PATH PLANNING GENERATION IN MOBILE ROBOTS USING EVOLUTIONARY HARMONIC POTENTIAL FIELDS.

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Abstract: Path planning by geometric methods bond to a complete knowledge of the environment in order to obtain a feasible solution are not the best option when solving the problem of moving in variable structure environments. Here a method based on the generation of local segments that are concatenated to form the total path from a starting point to a goal point free of collisions is given . The individual segments are the solutions of local, with respect to the robot, harmonic potential field problems. The information needed to properly outline the local harmonic potential field problems is obtained by using a system of range sensors that recognize the environment that surrounds the robot.

Keywords: Harmonic Potential Fields, Mobile Robots, Recognition System, Local Path.

I INTRODUCTION

The mobile robot path planning problem can be described as follows: "given a robot and information of its workspace find an collision free route between two specified points" Schwartz (1987). There are many methods to derive a solution to this problem: the visibility graph (Jarvis, 1985), voronoi diagrams (Canny and Donald, 1988), grid cells (Stentz, 1994), and potential fields (Khatib, 1985).

The potential field paradigm (PF) began from the simple idea of attaching an attractor field to the target and a repeller field fencing the obstacles. An atractor force from the goal point and repeller forces from the obstacles are exerted on the mobile. The direction of the resultant of these forces is the generated path towards the goal, see Fig. 1. A great advantage on this type of methodology, is that the solution may be used as part of the control signal for the generation of the trajectory; unfortunately, the Kathib`s atractor-repeller method has some problems, be the most important the lack of guarantee of convergence toward the target. This problem is defined as minimal local problem.

A lot of improvements to the Khatib's method have been proposed in order to convey the convergence problem (Koditschek, 1987); in the 90's Conolly (Conolly, et al., 1990) began to work with the artificial harmonic potential fields (HPF) technique, that satisfy the Laplace equation, these techniques guarantee displacements in complex environments. Masoud (Masoud, 1997; Masoud and Masoud, 2002; Masoud, 2003) has worked in different problems using HPF included an evolutionary technique.

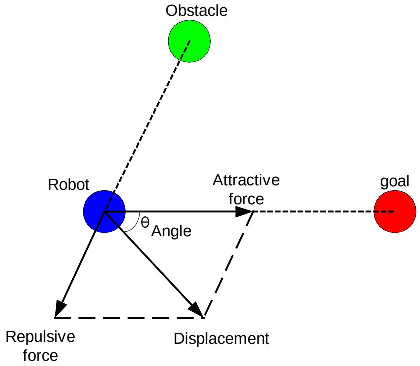

Fig. 1. Local forces acting on the robot

PF path planning methods are classified in two areas: the artificial potential field (APF) methods (Khatib, 1985; Koditschek, 1987; Canny 1988) and the artificial intelligence (AI) methods (Baba and Kubota, 1994; Prahlad, et al. 2003).

Many of the AI methods are based on tools like, genetic algorithms (Prahlad, et al. 2003; González and Reyes, 2006), fuzzy logic (Gerke and Hoyer, 1998) and neural networks (Kassim and Kumar , 1992). These methods are associated with optimization algorithms, resulting in optimal global path planning, But, this algorithms are relatively complex, and computational time-consuming, making them in most of the cases useless for real time applications.

The APF approach has the quality of working in real time when the environment is known, the modifications of the general technique assure the convergence of the method and allow the application of an optimization approache.

Masoud (Masoud, 1997) introduced the evolutionary harmonic potential field (EHPF) method to work in partial known environments. The method starts with a definition of the goal point and the exterior boundaries of the workspace. Then solve the boundary value problem (BVP) for an biharmonic potential and obtains the possible paths that lead to a mobile to achieve the goal. The planner manages to lay a trajectory to the target that avoids the obstacles relying only on the data its sensor provide. Each time that the sensors detects the presence of obstacles to adjust the steering field so that the presence of the newly acquired data is accomodate. Unlike the Masoud's method, the method presented here makes use of sensor recognition system in order to derive local real time solutions to the EHPF. These partial solutions are concatenated to generate the general solution that takes the robot to the target. Simulation has been carried out on cluttered environments and excelent results have been obtained.

The paper is divided as follows: Section II contains the problem formulation, Section III shows simulation results, and finally conclusions and recommendations are given in section IV.

II. EVOLUTIONARY HARMONIC POTENTIAL FIELD

The harmonic potential fields approach was brought independently and simultaneously by different researchers (Connolly, et al. 1990; Tarassenko and Blake, 1991; Akishita, et al. 1990). A significant advantage of the HPF approach is that it avoids local minima problem by forcing the differential properties of the potential field to satisfy the Laplace equation inside the workspace of the robot (Ω) while constraining the properties of the potential at the boundary of Ω ($\Gamma=\partial\Omega$). The boundary set Γ includes both the boundaries of the forbidden zones (O) and the target point (x_T). A basic setting of the HPF approach is:

$$\nabla^2 V(x) \equiv 0 \qquad x \in \Omega$$

subject to:

$$V = 0\big|_{x=x_T} \qquad V = 1\big|_{x\in\Gamma} \tag{1}$$

Where $V(x)$ is the harmonic potential field. The direction of the gradient generates the paths that take the robot from the starting point to the goal point.

As it was mentioned before it is necessary to generate boundary conditions (BC). Appropriate application of these conditions allows the correct directionality of the field. The problem presented above is known as the Dirichlet boundary value problem that is based on border constant conditions. The solutions derived from this BVP produces vanishing constant fields making them useless for planning.

The Newmann BVP is defined as follows:

$$\nabla^2 V(x) = 0$$

subject to:

$$\frac{\partial V(x)}{\partial n} = C\Big|_{x=\Gamma} \qquad V(x) = 0\big|_{x=\Gamma_p} \qquad V(x_s) = 1 \tag{2}$$

where C is a constant, n is a unit vector normal to Γ, $\Gamma_p = \{x : |x - x_T| > \rho, \rho > 0\}$ and x_s is the starting point. Solutions for this problem show no vanishing regions even in workspaces with complex geometry. A disadvantage present in this approach is that it may generate paths dangerously close to the obstacles.

One advantage of the use of HPF, is the possibility to obtain a diversity of paths through which the mobile element can arrive to the goal point, making viable to readdressed the mobile to orthogonal paths, when in operation.

HPF approach is a special case of a broader class of planners called: PDE-ODE motion planners where the field is generated using the BVP on the basis of the BC established by the workspace. It is necessary to have a priori knowledge of the complete environment to obtain appropriate solutions.

2.1 Problem Outline

Different from the classical methods of HPF technique where full knowledge of the environment is a precondition to obtain a general solution, here the general solution is obtained by the union of local HPF solutions that allow the mobile move to the target. The mobile uses a real time sensor recognition system to get the information of the local environment needed for outline the HPF problem.

The environment: Let Ω be a space in which the agent is permitted to operate in an n-dimensional region $\boldsymbol{R}^n$ ($\Omega \in \boldsymbol{R}^n$); let O be a set of unknown regions occupied by obstacles in $\boldsymbol{R}^n$ ($O=\boldsymbol{R}^n-\Omega$), and Γ be the boundary of Ω, *and* O together $(\Gamma = \partial\Omega + \partial O)$.

The agent: It is cover by a circle $R(x)$ of radius δ with boundary $\gamma(x)$.

Assume the agent starts at location $q_s \in \Omega_{s1}$ and its target is $q_g \in \Omega$. Then, using a set of sensors located on the agent, with maximum range ε, a local space $\Omega_s \in \Omega$ is recognized. Let Γ' be a subset of Γ inside Ω_s, with boundary $\partial\Omega_s = \Gamma'' + \Gamma'$ where Γ'' are the boundaries free of obstacles on Ω_s and let q_{p1} be the projected point, along the line of sight between the starting point and the goal point, on the boundary of Ω_{s1}. Fig. 2 shows the workspace, and the definition of the local conditions needed for the outline of the local evolutionary harmonic potential field problem.

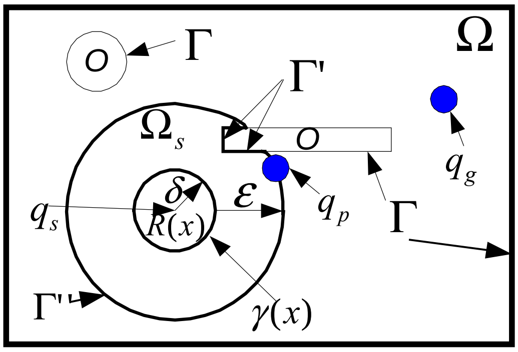

Fig. 2. Local conditions stablished.

Now the local BVP to solve for the local HPF is posed as follows:

$$\nabla^2 V_1(x) \equiv 0 \qquad x \in \Omega_s$$

subject to:

$$\frac{\partial V_1(x)}{\partial n} = 0\Big|_{x=\partial\Omega_{s1}} \qquad V_1(x) = 0\Big|_{x=q_{p1}} \qquad V_1(x) = 1\Big|_{x=q_s} \tag{3}$$

Assuming that there is any obstacle between q_s and q_{p1} and using the gradient of the local potential field, a segment of the path is obtained and the agent can move from q_s to q_{p1}. Now, the point q_{p1} is taken as the point for recognition ($q_{p1} = q_{s1}$) of the local environment and new boundary conditions are derived together with a new projected point q_{p2}, establishing the conditions for the next local harmonic potential field problem. This process is repeated until the agent reaches the target point. So, the general path connecting starting point with the target turns out to be the finite sum of individual segments $P_i(x)$ $i=1,2,\ldots,k$ or:

$$P(x) = \sum_{i=1}^{k} P_i(x) \tag{4}$$

Where $P(x)$ is the total path.

Due to uncertainty of the environment, any different scenarios may be encounter by the agent as it moves ahead.

2.2 Local Planning Algorithm

Following is the description of the algorithm to find the total path for different scenarios encountered by the agent during the search of the path.

Step 1.- Activate the sensor system. Switch on a sweeping process to obtain a map of the local environment. A sensor flags S_k k=1,2,...n, are set to one if an obstacle is detected or zero otherwise, n is the number of sensors.

Step 2.- The informaction of the environment, received by the sensors leads to two situations:

a).- If S_k =1 for k=1,2,…,n then there is a wall, go to step 4.

b).- If S_k = 0 for at least one k, then go to step 3

Step 3.- Set q_p on the boundary $\partial\Omega_s$, solve the BVP for the local HPF problem. If $\left\| q_g - q_p \right\| > \varepsilon$ generate the segment of the path from q_s to q_p and go to step 1. If not determine the path between q_g and q_s and go to step 5.

Note: When the movement in the mobile is generated and the sensors detect a very close obstacle (< 1.5δ), stop the mobile, saving the current position as the q_p value and turns to step 1.

Step 4.- In this case there could be two possible scenarios as shown in Fig. 3. Let α, and β be the angles between the line of sight of q_s and q_p and the direct lines between the agent and the points O_1, and O_2 respectively. If $\alpha > \beta$ then q_p must be placed on $\partial\Omega_s$ at a distance 2δ from the point O_2.. If not q_p must be placed on $\partial\Omega_s$ at a distance 2δ from the point O_1. Solve the HPF problem then go to step 1.

Note: If it is a wall the agent will moves along a line parallel to it until a different scenario is found.

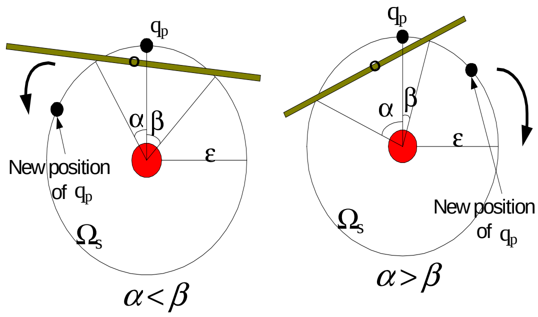

Fig. 3. Place of q_p when a wall is in the way of the agent.

Step 5. End

2.3 Path improvements

Due to the high uncertainty present during the process of determining a path from an starting point to a goal point, a first attempt may give as result paths with redundancy, longer or with sharp changes on orientation . The agent is programmed to store in memory the whole path, so it learns, and may improve the path after several attempts.

Next are described some geometric techniques to improve or get rid of the cases mentioned above.

Case 1. Sharp change on orientation.

If the angle between the points q_s and q_p in the ε range is greater than 45, use the value of the point q_{s-1} that is on the border of the actual Ω_s , as the new initial point and solve HPF problem for the same q_p. That gives as result a more soft path between the points q_{s-1} and q_p. Fig. 4. shows two possible scenarios.

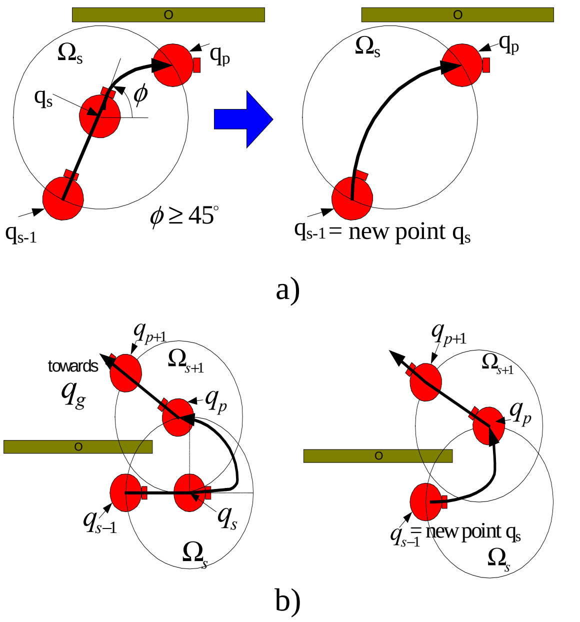

Fig. 4. Softness of a sharp turn greater then 45 degrees. a) angle less than 90° b) angle greater than 90°.

Case 2. Loops

It is possible that when moving the agent is faced with the problem to decide between two or more directions to continue. That it is the case of a corner between two corridors. Due to uncertainty, the agent may take the wrong direction, and faced with the decision of turning back to the corner. This at the end form a loop that must be removed, and the agent learns not to take that direction. In this case, it is necessary to lock backward from the point q_s, a point with change of direction greater than 45 degrees and from this point again, find that point where the error is less than a value λ.

$$e = \left\| \vec{q}_{s+i} - \vec{q}_s \right\| < \lambda \qquad i=1,..., k \tag{5}$$

If this point exist, all values between q_s and that point are removed from the approach y solve the new local HPF, Fig. 5 shows this case.

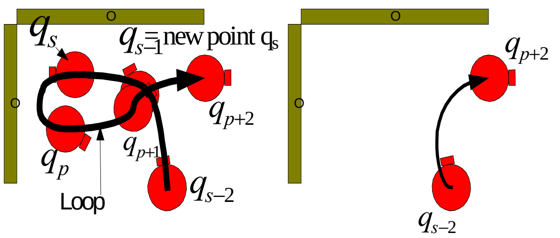

Fig. 5. Loops found during the path generation.

Case 3. Shorter paths.

The agent may find long intermediate routes free of obstacles as can be seen in the first attempt in Fig.6. to move from poit q_s to point q_r, So, it may be possible to find a short route between these two points. In order to find out this, a subsequent attempt is made by taken the point q_r as a regional goal point, and start the process of HPF again from $q_{s,}$ and taking the new intermediate poits q_p along the line of sight between q_s, and q_r.

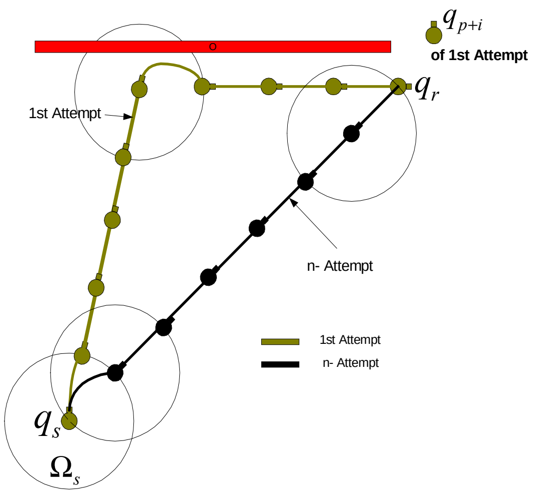

Fig. 6. Obtain a better path.

Case 4.- Extention corridor

The agent may also find free of obstacles straight long routes, so making the process of solving the HPF problem several times unsuitable. In order to find this path in a single attempt, a change is made to the process by using as Ω_s what is called a *extention corridor* this is shown in Fig.7. q_r is taken as q_p an the HPF problem is solved for this case. The result is a straight path between q_s and q_r.

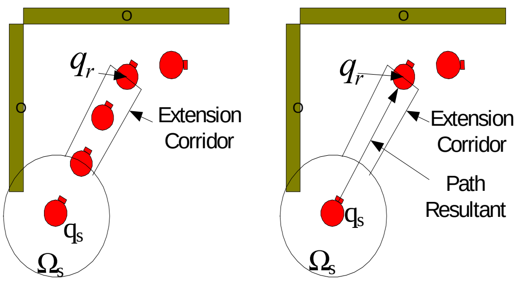

Fig. 7. Extension corridor technique.

III SIMULATIONS RESULTS

The PDE toolbox of MATLAB is used to derive the solutions to the BVP of the elliptical problems. Other toolboxes were used to obtain the gradients and derive the optimal local routes. The first simulation considers an obstacle between the mobile and the goal point. The mobile and the target points are (10, 11, 0°) and (2, 2, 48°) respectively with respect to an inertial frame. The rectangular obstacle starts at point (4, 7, 0°) with 6 meters of length and 0.5 meters of width. It is assumed that the sonar systems has a maximun range of 3 meters. The first scan produces the potential field shown in Fig. 8.

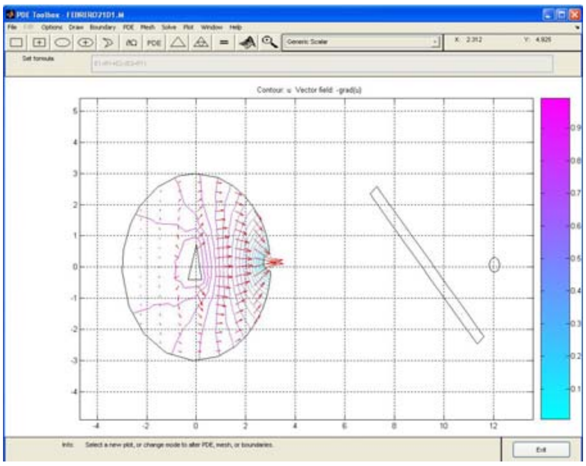

Fig. 8. Case of an obstacle between the mobile and the goal point.

After applying the algorithm, a first attempt is show in Fig. 9.

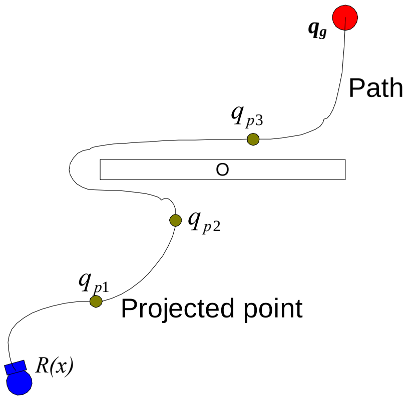

Fig. 9. General route for the first attempt.

By applying some of the route improvement techniques defined above a more suitable path is found as shown in Fig. 10.

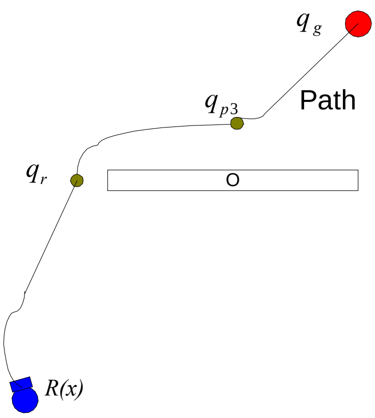

Fig. 10. Final path obtained by the EHPF.

Fig.11. shows the path obtained by a classical method where the entire workspace needs to be known. Clearly, sharp undesirable changes are present.

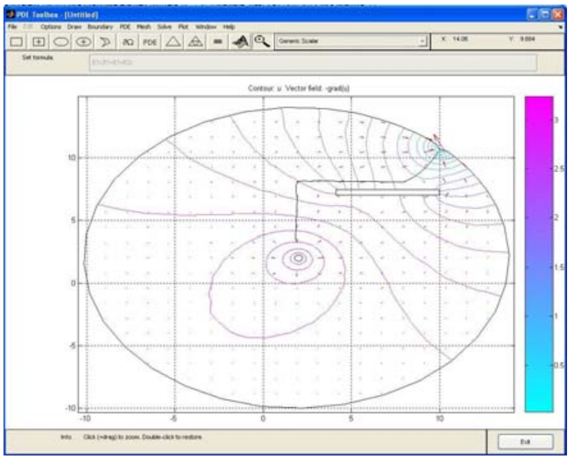

Fig. 11. Path obtained by classical PF method.

Simulation on more complex environments were carried out. Fig. 12 and Fig. 13 show the first attempt, and the final result respectively obtained after applying the EHPF method. In Fig. 14 it is shown the path obtained by a classical method. The path obtained by our method resembles the one obtained by classical methods, but with less sharp changes.

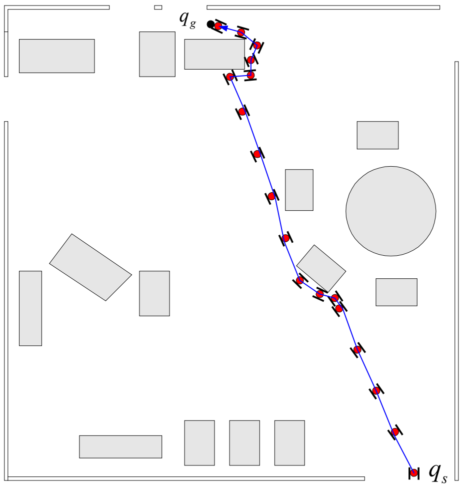

Fig 12. Path obtained by local EPHF.

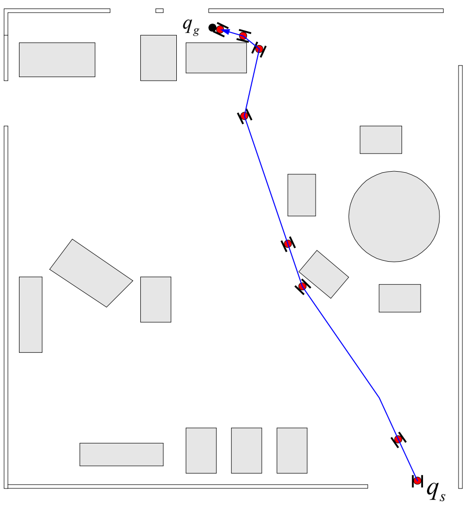

Fig. 13. Final path after improvements.

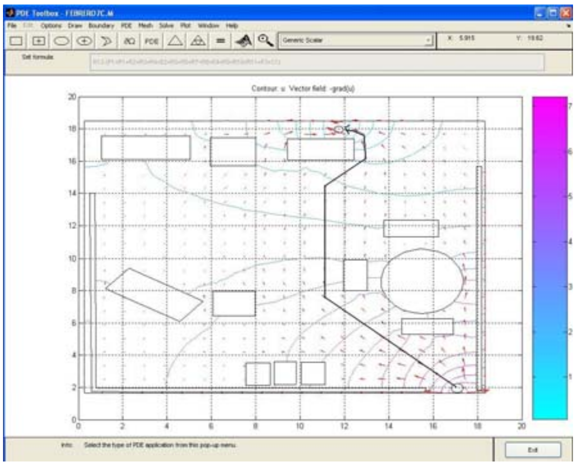

Fig. 14. Path obtained by using the entire map.

IV CONCLUSIONS

In this paper the use of evolutionary harmonic potential field techniques was presented. By solving the local EHPF based on local sensed information, segments of the path were derived in uncertain environments. The total path between the starting and target points is derived from the concatenations of the segments. The method can be used for the case of workspace with changing environments, since, different from classical PF methods it does not require the knowledge of the entire workspace. The authors believe that this technique is better to that submitted by Masoud, since it requires less information to achive similar responses. Path improvement may give as result paths more suitable for smooth, faster trajectories of the agent. For future research we are looking to make an extension of the method to a real time process.

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