ISSN: 1687-1006 p
ISSN: 2682-3640 e

The Egyptian International Journal of Engineering Sciences and Technology

https://eijest.journals.ekb.eg/

Vol. 44 (2023) 89–98

DOI: 10.21608/EIJEST.2023.185614.1213

Artificial Potential Field Approaches for Indoor Mobile Robot Path Planning: A Review

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ARTICLE INFO

Article history:

Received 15 January 2023
Received in revised form 23 April 2023
Accepted 25 May 2023
Available online 25 May 2023

Keywords:

Artificial Potential Field
Path Planning
Mobile Robot

ABSTRACT

Path Planning is critical for a mobile robot (MR) to navigate safely towards its target position, without collision with the surrounding obstacles. There are many aspects that need to be considered in path planning; computation time, path smoothness, and path length. The Artificial Potential Field (APF) approach is popular for solving the path planning problem. It is a unique approach that has a simple computation model, which makes it a good choice for real-time and dynamic environments. The principle of the APF approach is based on attracting the MR to its target position and repelling it away from obstacles. The APF approach has some inherent limitations, such as local minima and path oscillations in narrow passages. This paper reviews the traditional APF approach and several modified versions that aimed to overcome these limitations. A brief comparison is made to give an overview of the performance of each modified version. In addition, the main advantages and disadvantages are discussed to highlight the parameters affecting the performance of the modified methods.

1. Introduction

Mobile Robots (MRs) have been included in different applications in recent decades [1]. Such applications cover wide areas such as military [2], security [3], industry, and indoor environments to execute critical tasks that are dangerous or menial [1]. Path planning is a fundamental function to enable MRs to safely navigate through the working environments autonomously. The difficulty of path planning increases in complex environments.

The main focus in this article is on traditional approaches rather than Learning-based approaches, which use machine learning to learn path planning either from data or by imitation. Traditional Path planning approaches can be categorized into classical approaches and heuristic approaches [4-6]. Heuristic approaches like Genetic Algorithm (GA)[7], Particle Swarm Optimization (PSO)[8], Bacteria Foraging Optimization (BFO)[9], and Ant Colony Optimization (ACO)[10] are expected to perform as well as, or better than, classical approaches like Cell Decomposition (CD)[11], Probabilistic Roadmap (PRM)[12], Rapidly-Exploring Random Tree (RRT)[13], Visibility Graph (VG)[14], Voronoi Diagrams(VD)[15], and Artificial Potential Field (APF)[16]. However, due to the computational complexity of most heuristic approaches, classical approaches are still preferable in many applications that are time sensitive and require fast real-time actions [17, 18].

Amongst classical path planning approaches, APF is gaining popularity in obstacle avoidance applications for MRs and manipulators. The APF approach introduced by Khatib [16] is based on the concept of introducing attractive and repulsive

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potential forces. The MR is attracted to its target position and is repulsed away from the obstacles. This approach is attractive because of its simplicity [19]. It enables the MR to maneuver obstacles while following its path to the target position. The APF approach is deterministic in its nature, which leads to a repeatable solution for every run of the algorithm with the same input data [20]. This feature is not available in heuristic methods, which usually give a different solution for every run.

APF has some inherent limitations that are independent of its implementation, which are as follows [21]: trap situations due to local minima (cyclic behavior), no passage between closely spaced obstacles, oscillations in the presence of obstacles, and oscillations in narrow passages.

Local minima problem is a common limitation of APF [21]. All modified versions tried to solve local minima by one of two approaches. The first approach is by modifying the field equations and the second one by using extra integrated algorithm. In first approach, the field equation is modified to guarantee that there is only one global minimum at the target position [22]. It usually adds additive or multiplicative terms of relative distance, velocity, or acceleration of the target to the repulsive field equation. In second approach, the mentioned studies included five common methods integrated with APF so that the MR can escape from local minima positions. These methods are Virtual obstacles / Obstacle filling [23, 24], Wall following / BUG [25-27], Sub-goal/ Virtual targets [28-33], Spin fields [23, 33-37], and Regular Hexagon Guided (RHG) [38].

This study analyzes a total of 24 research articles published between 1985 and 2022. The aim is to highlight the contribution of the existing literature on the APF approach with a particular focus on the modified field equation. This study can be useful to researchers and practitioners working in the field of robotics, automation, and artificial intelligence, who are interested in understanding the latest advancements in mobile robot path planning using the APF approach.

The remainder of this paper is organized as follows: in section 2, the path planning problem is defined. In section 3, the conventional APF approach is described. In section 4, some modified versions of APF are proposed. In section 5, a brief comparison is given for each modified version included in this paper and a summary is given with a recommended roadmap for APF implementation in different scenarios.

2. Path planning

The path planning problem can be described as follows: given an MR and its working environment, the MR searches for an optimal or suboptimal path from the initial position to the target position according to a certain performance criterion [39]. One of the key issues in path planning [40] is that the path should be safe and free of any collision with different environment components. All MRs implement some sort of collision avoidance, ranging from basic algorithms, which detect the obstacle and stop the MR, to complex algorithms, which enable the MR to maneuver obstacles while moving towards the target position. The need for a safe path arises when the environment includes pedestrians. There are five main components in the path planning process [5, 41, 42]:

- Perception: the MR receives data from its installed sensors to extract meaningful information about the environment.
- Localization: the MR determines it position within the environment map.
- Path Planning: the MR searches and creates a set of ordered configurations that connects the start position to its target.
- Path Generation: the MR tries to obtain a safe and smooth path from the discrete configurations obtained from the planning step.
- Path Tracking: the MR regulates its motion to follow the generated path while following the environment safety measures.

Path tracking is a complementary task to path planning, which determines how to move the MR in a way that is acceptable for its mechanical limitations such as steering rate and acceleration. Path tracking is used when the MR is applied in a dynamic environment because it needs to re-plan its path when it faces a dynamic obstacle while tracking its initially generated path.

There is an abundance of research on path planning, which has a critical role in MR applications. There are two main approaches in MR path planning: (i) global path planning or off-line path planning, and (ii) local path planning or on-line path planning [5, 43, 44]. A global path planner usually generates a high-level path based on its prior knowledge about the environment. It can fit with static and structured environment that can be mapped easily and once. Meanwhile, a local path planner does not need a predefined map of the environment. It usually gives a high-resolution low-level path over a portion of the total path based on data processed from the installed sensors. It works effectively in dynamic environments where the map is continuously changing [5]. However, local path planning becomes inefficient when dealing with environments where the target position is a long distance away from the initial position.

For a partially known environment, which contains known and static obstacles in addition to a set of unknown obstacles, an initial map is provided for the static obstacles like walls, assets and doors. In this case, an initial full path can be planned using a global planner [17]. Once the MR starts moving, a local planner guides the MR along the path and avoids dynamic and unknown obstacles that may face the MR.

There are four essential trade-offs that should be considered in a path planning algorithm [45]. The first is optimization, which ensures that the generated path is optimal or suboptimal in terms of distance, travel time, smoothness, and so on. The second criterion is completeness, which ensures that the planning algorithm is guaranteed to provide all possible solutions for the path at hand. The following is accuracy/precision. This criterion is very crucial to driving all states from the initial position to the target position. The last criterion is the algorithm execution time. The objective of this criterion is to guarantee the best-case setting for handling a given problem in reasonable time that fits the application time constraints.

3. Conventional APF approach

APF was first introduced by Khatib [16] based on the artificial fields, which attract the MR towards its target position while repelling it away from obstacles. The total potential field applied on the MR is calculated by:

$$U_{total}(q) = U_{att}(q) + U_{rep}(q), \quad (1)$$

where $U_{total}(q)$ is the total potential field applied on the MR at position q, U_{att} is the target attractive field, and U_{rep} is the total repulsive field by obstacles. The attractive potential field at position q is calculated by:

$$U_{att}(q) = \frac{1}{2} k_a (q_t - q)^2, \quad (2)$$

where k_a is the attractive proportional constant, and q_t is the target position. Finally, the repulsive potential field at position q is calculated by:

$$U_{rep}(q) = \sum_o U_o(q), \quad (3)$$

where $U_o(x)$ is the repulsive field exerted by the obstacle o, and it is calculated by:

$$U_o(q) = \begin{cases} \frac{1}{2} k_r \left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 & \rho \le \rho_0 \\ 0 & \rho > \rho_0 \end{cases}, \quad (4)$$

where ρ is the shortest distance between the MR and obstacle o, and ρ_0 is the distance of influence for the obstacle. The force applied to the MR is calculated by:

$$F(q) = -\nabla U_{total}, \quad (5)$$

The flowchart for path planning using the conventional APF approach is shown in Fig. 1.

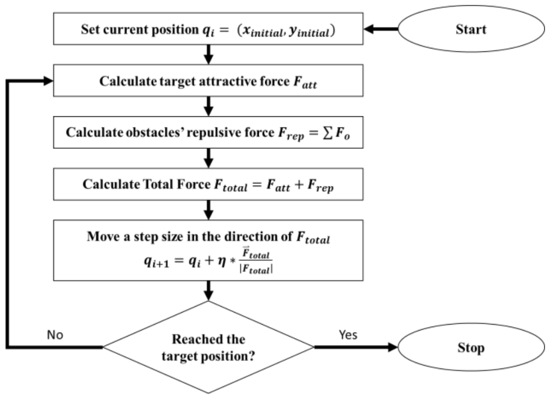

Fig. 1: shows the flowchart for path planning using the conventional APF approach, where F_{att} is the target attractive force, and F_{rep} is the total repulsive force exerted by obstacles.

The conventional APF has some inherent limitations such as trap situations due to local minima, no passage between closely spaced obstacles, and path oscillations. Traps are generated due to the equilibrium between repulsive and attractive field components as described in Fig. 2(a). When both fields have the same value with opposite direction, the resultant force applied on the MR becomes zero. In this case, the MR stops in this position. The no-passage problem happens when there are two closely spaced obstacles facing the MR with the target position on the other side. In this case, the resultant repulsive field pulls the MR in the opposite direction of the target as shown in Fig. 2(b). In narrow passages, the path tends to have oscillations because of the continuous change in repulsive field of each passage side when the MR moves towards or away from that side as shown in Fig. 2(c).

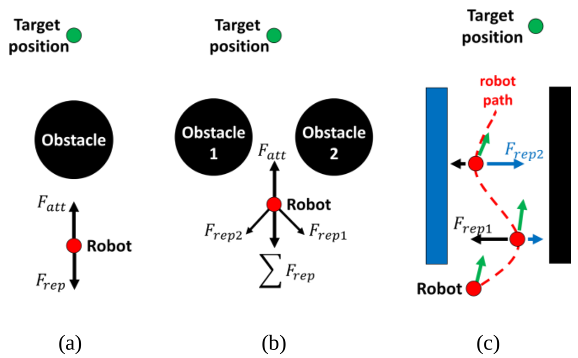

Fig. 2: Inherent Limitations of the conventional APF approach; (a) shows local minima due to field equilibrium, (b) shows two closely separated obstacles repelling the MR away from the target, and (c) shows path oscillations in narrow passages.

4. Modified versions of APF approach

The modifications to the APF method can be done to one or more of the following factors: environment representation, dealing with dynamic target and obstacles, field equations, and hybridization with another algorithm.

In terms of environment map representation, APF approaches take one of two representations; grid map and geometric based representation. Grid map fits in unknown environments where the mapping process is simultaneous with the path planning. Borenstein and Koren [25, 40] used the certainty grid method to handle the sensors inaccuracy problem. Grid maps also fit for unstructured environments. Meanwhile, geometric based representation fit for structured environments, where environment components had uniform shapes and their positions were known. It saved more time in path planning because each obstacle was taken into consideration once. Meanwhile, grid maps dealt with each cell of the obstacle as a separate repelling source. Time complexity in grid maps proportionally increased with the map resolution.

The target and obstacles in the working environment can be static such as walls, movable such as chairs and bags, or dynamic such as other MRs and pedestrians. The majority of proposed methods dealt with static environment to focus on the planning process and did not investigate issues related to map building or monitoring environmental changes. However, real-life applications include moving obstacles and pedestrians. Hong et al. [20], Lazarowska [29], Fan et al. [38], and Lu et al. [46] proposed methods that handled the moving obstacles scenario. Meanwhile, Ge and Cui [35], Huang [47], and Yin et al. [19] dealt with moving obstacles and tracked dynamic targets. For simplicity, all dynamic obstacles were considered to be measurable and known to focus the comparison on the planning process and obstacle avoidance strategy.

Borenstein and Koren [48] introduced a real-time map building method using on-board range sensors called Histogram In-Motion Mapping (HIMM). HIMM represented the environment as a two-dimensional array of cells. Each cell value contained a certainty value for corresponding position to be occupied by an obstacle and the repulsive force was calculated by:

$$F_{rep} = \sum_{i,j} F_{rep}(i,j), \tag{6}$$

where $\mathrm{F_{rep}}$ is the total repulsive force, and $\mathrm{F_{rep}(i,j)}$ is the repulsive component exerted by cell at position $(\mathrm{i,j})$ calculated by:

$$F_{rep}(i,j) = \frac{(k_r \times C(i,j))}{\rho^2(i,j)} \left[\frac{x_i - x_q}{\rho(i,j)} \vec{x} + \frac{y_j - y_q}{\rho(i,j)} \vec{y} \right], \tag{7}$$

where $\mathrm{C(i,j)}$ is the certainty value of cell at position $(\mathrm{i,j})$.

This work was followed by a proposed method for real-time obstacle avoidance called Virtual Force Field (VFF) by Borenstein and Koren [25]. The main advantage of VFF was that it allowed adding and retrieving data on the fly, enabled easy integration of multiple sensors, and overcame the shortcomings of range sensors, like poor directionality, frequent misreadings, and specular reflections. Some dynamic enhancements were also introduced by Borenstein and Koren [25] to guarantee path smoothness. These enhancements were low pass filter for steering control and damping factor for linear velocity when the MR faces an obstacle. More investigation was done to overcome local minima problem with the use of the Wall Following method (WF).

Borenstein and Koren [40] proposed a two-stage data reduction method called Vector Field Histogram (VFH), which was applied on the environment certainty grid map mentioned by Borenstein and Koren [48]. In the first stage, VFH converted the histogram grid data into a one-dimensional polar histogram around the MR by:

$$h_k = \sum_{i,j} m_{i,j} \,, \tag{8}$$

where h_k is the polar obstacle density, $m_{i,j}$ is the magnitude of obstacle vector cell (i, j), and the sector number k is established by:

$$k = INT\left(\frac{\beta_{i,j}}{\alpha}\right), \tag{9}$$

where $\beta_{i,j}$ is the direction from active cell (i, j) and the MR, and α is the angular resolution such that the number of sectors $(N) = 360°/\alpha$ is an integer.

In the second stage, a steering control action was calculated based on the sector with lower polar obstacle density. This method enabled the MR to navigate in narrow passages and closely located obstacles, which is a main shortcoming of the conventional APF approach.

Hou and Zheng [49] proposed a hybrid path planning method based on hierarchical hexagon cell decomposition and APF. A potential value was calculated for each cell so that the MR can efficiently select the next cell. The heuristic value of a cell at position q was calculated by:

$$h(q) = \sum_o \frac{k_r}{\rho_o^2} - k_a(1 - S\gamma), \tag{10}$$

where S is a scaling factor, and γ is the angle between the line connecting the target position and the MR and the direction of motion of the MR.

Lazarowska [20, 50] introduced a discrete artificial potential field method. The map was represented as two-dimension grid with potential value for each cell based on its distance from the target and neighbor cells' values as follows:

$$c_{ij} = \begin{cases} c_{00} - 10y & if\ x = 0, \quad 0 \le y \le n-1 \\ c_{0y} + x & if\ 1 \le x \le \dfrac{m-1}{2} \\ c_{0y} - x + 0.5 & if\ \dfrac{-m-1}{2} \le x \le -1 \end{cases} \tag{11}$$

where n is the number of horizontal cells, and m is the number if vertical cells.

A path optimization method was applied on the resulting discrete path configurations to make the path smoother and shorter while keeping it free from collisions. The path optimization was based on an iterative elimination of unnecessary cells belonging to the collision-free path.

Ge and Cui [22] modified the potential field by adding the relative distance between the MR and its target to the repulsive field, which can be described as follows:

$$U_o(q) = \begin{cases} \dfrac{1}{2} k_r \left(\dfrac{1}{\rho} - \dfrac{1}{\rho_0}\right)^2 (q_t - q)^a & if\ \rho \le \rho_0 \\ 0 & if\ \rho > \rho_0 \end{cases} \tag{12}$$

where a is a positive constant.

This modification made one global minimum at the target position and helped to solve the problem of non-reachable targets with obstacles nearby GNRON. All free path local minima were eliminated by carefully tuning the APF parameters. Sfeir et al. [36] and Wang et al.[23] expressed the relative distance between the MR and its target in an exponential form to reduce the distortion of repulsive field when the MR is far from the target, which can be described as follows:

$$U_o(q) = \begin{cases} \frac{1}{2} k_r \left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 \left(1 - e^{-\frac{(x_q - x_o)^2 + (y_q - y_o)^2}{R^2}}\right) & if\ \rho \le \rho_0 \\ 0 & if\ \rho > \rho_0 \end{cases}, \tag{13}$$

where (x_q, y_q) is the coordinate of the MR, and R is radius of the MR.

Ge and Cui [35] proposed a potential field approach to work within a dynamic environment in which both the target and the obstacles were moving. The used potential function took into consideration the relative velocity between the MR and the target, and also between the MR and the obstacles, which can be described as follows:

$$U_{att}(q, v) = k_a \|q_t - q\|^m + k_v \|v_t - v\|^n \tag{14}$$

where k_v is velocity attraction proportional constant, (q, v) are the position and velocity of the MR respectively, and m and n are positive constants.

$$U_o(q, v) = k_r \left(\frac{1}{\rho - \rho_m(v_{RO})} - \frac{1}{\rho_0}\right) \tag{15}$$

when $0 < \rho - \rho_m(v_{RO}) < \rho_0$ and $v_{RO} > 0$, otherwise $U_o = 0$, where v_{RO} is the relative velocity between the MR and obstacle o, and $\rho_m(v_{RO})$ is the distance travelled by the MR when decelerating by a_{max} and is calculated by $\frac{v_{RO}^2}{2a_{max}}$.

The resulting force was calculated as the negative gradient of position and velocity potential. Such force was translated into a steering control action depending on the MR configuration. Huang [47] introduced a velocity planning for the MR to follow the moving target. The velocity planning provided both speed and direction control for the MR to track the moving target while avoiding the moving obstacles. Yin et al. [19] included the relative acceleration of the MR with regard to both the target and the obstacles in the potential field equations, which can be described as follows:

$$U_{att}(q,v,a) = k_a\|q_t - q\|^m + k_v\|v_t - v\|^n + k_c\|a_t - a\|^c \quad (16)$$

where k_c is the acceleration attraction proportional constant, and c is a positive constant.

$$U_{rep}(q,v,a) = k_r\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 + \eta_1 v_{RO} + \eta_2 a_{RO} \quad (17)$$

where a_{RO} is the relative acceleration between the MR and obstacle o. η_1 and η_2 are two positive scaling factors.

Three scenarios when tracking a moving target were discussed by Yin et al. [19]; hard landing, semi-soft landing, and soft landing. For simplicity, the local minima problem was handled by waiting until the dynamic environment changes its potential, otherwise the WF method was used. Fan et al. [38] proposed a path planning method that was adaptable for static and dynamic environments. For dynamic environment, the method considered the spatial location and in addition the relative velocity of moving obstacles. For static environment where a local minima problem most probably occurred, the RHG method was used to escape from this trap.

The virtual obstacle concept was introduced by Park and Lee [24] to escape local minima positions. When the MR was trapped in a local minimum along the path, a virtual obstacle was generated at this position to repel the MR away from it with repulsive field calculated by:

$$U_{virtual}(q) = \begin{cases} k_b \dfrac{1}{|q - q_l|^2}, & if\ |q - q_l| \le d_l \\ 0 & if\ |q - q_l| > d_l \end{cases} \quad (18)$$

where k_b is the repulsive field coefficient of virtual obstacle, q_l is the local minimum position, and d_l is the new filling potential distance.

Zou and Zhu [31] proposed a navigation algorithm based on the potential field approach with global path generation capability. When the MR encountered a local minimum or danger location, the algorithm generated a virtual target that replaced the actual target. After the MR reached the virtual target position, it continued its journey to the actual target position.

Kim [28] modified the total potential field equation by using additive and multiplicative structure of attractive and repulsive fields, which can be described as follows:

$$U_{total}(q) = \frac{1}{k_a} U_{rep} \,.\, U_{att} + U_{att} \quad (19)$$

$$U_{att} = k_a\left(1 - e^{-\frac{\|q-q_g\|^2}{l_g^2}}\right) \quad (20)$$

$$U_{rep} = \sum_o k_r\left(1 - e^{-\frac{\|q-q_o\|^2}{l_o^2}}\right) \quad (21)$$

where l_o, l_g are correlation distance for obstacle avoidance and the target distance respectively.

The trap situation was detected by Kim [28] when four conditions were satisfied, which can be described as follows:

$$\begin{aligned} &|F_{total}| < a_1, \\ &|\theta^g - \textstyle\sum_o \theta^o| < a_2, \\ &|q - q_g| > a_3,\ and \\ &|q_t - q_{t-1}| < a_4 \end{aligned} \quad (22)$$

where $a_1, a_2, a_3, and\ a_4$ are positive constants close to zero, θ^g is the angle between the MR and the target, and θ^o is the angle between the MR and obstacle o.

Hong et al. [29] introduced a two-stage planner. It was based on two procedures; sub-goal generator and inner re-planner. The potential field was integrated as the evaluation of MR configuration. Yingkun [32] simplified the virtual target generation by randomly selecting a position in the neighborhood. Di et al. [33] applied the virtual target concept along with left turning method to escape from the local minimum position.

Zhang et al. [26] proposed a new method that enabled the MR to change its behavior based on online sensors data. These behaviours were APF-based obstacle avoidance, goal seeking, and WF. The MR started to navigate based on APF to avoid obstacles. When it was trapped in a local minimum, it switched to Goal-Seeking behavior. In Goal-Seeking behavior, the MR neglected the repulsive field and moved in a straight line to the target. When there was an obstacle between the MR and the target, the MR switched to WF behavior. In WF, the MR followed the contour of the facing obstacle until it bypassed the trap position. In this case, the MR turned back to move by ordinary APF behavior. The flowchart of this algorithm is shown in Fig. 3.

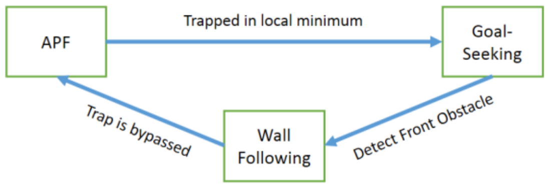

Fig. 3: Flowchart of behavior switching of the MR proposed by Zhang et al. [26]

Sfeir et al. [36] introduced a rotational field for obstacles to overcome the local minima problem and reduce the oscillations that resulted when the MR was too close to the obstacle. Instead of repelling the MR away from the obstacle, the repulsive field guided the MR along the obstacle contour until it passed that obstacle and then followed its journey to the target. Wang et al. [23] added a rotation matrix to the attractive field in local minimum position. This rotational field helped to overcome the equilibrium of potential fields and repel the MR from the position it got stuck at.

Mei et al. [27] introduced a hybrid model based on Bug algorithm [51, 52] with APF to enable the MR to escape from local minima positions. When the MR got stuck in a local minimum, it switched to the Bug-behavior and searched for an obstacle boundary to follow until it escaped that local minimum.

The APF approach was used with other robotic systems such as autonomous driving and unmanned aerial vehicles (UAVs). Lu et al. [46] proposed a hybrid planner based on the potential field and sigmoid curves. The potential field was used to determine the parameters to generate a sigmoid path, which aimed to achieve both safety and smoothness for autonomous driving. Zhang et al. [34] introduced a multi (UAV) formation control system. A Leader-Follower strategy was implemented with an independent obstacle maneuver for each UAV. The obstacle avoidance was based on a spin field for the obstacle with angle depending on the angel between the robot-target and the robot-obstacle vectors. Souza et al. [37] applied a 3D rotational operation on the repulsive field of each obstacle so that the MR can determine its rotation vector. The spin vector was calculated from the vector multiplication of the robot-target and the robot-obstacle vectors.

5. Brief comparison

The following table includes a comparison between the studies mentioned in the literature section to show the contribution of each approach.

Table 1: Comparison between modified versions of APF approach.

Article	Year	Environment /Obstacles Representation	Moving obstacles (O) / target (T)	Integrated method	Modified Field Equation: Relative (p, v, a) of target included in U_{rep}	Modified Field Equation: Relative (v, a) of obstacle included in U_{rep}	Modified Field Equation: Spin Field
[25]	1989	Grid	-	Wall Following	-	-	-
[40]	1991	Grid	-	-	-	-	-
[49]	1994	Hex Grid	-	Cell Decomposition	-	-	-
[22]	2000	Rectangles	-	-	p	-	-
[35]	2002	Rectangles	O, T	-	p, v	v	yes
[24]	2003	Grid	-	Virtual Obstacle	-	-	-
[31]	2003	Rectangles	-	Virtual Target	-	-	-
[47]	2009	circles	O, T	-	p, v	-	-
[19]	2009	Point	O, T	-	p, v, a	v, a	-
[28]	2009	circles	-	Virtual Target	p	-	-
[29]	2010	Rectangles	O	RRT/DRM with Virtual Target	-	-	-
[26]	2010	Grid	-	Wall Following	p	-	-
[36]	2011	Rectangles	-	-	p	-	yes
[27]	2013	rectangles	-	Bug algorithm	p	-	-
[23]	2017	circles	-	Virtual Obstacle	p	-	yes
[32]	2018	arbitrary	-	Virtual Target	-	-	-
[34]	2018	Cylinders	-	-	p, v	-	yes
[20]	2019	Grid	O	Path Optimization Algorithm	-	-	-
[50]	2019	Grid	-	Path Optimization Algorithm	-	-	-
[38]	2020	circles	O	Regular Hexagon Guide	p, v	v	-
[33]	2020	Grid	-	Left Turning/ Virtual Target	-	-	yes
[46]	2020	Car / lane	O	Sigmoid Curve	p, v	-	-
[30]	2021	Circles	-	Dynamic window/ Virtual Target	p	-	-
[37]	2022	cubes	-	-	p	-	yes

From the various modified versions of APF, each approach has its own advantages and disadvantages regarding the local minima problem and the quality of generated path.

Map representation is a main factor that affects the path planning process. Grid maps and geometric based representation are both used in the mentioned studies. Grid maps are suitable for environments with non-uniform obstacles. However, they are time consuming because the repulsive filed for each obstacle is calculated as the summation of the repulsive fields generated by each cell occupied by that obstacle. High resolution grid maps require more computation time. The cell decomposition [49] method helps to minimize the number of cells that represent the obstacle by using iterative decomposition with variable-size hexagonal cells. Meanwhile, geometric based representation is suitable for structured environments. Each obstacle is represented as a uniform shape and is considered as a single source of repulsion. The challenge in geometric representation is the computation of the nearest point between the MR and the obstacle.

The field equations, (2) and (4), are modified so that there is only one global minimum at the target position. The modified equations take into consideration the relative distance between the MR and the target either in a simple linear form as in (12), or in an exponential form as in (13), (20) and (21).

The discussed studies include five common methods integrated with APF to solve the local minima problem. These methods are Virtual obstacles / Obstacle filling [23, 24], Wall following / BUG [25-27], Sub-goal/ Virtual targets [28-33], Spin fields [23, 33-37], and RHG [38]. Virtual obstacles and obstacle filling methods try to generate extra potential fields in a trap position to repel the MR and mark this position as occupied so that the MR cannot be trapped again. Wall Following and BUG methods depend on using the obstacle boundary as a guide for the MR to walk along until the MR escapes the trap and then resumes its main path to the target. Sub-goal and virtual targets replace the main target position with another to change the balance in the resultant potential field and guide the MR to a position where it can continue its path to the main target. Spin field introduces a good solution in densely cluttered environments because it guides the MR along the obstacle contour rather than repelling it away. The RHG method is based on cell decomposition and generates a hexagon path to maneuver the facing obstacles that caused local minimum position.

6. Conclusion

This paper summarizes various modified versions of the AFP approach for the path planning problem of MRs. AFP is a unique approach since it is simple and requires less computational time. However, AFP suffers from local minima problem, which causes a robot to trap at a particular position before reaching the target position. Modified versions of AFP approach addressed the local minima problem, each with its own advantages and disadvantages. Nevertheless, the research on AFP has not been fully explored and is still open especially in addressing the local minima problem.

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