An Exponential Field Path Planning Method for Mobile Robots Integrated with Visual Perception

Magdy Roman, Mostafa Shoeib, Mostafa Rostom

***Abstract*—**Global vision, whether provided by overhead fixed cameras, on-board aerial vehicle cameras, or satellite images can always provide detailed information on the environment around mobile robots. In this paper, an intelligent vision-based method of path planning and obstacle avoidance for mobile robots is presented. The method integrates visual perception with a new proposed field based path-planning method to overcome common path-planning problems such as local minima, unreachable destination and unnecessary lengthy paths around obstacles. The method proposes an exponential angle deviation field around each obstacle that affects the orientation of a close robot. As the robot directs toward the goal point obstacles are classified into right and left groups, and a deviation angle is exponentially added or subtracted to the orientation of the robot. Exponential field parameters are chosen based on Lyapunov stability criterion to guarantee robot convergence to destination. The proposed method uses obstacles shape and location, extracted from global vision system, through a collision prediction mechanism to decide whether to activate or deactivate obstacles field. In addition, a search mechanism is developed in case of robot or goal point is trapped among obstacles to find suitable exit or entrance. The proposed algorithm is validated both in simulation and through experiments. The algorithm shows effectiveness in obstacles avoidance and destination convergence, overcoming common path planning problems found in classical methods.

***Keywords*—** Path planning, collision avoidance, convergence, computer vision, mobile robots.

I. Introduction

ROBOT navigation is a process of guiding robots to a goal point while avoiding collision with encountering obstacles. Successful navigation process depends on four cornerstones [1, 2]: (i) localization, determining robot position in the environment; (ii) perception, using sensors to understand robot environment; (iii) path planning, finding a proper collision-free path toward destination; (iv) motion control, executing the planned path by "wisely" controlling robot motion. Generally speaking, there are two main strategies that cover all approaches in robot path planning, namely global path planning and local path planning. In global path planning, the robot reaches its goal point along a predefined path based on a complete knowledge of the environment. An optimized path is usually achievable in this method, however the method is considered inadequate when dealing with dynamic environment. In the local path planning a priori knowledge about the environment is not required and the robot, based on on-board sensors, finds its way to the target avoiding collision with obstacles. The method is more flexible and works effectively in unknown and dynamic environment, however it is inefficient in cluttered environment and may give solutions far from optimality. A combination of both techniques is normally found in literature in order to enhance the overall performance [3-5].

The robot path planning are further classified into classical approaches and heuristic approaches [6, 7]. Classical path planning approaches include cell decomposition method, artificial potential field (APF) method, subgoal method and sampling-based method. In the cell decomposition method the available space around the robot is divided into cells and the target is to find a safe path to the destination [8, 9]. In APF method the robot is considered as a point that moves in artificial force field [10]. The force field consists of two types: attractive potential, generated by the goal point, and repulsive potential, generated by the set of obstacles. The robot driving force is then calculated by applying negative gradient of the total potential field. Along the decline direction of the total potential field, robot can find a free-of-collision path to the goal point. APF method, in its simple form, exhibits many drawbacks such as oscillatory behavior of robots in narrow spaces and sensitivity to local minima [11]. Therefore, modified versions of APF method are introduced in literature to enhance the performance [12-17]. Subgoal-based methods use a set of reachable configurations to find a free-of-collision path from the starting point to the goal point [18-20].

During the last years, sampling-based planning (SBP) method has received significant attention due to its ability to handle complex real-world path planning problems. A comprehensive review of robot path planning based on SBP method is given in [21]. Of the most commonly used SBP algorithms are probabilistic road-map (PRM) and rapidly-exploring random trees (RRT) [22]. The PRM, whether formed by straight lines or curved lines, allows the robot to reach any point in its free space. The algorithm has been implemented effectively in high-dimensional state spaces. Classical roadmap methods, like visibility graphs [23-25] and Voronoi diagrams [26, 27], have comprehensively investigated in literature. In visibility graph the shortest path is guaranteed by coming very close to the obstacles. Actually, the path touches obstacles at vertices, increasing by that the risk of collision. On the other hand, Voronoi diagram generates a path by maximizing the distances between robot and obstacles. As a result, the created path may become far from being optimal, with respect to the path length. However,

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Voronoi diagram method uses a limited number of sensors, which is advantageous with respect to navigation tasks.

Lack of adaptability to environmental change and tendency to being trapped in local minima have led to the appearance of heuristic path planning approaches. There are a huge number of researches in heuristic approaches in literature. One of the important comprehensive surveys in this field is [28]. The most used techniques include artificial neural network (ANN), fuzzy logic (FL), and nature-inspired algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), and ant-colony optimization (ACO). The ANN-based methods are usually applied in navigation task to model complicated input-output relationships. They are recorded as an efficient way to implement autonomous motion planner of mobile robots [29-36]. Common recorded drawbacks represented in time consumption and the disability to guarantee an optimal solution. Normally, integrated methods are used for real-world navigation problem. Fuzzy logic has been implemented successfully in many applications, where an accurate mathematical model does not exist. The human mind has the capability to accomplish navigation tasks using only fuzzy measurements and calculations. Fuzzy-based algorithms in robot navigation are aimed to mimic this capability [37]. Literature has many successful implementations of fuzzy logic in robot navigation in case of unknown dynamic environment [38], cluttered environment [39], and sensor uncertainty [40]. Although, fuzzy logic presents a straight-forward way to implement human expert, its main difficulty represented in choosing the proper rules and membership functions.

The nature-inspired techniques have recently received a great attention. One of the most specific characteristics of these intelligent techniques is that the ways they work are similar to a natural behavior that can be easily understood. Nature-inspired techniques usually perform more efficiently than conventional artificial intelligent methods. Genetic algorithm (GA) is an optimization technique based on natural selection process that mimics biological evolution. [41]. Taking advantage of its powerful optimization ability, GA technique has been successfully implemented to generate an optimal path from robot start point to target point [42, 43]. However, implementation of GA in dynamic environments has indicated some imperfections. As GA works in a grid map and with no control on the population diversity, a premature convergence might occur. Normally, GA is combined with algorithms like PSO or fuzzy logic to enhance robot performance in path planning [28]. PSO is a population-based stochastic optimization technique that is originally inspired by the behavior of fish schooling or bird flocking. PSO starts by a set of random solutions and then updated each generation according to a global optimum schema. In each iteration, particles update their positions in a search region until they reach the goal [44]. Existing studies in PSO technique shows success in implementing PSO in uncertain environment [45] and dynamic environment [46]. However, PSO in its basic form can easily be trapped in local minima and rapid convergence is not guaranteed in complicated maps. ACO is another swarm behavior based optimization algorithm inspired by natural ant colony behavior. In real ant colony, the communication among the ants leads them to find the shortest path to the food or water. The amount of pheromones (a chemical substance produced and released by ants) deposited on the paths determines the optimal route. The ACO method works more properly in case of origin and goal locations are well predefined. In literature, ACO method has been applied, both single and combined with other algorithms, to find the optimal route to the destination [47, 48]. The basic form of ACO algorithm involves some drawbacks. Since evolution starts with equally-distributed pheromone concentration the algorithm could take long time to find the optimal path, especially in large scale problems.

By analyzing the existing researches in the field of robot path planning we may notice a lack in investigating the integration of robot perception in path planning problem. Most of the heuristic methods discussed above have a backbone of heavy computations and/or iterations behind their algorithms during the learning or online phases. On the other hand, classical methods have attractive, simple and easy to implement algorithms, however, issues such as local minima, unreachable destination and dynamic environment are still considerable. Moreover, they require precise information about robot surrounding in real-time applications and thus more accurate sensing of the environment. Solving path planning and obstacle avoiding problems in the last decade was done primarily by investigating more complicated algorithms rather than merging perception into path planning problem.

Vision is the sense that humans rely on most to explore the physical world around them. Unlike active sensors, such as laser, infrared, and sonar sensors, the vision system is considered a passive sensor. Cameras do not disturb environment by emitting waves or light to acquire data. Meanwhile, obtained images contain more information than active sensors (i.e. spatial, temporal, and substantial information) [49]. Vision-based robot navigation is the technique that primarily uses vision sensor to safely guide mobile robot to its target point or along a defined path [50]. The following researches present recent studies that tackle vision-based path planning problem and focus on global-vision techniques. In [51], based on top-view images, corners of the obstacles are detected and used to generate a C-space. Using A* algorithm, an optimal path is found and replaced by a smoother one generated using piecewise quintic Bézier curves. In [52] a hybrid path planning algorithm for unmanned ground vehicle (UGV) is proposed based on images obtained from aerial vision. The images are processed and used to construct ground map, on which an optimized path is designed using hybrid GA and local rolling optimization. The method proved effectiveness in getting an optimized path to the destination. However, in [51] and [52], only straight forward non-problematic obstacles are studied. In addition, the algorithms are tested with only one simple starting point for robot; the vision system is merely used as a mapping element with no added perception. In [53], a path planning method is

presented for a ground robot using images provided from another flying robot. The robot is used in search and rescue missions in unknown terrain. The extracted terrain information (grass, rubble, water, and concrete) is used to find feasible and optimal paths for the ground robot based on a modified D* algorithm. The proposed system shows success in finding robot optimal path and classifying the environment. However, building a classified map for the environment is such a computationally expensive task especially when the search space is large. Other related issues have been also studied. This includes vision-based path coordination between multiple mobile robots [54] and formation control of a group of aerial vehicles with on-board cameras to assist motion planning of a UGV [55].

The current study presents an intelligent new vision-based path planning and obstacle avoidance method. Preserving the simplicity and ease of implementation of the classical methods, the presented method integrates visual perception with a new proposed field-based path-planning algorithm. The integration is done to overcome common path planning problems such as local minima, unreachable destinations and unnecessary lengthy paths around obstacles. The proposed method uses obstacles shape and location, extracted from global vision system, through a collision prediction mechanism to decide whether to activate or deactivate obstacles exponential field. In addition, a search mechanism is presented in case of robot or goal point is trapped among obstacles to find suitable exit or entrance. Exponential field parameters are chosen based on Lyapunov stability criterion to guarantee robot convergence toward destination. The proposed algorithm is validated both in simulation and through experiments. The algorithm shows effectiveness in destination convergence, overcoming common path-planning problems found in classical methods.

The remainder of this paper is organized as follows. Section II illustrates the proposed path planning method and discusses goal convergence condition based on Lyapunov stability criterion. Section III demonstrates the image analysis and visual perception algorithms and presents simulation results in different cases. Section IV illustrates the experimental platform used in the study and discusses the experimental results. Finally, section V provides a brief conclusion and recommendations for future work.

II. Proposed Path Planning Method

A. Obstacle avoidance

The introduced new method proposes an exponential angle field around each obstacle. As the robot approaches an encountering obstacle, a small deviation in its orientation is generated. This deviation grows exponentially as the robot gets more close to the obstacle. Based on the robot and goal positions, the robot is directly oriented toward the goal point. The encountering obstacles are classified into two groups according to the robot direction. Obstacles to the left of the robot reduce its orientation angle by subtracting the generated angle deviation, while the right group obstacles do the opposite. The following assumptions are made in developing the proposed method:

- The robot moves in the 2-D Euclidian coordinate system.
- The robot is modeled by a circle of center $c(x,y)$ and radius r_r, which represents its physical dimension.
- Robot start position (x_o,y_o), destination position (x_d,y_d), and obstacle shapes and positions, o_1, ..., o_n, are known.

Now, referring to Fig. 1, suppose that at a given instant the robot is at position (x,y) in the world coordinates and is directed toward the destination with angle φ_d , where

$$\varphi_d = \tan^{-1}\left(\frac{y_d - y}{x_d - x}\right). \tag{1}$$

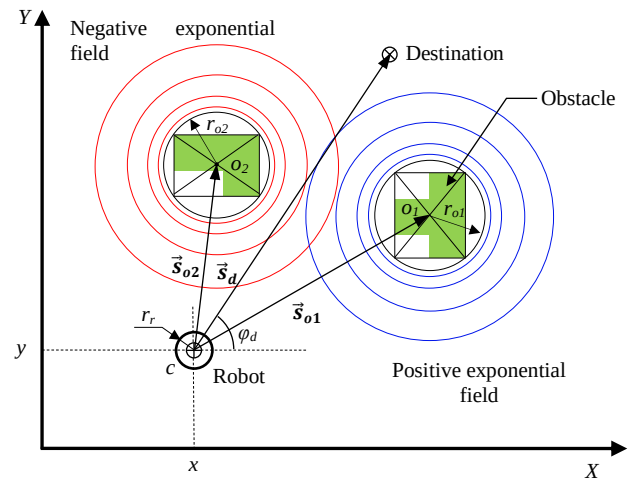


Fig. 1 Illustration of the robot and obstacles field in world coordinates

As the robot approaches an obstacle i, a deviation $\Delta\varphi_i$ is generated in the robot orientation to avoid obstacle collision. Let's define $\Delta\varphi_i$ as

$$\Delta\varphi_i = \frac{\pi}{2} e^{-c\left[\|\vec{s}_{oi}\| - (r_r + r_{oi})\right]} \tag{2}$$

Where, $\|\vec{s}_{oi}\|$ is Euclidean distance between robot center (x,y) and obstacle center o_i. The later is defined as the center of the obstacle axis-aligned bounding box (AABB). r_{oi} is half-diagonal of the obstacle AABB, and c, where $\in \mathbb{R}$, is the field strength coefficient. Obviously, as the robot approaches an obstacle the angle deviation $\Delta\varphi_i$ is getting larger and reaches $\pi/2$ if the robot touches the obstacle circle (in this case $\|\vec{s}_{oi}\| = r_r + r_{oi}$).

Now, as mentioned before, the generated angle deviation is added to or subtracted from robot orientation based on the obstacle position relative to the direction of the robot. To do this, the cross product term $\vec{s}_{oi} \times \vec{s}_d$ is used. A positive sign of the z component of the product indicates that the obstacle is to the right of the robot, i.e., angle between $\vec{s}_{oi}$ and $\vec{s}_d$ is 0°-180°. In this case the deviation angle in (2) is added to the

robot orientation. On the other hand, a negative sign indicates that the obstacle is to the left of the robot (angle between $\vec{s}_{oi}$ and $\vec{s}_d$ is 180°-360°) and deviation angle in (2) is subtracted from robot orientation. So, let's define a classification function, clas($\vec{s}_{oi}$, $\vec{s}_d$), as

$$\text{clas}(\vec{s}_{oi},\vec{s}_d)=\begin{cases}+1 & (\vec{s}_{oi}\times\vec{s}_d)_z\geq 0\\ -1 & (\vec{s}_{oi}\times\vec{s}_d)_z<0\end{cases} \tag{3}$$

Including the above function in equation (2) it becomes

$$\Delta\varphi_i=\text{clas}(\vec{s}_{oi},\vec{s}_d)\frac{\pi}{2}e^{-c\left[\|\vec{s}_{oi}\|-(r_r+r_{oi})\right]}. \tag{4}$$

By classifying the obstacles into two groups, adding or subtracting a deviation angle from robot orientation, we thus avoid a common drawback in the traditional APF method. All obstacles in the APF method have repulsive fields pointing outwards. So, robot can easily stuck into local minima if the total repulsive force generated by obstacles equals the attractive force generated by the goal. This more likely happens when passing between two obstacles close to each other.

Adding repulsive potential fields of crowded obstacles in the traditional APF method and many of its modified forms may create, unnecessarily, zones of powerful repulsive field that could hamper the smooth motion of the robot. To overcome this drawback, the proposed method considers only two obstacles at a time; the nearest right and the nearest left obstacles (see Fig. 2). As the robot moves toward the target point, it leaves the field of one obstacle, once was the nearest, and gets into a field of another nearer one. However, the transition between both fields is done smoothly since at the transition point the robot is at equal distances from both obstacles, i.e., equal field strengths. This is illustrated in Fig. 2, where the robot leaves right-field № 1 (indicated by dotted line) and gets into right-field № 2 (indicated by solid line). The left field № 6 remains active as long as it is the nearest obstacle in the left group.

Adding the above modifications, equation (2) becomes

$$\Delta\varphi=\frac{\pi}{2}\left[e^{-c\left[\|\vec{s}_{on}\|-(r_r+r_{on})\right]}-e^{-c\left[\|\vec{s}_{om}\|-(r_r+r_{om})\right]}\right] \tag{5}$$

Where, n and m indicate the nearest right and left obstacles respectively.

Now let's consider the situation when the distance between two obstacles is smaller than robot dimensions. This is shown in Fig. 2 by obstacles № 7 and № 8. The situation can be expressed as

$$d_{ij}=\|\vec{s}_{oi}-\vec{s}_{oj}\|-r_{oi}-r_{oj}\leq 2r_r \tag{6}$$

Where, d_{ij} is the distance between the boundaries of two obstacle circles. In this case, to avoid a possible collision, as the robot may pass between these obstacles, it is better to treat them as one obstacle with larger border. This situation is further explained in simulation section III-B.

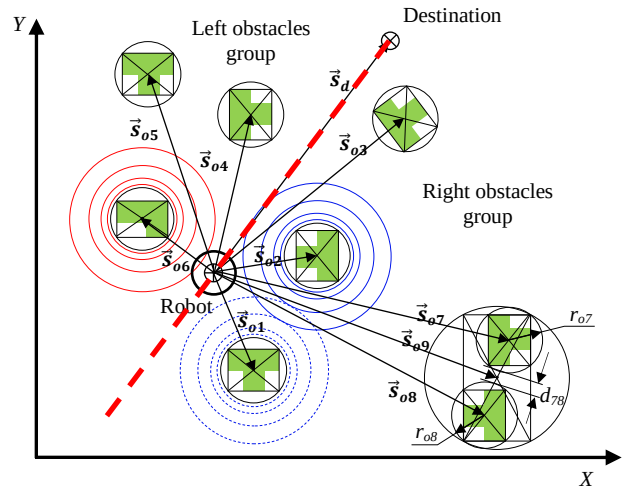


Fig. 2 Illustration of obstacles classification

B. Goal convergence

Starting from an arbitrary point in the world coordinates, the aim of this section is to define conditions for robot convergence to the goal point. Referring to Fig. 3, it is supposed that at a certain instant the robot moves with a velocity $\vec{v}_r$ and encounters an obstacle that deviates its orientation toward destination by an angle $\Delta\varphi$. In order to investigate the convergence of the robot toward the destination a global-positive-definite Lyapunov function is defined as

$$V=\frac{1}{2}s^2 \tag{7}$$

Where, s = $\|\vec{s}_d\|$ is Euclidean distance between robot center and goal point. The time derivative of the candidate Lyapunov function becomes

$$V^{\cdot}=ss^{\cdot} \tag{8}$$

Decomposing the robot velocity $\vec{v}_r$ in direction pointing to the goal point, v_{rd}, and its tangent, v_{rt}, it can be deduced that $v_{rd}=v\cos\Delta\varphi=-s^{\cdot}$, where v is the robot absolute velocity. Substituting in (8) we get

$$V^{\cdot}=-s\,v\cos\Delta\varphi \tag{9}$$

Since s and v in (9) are positive values, thus for $V^{\cdot}$ to have a negative value, cos($\Delta\varphi$) must be positive. In other words, $|\Delta\varphi|<\pi/2$, which can be written using (5) as

$$\left|\frac{\pi}{2}\left[e^{-c\left[\|\vec{s}_{on}\|-(r_r+r_{on})\right]}-e^{-c\left[\|\vec{s}_{om}\|-(r_r+r_{om})\right]}\right]\right|<\frac{\pi}{2} \tag{10}$$

Since the left term in (10) is a difference value, the maximum deviation angle $|\Delta\varphi|$ occurs when only one exponential term

exists. Taking only the left or the right exponential term, as the worst case, equation (10) reduces to

$$e^{-c\left[\|\vec{s}_{on}\|-(r_r+r_{on})\right]}<1 \qquad (11)$$

For this inequality to be true, the index $-c\left[\|\vec{s}_{on}\|-(r_r+r_{on})\right]$ must be a negative value. Since $\left[\|\vec{s}_{on}\|-(r_r+r_{on})\right]\geq 0$, as the robot cannot be physically inside an obstacle, it follows that c should be a real positive value. In case of $\left[\|\vec{s}_{on}\|-(r_r+r_{on})\right]=0$, the robot touches obstacle circle and the value of $\dot{V}$ becomes zero.

From the above analysis it can deduced that choosing $c > 0$ guarantees a global convergence to destination, except in conditions when the robot touches obstacle circle. In this case the derivative of the Lyapunov function equals zero and the robot is given a maximum deviation angle of $\pi/2$. This makes sense, as the priority in this case is to get away from the obstacle rather than to converge to destination.

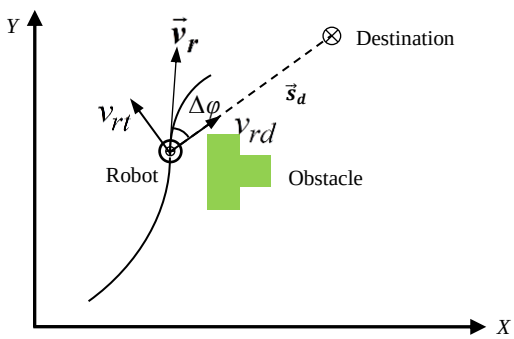


Fig. 3 Robot convergence to destination

III. Image Analysis and Visual Perception

This section illustrates the developing of visual perception algorithm and how it is integrated with the proposed path planning method. Some common path planning problems such as unreachable destination, trapped robot, and urgency of avoiding an obstacle are discussed. The focus of the current research is on the intelligent use of available visual information in developing an efficient path planning method. So, without loss of generality, a simple color-based object detection method is used for robot and obstacles localization. The detection method may vary according to the condition of the robot environment, however the concepts presented here still applicable.

A. Collision prediction

The urgency to avoid an obstacle right encountering robot path is clearly greater than when the obstacle is parallel to robot motion. In addition, it is illogical to consider avoiding an obstacle located behind the robot while the robot is moving forward. To help in better perceive robot surrounding, a collision prediction algorithm is proposed. In the previous section we indicated that the robot is oriented directly toward the goal point by angle φ_d and is deviated due to obstacles by a deviation angle $\Delta\varphi$. In this section a virtual sightline from the robot center to the goal point is presented to help the robot to predict collision with encountering obstacles. The sightline thickness is made equal to the robot diameter plus some safety value (e.g. 10 % of the robot diameter). The images of the robot scene are first processed by using color filters to detect obstacles and robot. The images are then thresholded and converted to binary images. After converting the scene image to binary, blob analysis is used to extract basic information such as obstacles location, area, and AABB. The binary image of the sightline is then augmented to the scene binary image; blob areas are recalculated, and a possible collision to an obstacle is informed if a change in its blob area occurs. Obstacle that has a possibility to collide with robot will have its field activated and vice versa. Thus, as the robot moves toward the goal point it is not affected by the field of an obstacle that has no chance to collide with.

B. Simulation

1) Single Obstacle:

Fig. 4 illustrates a simulation of the proposed path planning method combined with the collision prediction algorithm. The simulations are done using Simulink and computer vision toolbox in MATLAB® of MathWorks company. Fig. 4 shows two different cases when a single obstacle encounters robot path. The left case in the Fig. 4 represents situation when the obstacle is directly facing the robot motion. Fig. 5 shows the binary images of the obstacle augmented by robot sightline taken at different instants on the robot path. As can be seen, the robot is affected by the obstacle field till point D at which the sightline toward destination starts to be clear and the field is deactivated. The robot then starts to move straight toward the destination. This clearly shortens the path the robot should go compared with the case if obstacle field was permanent. The right case in Fig. 4 describes a similar situation except that the obstacle is put parallel to robot motion. We can see that the robot starts to deviate away from the obstacle till point A at which the sightline is clear and robot continues straight toward the destination.

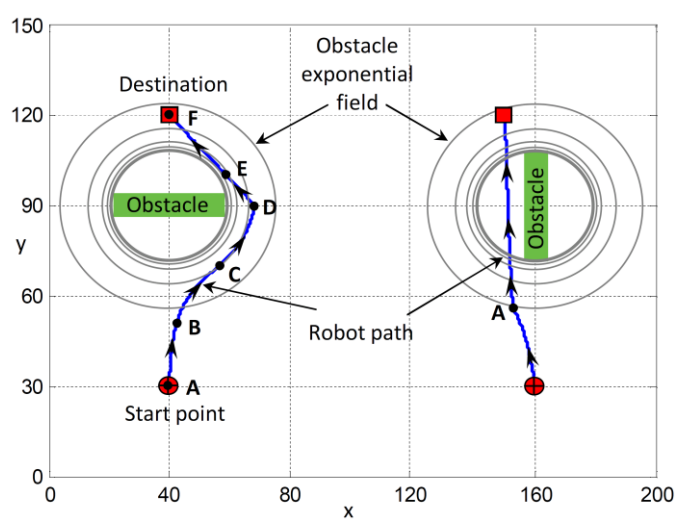


Fig.4 Obstacles activation and deactivation

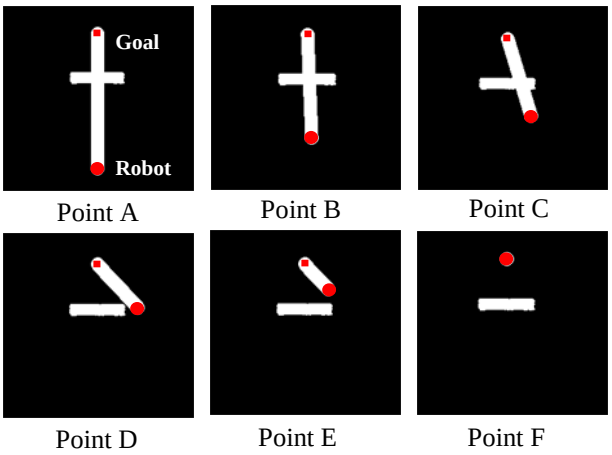


Fig. 5 Illustration of the collision prediction mechanism

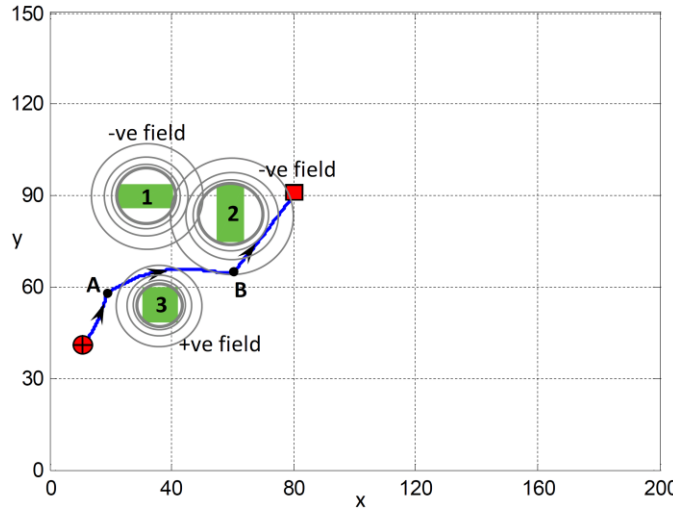


Fig. 6 Robot path through multiple obstacles

2) Multiple Obstacles:

Now, let's discuss the situation when the robot has to go through a number of obstacles. Fig. 6 illustrates this case and Fig. 7 shows the binary images at different instants. As shown in Fig. 7, at the start point obstacles 2 and 3 are activated and the robot is deviated according to (5). As the robot moves to point A, obstacle 3 becomes inactive and the robot keeps moving toward the goal point affected only by the field of obstacle 2. At point B the three obstacles become inactive and the robot continues undeviatingly to the goal point.

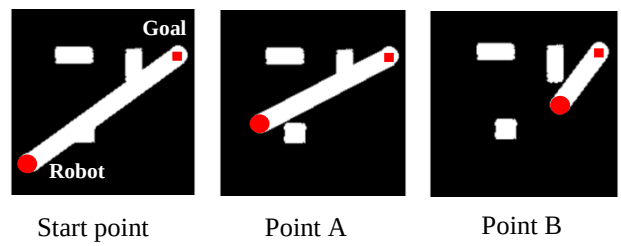


Fig. 7 robot sightline during obstacle avoidance

3) Crowded Obstacles:

The above situation is repeated with new goal point lying between obstacles 1 and 2, as shown in Fig. 8. The difference between the left and right cases is that the distance between obstacles 1 and 2 has been reduced, in the right case, so that the robot can't physically pass between them. Such a situation was described mathematically in (6). As the shortest distance to the goal point is the straight line, the robot in the left case goes among the obstacles, avoiding the active ones, until it reaches the goal point. In the right case, as illustrated in the previous section, the two obstacles are treated as one with a larger field by which the robot is deviated away to avoid a possible robot trapping.

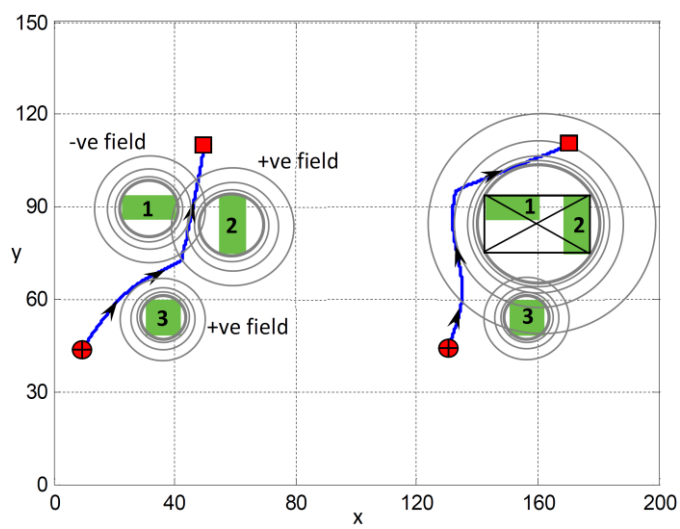


Fig. 8 Robot paths through and around crowded obstacles

4) U-shaped Obstacles

One of the path-planning concerning issues is the possibility to get stuck into obstacles with problematic topology such as concave or U-shaped obstacles. Fig. 9 illustrates two cases in which the robot is approaching a U-shaped obstacle while the goal point is once in the back of the obstacle (the left case) and once inside the obstacle AABB (the right case). In the left case, collision is predicted as the obstacle obstructs the robot sightline. The obstacle field is activated and the robot path is deviated. In the right case, the obstacle field is deactivated, since the robot sightline is not obstructed, and the robot goes directly towards the goal point.

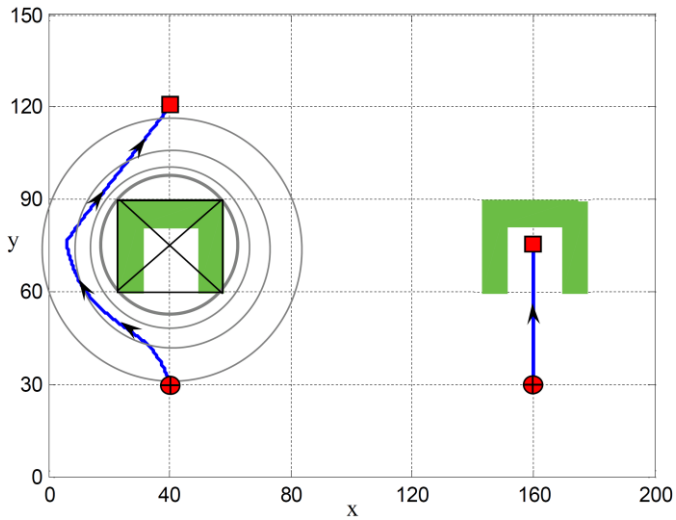


Fig. 9 Robot reaction to U-shaped obstacles

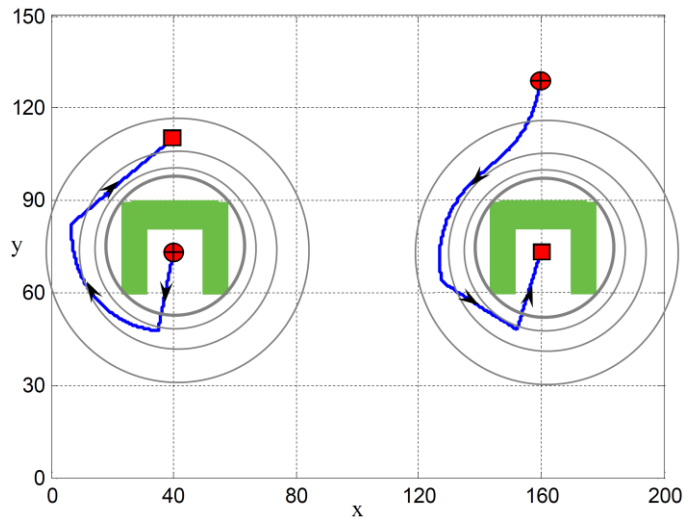


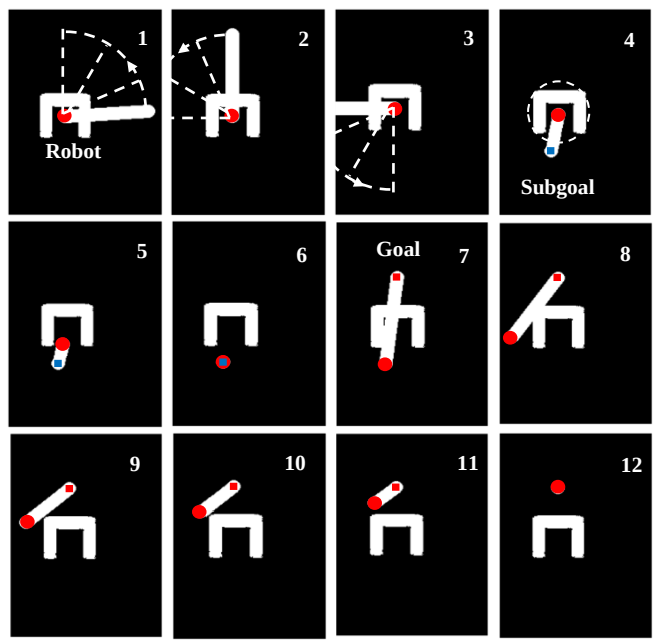
Fig. 10 Surrounded robot and goal point

5) Surrounded Robot and Destination:

Fig. 10 describes two other situations when either the robot or the goal point is located inside an activated U-shaped obstacle; the cases can be expressed mathematically as

$$\left\|\vec{s}_{oi}\right\| \le r_{oi} \quad \text{or} \quad \left\|\vec{s}_d - \vec{s}_{oi}\right\| \le r_{oi} \tag{12}$$

In order to treat these cases a search algorithm is proposed to find suitable exit and/or entrance. First, let's consider the left case in Fig. 10. Fig. 11 shows the binary sequence images of the robot motion. The algorithm starts by rotating the sightline, centered at the robot, around the obstacle until it becomes clear (sequences 1-4). An intermediate goal (subgoal) is then set outside the obstacle boundary to guide the robot out (sequences 5, 6). As the robot gets out of the obstacle boundary it directs toward the original goal in the same normal way (sequences 7-12). In the right case shown in Fig. 10 the same algorithm is used except that the search is centered at the goal point until an entrance found. A subgoal is set outside the obstacle boundary and the robot follows the sequences described before.



Fig, 11 Illustration of exit search mechanism an subgoal point

IV. Experimental Results

A. Experimental Setup

The experimental platform designed to implement the proposed algorithms is shown in Fig. 12 and 13. A workspace measuring 2 × 1.3 m^2 is used as a playground. The candidate robot used in the research is a small (190 × 150 × 100 mm^3) differential derive mobile robot. The robot is equipped with an onboard single-board microcontroller (Arduino Mega, based on the ATmega1280) to manage onboard peripherals. A DC-motor driver module L298 is used to control robot speed and orientation. The motors are powered by 10V lithium-ion batteries. All communications between the robot and a host PC is done via APC 220 Kit RF wireless module. The host PC is Intel core i3 (3.4 GHz) and 4 GB RAM. An overhead digital camera (Sanyo x1250 12Mb) is used for video stream and is USB connected to PC

The overhead digital camera is calibrated using a planner checkerboard to determine the intrinsic and extrinsic camera parameters. The camera established pinhole model is tested and a maximum error of 2 cm is found in robot and obstacles localization process. The video stream rate sent by the camera is set to 10 frame/s. This is chosen to fit the real-time running of the algorithms on the MATLAB environment provided by the specified host PC. The images sent by the camera are analyzed as discussed in section III-A, and motion decisions are sent wirelessly to the robot. A motion control program,

downloaded on robot onboard microcontroller, implements the required robot orientation and speed using differential drive kinematic model. Throughout the investigation the robot forward speed is kept 0.1 m/s.

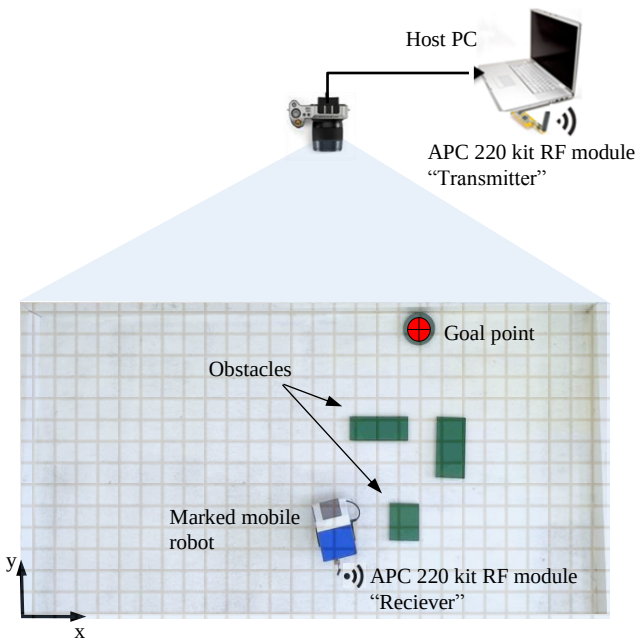


Fig. 12 Experimental platform

Designed mobile robot:
190 × 150 × 100 mm^3;
differential derive;
RF control;
color marker.

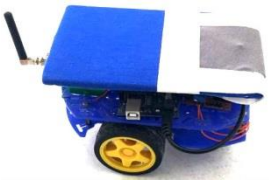


Fig. 13 Research mobile robot

B. Experimental Results

In this section we demonstrate the experimental implementation of the proposed algorithms in MATLAB real-time environment. The same cases studied in simulation are repeated here to validate the algorithms. During the experiments robot starting position, goal position, and obstacles shape and position are the same as those in simulation. In Fig. 14, which corresponds to the left case in Fig. 8, the robot finds its way among obstacles to the destination. Relying on the sightline, the robot activates or deactivates the encountered obstacles (frames 1-8). At frame 8 the robot starts to go straight to the goal point, as its sightline becomes clear. Fig. 15 describes the same case as in Fig. 14 except that the space between obstacles is narrowed. As shown in the figure, the robot in this case avoids the total bulk of the crowded obstacles, since it can't physically goes between them.

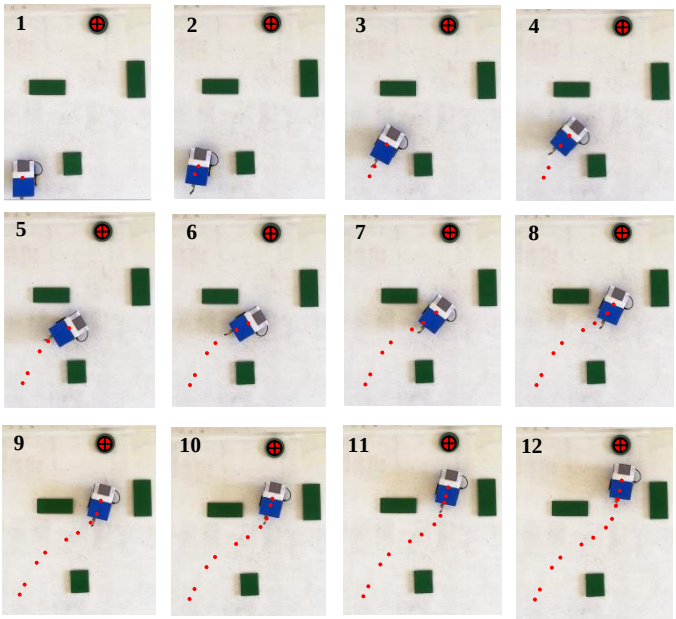


Fig. 14 Experiment 1: Robot path among multiple obstacles

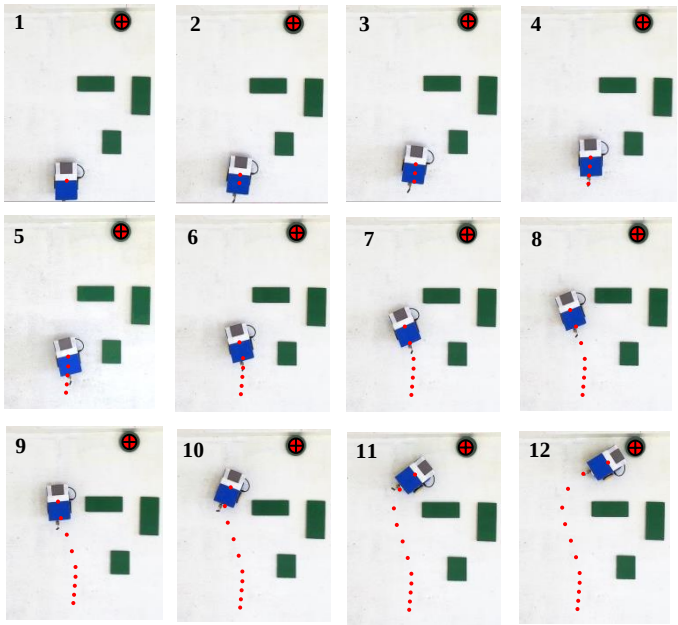


Fig. 15 Experiment 2: Robot path around a bulk of crowded obstacles

Fig. 16 and 17 show how the robot reacts with U-shaped obstacles. The cases correspond to Fig. 9 in simulation. As shown in Fig. 16, the robot is affected by the activated obstacle exponential field and avoids it without getting trapped inside. In frame 8 the sightline to the goal point is clear and the robot goes straight, shortening by that any unnecessary paths around the obstacle. In Fig. 17 the robot goes directly straight to the goal as the obstacle field is deactivated.

Finally, Fig. 18 and 19 demonstrate the cases when robot start point and goal point are surrounded. In these cases, as discussed in the simulation section, a search mechanism is adopted. As shown in Fig. 18, the robot first directs to a subgoal point found by the search mechanism (frames 1-3). From frame 4 to 8 the obstacle field is activated and the robot avoids it. Finally the robot goes straight to the original goal point (frames 9 to 12). Fig. 19 shows the case when the goal point is surrounded. Again, using the search mechanism, the robot goes first to a proper subgoal point located outside the obstacle boarder and then to the destination.

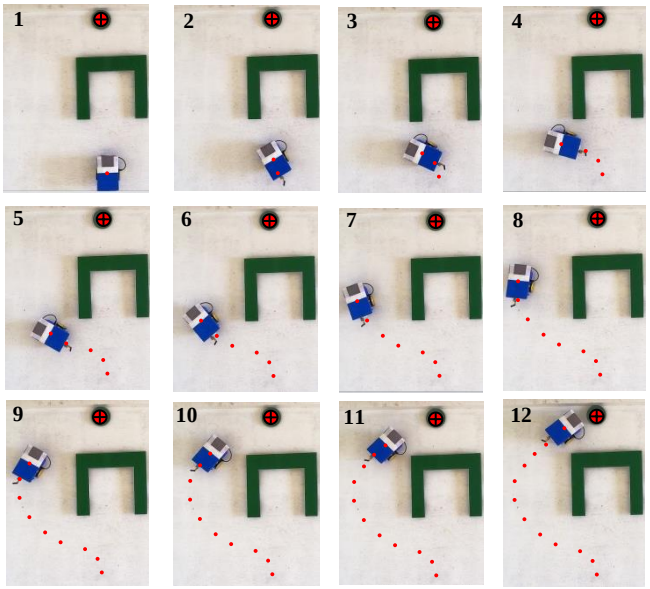


Fig. 16 Experiment 3: Robot reaction toward U-shaped obstacle (case 1)

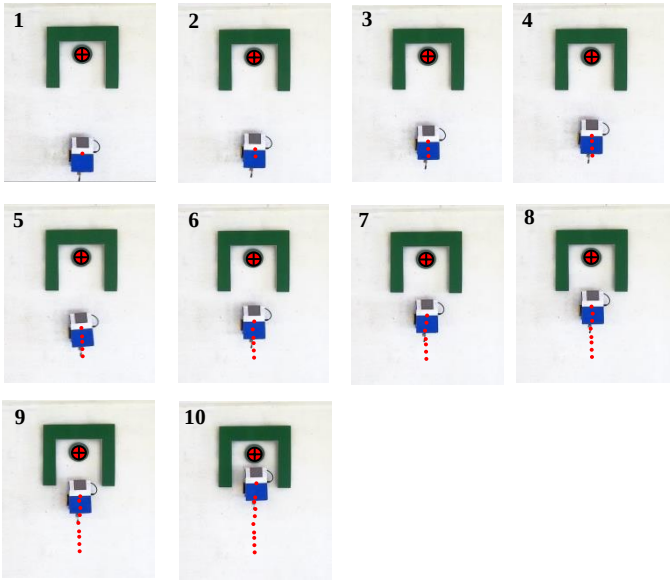


Fig. 17 Experiment 4: Robot reaction toward U-shaped obstacle (case 2)

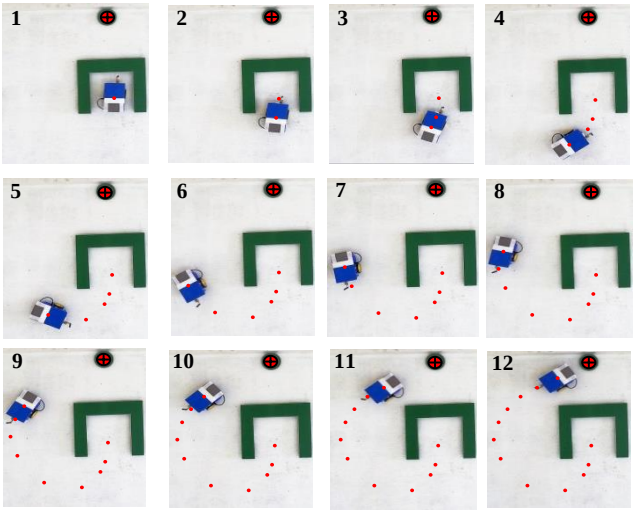


Fig. 18 Experiment 5: Surrounded robot

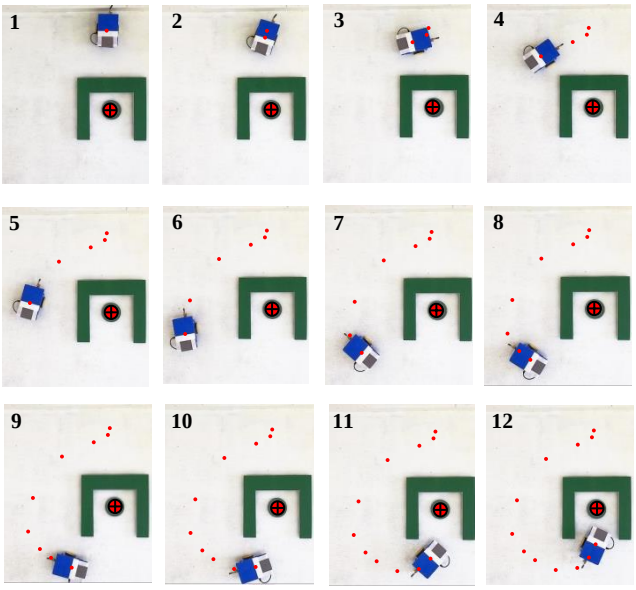


Fig. 19 Experiment 6: Surrounded goal point

V. Conclusion and Recommendation for Future Work

In this paper we presented a new technique of robot path planning and obstacle avoidance integrated with visual perception. The method keeps the simplicity of the classical methods, however it overcomes common path planning problems such as local minima, unreachable destination and unnecessary lengthy paths around obstacles. The proposed method uses obstacles shape and location, extracted from global vision system, through a collision prediction mechanism to decide whether to activate or deactivate obstacles field. In addition, a search mechanism is developed in case of robot and/or goal points are trapped among obstacles to find suitable exit or entrance. Designed obstacle field parameters have been chosen based on Lyapunov criterion to guarantee global convergence to destination. The proposed algorithm has been validated both in simulation and

through practical experiments. The algorithm showed effectiveness in both obstacle avoidance and destination convergence. The research is considered a preliminary study of the validity of the proposed method. The future work will intend to concentrate on other related issues such as path optimization proof and the effect of dynamic environment.

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