Path Planning and Obstacles Avoidance using Switching Potential Functions

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Keywords: Mobile Robots Path Planning, Obstacles Avoidance, Artificial Potentials Field Method.

Abstract: In this paper, a novel path planning and obstacles avoidance method for a mobile robot is proposed. This method makes use of a switching strategy between the attractive potential of the target and a new helicoidal potential field which allows to bypass an obstacle by driving the robot around it. The new technique aims at overcoming the local minima problems of the well known artificial potentials method, caused by the summation of two (or more) potential fields. In fact, in the proposed approach, only a single potential is used at a time. The resulting proposed technique uses only local information and ensures high robustness, in terms of achieved performance and computational complexity, w.r.t. the number of obstacles. Numerical simulations and comparisons with traditional artificial potential field technique confirm a robust behavior of the method, also in the case of a framework with multiple obstacles.

1 INTRODUCTION

Robot motion planning and obstacles avoidance have been a research topic for around three decades. The problem can be formulated as follows: given an initial position of the robot, it should compute how to gradually move itself to the desired goal placement, without entering in the obstacles regions.

When an exhaustive knowledge about the environment and all the obstacles inside, is available, the robot path planning can be performed offline before the execution starts. Methods based on these assumptions belong to the family of global path planning techniques. The global path planning problem is well studied and fairly solved (see(Mac et al., 2016)). Traditional techniques are cell decomposition method, shown by (Rosell and Iniguez, 2005; Šeda, 2007), and roadmap based techniques, described by (Choset et al., 2005) and (Bopardikar et al., 2015). Other approaches are based on set-theoretic arguments coupled with a receding horizon control algorithm and have been proposed by (Franzè and Lucia, 2015).

However, in a real context, the environment is usually partially known and having a complete knowledge of the obstacles and their positions in advance is unrealistic. In this case, information from available sensors has to be continuously updated resulting in a more complex planning problem. This situation is denoted as online path planning or local path planning and it has been described by (Chu et al., 2012). In this context, some of the solutions have been formulated by applying traditional approaches to real-time motion planning, e.g. (Lau et al., 2013), (Chamberland et al., 2010). In order to avoid the inefficiency of traditional methods, research interest is pointing to new approaches based on neural networks ((Yang and Meng, 2000)), fuzzy logic ((Araujo, 2006)) and nature inspired methods like genetic algorithms ((Alajlan et al., 2013)). Other approaches face the problem using one-step ahead controllable sets and robust positively invariant regions, see (Franzè and Lucia, 2016), and mathematical approaches ((Benzerrouk et al., 2012), (Kim and Kim, 2003)). In particular, the latter papers face the obstacles avoidance problem by adapting limit cycles theory to the context of interest. If an obstacle has to be bypassed, an artificial limit cycle is placed on it and is used to drive the robot around it.

Both local and global algorithms have advantages and drawbacks. Global planning allows for optimal paths design but these methods are not robust to avoid moving obstacles when high computational power is

Fedele, G., D'Alfonso, L., Chiaravalloti, F. and D'Aquila, G.
Path Planning and Obstacles Avoidance using Switching Potential Functions.
DOI: 10.5220/0006427703430350
In *Proceedings of the 14th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2017) - Volume 2*, pages 343-350
ISBN: Not Available

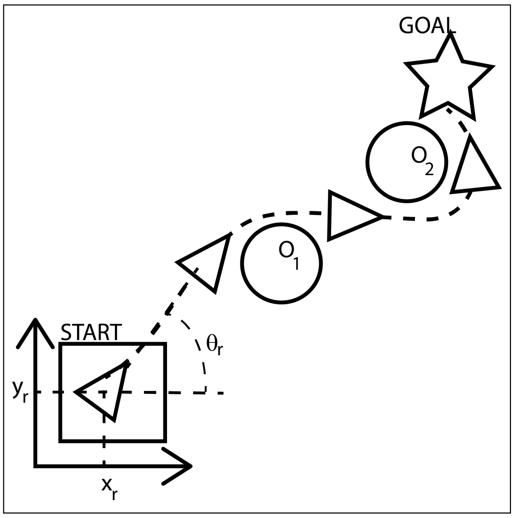

Figure 1: Configuration example.

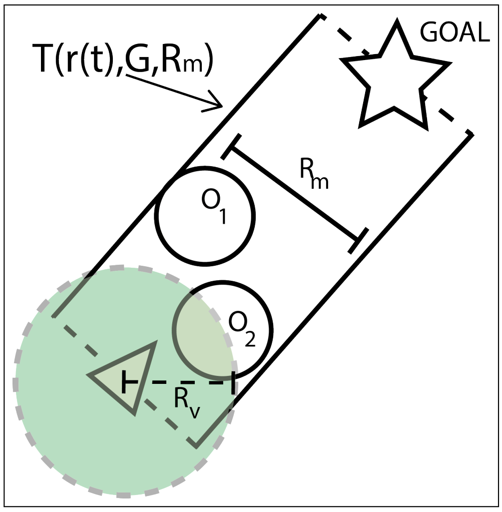

Figure 2: Detection field and $T(r(t),G,R_m)$ region: O_2 satisfies Eq. (7).

not available. On the other hand, local path planning methods can be used also in the case the obstacles are not static but their performance are really affected by robot sensors quality and robot allowed maximum velocity. Moreover, in a local point of view, global optimality criteria usually cannot be satisfied.

Aiming at enhancing both methods advantages, avoiding their drawbacks, some techniques based on the combination of local and global path planning have been developed by (Zhang et al., 2012) and (Bi et al., 2008).

The artificial potentials method (APF) is one of the first solutions proposed to solve the planning problem online. The basic concept of APF has been presented in the seminal work by (Khatib, 1990) where the author proposes to fill the robot's workspace with an artificial potential field in which the robot is attracted to its goal position and is repulsed away from the obstacles. To this end a potential function which sums the effects of both attractive and repulsive potentials is used. However, as stated by (Siciliano et al., 2008), the summation of a repulsive potential field and of an attractive one may result in local minima, when the repulsive potential is equal to the attractive one in the same area.

In this paper, a novel approach to the artificial potentials field method is described. To avoid local minima problems due to the superposition of two or more potentials, the proposed method uses only one artificial potential field at a time, choosing it between an attractive one or an obstacle bypassing one. The potential field selection is performed following a set of rules with no requirements about global information on the positions of all the obstacles. Moreover, a new potential field is proposed which allows to bypass an obstacle by going around it. Since only local information is used, the proposed technique ensures high robustness, in terms of achieved performance and computational complexity, w.r.t. the number of obstacles.

The paper is organized as follows: in Section 2 the problem is stated; in Section 3 the proposed helicoidal potential field is described; in Section 4 the path planning and obstacles avoidance rules are shown; a new Lyapunov based control law is proposed in Section 5; in Section 6 numerical results are shown and the last Section is devoted to conclusions.

2 PROBLEM STATEMENT

Let $r(t) = [x_r(t), y_r(t), \theta_r(t)]^T$ be the pose (position and orientation) of a moving robot and let $\{O_i = [x_{O,i}, y_{O,i}]^T\}, i = 1, \ldots, N$ be a set of circle shape static fat obstacles, with center in $[x_{O,i}, y_{O,i}]^T$ and known radius R_i, computed considering the robot size[1]. The fat obstacles are assumed to not intersect so that the robot is always allowed to go between two obstacles. Note that there is no loss of generality due to this assumption since if two obstacles are near enough to have an intersection between their fat versions, then a single bigger fat obstacle can be considered which circumscribes them. Fig. 1 depicts a possible configuration of the robot and the obstacles.

The robot is assumed to have a detection field of R_v meters and to be able of inferring each obstacle in the detection field. Two kinds of detection may occur: in the first case, the center of the obstacle is

[1]If the obstacle shape is not circle-like, than the circumscribing circle can be considered instead of real obstacle shape.

inside the detection field, in the second one, only a portion of the obstacle is detected. In the latter case, a virtual obstacle can be considered instead of the one detected, placing it in the nearest portion of the obstacle detected by the robot and assuming that the virtual radius is equal to the actual distance from the robot to the detected obstacle portion. For the sake of simplicity, in the following the results will be described assuming that the centers of all the obstacles into the detection field are available.

Note that this is not a restrictive assumption since it can be easily accomplished by equipping the robot with distance or vision based sensors. Fig.2 shows an example of obstacle detection field.

Moreover the robot is assumed to have knowledge about its current pose and about the goal position, denoted as $G = [x_G, y_G]^T$. To this end, depending on the environment configuration, GPS based localization techniques (outdoor configurations) or SLAM algorithms (indoor configurations) may be used to provide the required information to the robot.

This work aims at planning a feasible path for the mobile robot so that the desired goal position G is reached avoiding collisions with the obstacles $\{O_i\}, i = 1, \ldots, N$.

3 OBSTACLE BYPASSING POTENTIAL

The artificial potentials path planning method relies on the use of artificial potential fields to simultaneously reach the desired position avoiding obstacles in the robot environment. The goal is assumed to generate an attractive potential field $U_a(r(t), G)$ and each obstacle O_j is assumed to generate a repulsive potential field $U_r(r(t), O_j)$. The robot moves in the configuration space under the influence of the artificial potential field

$$U_{sum}(t) = U_a(r(t), G) + \sum_{j=1}^{N} U_r(r(t), O_j) \qquad (1)$$

which has to drive the robot to the goal, using the attractive part, and simultaneously repel the robot from the obstacles. At this point, planning is performed in an incremental way. The negative gradient $-\nabla U_{sum}(r(t))$, representing the most promising direction of local motion to reach the goal, is used at each robot configuration $r(t)$, to obtain the robot command input.

Despite its simplicity, the artificial potentials method, in its traditional formulation, is affected by known local minima problems, as shown by (Park and Lee, 2003).

In the traditional artificial potentials method, the bypassing of an obstacle is provided by summing an attractive and a repulsive potential. If only the repulsive potential is used, the robot is taken away from the obstacle but it is not driven to the goal and no assurance about moving in a pose where the obstacle can be bypassed is given. In this context, a new artificial potential is now proposed, the main idea of which is to allow for bypassing an obstacle by going around it using the effects of only one artificial potential.

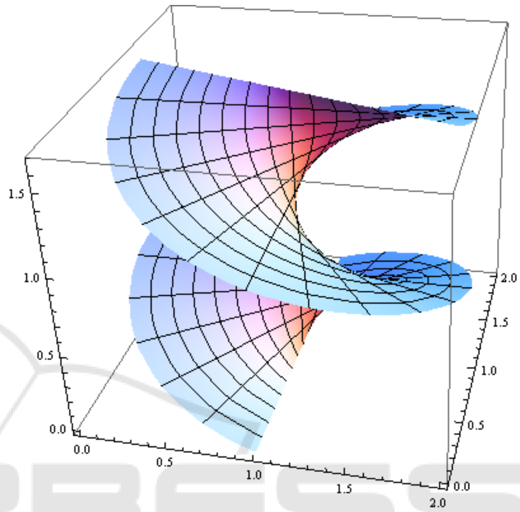

Figure 3: Helicoid (2) centered in $(x_0, y_0) = (1, 1)$ with $c = 1/3$, $0 \le r \le 1$ and $0 \le \zeta \le 5$.

A useful configuration to avoid an obstacle consists in having field lines of the gradient that turn around the obstacle. In particular, in the case of a circular obstacle, in the sense defined above, a suitable geometry is obtained with closed-like circular field lines centered in the position of the obstacle.

This configuration can be obtained starting by the circular helicoid described in parametric form by (Struik, 1961):

$$\begin{cases} x = x_0 + r\cos(\zeta) \\ y = y_0 + r\sin(\zeta) \\ z = c\zeta \end{cases} \qquad (2)$$

which represents the minimal surface in $\mathbb{R}^3$ having a circular helix of radius r and centered in x_0, y_0, as its boundary (Fig. 3).

The parameter ζ determines the number of windings of the surface. For example, if $0 \le \zeta \le 2\pi$ there is a single full-twist.

In Cartesian coordinates Eq. (2) becomes:

$$\frac{y - y_0}{x - x_0} = \tan\left(\frac{z}{c}\right) \qquad (3)$$

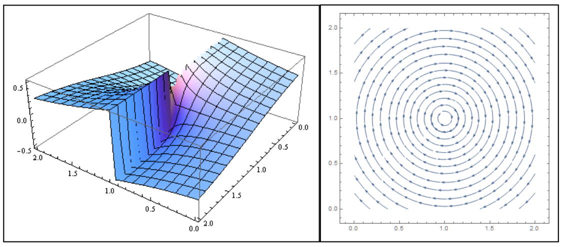

Figure 4: left: potential centered in $(x_0, y_0) = (1,1)$ with $c = 1/3$; right: Example of stream plot of the vector field (6).

where, in the case of interest, (x_0, y_0) is chosen as the obstacle position. The required potential is now obtained by inverting Eq. (3) in the form:

$$\Gamma(x, y, x_0, y_0) = c \tan^{-1}\left(\frac{y - y_0}{x - x_0}\right) \tag{4}$$

which is shown in Fig. 4 and represents a descending surface around (x_0, y_0) in clockwise sense. The above potential field can be seen as a function of the robot pose and of the j-th obstacle position

$$U_b(r(t), O_j) = \Gamma(x_r(t), y_r(t), x_{O,j}, y_{O,j}) \tag{5}$$

which allows the robot for bypassing the obstacle.

It follows that the negative gradient, for $x_r(t) \neq x_{O,j}$, is

$$-\nabla U_b(r(t), O_j) = \begin{bmatrix} \dfrac{c(y_r(t) - y_{O,j})}{(x_r(t) - x_{O,j})^2 + (y_r(t) - y_{O,j})^2} \\ \dfrac{c(x_{O,j} - x_r(t))}{(x_r(t) - x_{O,j})^2 + (y_r(t) - y_{O,j})^2} \end{bmatrix} \tag{6}$$

as shown in Fig. 4. This negative gradient ensures that the closer the robot is to the obstacle, the higher is the gradient intensity, so that to speed up the bypassing when the obstacle is near to the robot. In the case this behavior is not desirable, due to saturation on the robot speed, the negative gradient can be normalized so that to use only information about its direction.

Remark 1. *Note that the proposed potential field has a discontinuity on the line $x = x_{O,j}$ and, from a theoretical point of view, the gradient is not defined on this line. However, the function (6) is continuous in each point $(x_r(t), y_r(t)) \neq (x_{O,j}, y_{O,j})$. Since the robot is forbidden to exactly go in the obstacle position, this discontinuity is not a problem for the robot motion. As a consequence, from a practical point of view, the function (6) will be used in each point $(x_r(t), y_r(t)) \neq (x_{O,j}, y_{O,j})$ considering it as a negative gradient field able to bypass the obstacle.*

4 PATH PLANNING AND OBSTACLES AVOIDANCE RULES: A SWITCHING STRATEGY

In this Section a switching strategy between attractive and bypassing potentials is discussed. The robot checks its detection range and its relative position w.r.t. the goal so that to choice the proper potential field $U(r(t))$ to follow.

First of all, the robot checks if a free way to the goal is available: the robot looks for the obstacles which are in a radius R_v from its position and in a tube of width R_m from the robot to the goal.

The above check can be summarized by the following condition

$$\begin{aligned} &\exists O_j \in \{O_i, i = 1, \ldots, N\} \; s.t. \\ &O_j \in \mathcal{D}(R_v, r(t)) \cap T(r(t), G, R_m) \end{aligned} \tag{7}$$

where $T(r(t), G, R_m)$ is a tube starting from $r(t)$, pointing to G and ending in it, with an amplitude of R_m, as shown in Fig.2, and $\mathcal{D}(R_v, r(t))$ is the robot detection field at time t.

If condition (7) is not satisfied, then a free way to the goal exists and the robot can follows the attractive potential: $U(r(t)) = U_a(r(t), G)$.

Otherwise, the obstacles in the tube $T(r(t), G, R_m)$ are processed and among them the nearest one, say it $\tilde{O}$[2], to the robot is chosen. The bypassing potential from $\tilde{O}$ is then used to drive the robot: $U(r(t)) = U_b(r(t), \tilde{O})$.

The robot is now driven according to a gradient descent method and it follows

$$-\nabla U(r(t)) = -[\nabla U_x(r(t)), \nabla U_y(r(t))]^T;$$

the overall robot path follows the dynamics:

$$\begin{bmatrix} \dot{x}_r(t) \\ \dot{y}_r(t) \\ \dot{\theta}_r(t) \end{bmatrix} = \begin{bmatrix} -\nabla U_x(r(t)) \\ -\nabla U_y(r(t)) \\ \dfrac{d}{dt} \angle(-\nabla U(r(t))) \end{bmatrix}. \tag{8}$$

In the case the bypassing potential from $\tilde{O}$ is used to drive the robot, depending on obstacle position, the gradient has to be properly oriented aiming at avoiding the obstacle $\tilde{O}$ and simultaneously choosing the shortest way to reach the goal.

More precisely, the robot has to choose if the obstacle has to be bypassed going around it in clockwise or in counterclockwise sense. The negative gradient related to the bypassing potential described in Section

[2] If more obstacles are equally far from the robot, one of them is randomly chosen.

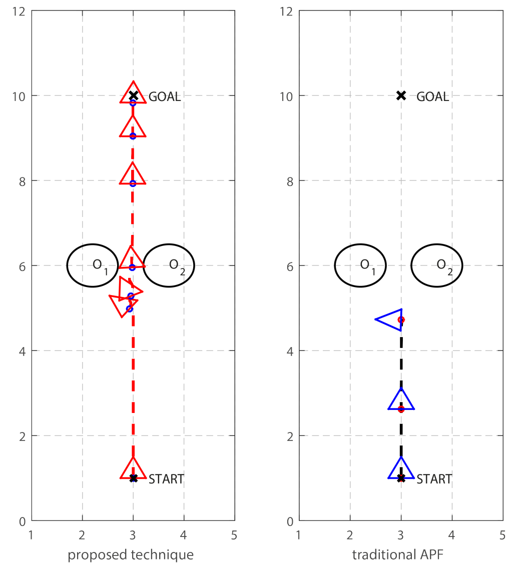

Figure 5: Proposed method (red robot on the left) versus traditional APF (blue robot on the right).

3 is always tangent to the circle centered in the obstacle of interest and passing by the robot pose. As a consequence, if $D = -\nabla U_b(r(t), \tilde{O})$ is the vector which allows for bypassing the obstacle in a sense, the vector $-D$ lets the robot be driven around the obstacle in the reverse sense. Aiming at reaching the target using the shortest path, the points

$$r_1 = \begin{bmatrix} x_r(t) \\ y_r(t) \end{bmatrix} + \tau D, \quad r_2 = \begin{bmatrix} x_r(t) \\ y_r(t) \end{bmatrix} - \tau D \qquad (9)$$

are computed, where τ is a small parameter, and depending on the point $r_j, j = 1,2$, nearest to G, in the Euclidian sense, the bypassing verse is chosen.

In conclusion, the overall potentials selection rules can be summarized by the algorithm 1.

Note that the proposed technique may suffer of discontinuity in the negative gradient $-\nabla U(r(t))$ due to the switching between potentials. If the planning requirements demand for a smooth path, compliant with non-holonomic robot movements, the obtained trajectory can be properly adapted by stopping the robot at each switch and rotating it to the direction imposed by the new negative gradient and then starting the movement. Otherwise, $-\nabla U(r(t^-))$ and $-\nabla U(r(t))$ may be linked by a properly chosen smoothing function.

Remark 2. *Note that in a standard configuration, the use of a switching among two or more potentials may not solve the local minima problem since it could be possible that the potential fields create an oscillation between the local minima yielding to a never ending local minimum oscillation configuration. However, since the obstacles are assumed to be static and the proposed bypassing potential drives the robot around the obstacle in clockwise or counterclockwise sense depending only from the goal position and not from the obstacles locations, the never ending oscillation can not occur.*

Algorithm 1: Artificial Potentials selection algorithm, applied for each $t \in \mathbb{R}^+$

input : Goal position G; robot pose $r(t)$
while *G is not reached* **do**
  if *$\nexists O_j$ satisfying* (7) **then**
    $U(r(t)) = U_a(r(t), G)$;
  else
    $\tilde{O}$ =obstacle at minimum distance in the tube $T(r(t), G, R_m)$;
    compute r_1 and r_2 using Eq. (9);
    if $||r_1 - G|| \leq ||r_2 - G||$ **then**
      $-\nabla U(r(t)) = D$;
    else
      $-\nabla U(r(t)) = -D$;
    end
  end
end

Remark 3. *According to the proposed method, a convex/concave obstacle or a wall-like obstacle can be avoided by considering the circumscribing circle instead of the real obstacle shapes. In an alternative way, this obstacle can be bypassed by using virtual obstacles placed in the detected nearest obstacle part and with the virtual radius equal to the actual distance from the robot to the detected obstacle portion. Within this context, to avoid stall configurations, the bypassing sense is a-priori chosen and used for all the virtual obstacles related to the real one; the strategy remains then the same.*

5 CONTROL LAW

As explained in (Siciliano et al., 2008), the negative gradient can be interpreted as a desired velocity for the robot. Let now assume the robot can be modeled by the standard non-holonomic model

$$\begin{cases} \dot{x}_r(t) = v_r(t)\cos(\theta_r(t)) \\ \dot{y}_r(t) = v_r(t)\sin(\theta_r(t)) \\ \dot{\theta}_r(t) = \omega_r(t) \end{cases} \qquad (10)$$

where $v_r(t)$ and $\omega_r(t)$ are the robot linear and rotational velocities respectively. Let $v_\nabla(t) = -\nabla U(r(t))$ be the desired robot velocity, chosen using the proposed path planning method, where $M_v = ||v_\nabla(t)||$, $\theta_\nabla = \angle v_\nabla(t)$.

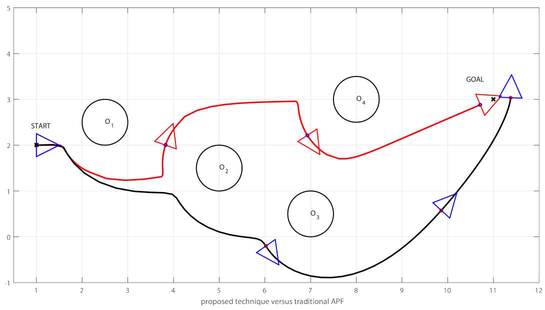

Figure 6: Proposed method (red line) versus traditional APF (blue line).

Theorem 1. *The control law*

$$v_r(t) = M_v \cos(\theta_\nabla(t) - \theta_r(t)) \quad (11)$$
$$\omega_r(t) = K_\omega(t)(\theta_\nabla(t) - \theta_r(t)) \quad (12)$$

with

$$K_\omega(t) = \begin{cases} \dfrac{\dot{\theta}_\nabla(t) + K_c(\theta_\nabla(t) - \theta_r(t))}{\theta_\nabla(t) - \theta_r(t)}, \\ \qquad \qquad \text{if } |\theta_\nabla(t) - \theta_r(t)| > 0 \\ 0, \text{ otherwise;} \end{cases} \quad (13)$$

where $K_c > 0$ is a control tuning parameter, ensures the robot to track the desired velocity $v_\nabla(t)$.

Proof. Consider the Lyapunov function

$$V(r(t)) = \frac{1}{2}(\theta_\nabla(t) - \theta_r(t))^2 \quad (14)$$

with

$$\dot{V}(r(t)) = (\theta_\nabla(t) - \theta_r(t))(\dot{\theta}_\nabla(t) - \dot{\theta}_r(t)). \quad (15)$$

Using Eqs. (10), (12) and (13) it follows that

$$\dot{V}(r(t)) = (\theta_\nabla(t) - \theta_r(t))(\dot{\theta}_\nabla(t) - \omega_r(t)) =$$
$$= (\theta_\nabla(t) - \theta_r(t))(\dot{\theta}_\nabla(t) - K_\omega(t)(\theta_\nabla(t) - \theta_r(t))) =$$
$$= -K_c(\theta_\nabla(t) - \theta_r(t))^2. \quad (16)$$

Since $\dot{V}(r(t)) < 0 \ \forall \theta_r(t) \neq \theta_\nabla(t)$, the proposed control law ensures $\theta_r(t) \to \theta_\nabla(t)$ and, as a consequence, $\omega_r(t) \to 0$ and $v_r(t) \to M_v$.

□

Remark 4. *Note that, using the proposed control law, the derivative of the Lyapunov function can be written as*

$$\dot{V}(r(t)) = -2K_c V(r(t)) \quad (17)$$

and then

$$V(r(t)) = e^{-2K_c t} V(r(0)) \quad (18)$$

where $V(r(0))$ is the square of the angular error between the robot heading and the negative gradient angle at the switching time. As a consequence, the transient time required by the control to ensure the error is lower than a given error threshold, can be computed.

Remark 5. *Since neither the attractive potential U_a nor the bypassing potential U_b depend on $\theta_r(t)$, the value $\dot{\theta}_\nabla(t)$ can be easily computed given the robot current pose and the active potential field $U(r(t))$:*

$$\dot{\theta}_\nabla(t) = \frac{\partial \theta_\nabla(t)}{\partial x_r} \dot{x}_r(t) + \frac{\partial \theta_\nabla(t)}{\partial y_r} \dot{y}_r(t),$$

where $\dot{x}_r(t)$, $\dot{y}_r(t)$ are given by Eqs. (8) *and* (11).

6 RESULTS

To evaluate the performance of the proposed path planning and control technique, three numerical configurations have been tested, using the following parameters

$$R_v = 1.5m, \quad R_i = 0.5m \ \forall i, \quad R_m = 2m,$$
$$\tau = 0.05, \quad K_c = 10, \quad c = 1,$$
$$\delta = 10^{-4},$$

and the traditional attractive potential

$$U_a(r(t), G) = \left\| G - \begin{bmatrix} x_r(t) \\ y_r(t) \end{bmatrix} \right\|^2.$$

In the first two testing configurations, the described new method has been contrasted with the traditional APF technique shown in (Siciliano et al., 2008).

First of all, the proposed method has been tested by placing the robot in $[3,1]^T$ with an initial heading of $\theta_r(0) = \frac{\pi}{2}$ and requiring to reach the goal $[x_G, y_G] = [3,10]^T$ avoiding collisions with two obstacles placed in $[2.2,6]^T$ and $[3.7,6]^T$. The robot motion in this context, using traditional APF or the proposed path planning rules, is shown in Fig. 5.The traditional method incurs in a local minima problem while the proposed technique avoids this trouble thanks to the use of a single artificial potential at time, switching it between the attractive one and the bypassing one. The robot is then driven between the two obstacles with no stall configurations or collisions.

The second tested configuration consists in four obstacles placed in $[2.5,2.5]^T$, $[5,1.5]^T$, $[7,0.5]^T$, $[8,3]^T$. The robot starts its path from in $[1,2]^T$ with an initial heading of $\theta_r(0) = 0$ and aims at reaching $[x_G, y_G] = [11,3]^T$. A comparison between traditional APF and the proposed technique is depicted in Fig. 6. Both the methods properly drive the robot to the goal.

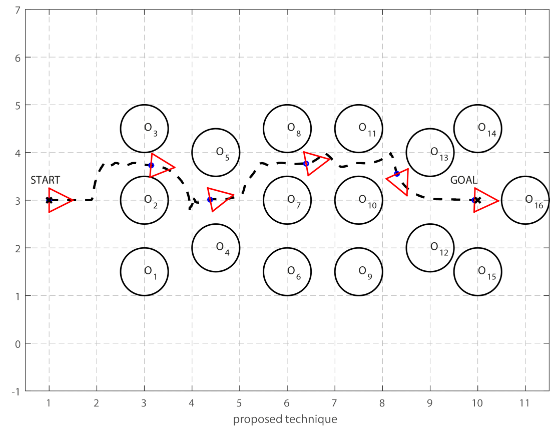

Figure 7: Proposed method when the environment contains a large number of obstacles.

As expected, the use of a switching strategy yields to a less smooth trajectory w.r.t. the one obtained by the traditional APF method. Note that the proposed planning rules aim at driving the robot to the goal whatever is the obstacles configuration with no regards on other trajectory optimality criteria. It follows that the obtained robot path could be slower/faster or more complicated w.r.t. the one obtained with other techniques but, on the other hand, the proposed method will always provide a solution to the target reaching with obstacles avoiding problem.

In the third testing configuration, the robot has been placed in $[1,3]^T$ with an initial heading of $\theta_r(0) = 0$, the goal is in $[x_G, y_G] = [10,3]^T$ and a 16 obstacles, placed as shown in Fig. 7, have been used to obstruct the robot movements. This testing configuration proposes various local minima situations in the traditional APF case. For example, if the obstacle O_{16} is equipped with a traditional artificial repulsive potential, it could prevent the robot from reaching the goal due to the imposed repulsion when the robot is close to its target. On the contrary, using the proposed planning method, the robot is driven to the goal with no local minima situations and avoiding all the obstacles in the environment, as shown in Fig. 7. In particular, obstacle O_{16} does not affect robot path since it is placed after the goal, in the robot point of view, and as a consequence it is out of the tube $T(r(t), G, R_m)$.

7 CONCLUSIONS

In this work, a novel approach to the artificial potentials method has been proposed to face the path planning and obstacles avoidance problem for a mobile robot. The new method has been developed aiming at overcoming the well known local minima problem of the traditional APF technique. A novel helicoidal potential has been proposed to allow for bypassing an obstacle using only the effect of a single potential field, with no need for the summation of a repulsive one and an attractive one, in order to avoid local minima. In this context, the proposed method is based on the use of a single potential at a time, switching from attractive to bypassing case depending on a set of defined switching rules.

Moreover, since only local information is used, the proposed technique ensures high robustness, in terms of achieved performance and computational complexity, w.r.t. the number of obstacles.

The described method has been compared, in a numerical way, with traditional APF technique, and has shown a more robust behavior w.r.t. it, providing a feasible path to the robot goal also in the case of a framework with multiple obstacles to be avoided.

As a future research direction, the proposed technique will be extended to the case of mobile obstacles.

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