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Efficient robotic path planning algorithm based on artificial potential field

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ABSTRACT

Path planning is crucial for a robot to be able to reach a target point safely to accomplish a given mission. In path planning, three essential criteria have to be considered namely path length, computational complexity and completeness. Among established path planning methods are voronoi diagram (VD), cell decomposition (CD), probability roadmap (PRM), visibility graph (VG) and potential field (PF). The above-mentioned methods could not fulfill all three criteria simultaneously which limits their application in optimal and real-time path planning. This paper proposes a path PF-based planning algorithm called dynamic artificial PF (DAPF). The proposed algorithm is capable of eliminating the local minima that frequently occurs in the conventional PF while fulfilling the criterion of path planning. DAPF also integrates path pruning to shorten the planned path. In order to evaluate its performance, DAPF has been simulated and compared with VG in terms of path length and computational complexity. It is found that DAPF is consistent in generating paths with low computation time in obstacle-rich environments compared to VG. The paths produced also are nearly optimal with respect to VG.

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1. INTRODUCTION

Path planning is among the important aspects that need to be considered in enhancing robot autonomy level [1], [2]. In robotics, path planning is the task of finding a collision-free and feasible path for a robot to traverse from an initial point to a target point. The path planning problem concentrates on three criteria; computational time, optimal path and completeness [3]. Computation time relates exponentially to the number of degrees of freedom of the robot and is affected by the number of obstacles in the environment. An optimal path, which is referred to a shortest distance from the starting point to the target point, is essential to minimize the energy consumption and time needed for the robot to accomplish its mission. Finally, completeness means that the robot can to produce a path if one exists [4]. Once a robot is required to move from a starting point to a target point, the robot needs to produce the shortest path to reach the target safely with low computational time. In a real-time applications, low computation time is vital.

There are several popular methods used for path planning such as voronoi diagram (VD), cell decomposition (CD), visibility graph (VG), and artificial potential field (APF) to name a few [5]-[13]. CD is commonly used in outdoor scenarios. This method introduces the configuration space (C-Space) by a simple

and connected region named cells. These cells are discrete and do not overlap with each other in the region, but each cell is adjacent to one another. A connectivity graph is then developed and a graph search algorithm is consequently used to generate a path. A larger cell size makes the path sub-optimal, whereas a smaller size will increase its computational time [14].

VD defines nodes that are equidistant from all the nearest obstacles in C-Space. This method is capable in generating a safe path with a low risk of local minima due to the edges of the path being located quite far from the obstacles. However, VD is incompetent to yield an optimal path [5]. VG is capable of producing an optimal path without possibilities of local minima, which is easy to implement. The generated path is optimal, but its computation time increases as the number of obstacles in C-Space increases [15]-[17].

As for PF, it is simple, fast and highly safe [18]-[20]. PF generates two kinds of forces. The attractive force created by the target point pulls the robot to it; whilst the obstacles generate a repulsive force that keeps the robot from it. The robot direction was determined by the total force. PF is ideal for real-time environments since this method produces a single path with low computation time [21]. However, PF has a significant drawback known as local minima that causes the robot unable in producing a path.

Due to the above-mentioned advantages of PF, this paper proposes a PF-based path planning algorithm called dynamic artificial potential field (DAPF) that successfully eliminates the local minima problem and is able to generate a sub-optimal and collision-free path in obstacle-rich environments with low computation time. In order to further improve the planned path optimality, the path pruning technique is applied. A simulation has been conducted to evaluate the capabilities of DAPF and VG in various scenarios in terms of computation time and path length.

2. OVERVIEW OF POTENTIAL FIELD

Artificial potential field (APF) is one of the most common path planning techniques. It is based on the idea of two forms of forces called attractive force and repulsive force. Many researchers have utilized this method due to its characteristics such as elegant, safe and simple [22]. APF was first proposed by Khatib in [23] where the robot is seen as a point influenced by fields created by the starting point, target point and obstacles within the search space. The target point generates an attractive force, while the starting point and obstacles generate a repulsive force.

APF technique has benefits like real-time path planning application due to its; i) low computational time, and ii) capability to produce a collision-free path. On the other hand, the technique suffered from its main disadvantages including local minima, goal not-reachable problem, and narrow passages [24], [25]. A number of researchers have implemented the APF technique for path planning. Li *et al.* proposed a PF and regression search path planning method for the robot. It was claimed to effectively generate a global sub-optimal/optimal path and minimize local minima and oscillation problems in a known environment with incomplete information [26]. Sfeir *et al.* Performed real-time mobile robot navigation in an unknown environment based on improved APF technique to develop a steady trajectory around the obstacles by evolving integration of rotational force [27]. The present technique efficaciously avoided the hindrance in APF due to goal non-reachable when obstacles are nearby (GNRON) problem. Research by Park *et al.* presented a potential field method and vector field histogram (VFH) to overtake the PF barriers by creating a new obstacle avoidance method for mobile robots based on advanced fuzzy PFM (AFPFM) [28].

Lifen *et al.* enhanced the APF by replacing the repulsive potential function that assists an unmanned aerial vehicle (UAV) in generating an optimal path while avoiding collision with obstacles [20]. Li *et al.* proposed an improved APF in robot path planning, which reconsidered the potential function to compute a legitimate path and therefore minimalize the length of the generated path [29]. Debnath *et al.* have described the APF as practical to produce a terser path [30].

3. POTENTIAL FIELDS METHOD FOR PATH PLANNING

3.1. Field function based on traditional PF

The potential field method produces two kinds of force; the attractive force and the repulsive force. The target point generates an attractive force by pulling the robot close to it. In the meantime, the repulsive force is generated by the obstacle and the starting point to repel the robot away from it. The resultant total force will generate the path for the robot. The attractive potential field, V_g at target point is defined as (1).

$$V_g = K_g r_g \tag{1}$$

Where K_g is the attractive gain that is is equal to or greater than zero and r_g is the distance between the present robot position and the goal.

The repulsive potential field, V_o produced at obstacle can be represented as (2).

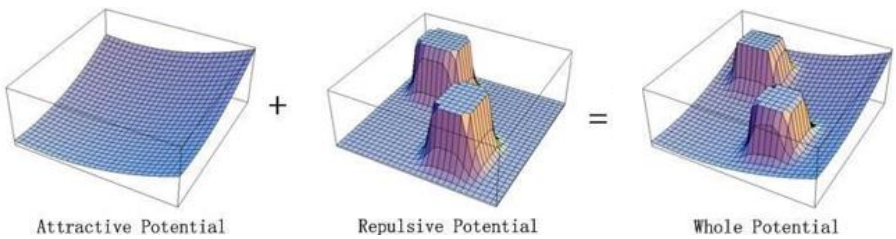
$$V_o = \frac{K_o}{r_o} \tag{2}$$

Where K_o is the repulsive gain at obstacle which is larger than zero and r_o is the distance from the robot. The repulsive potential field, V_r generated by the starting point can be written as (3).

$$V_r = \frac{K_r}{r_r} \tag{3}$$

Where K_r is the repulsive gain at starting point that is equal to or greater than zero and r_r is the distance between the present robot position and the starting point. Thus, the total potential field can be written as in (4). The potential fields are illustrated in Figure 1(a)-(c) [13].

$$V_{total} = V_g + V_r + V_o \tag{4}$$



(a) (b) (c)

Figure 1. These figures are; (a) the attractive potential generated by the target point; (b) the repulsive potential generated by the obstacle and starting point; (c) the resulting potential fields

3.2. The proposed algorithm

3.2.1. Parameters setting

In this paper, we propose a path planning algorithm based on PF called dynamic artificial PF (DAPF). In DAPF, there are some important parameters namely sampling distance dh and the number of discrete points p along the perimeter of an obstacle that will determine the computation time of the algorithm. These parameters have to be set adequately in order to minimize the computation time while guaranteeing the path is collision-free. As such, the parameter values are dynamic depending on the scenario in which the path planning takes place. Through simulations, dh and p can be found from the (5), (6).

$$dh = \frac{0.085 \times O}{3500} \tag{5}$$

$$p = (p \times 4) - 4 \tag{6}$$

O in (5) represents the obstacle number in a scenario. In PF, a two-dimensional mesh in x and y axes that covers the entire search space has to be created first. The mesh consists of smaller grid lines whose number is determined by dh and the range of the search space XY. The smaller the value of dh, the higher the number of grid lines, which will increase the computation time. Hence a suitable dh value has to be set adequately. By making the mesh size dynamics, the computation time could be improved, especially in a non-obstacle-rich environment to generate a free-collision path. As for the attractive gain at the target point,

$$K_g = \frac{0.8}{\sqrt{(X)^2+(Y)^2}} \tag{7}$$

where X and Y represent the ranges of the search along x and y axes, respectively. Contrarily, the repulsive gain at the obstacle, K_o and the repulsive gain at the starting point, K_r are stated as (8), (9).

$$K_o = \frac{\sqrt{(X)^2+(Y)^2}}{(p \times o)} \tag{8}$$

$$K_r = 10 \times dh \tag{9}$$

K_o is determined referred on the surrounding dimension (search space diagonal distance) and the sum of obstacles, meanwhile K_r is a function of dh.

3.2.2. The algorithm

In DAPF, the potential field V_{total} is first generated using equations derived in Sections 3.1. Next, the initial point x_i is set to the starting point x_S. Consequently, the robot starts to maneuver from x_i to the subsequent point x_l by identifying and selecting the lowest point out of eight surrounding points produced by the potential field. It will then move to x_l once the lowest point has been selected. If the point is a local minima, the next lowest point will be identified. This process is repeated until x_l is no longer a local minima and x_i is then updated to x_l. The process repeats until $x_i = x_T$ (target point). The pseudocode of the DAPF algorithm is presented in Figure 2 and the flowchart of the DAPF algorithm is shown in Figure 3. The proposed DAPF is capable of eliminating the local minima problem, oscillation, goal non-reachable problem, and narrow passages. Besides that, it can also produce a path with low computation time so that the robot can be deployed in a real-time mission.

```
BEGIN DAPF
READ x_T, x_S and O
INITIALISE x_i = x_S
CALCULATE V_total
WHILE x_i ≠ x_T
        FIND the lowest point x_l
                WHILE x_l is local minima
                        FIND the next lowest point x_l
                END WHILE
                UPDATE x_i = x_l
        END WHILE
END DAPF
```

Figure 2. DAPF algorithm

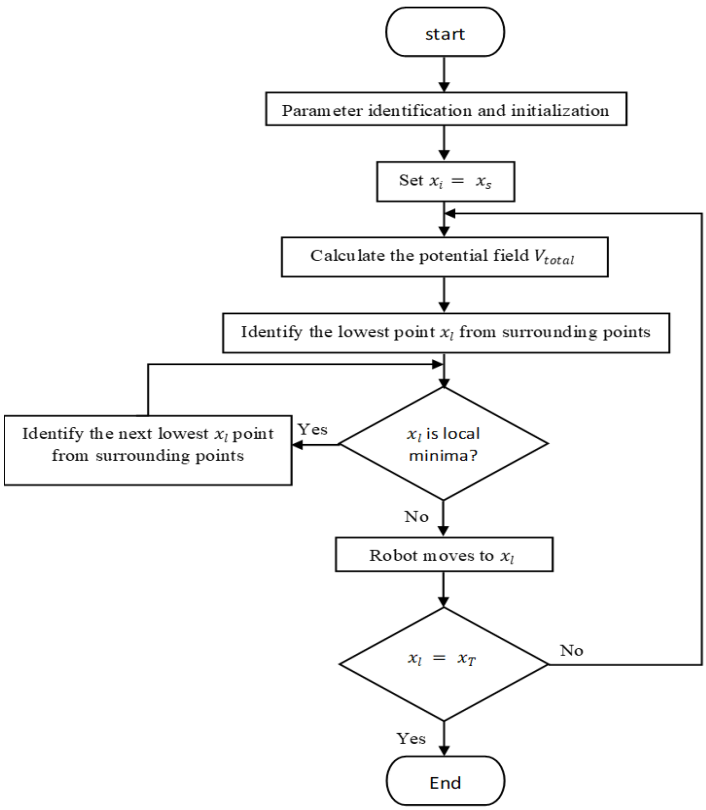


Figure 3. The flowchart of DAPF

3.3. Path pruning

After a path has been generated by DAPF, the path can normally be shortened by passing the areas with high potential values avoiding all the obstacles. Therefore, a path pruning method is applied and its algorithm is shown in Figures 4 and 5. Path pruning makes the robot to be able to perform the mission with a shorter path and hence saves its energy.

A path is a series of waypoints that consists of $\{p_i, p_{i+1}, p_{i+2}, \dots p_n\}$ where p_i is the starting point and p_n is the target point. The pruning procedure begins with scanning the obstacles between p_i and p_{i+j}. If there is no obstacle between p_i and p_{i+j}, the algorithm will eliminate p_{i+j-1} from W and the value j is updated to $j+1$. On the other hand, if there are obstacles between p_i and p_{i+j}, p_i is then updated to p_{i+j-1} and $j=j+1$, and the algorithm continues to scan obstacles between the updated p_i and p_{i+j}. The process ends if $p_i = p_n$.

```
Line 1  BEGIN path pruning
Line 2      READ  W = {p_i, p_{i+1}, p_{i+2}, ..., p_n}
Line 3      INITIALISE j = 2
Line 4      WHILE p_i ≠ p_n
Line 5      SCAN obstacle between p_i and p_{i+j}
Line 6              IF no obstacle between p_i and p_{i+j}
Line 7                      REMOVE p_{i+j-1} from W
Line 8              ELSE
Line 9                      SET  p_i = p_{i+j-1} and j = 2
Line 10             END IF
Line 11             SET j = j + 1
Line 12     END WHILE
Line 13 END path pruning
```

Figure 4. The pseudocode for path pruning

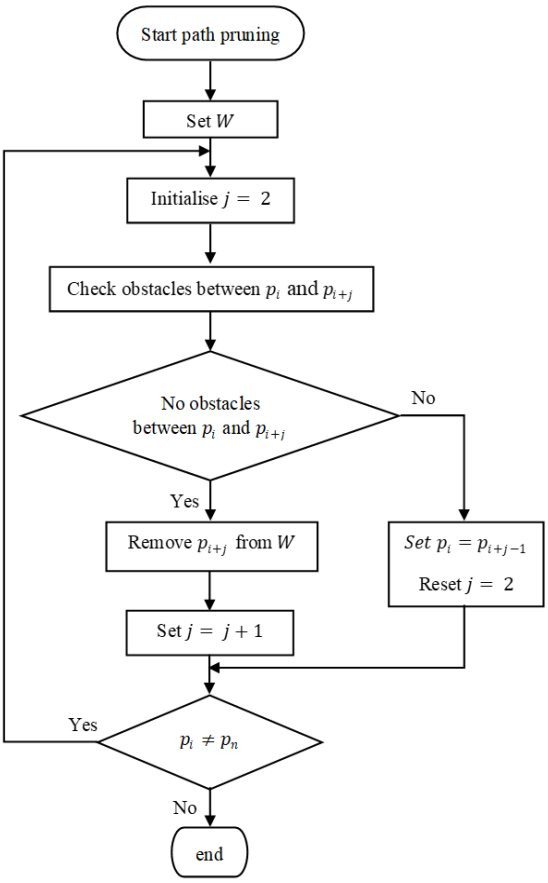


Figure 5. Flowchart for path pruning

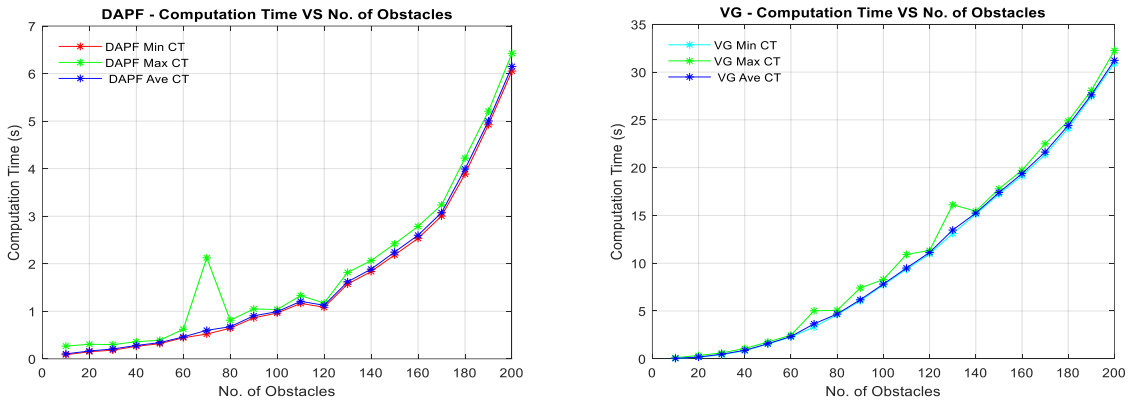
4. SIMULATION RESULTS AND DISCUSSION

4.1. Computation time of DAPF and VG

A simulation has been performed to assess the performance of the proposed DAPF from the aspect of computation time and path length in random scenarios with a variety number of obstacles. Besides that, a simulation of VG has also been done in identical scenarios to compare its performance against DAPF. The simulation of both methods has been executed in 100 random scenarios with varied obstacles number between 10 to 200. It has successfully been implemented using MATLAB R2016a on a PC with Intel i5-4200U 1.6 GHz CPU and Windows 10 OS. The ranges of X and Y were set to 750 units. Figure 6 shows the simulation in terms of computation time for DAPF and VG methods. It also shows the result of minimum, average and maximum computation time against the number of obstacles for the DAPF and VG methods.

From Figure 6, it can be observed that the computation time of both DAPF and VG methods were exponentially increased but at a different pace. According to Figure 6(a), with 70 obstacles (green line) in the scenario, it shows that the computation time increases due to local minima. The algorithm took time to eliminate the problems and replanned a new path. Figure 6(b) shows a fluctuated computation times but it seems intangible. VG method resulted in low computation time at 5 s for a number of obstacles below 80. Between 100 and 200 obstacles, the computation time of VG was between 7 s to 32 s. Meanwhile, the computation time for the DAPF method for all scenarios was below 7 s.

Table 1 shows the result of minimum, average and maximum computation time of DAPF and VG in environments with 50, 100, 150 and 200 obstacles, each generated in 100 random scenarios. The computation time of the two methods in finding a collision-free path increased with the increment of the number of obstacles. From Table 1, DAPF produced relatively shorter computation times in all scenarios. The computation times for DAPF were slightly increased in scenarios with 50 and 200 obstacles with average of 0.34 and 6.15 seconds, respectively. However, the increment of computation time of VG in environments with 50 and 200 obstacles was abrupt with an average of 1.58 and 31.23 seconds, respectively. Note that, throughout the simulation, there was no single occasion that the algorithm failed to plan a path. It proves that the algorithm is complete, i.e., manages to find a path if one exists.



(a) (b)

Figure 6. Computation time with 10 to 200 various obstacles numbers; (a) DAPF, (b) VG

4.2. The effect of path pruning in DAPF

Figures 7(a) and (b) show the path lengths produced by VG and DAPF, respectively. It is worth to note that in the simulations, path pruning has not been implemented in DAPF. From the figure, it can be seen that the resulting minimum, average, and maximum path lengths of DAPF are slightly longer than those of VG. From Figure 7(a), it can be seen that the results of minimum, average and maximum path length were identical. In 40 obstacles environments, the resulting path was 1339 units. The graph fluctuates drastically as a result of local minima problems. The robot needed to remove the local minima points and find a new lowest point surrounding it to reach the target point. This process results in a longer path length. Based on Figure 7(b), the path length produced by the VG method increased consistently. VG produced an optimal path length compared to DAPF. Table 2 illustrates the path length by both methods in scenarios with 50, 100, 150 and 200 obstacles. Compared with VG, the path generated by the DAPF method was 83.4% of the optimum length in the environment with 50 obstacles, 88.3% in 100 obstacles, 87.6% in 150 obstacles and 89.5% in 200 obstacles.

Table 1. Computation time in environments with 50, 100, 150 and 200 obstacles

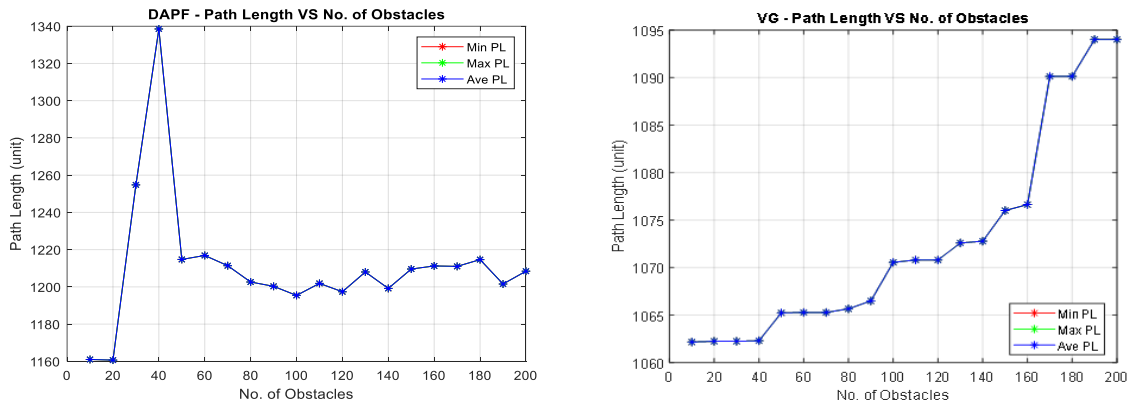
Number of Obstacle	Method	Computation time (s)		
		Min	Ave	Max
50	DAPF	0.32	0.34	0.39
	VG	1.54	1.58	1.76
100	DAPF	0.96	0.99	1.04
	VG	7.73	7.82	8.30
150	DAPF	2.18	2.25	2.42
	VG	17.22	17.39	17.78
200	DAPF	6.05	6.15	6.43
	VG	30.93	31.23	32.25

Table 2. Lengths of the paths produced by DAPF and VG

Number of Obstacle	Method	Path length (unit)
50	DAPF	1214.7
	VG	1065.2
100	DAPF	1195.4
	VG	1070.5
150	DAPF	1209.5
	VG	1076
200	DAPF	1208.4
	VG	1094

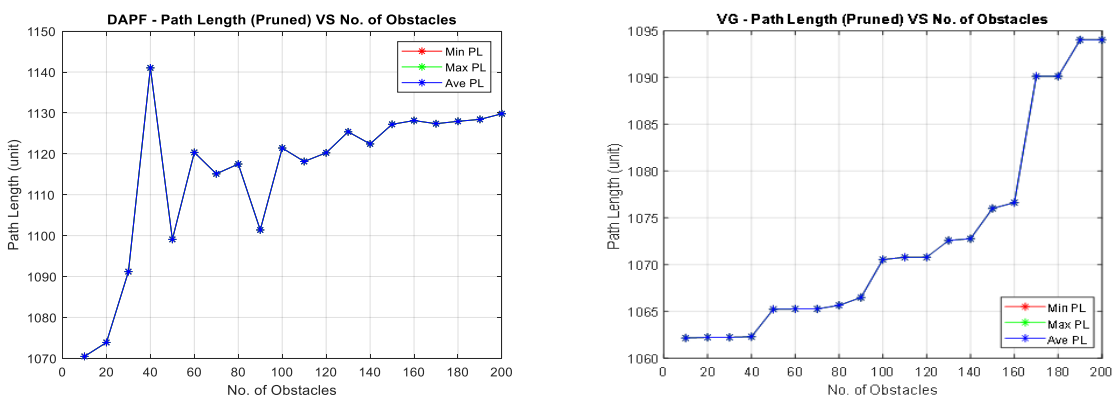
Figure 8 illustrates the path lengths produced by DAPF with path pruning and VG. DAPF with path pruning was found to have a shorter path compared to those without path pruning. From Figure 8(a), with 40 obstacles, the produced path length was 1140 units. It proved that DAPF with pruning could generate a shorter path although needed to encounter the local minima problems. Table 3 shows the resulting pruned path length of DAPF. DAPF with path pruning technique successfully generated shorter paths with greater than 96% of those planned by VG in all scenarios with obstacles number between 50 and 200. The comparison of path lengths of DAPF with and without pruning is depicted in Figure 9.

From Figure 9, DAPF with pruning yielded shorter paths for the entire scenarios as mentioned in Table 3 compared to DAPF without pruning in Table 2. DAPF with path pruning has been successfully proven to produce a shorter path by an average of 10% compared to DAPF without path pruning. This is important in saving the robot energy as the robot traverses the path.



(a) (b)

Figure 7. Path length generated by; (a) DAPF and (b) VG



(a) (b)

Figure 8. Path length generated by; (a) DAPF with path pruning and (b) VG

Table 3. Lengths of planned pruned path for dynamic PF and VG

Number of Obstacle	Method	Pruned Path length (unit)
50	DAPF	1099.1
	VG	1065.2
100	DAPF	1121.4
	VG	1070.5
150	DAPF	1127.2
	VG	1076
200	DAPF	1129.8
	VG	1094

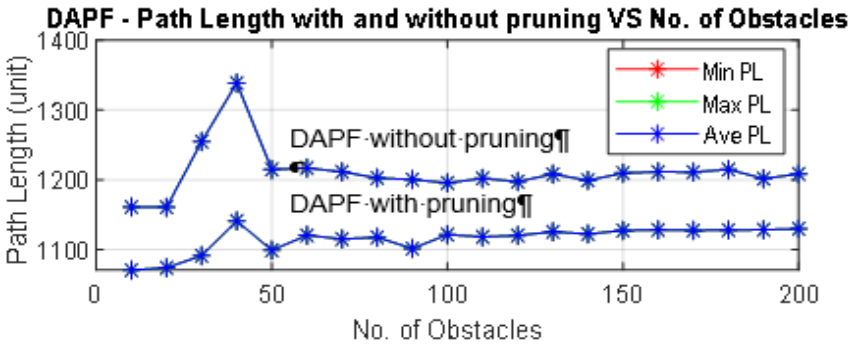


Figure 9. Comparison of DAPF path length with and without path pruning

4. CONCLUSION

In this paper, dynamic artificial potential field (DAPF) with path pruning method has been proposed for robot path planning in known environments. The proposed algorithm has successfully overcome the local minima problems of conventional PF. The algorithm is also capable of producing a path with low computation time in obstacle-rich environments, as it is crucial for real-time path planning applications. DAPF has also been validated to produce paths with shorter lengths, which is close to 95% of those produced by the visibility graph (VG) method. Besides that, DAPF has also been proven to be complete. Therefore, the proposed algorithm fulfills the criterion of path planning.

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