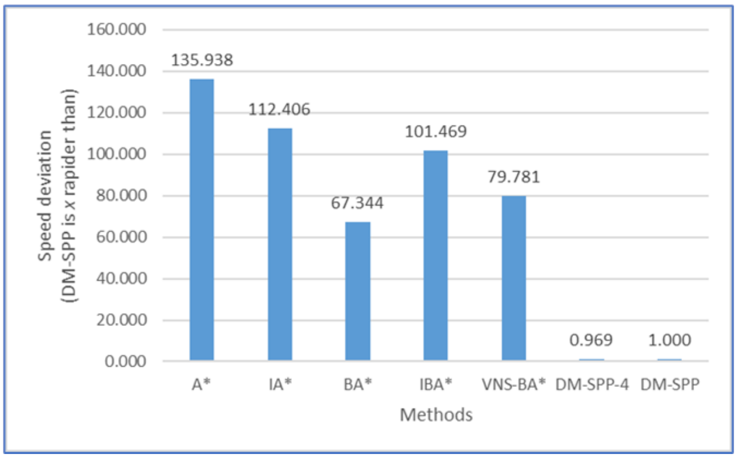

Figure 5. Comparing DM-SPP to recent developed methods on a (20 x 20) grid map.

3.2. Case study 2

In this subsection, a wider (40 x 40) grid map is considered (taken from [13]). This problem is converted as a graph with (1600) vertices, (6400) edges for DM-SPP-4 (using four movement directions) and (12800) edges for the DM-SPP (using eight movement directions). Figure 6.a and Figure 6.b represent the shortest path distance respectively generated by DM-SPP-4 and DM-SPP where the shortest distance (61.006) is planned by DM-SPP (the blue waypoints) after just (0.286) second.

As it can be seen in Table 2, all the simulation results are gathered and again DM-SPP is the fastest method with a wide gap: DM-SPP is (540.566) times rapider than the A* algorithm, (366.979) times speedier than the IA* method, (98.353) times faster than the IBA* technique, (118.402) times quicker than the IBA* method and (71.395) times rapider than the VNS-BA* metaheuristic.

For more clarification, the Speed-Deviation is graphically depicted in Figure 7 (where the closed method VNS-BA* is still so far: DM-SPP is (71.395) times faster).

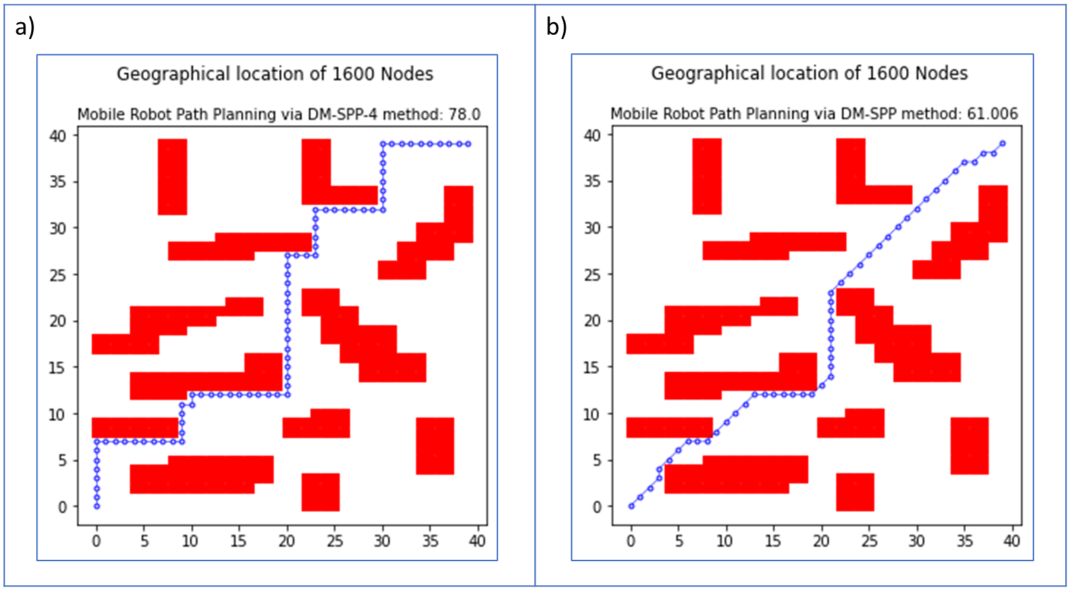

Figure 6. DM-SPP Navigation for a (40 x 40) grid map.

Table 2. Comparing the experimental results for several methods applied on a (40 x 40) grid map.

	A*	IA*	BA*	IBA*	VNS-BA*	DM-SPP-4	DM-SPP
Path Length	61.598	64.083	61.598	61.598	61.263	78.000	61.006
Path-deviation	0.970	5.044	0.970	0.970	0.421	27.856	0.000
Path Time (s)	154.602	104.956	28.129	33.863	20.419	0.193	0.286
Speed-Deviation	540.566	366.979	98.353	118.402	71.395	0.675	1.000

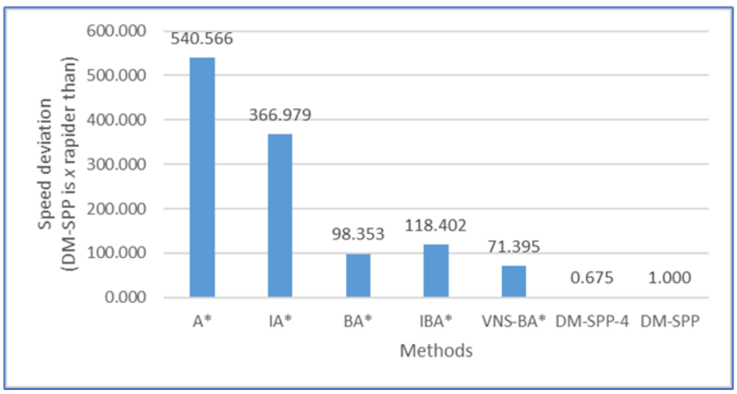

Figure 7. Comparing DM-SPP to recent developed methods on a (40 x 40) grid map.

3.3. Case study 3

This case study considers a large environment with a (60 x 60) grid map. This case study is a very complicated example, it will be converted as a graph with (3600) vertices, (14400) edges for DM-SPP-4 (using four movement directions) and (28800) edges for DM-SPP (using eight movement directions). DM-SPP-4 solves this problem (see Figure 8.a) with a distance of (67), in just (0.635) second. Whereas, DM-SPP rapidly plan the shortest pathway (Figure 8.b) with a distance of (59.382) in (0.673) second.

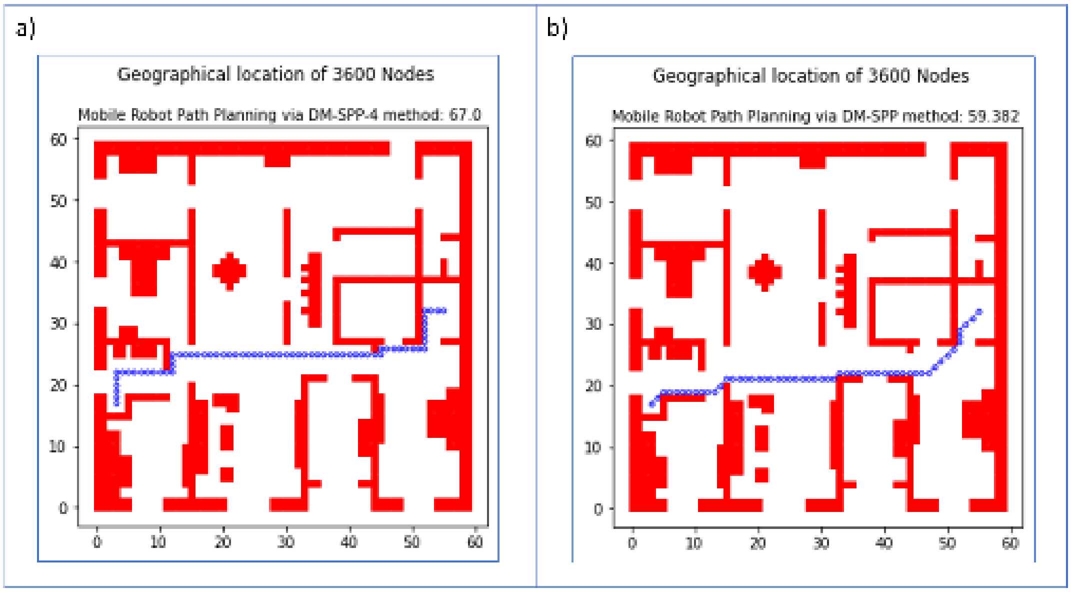

Figure 8. DM-SPP Navigation for a (60 x 60) grid map.

The results generated by all the methods are summarized in Table 3. More again, the DM-SPP method outperforms all the methods, it is the fastest technique: DM-SPP is (440.382) times rapider than the A* algorithm, (108.464) times speedier than the IA* method, (315.973) times faster than the BA* method, (33.478) times quicker than the IBA* algorithm and (18.321) times faster than the VNS-BA* metaheuristic.

Table 3. Comparing the experimental results for several methods applied on a (60 x 60) grid map.

	A*	IA*	BA*	IBA*	VNS-BA*	DM-SPP-4	DM-SPP
Path Length	59.385	69.0833	59.3848	61.598	57.517	67.000	59.382
Path-deviation	0.005	16.337	0.005	3.732	-3.141	12.829	0.000
Path Time (s)	296.377	72.996	212.650	22.531	12.330	0.635	0.673
Speed-Deviation	440.382	108.464	315.973	33.478	18.321	0.944	1.000

As shown on Figure 9, DM-SPP presents the best performance with a wider gap. The closed method to DM-SPP is the VNS-BA* metaheuristic (where DM-SPP is (18.321) times faster), however, VNS-BA* is a very complicated hybrid metaheuristic which requires several parameters to be fixed. Whereas, DM-SPP is a deterministic technique with parameter-free (practical deployment reducing implementation complexity).

3.4. Case study 4

In this subsection, a more complicated case study with an environment represented by a (80 * 80) grid map is studied. In the beginning, a graph is generated with (6400) vertices. Regarding the DM-SPP-4 method (using four movement directions) the number of edges will be (25600) and concerning the DM-SPP method (using eight movement directions), the number of the edges will be then (51200). DM-SPP-4 rapidly (in (2.551) seconds) generates a trajectory illustrated in Figure 8.a. Similarly, DM-SPP speedily (in (2.680) seconds) plans the shortest path (101.7).

As it can be seen in Table 4, the generated results by all the methods are gathered with Path-Deviation and Speed-Deviation criteria. Obviously, the DM-SPP method is the fastest technique, it is (40.413) times rapider than the A* algorithm, (39.225) times speedier than the IA* method, (29.933) times faster than the BA* technique, (24.993) times quicker than the IBA* method and (13.188) times faster than the VNS-BA* metaheuristic.

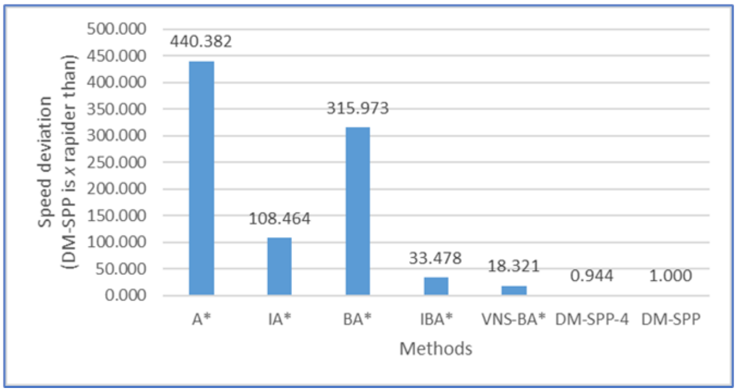

Figure 9. Comparing DM-SPP to recent developed methods on a (60 x 60) grid map.

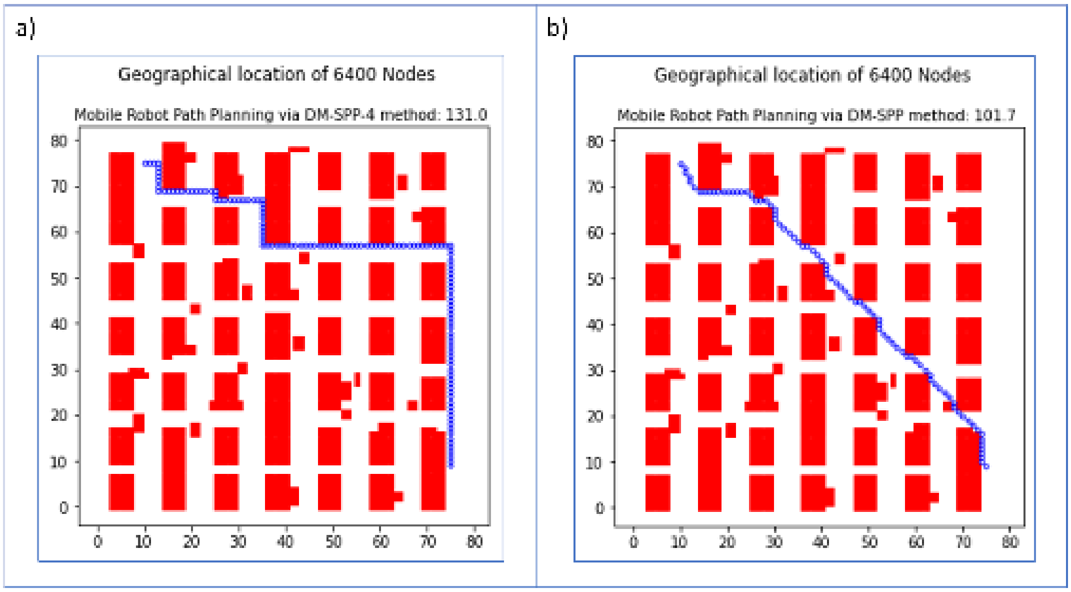

Figure 10. DM-SPP Navigation for a (80 x 80) grid map.

Table 4. Comparing the experimental results for several methods applied on a (80 x 80) grid map.

	A*	IA*	BA*	IBA*	VNS-BA*	DM-SPP-4	DM-SPP
Path Length	103.297	104.125	102.125	106.225	103.700	131.00	101.7
Path-deviation	1.570	2.384	0.418	4.449	1.967	28.810	0.000
Path Time (s)	108.308	105.124	80.221	66.982	35.345	2.551	2.680
Speed-Deviation	40.413	39.225	29.933	24.993	13.188	0.952	1.000

Figure 11. proves that, for the case study of a (80 x 80) grid map, DM-SPP is the highest rapid technique with a greater gap (and especially compared to the A* algorithm).

The data in Table 5 represents the generated results by all the methods on the four case studies. It is clearly seen that DM-SPP is rapider than all the above methods: DM-SPP (using 8 movement directions) and DM-SPP-4 (using 4 movement directions) are concurrent in running time, however, DM-SPP is more accurate in distance. The average Speed-Deviation is computed for all the methods: Generally, the DM-SPP method is (289.325) times faster

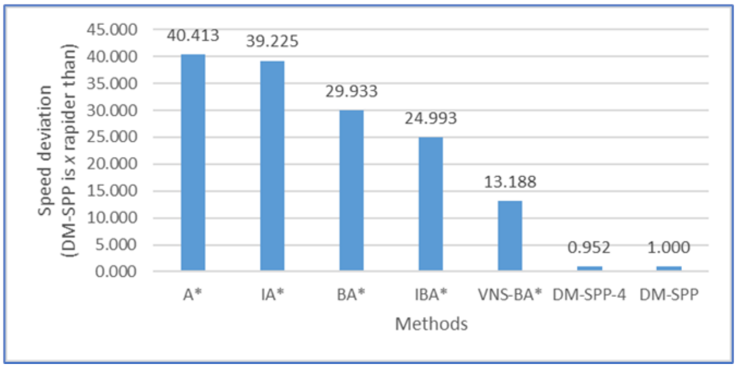

Figure 11. Comparing DM-SPP to recent developed methods on a (80 x 80) grid map.

than A* algorithm, (156.769) times rapider than IA* method, (127.901) times faster than BA* technique, (69.586) times speedier than IBA* method and (45.671) times faster than VNS-BA* metaheuristic.

Table 5. Speed deviation comparison for different algorithms on all the case studies.

Grid Maps	A*	IA*	BA*	IBA*	VNS-BA*	DM-SPP-4	DM-SPP
20x20	135.938	112.406	67.344	101.469	79.781	0.969	1.000
40x40	540.566	366.979	98.353	118.402	71.395	0.675	1.000
60x60	440.382	108.464	315.973	33.478	18.321	0.944	1.000
80x80	40.413	39.225	29.933	24.993	13.188	0.952	1.000
Average	289.325	156.769	127.901	69.586	45.671	0.885	1.000

Figure 12 illustrates the average Speed-Deviation of all the methods and for all the case studies. To summarize, it can be concluded that the path obtained via the DM-SPP optimization method is accurate and it is rapidly obtained (DM-SPP is faster than the last methods developed in the literature: A*, IA*, BA*, IBA*, VNS-BA*). Nevertheless, the DM-SPP method has certain limitations that can be considered areas for further research. Primarily studied for discrete environments represented by grids, its application to non-grid environments remains to be explored. Furthermore, DM-SPP plans the shortest path using four, height, and twenty-four directions of movement. However, to obtain a smoother path, it is necessary to combine DM-SPP with other technologies.

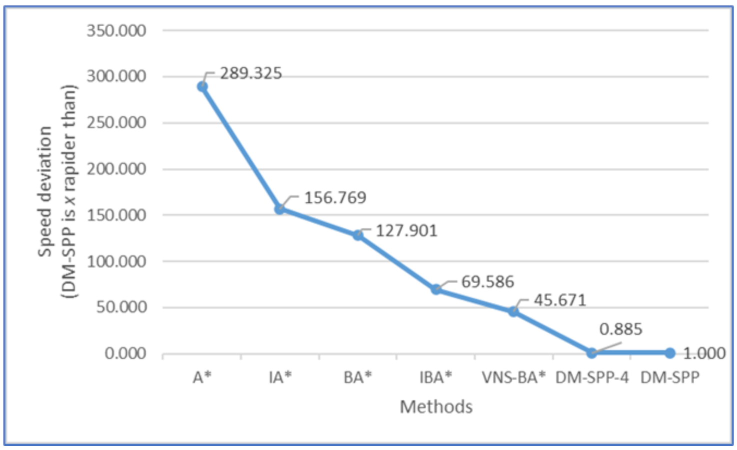

Figure 12. Comparing DM-SPP to recent developed methods on a (80 x 80) grid map.

4. Conclusion

In this paper, several recent optimization approaches are used in order to prove the rapidity and the accuracy of the innovative DM-SPP technique in finding the shortest path of a mobile robot with obstacles collision-free. The simulation results prove that DM-SPP (using eight movement directions as well as four) successively plan the shortest trajectory. But the most important advantage is its rapidity. Obviously, DM-SPP extremely outperforms the recent developed artificial intelligence methods in rapidity. Indeed, DM-SPP is (289.325) times rapider than the A* algorithm, (156.769) times faster than the IA* method, (127.901) times speedier than the BA* algorithm, (69.586) times quicker than the IBA* technique and (45.671) times rapider than the VNS-BA* metaheuristic. DM-SPP offers a rapidity average of (137.850) to the above five optimization methods. Based on the obtained results, there is a potential to explore the enhancement of the DM-SPP method for tracing the trajectory for a drone (in three-dimensions environment, instead of the two-dimension environment developed in this paper). This will allow the representation of the environment as three axes and to perform the investigation to create high-quality trajectory. Furthermore, the innovative DM-SPP approach can contribute in unraveling the path planning problem under a dynamic context.

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