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A Novel Approach to Local Minima Problem in Robot Path Planning Using Artificial Potential Field

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Abstract

The autonomous mobile robots have vast applications which include industrial robots, service robots, drone-based robots etc. for supplying customer goods, for space exploration and much more. Path planning is one of the important steps of using mobile robots in any application. In autonomous mobile robot navigation, local minima describe a situation in which an object gets stuck with no next possible move attainable. This paper introduces a new concept to deal with the local minima problem in artificial potential based robot navigation methods. We propose a virtual plane based method which basically gets the robot out of the local minima successfully and inhibits it from getting into the same area again, thereby guaranteeing the convergence of the method. The proposed technique uses the concept of histograms and temporary objectives to achieve its goal. In particular, the histograms are used to find the wide enough gaps for the robot to pass through and the temporary objectives are used to escape the robot from local minima. The above technique is used, in particular, with the C and H type obstacles. The simulation results verify the effectiveness of this method.

Keywords: *Artificial potential, virtual plane, navigation, local minima, histogram, temporary objectives, robot*

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INTRODUCTION

The problem of autonomous navigation for mobile robots is considered one of the complicated issues attributable to the very fact that a mobile robot needs to deal with numerous and uncertain obstacles present within the environment to reach the goal safely. A robot has to find an optimal path, i.e., it should be able to find or set up a route between the two points (S, T) where S is the source and T is the target while avoiding any kind of obstacles present between these two points. On the analysis of current literature on autonomous motion planning, we found that the existing algorithms for path planning are divided into two main classes; offline and online.

An algorithm works in offline mode if it has the complete information beforehand regarding the atmosphere/environment within which the robot needs to navigate. There is complete information regarding the static as well as the moving or dynamic obstacles within the atmosphere. In offline algorithms, we have Voronoi diagram that is employed to search for the safest areas within the environment, then these safest areas are used to find the path by using the fast marching technique [1]. Grid technique provides a robot with a trajectory to be followed so as to maneuver from an initial position to the desired target [2]. Bacterial memetic was developed with the goal to minimize the number of turns without colliding with an obstacle and minimizing the path length [3]. GA based A* is used for global path planning of mobile robot [4]. The algorithm consists of three steps; the MAKLINK graph is used for generating free space model. Then Dijkstra algorithm is employed for generating a collision-free path. At last, the optimal global path is generated using genetic and A* algorithms.

In contrast, an algorithm is said to work in online mode when there is no information available regarding the surroundings (reactive) or environment in advance. The sensors of the robot are used to perceptually experience the surroundings and the robot react consequently. In online algorithms, Modified A* real-time algorithm finds an optimal path from a start point to a target point while avoiding the obstacles in its path [5]. In an unknown and dynamic environment, improved VFF algorithm provides a solution to the problem of real-time path planning of a robot [6]. Sensor based motion planning generates a collision-free path for a robot pursuing a moving target in presence of static and dynamic obstacles [7]. The core idea of this technique is to make a directive circle which is the set of all collision free directions, calculated from velocity vectors of the robot relative to every obstacle.

In the field of local or online robot path planning, Artificial Potential Field (APF) is one among the most popular strategies that was introduced by Khatib in 1986 [8]. It is a real-time collision avoidance technique based on the principle of attractive and repulsive forces by the target and the obstacles in the environment respectively. Khatib proposed that an object (robot) is attracted towards the target by its attraction force, whereas the obstacles in its path use repulsive forces to keep up a safe distance (collision-free). The notion is fairly easy and simple to implement and it is easy to calculate a path which is collision-free. The artificial potential field strategies use gradient descent to steer the robot from a source to the target. The environment consists of both the obstacles and the target, and APF uses two different forces, the attraction force and the repulsion force, to avoid collisions with the obstacles and to reach the goal. The target is characterized by an attractive potential (Figure 1a), and the obstacles are surrounded by the repulsive potential (Figure 1b), and the net force on the robot is the negative gradient of the potential (Figure 1c).

The robot is attracted towards the goal by a force F_T, which is the total force on robot x;

$$\boldsymbol{F_T}\ (\boldsymbol{x}) = \boldsymbol{F_R}\,(\boldsymbol{x}) + \boldsymbol{F_A}(\boldsymbol{x}) \qquad (1)$$

Where, F_R is the repulsive force by an obstacle and F_A is the attractive force by the goal. The attractive potential function (quadratic) [28] is given below:

$$\boldsymbol{G_{att}}\,(\boldsymbol{x}) = \boldsymbol{\omega}\mathbf{l}\boldsymbol{x_d}\mathbf{l}^{\mathbf{2}}, \boldsymbol{if}\ \mathbf{l}\boldsymbol{x_d}\mathbf{l}\ \leq \mathbf{r}, \qquad (2)$$

$$= \boldsymbol{\omega}(\mathbf{2rl}\boldsymbol{x_d}\mathbf{l})\boldsymbol{r}^{\mathbf{2}}, \boldsymbol{if}\ \mathbf{l}\boldsymbol{x_d}\mathbf{l} > \boldsymbol{r}$$

Where, 'x' represents the position vector of the object (robot), x_d represents the difference between the position of the robot and the position of the goal, 'r' is the radius of the quadratic range, and ω is the proportional gain of the function. The attractive force F_A may be obtained by the negative gradient of this attractive potential as:

$$\boldsymbol{F_A}(\boldsymbol{x}) = -\boldsymbol{\nabla}\boldsymbol{G_{att}}(\boldsymbol{x}) \qquad \ldots\ldots (3)$$

$$= \mathbf{2\omega l}\boldsymbol{x_d}\mathbf{l}, \mathbf{if}\ \mathbf{l}\boldsymbol{x_d}\mathbf{l}\ \leq \mathbf{r},$$

$$= \mathbf{2r\omega}\ \boldsymbol{x_d}/\mathbf{l}\boldsymbol{x_d}\mathbf{l}, \mathbf{if}\ \boldsymbol{x_d}\ > \boldsymbol{r}$$

The repulsive potential function for obstacle repulsion is given as:

$$\boldsymbol{O_{rep}}\,(\boldsymbol{x}) = \frac{\mathbf{1}}{\mathbf{2}}\,\boldsymbol{\eta}\ (\mathbf{1}/\boldsymbol{f}(\boldsymbol{x_{ob}}) - \mathbf{1}/\boldsymbol{f_o})^{\mathbf{2}}, \boldsymbol{if}\ \boldsymbol{f}(\boldsymbol{x_{ob}}) \leq \boldsymbol{f_o}$$

$$= \mathbf{0}, \boldsymbol{if}\ \boldsymbol{f}(\boldsymbol{x_{ob}}) > \boldsymbol{f_o} \qquad \ldots\ldots (4)$$

Where, 'η' is a positive scaling factor, $f(x_{ob})$ denotes the shortest distance from the robot 'x' to the obstacle, f_o is the largest impact distance of the obstacle or potential field's distance limit of influence or the obstacles radius of influence. The negative gradient of the repulsive potential function:

$$\boldsymbol{F_R}(\boldsymbol{x}) = -\boldsymbol{\nabla}\boldsymbol{O_{rep}}(\boldsymbol{x}) \qquad \ldots\ldots (5)$$

$$= \boldsymbol{\eta}(\mathbf{1}/\mathbf{f}(\boldsymbol{x_{ob}}) - \mathbf{1}/\boldsymbol{f_o})\ \mathbf{1}/\boldsymbol{f}(\boldsymbol{x_{ob}})^{\mathbf{2}}\ \boldsymbol{\delta}\mathbf{f}(\boldsymbol{x_{ob}})$$

$$/\boldsymbol{\delta x}, \mathbf{if}\ \mathbf{f}(\boldsymbol{x_{ob}}) \leq \boldsymbol{f_o}$$

$$= \mathbf{0}, \boldsymbol{if}\ \boldsymbol{f}(\boldsymbol{x_{ob}}) > \boldsymbol{f_o}$$

Where, $\delta f(x_{ob})/\delta x = (\delta f(x_{ob})/\delta x\ \delta x(x_{ob})/\delta y)^T = x_c/f(x_{ob})$ and where x_c is the difference between the position vector of the closest obstacle and the position vector of the object in the xy-coordinate system [8].

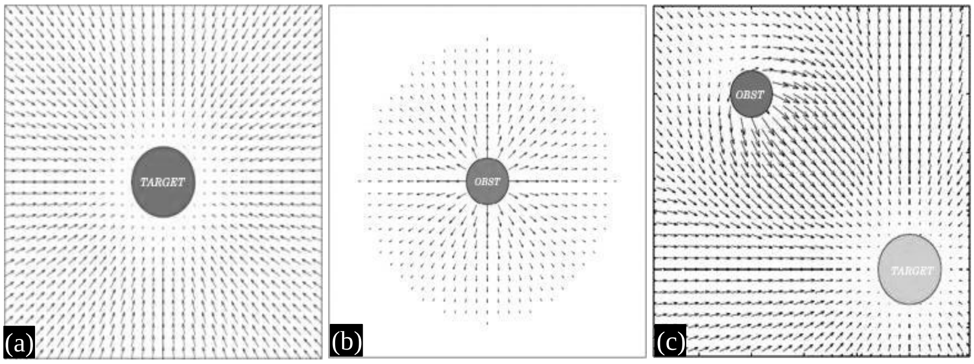

Fig. 1: *Artificial Potential Field. (a) Attractive Force, (b) Repulsive Force and (c) Total Force.*

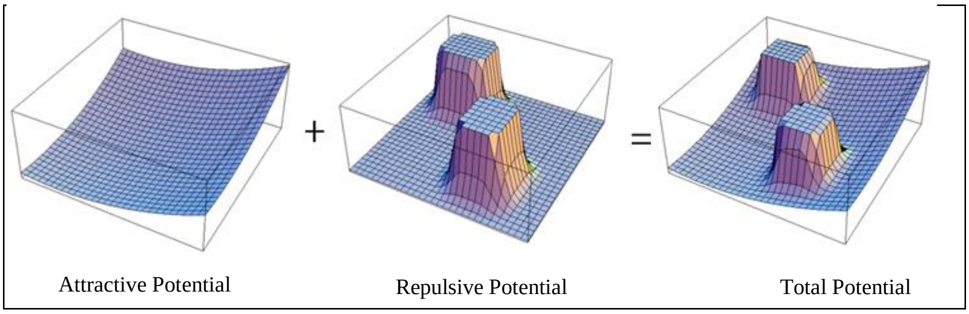

Fig. 2: *Potential Fields.*

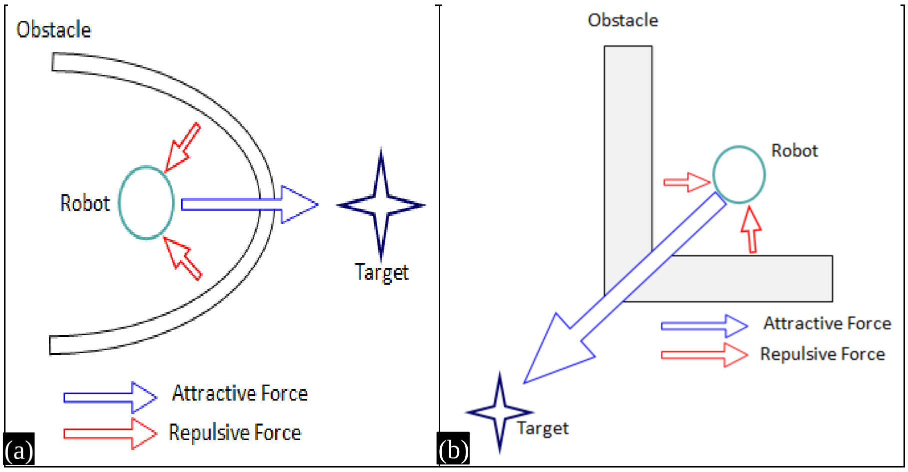

Fig. 3: *Examplesof a Robot Stuck in Local Minima. (a) Case 1 and (b) Case 2.*

Now total force on robot x is given by (Figure 2):

$$\boldsymbol{F_T}\,(\boldsymbol{x}) = \boldsymbol{F_A}\,(\boldsymbol{x}) + \boldsymbol{F_R}(\boldsymbol{x}) \quad \ldots (6)$$

$$= -\nabla \boldsymbol{G_{att}}\,(\boldsymbol{x}) - \nabla \boldsymbol{O_{rep}}\,(\mathbf{x})$$

Using the above total force, the robot progressively steers towards the goal while avoiding the obstacles in its path and reaches the goal successfully.

But there are some implicit issues in the artificial potential field theory which include local minima, oscillations and Goal Not Reachable with Object Nearby (GNRON). Local minima describe a situation within which an object gets stuck with no next possible move attainable. The object finds itself trapped in a configuration where it has not reached the target yet, however its velocity becomes zero or close to zero. In unknown environments, the object does not have the complete information regarding the obstacles. The object will reach the goal with success if the atmosphere/environment is free from complex shaped obstacles. However the environments are not always that straightforward, so it is inevitable that a robot could find itself in the situations where it gets stuck/trapped in local minima (Figure 3).

In both the cases, the target attracts the object along the shortest path possible but the obstacle repels it in the opposite direction, the resulting force becomes zero and therefore the object is stuck (Figure 3(a and b)). The problem of oscillations occurs whenever an object has to pass through a slim valley of obstacles. The trajectory followed is not as smooth as expected. The object makes little wobbles while crossing the passage. The last drawback is due to the fact that there can be a situation when the goal lies within the vicinity of the repulsive force of an obstacle. This makes the object reach close to the goal, however, inhibits it to actually reach the target. The problem of local minima is shown more vividly in Figure 4.

CURRENT STATE-OF-ART

The idea of virtual obstacle was proposed by Park *et al*. to help an object escape from the problem of local minima in local path planning of a mobile robot [9]. Whenever a robot detects local minima, a virtual obstacle is placed at that position which then repels the robot and helps it to escape the local minima. However, the robot may return to the local minimum area once the virtual obstacle is cleared. Sfeir *et al*. proposed a modified potential for obstacles so as to reduce the oscillations, mainly when the robot is close to the target [10]. They also introduced a rotational force for a smoother trajectory when the robot is moving along the boundary of the obstacles. However, the strategy does not guarantee that the robot can perpetually escape the local minima.

Cifuentes *et al*. introduced a local navigation technique based on the property of discerning among the various potentials available [11]. The various fields may come from different obstacles, robots, and targets. At each point in its motion, the robot tries to completely differentiate among different potential fields and consequently takes decisions during its motion towards the target. This technique solved the local minima or trapping problem of classical virtual force based methods to some extent. An improved artificial potential field based regression search (Improved APF-based RS) methodology was conferred by Guanghui *et al*. that may obtain a path efficiently with no local minima and oscillations [12]. They used new modified potential functions to escape from the local minima and also the virtual obstacle concept to avoid oscillations. However, the path obtained using this methodology is not essentially a sleek path. Based on the idea of Artificial Potential Field and Bug algorithm, a new hybrid algorithm was developed by Wang *et al*. [13]. Again the potential function was changed so as to handle the problem of GNRON. To take care of local minima, they introduced BUG algorithm into the artificial potential field. However, a limitation with the technique is that it does not guarantee convergence once there are narrow corridors to pass through. Okutomi *et al*. described potential fields based algorithm that used two main concepts; the state space and the oval potential [14]. They proposed to store the potential data in a state space that makes it very simple and easy to make motion decisions. Also, the oval potentials are used to denote the obstacles which require lesser memory space and therefore the value of a state can be found quite simply. The limitation of this methodology arises from the mapping of actual objects to the state space.

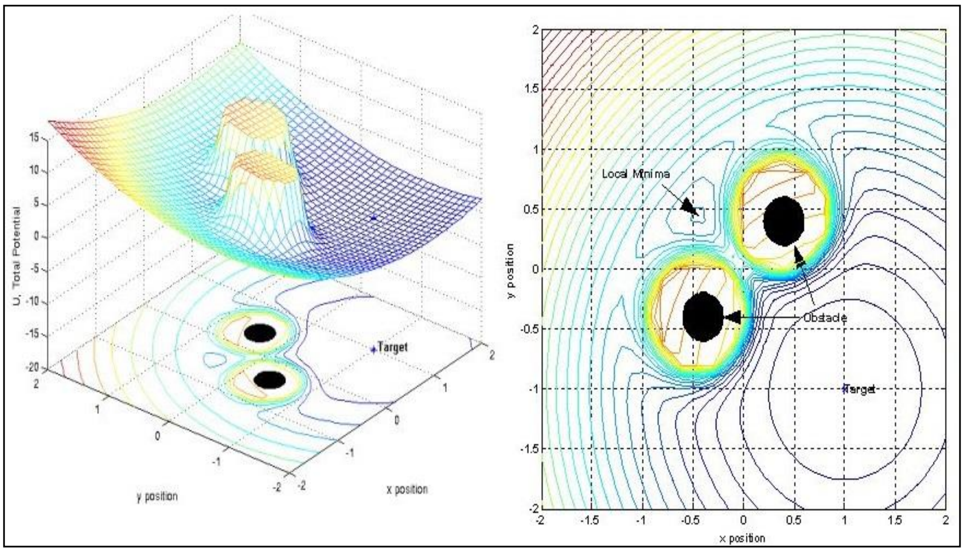

Fig. 4: *Local Minima.*

The focus of Yang *et al* was to handle the problems of local minima and GNRON [15]. They simply integrated the concept of reactive behavior with the artificial potential field methodology to create an algorithm applicable for the real-time applications whereas limiting the local minima and GNRON. However, the foremost common obstacle types that are the main reason behind local minima problem, the U and H types, were not thought-about in their work. Another hybrid approach based on Intelligent Bug Algorithm (IBA) and Follow the Gap Method (FGM) was introduced by Zohaib *et al*. [16]. They mainly targeted U and H type obstacles that are very arduous for a robot to escape from. They made their algorithm goal oriented whereas avoiding the local minima drawback. However, their work does not fully resolve the APF based local minima however provides a better approach of handling slim passages. Chen *et al*. used the chaos optimization theory to boost the artificial potential field technique for solving the issues of local minima and out of reach destination in traditional APF strategies [17]. They used a 2-stage chaos optimization with potential field function taken as the objective function. They successfully showed that their algorithm works but with the idea that the environment is partly known. Ma *et al*. came up with the concept of using intermediate objectives to escape from the local minima [18]. Whenever the robot gets stuck in local minima, a temporary objective is located and therefore the robot gets out of the loop to reach that objective. The algorithm is costlier attributable to switching and decision making times.

THE PROPOSED METHOD

In artificial potential filed technique, the robot gets attracted towards the target and tries to reach the target traversing a minimum distance (perpendicular distance), as shown in Figure 5. The above situation is ideal in case where there is no obstacle present in the environment but the situation is not always as simple as assumed. The environment is mostly filled with complex shaped obstacles which do not allow a simple (straight) path to exist from source to target and may lead to the problem of local minima, as shown in Figure 3.

Before getting along its path, the robot senses an obstacle, if there is straight path between the robot and the target, it moves along it but whenever an obstacle is detected, the robot starts to generate a polar histogram [19, 20]. In order to detect an obstacle, the robot can be configured with different sensors using different techniques for the detection. For example, range sensors like lasers and infra-red can be used [21, 22], we can also use sound based range sensors like sonar [23, 24] or we can use any of the vision-based techniques for the detection [25–27]. SONAR, Sound Navigation and ranging unit consists of an ultrasonic generator and a receiver [23]. The generator produces sound waves at a selected frequency. When these sound waves encounter obstacles, they mirror back as echoes that are received by the receiver. The output of the sonar receiver may be a distorted wave having a 10–20 mV peak to peak voltage. The received voltage varies proportionally to the strength of the signal. By calculating the time taken by the sound waves to reach the receiver after they have been transmitted, the distance of the object from the transmitter can be calculated accurately.

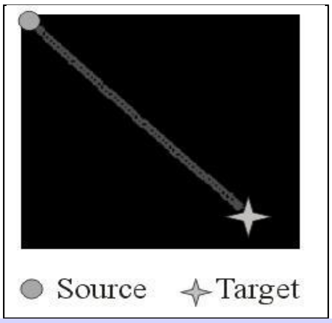

Fig. 5: *Path Planned with No Obstacle between Source and Target.*

Comment [A1]: pls confirm both image(same diffrent)

A high-accuracy environmental map employing a mobile robot can also be build using a technique presented by Ha and Kim [22]. The planning approach uses inexpensive infrared range finder sensors incorporating with neural networks. To reinforce the map quality, the errors occurring from the sensors are corrected. The non-linearity error of the detectors is compensated using a back propagation neural network and the random error of readings together with the uncertainty of the environment is taken into a sensor model as a probabilistic approach. The map is diagrammatic by an occupancy grid framework and updated by the Bayesian estimation mechanism. In VFH algorithm, a polar histogram is used to detect any valleys or passages in between the obstacles which can allow the mobile robot to pass through [19]. As shown in Figure 6, the x-axis is used to represent the angles corresponding to the sonar readings and y-axis represents the probability that an obstacle is present in that direction.

The VHF technique involves; angular sectors, polar histograms and finding the passage. We could set a minimum number of sectors that must be free to designate the passage as wide enough for the robot to pass. From the histogram, the robot learns about the obstacles and the openings between them. Also, the robot detects whether the opening is wide enough for its passage and consequently passes through the opening or decides to inhibit from it.

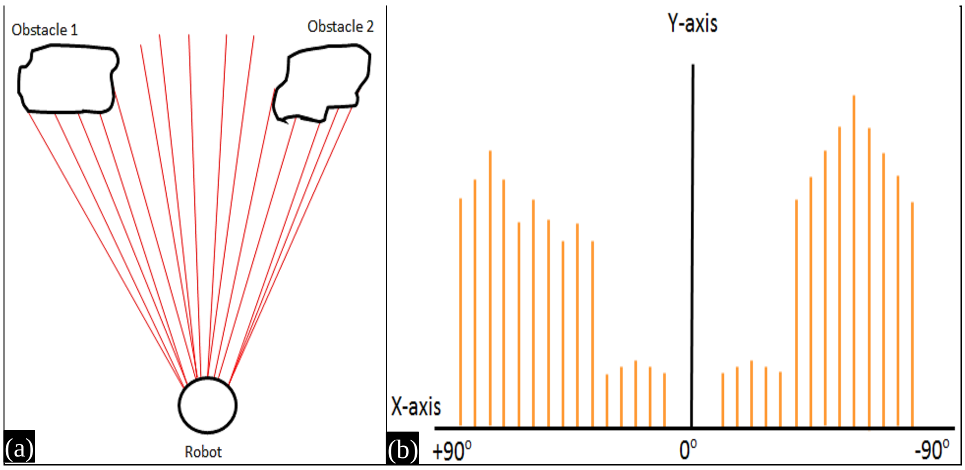

Fig. 6: *Histogram Generation. (a) Perceiving environment and (b) Histogram based on perceived environment.*

Algorithm 1
Pseudo-code

1. *Sensing the obstacles (laser range/vision sensors/sonar).*
2. *Calculate the attractive and repulsive forces by Eqs. (3) and (5) respectively.*
3. *Calculate the total force by Eq. (6).*
4. *If obstacle detected, generate polar histogram.*
5. *If concave obstacle not found, check if the passage is wide enough to pass through the obstacles.*
6. *Check if goal reached then STOP else go to step 1.*

The Main Algorithm

Whenever a robot is trapped in local minima, we use the notion of virtual plane from one end of the obstacle to the other and make the obstacle repel the robot altogether (Figure 3). The following conditions define a local minima configuration:

Criteria for Local Minima

- *If the velocity $v_r \leq v_{th}$, where v_r is the velocity of the robot and v_{th} is the threshold velocity, OR*
- *If the $d_t \leq d_{th}$, where d_t is the distance travelled by the robot in t time and d_{th} is the distance is the threshold distance which specifies the minimum distance that a robot must travel in t time.*

Let l_1 and l_2 be the distances of the two extreme points of the obstacle from the robot (Figure 7). Joining the two extreme points gives us the virtual plane. The angle between l_1 and l_2 is denoted as α.

A virtual new objective is defined along the angle bisector of the angle. This new objective attracts the robot out of the local minima and the virtual plane now acts as the repulsive force, restricting the robot from entering inside the concave surface again.

Algorithm 2
Escaping the Local Minima

1. *If $l_1 > l_2$ then dis=l_1 else dis=l_2.*
2. *The new virtual objective is located at a distance of 'dis' along the angle bisector α/2, opposite to the direction of the target. The robot moves to the new temporary objective.*
3. *At new virtual objective check if $x_{new} < x_{e1}$ AND $x_{new} < x_{e2}$ holds or not, if not, locate a new virtual objective a unit away and repeat this step until the above condition holds.*
4. *Activate the original target.*

The attraction function of the virtual new objective is given by F_A(vir) as:

$$\gamma(x_r - x_{new})^2 + (y_r - y_{new})^2 \tag{7}$$

Where, γ is the positive scaling factor as defined by the FIRAS potential function. (x_r, y_r) is the position of the robot and (x_{new}, y_{new}) is the position of virtual new objective (Figure 8).

After reaching the Virtual New Objective (VNO), the virtual plane will act as the repelling force given as:

$$F_R(plane) = \frac{1}{2}\eta\,(1/\mathrm{dis} - 1/\mathrm{r})^2, if\ dis \leq r \tag{8}$$
$$= 0, if\ dis > 0$$

Where, η is the scaling factor, 'dis' is the distance between the robot and the virtual plane and 'r' is the radius of influence of the virtual plane.

This potential function inhibits the robot from entering the local minima and the robot moves around the obstacle. The force exerted by the virtual objective is a vector of forces by each point on the plane. Let the force exerted by a point p_i on the virtual plane be F_i, then each point p_i on the plane will exert a force p_{ij} (Figure 9).

The repulsive potential function for each point on virtual obstacle is given as:

$$O_{rep}(i) = \frac{1}{2}\eta\,(1/f(x_{pi}) - 1/f_i)^2, if\ f(x_{pi}) \leq f_i \tag{9}$$
$$= 0, if\ f(x_{pi}) > f_i$$

Where, is a positive scaling factor, $f(x_{pi})$ denotes the shortest distance from the robot x to the point p_i, f_i is the radius of influence of p_i. The negative gradient of the repulsive potential function:

$$F_R(i) = -\nabla O_{rep}(i) \qquad \ldots\ldots (10)$$

$$= \eta(1/f(x_{pi}) - 1/f_i)\ 1/f(x_{pi})^2\ \delta f(x_{pi})/\delta x, \text{if } f(x_{pi}) \leq f_i$$
$$= 0, if\ f(x_{pi}) > f_i$$

where, $\delta f(x_{pi})/\delta x = (\delta f(x_{pi})/\delta x\ \delta x(x_{pi})/\delta y)^T = x_c/f(x_{pi})$

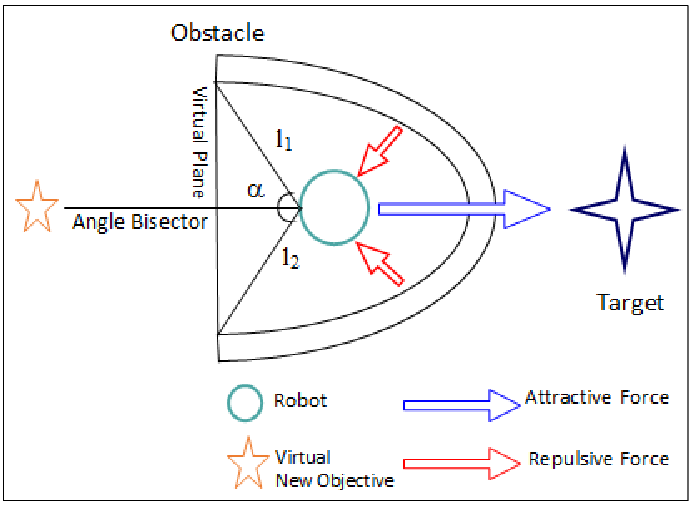

Fig. 7: *Local Minima.*

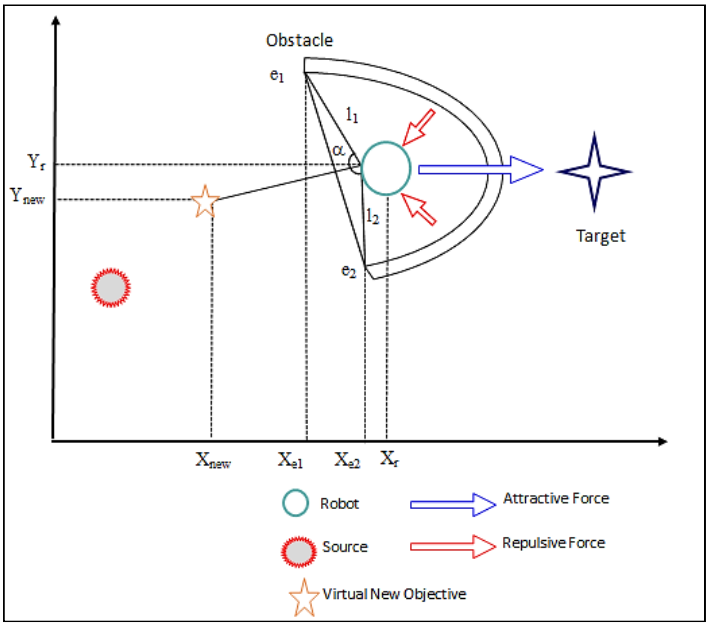

Fig. 8: *Local Minima.*

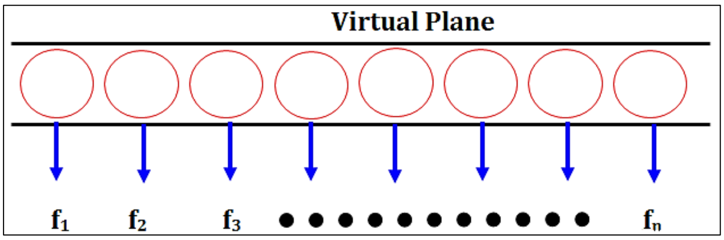

Fig. 9: *Force Exerted by Virtual Plane.*

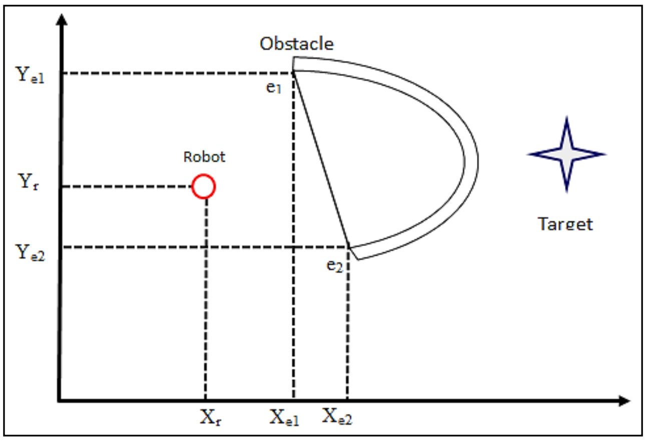

Fig. 10: *Virtual Force Activation.*

The potential function of the virtual plane gets activated only when the robot is positioned inside the trapezoid $y_{e1}e_1e_2y_{e2}$. So, the existence of virtual plane depends on the position of robot as shown in Figure 10.

Case 1:

If $x_{e1} \leq x_r \leq x_{e2}$, calculate

$$y_t = a.x_r + b \tag{11}$$

Where 'a' is the slope of line (Virtual Plane) joined by points e_1 and e_2 and 'b' is the intercept.

If $y_r < y_t$, the potential function of virtual plane is activated.

Case 2:

If $x_r \leq x_{e1}$ AND $y_{e2} \leq y_r \leq y_{e1}$, the potential function of the plane is activated.

The above cases make sure that the robot never re-enters the area where it can get trapped and hence guarantees the convergence.

Algorithm 3

Full algorithm

1. *Calculate attractive and repulsive forces using the FIRAS functions.*
2. *Use the net force to steer towards the goal.*
3. *If local minima occurs (check criteria for local minima), find points e_1 and e_2 store the values in a list L else go to Step 6.*
4. *Locate an intermediate goal, set tempGoal=true, at a distance of l_1 or l_2, whichever one is the longer along the angle bisector.*
5. *If $x_{new} > x_{e1}$ OR $x_{new} > x_{e2}$, redefine the intermediate goal by taking the difference between the x_{new} and the larger between the x_{e1} and x_{e2} and adding that value to the current x_{new} go to Step 1.*
6. *If goalReached == true AND tempGoal == true, set goalReached=false and tempGoal=false and goto Step 1.*
7. *If L is not empty and $x_{e1} \leq x_r \leq x_{e2}$ AND $y_{e2} \leq y_r \leq y_{e1}$, the function vplaneVirtual() is activated to repel the robot.*
8. *If goalReached == true AND tempGoal == false, Exit else repeat Step 1.*

SIMULATION

We conducted the simulation of the proposed approach in Matlab and found that the method works successfully. We have used the simulation to show that the robot can successfully avoid getting into the concave objects on its path and thereby avoiding probable local minima. In the second case, we have shown how a robot escapes the local minima. The environment is a 492×523 logical array with a maximum robot speed of 10 arbitrary units and the dimensions of the robot as 10×10. The environment consists of a concave obstacle that sits between the source and the target as shown in Figure 11.

Using the APF method, we tested our first simulation run on the environment shown in Figure 11 and the result was quite what was anticipated. The robot gets stuck in the local minima as shown in Figure 12.

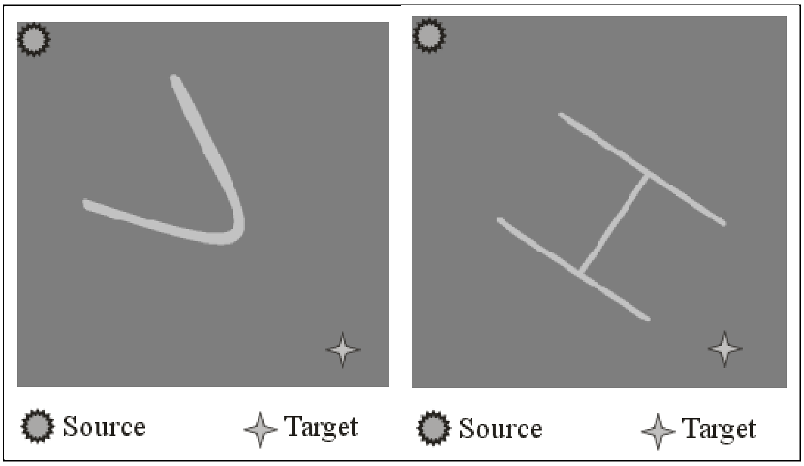

Fig. 11: *The Enviroment: C and H Type Obstacles.*

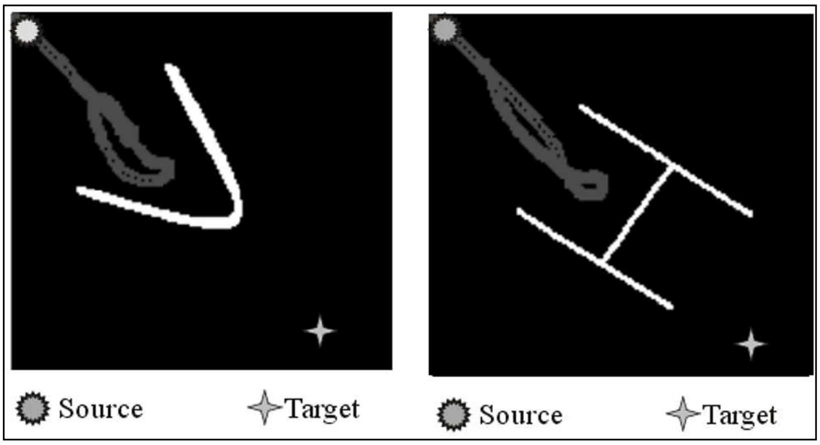

Fig. 12: *Local Minima.*

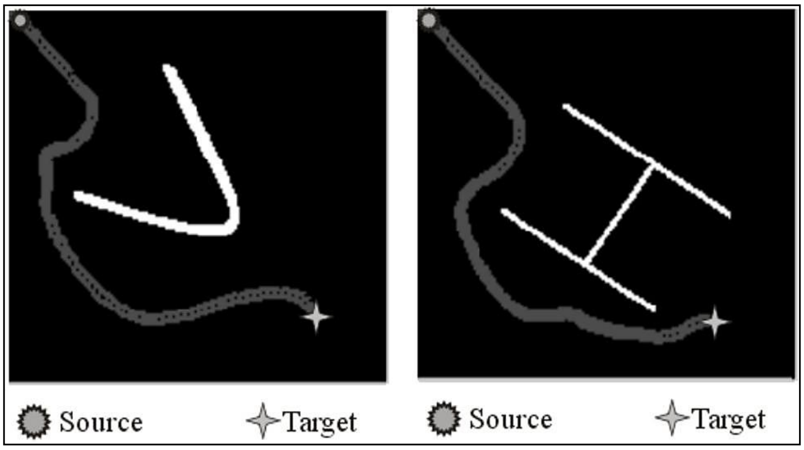

Fig. 13: *Avoiding Local Minima.*

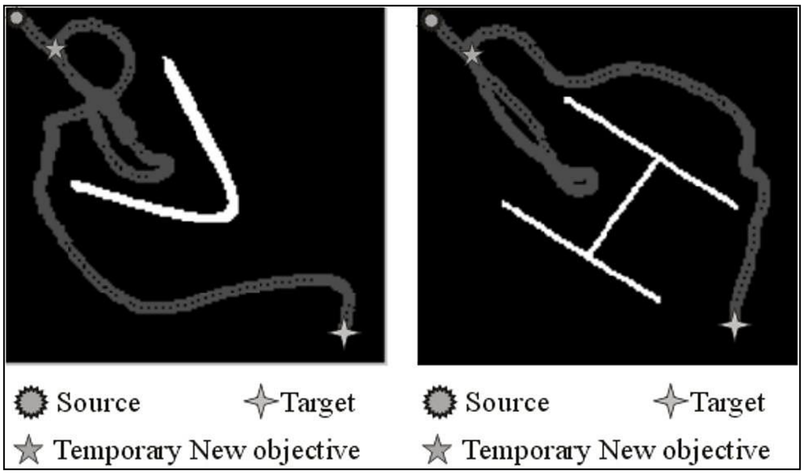

Fig. 14: *Final Path.*

Using the polar histogram, the robot detects that there is a concave obstacle in front of it, so it detects one of its edges and tries to reach towards it and cross that, thereby avoiding the entry inside the obstacle, as shown in Figure 13.

The time taken in case of U type obstacle was 4.118886 sec and the time taken in case of H type obstacle was 6.235565 sec.

But sometimes it is not possible to avoid local minima using histogram or any other technology for that matte and eventually the robot gets stuck in the local minima. In this last scenario, the robot enters the concave obstacle, and gets trapped in the local minima as shown in Figure 12. In this scenario, after detecting that the object is stuck, the algorithm uses a temporary objective to get the robot out of there and then the virtual plane is used to restrict its entry back into the obstacle, as shown in Figure 14. The robot reaches the target with processing time of 1.625159e+01 sec in U or C type obstacle. The robot reaches the target with processing time of 1.724096e+01 sec in H type obstacle.

CONCLUSION

Obstacle avoidance and path planning play a vital role in achieving autonomous navigation of a mobile robot, whether it is in a static or a dynamic environment. There are many different approaches deployed to achieve successful navigation without local minima and the other issues inherent in APF based methods, the choice of which depends on the application area or task of the robot. The proposed method uses a virtual plane to inhibit the robot from entering the local minima area. The intermediate or temporary objectives were used to successfully steer the robot out of the local minima. The technique used in this paper is fairly novel with the emphasis on making the path local minima free. The main features of the proposed method include that the robot escapes local minima successfully and never returns to the same area, the method is very efficient as far as the convergence is concerned, and the technique is fairly simple and easy to understand. Although we have simulated this method on C and H type obstacles successfully but in future we expect it to be modified and tested in environments with dynamic obstacles.

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