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SLAM and Exploration using Differential Evolution and Fast Marching

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1. Introduction

The exploration and construction of maps in unknown environments is a challenge for robotics. The proposed method is facing this problem by combining effective techniques for planning, SLAM, and a new exploration approach based on the Voronoi Fast Marching method.

The final goal of the exploration task is to build a map of the environment that previously the robot did not know. The exploration is not only to determine where the robot should move, but also to plan the movement, and the process of simultaneous localization and mapping.

This work proposes the Voronoi Fast Marching method that uses a Fast Marching technique on the Logarithm of the Extended Voronoi Transform of the environment's image provided by sensors, to determine a motion plan. The Logarithm of the Extended Voronoi Transform imitates the repulsive electric potential from walls and obstacles, and the Fast Marching Method propagates a wave over that potential map. The trajectory is calculated by the gradient method.

The robot is directed towards the most unexplored and free zones of the environment so as to be able to explore all the workspace.

Finally, to build the environment map while the robot is carrying out the exploration task, a SLAM (Simultaneous Localization and Modeling) algorithm is implemented, the Evolutive Localization Filter (ELF) based on a differential evolution technique.

The combination of these methods provide a new autonomous exploration strategy to construct consistent maps of 2D indoor environments.

2. Autonomous exploration

Autonomous exploration and mapping are fundamental problems to solve as an autonomous robot carries out tasks in real unknown environments. Sensor based exploration, motion planning, localization and simultaneous mapping are processes that must be coordinated to achieve autonomous execution of tasks in unknown environments.

Sensor based planning makes use of the sensor acquired information of the environment in its latest configuration and generates an adequate path towards the desired following position. Sensor-based discovery path planning is the guidance of an agent - a robot - without a complete a priori map, by discovering and negotiating the environment so as to reach a goal location while avoiding all encountered obstacles. Sensor-based discovery (i.e., dynamic) path planning is problematic because the path needs to be continually recomputed as new information is discovered.

In order to build a map of an unknown environment autonomously, this work presents first a exploration and path planning method based on the Logarithm of the Extended Voronoi Transform and the Fast Marching Method. This Path Planner is called Voronoi Fast Marching (8). The Extended Voronoi Transform of an image gives a grey scale that is darker near the obstacles and walls and lighter when far from them. The Logarithm of the Extended Voronoi Transform imitates the repulsive electric potential in 2D from walls and obstacles. This potential impels the robot far from obstacles. The Fast Marching Method has been applied to Path Planning (34), and their trajectories are of minimal distance, but they are not very safe because the path is too close to obstacles and what is more important, the path is not smooth enough. In order to improve the safety of the trajectories calculated by the Fast Marching Method, avoiding unrealistic trajectories produced when the areas are narrower than the robot, objects and walls are enlarged in a security distance that assures that the robot does not collide and does not accept passages narrower than the robot's size.

The last step is calculating the trajectory in the image generated by the Logarithm of the Extended Voronoi Transform using the Fast Marching Method. Then, the path obtained verifies the smoothness and safety considerations required for mobile robot path planning.

The advantages of this method are the ease of implementation, the speed of the method and the quality of the trajectories. This method is used at a local scale operating with sensor information (sensor based planning).

To build the environment map while the robot is carrying out the exploration task, a SLAM (Simultaneous Localization and Modelling) is implemented. The algorithm is based on the stochastic search for solutions in the state space to the global localization problem by means of a differential evolution algorithm. This non linear evolutive filter, called Evolutive Localization Filter (ELF) (23), searches stochastically along the state space for the best robot pose estimate. The set of pose solutions (the population) focuses on the most likely areas according to the perception and up to date motion information. The population evolves using the log-likelihood of each candidate pose according to the observation and the motion errors derived from the comparison between observed and predicted data obtained from the probabilistic perception and motion model.

In the remainder of the chapter, the section 3 presents the state of the art referred to exploration and motion planning problems. Section 4 presents our Voronoi Fast Marching (VFM) Motion Planner. The SLAM algorithm is described briefly in Section 5. Then, section 6 describes the specific Exploration method proposed. Next, section 7 demonstrates the performance of the exploration strategy as it explores different environments, according to the two possible ways of working for the exploration task. And, finally the conclusions are summarized in section 8.

3. Previous and related works

3.1 Representations of the world

Roughly speaking there are two main forms for representing the spatial relations in an environment: metric maps and topological maps. Metric maps are characterized by a representation where the position of the obstacles are indicated by coordinates in a global frame of reference. Some of them represent the environment with grids of points, defining regions that can be occupied or not by obstacles or goals (22) (1). Topological maps represent the environment with graphs that connect landmarks or places with special features (19) (12). In our approach we choose the grid-based map to represent the environment. The clear advantage is that with grids we already have a discrete environment representation and ready to be used in conjunction with the Extended Voronoi Transform function and Fast Marching Method for path planning. The pioneer method for environment representation in

a grid-based model was the certainty grid method developed at Carnegie Mellon University by Moravec (22). He represents the environment as a 3D or 2D array of cells. Each cell stores the probability of the related region being occupied. The uncertainty related to the position of objects is described in the grid as a spatial distribution of these probabilities within the occupancy grid. The larger the spatial uncertainty, the greater the number of cells occupied by the observed object. The update of these cells is performed during the navigation of the robot or through the exploration process by using an update rule function. Many researchers have proposed their own grid-based methods. The main difference among them is the function used to update the cell. Some of them are, for example: Fuzzy (24), Bayesian (9), Heuristic Probability (2), Gaussian (3), etc. In the Histogramic In-Motion Mapping (HIMM), each cell, has a certainty value, which is updated whenever it is being observed by the robots sensors. The update is performed by increasing the certainty value by 3 (in the case of detection of an object) or by decreasing it by 1 (when no object is detected), where the certainty value is an integer between 0 and 15.

3.2 Approaches to exploration

This section relates some interesting techniques used for exploratory mapping. They mix different localization methods, data structures, search strategies and map representations. Kuipers and Byun (13) proposed an approach to explore an environment and to represent it in a structure based on layers called Spatial Semantic Hierarchy (SSH) (12). The algorithm defines distinctive places and paths, which are linked to form an environmental topological description. After this, a geometrical description is extracted. The traditional approaches focus on geometric description before the topological one. The distinctive places are defined by their properties and the distinctive paths are defined by the twofold robot control strategy: follow-the-mid-line or follow-the-left-wall. The algorithm uses a lookup table to keep information about the place visited and the direction taken. This allows a search in the environment for unvisited places. Lee (16) developed an approach based on Kuipers work (13) on a real robot. This approach is successfully tested in indoor office-like spaces. This environment is relatively static during the mapping process. Lee's approach assumes that walls are parallel or perpendicular to each other. Furthermore, the system operates in a very simple environment comprised of cardboard barriers. Mataric (19) proposed a map learning method based on a subsumption architecture. Her approach models the world as a graph, where the nodes correspond to landmarks and the edges indicate topological adjacencies. The landmarks are detected from the robot movement. The basic exploration process is wall-following combined with obstacle avoidance. Oriolo et al. (25) developed a grid-based environment mapping process that uses fuzzy logic to update the grid cells. The mapping process runs on-line (24), and the local maps are built from the data obtained by the sensors and integrated into the environment map as the robot travels along the path defined by the A^* algorithm to the goal. The algorithm has two phases. The first one is the perception phase. The robot acquires data from the sensors and updates its environment map. The second phase is the planning phase. The planning module re-plans a new safe path to the goal from the new explored area. Thrun and Bucken (37) (38) developed an exploration system which integrates both evidence grids and topological maps. The integration of the two approaches has the advantage of disambiguating different positions through the grid-based representation and performing fast planning through the topological representation. The exploration process is performed through the identification and generation of the shortest paths between unoccupied regions and the robot. This approach works well in dynamic environments, although, the walls have to be flat and cannot form angles that differ more

than 15° from the perpendicular. Feder et al. (4) proposed a probabilistic approach to treat the concurrent mapping and localization using a sonar. This approach is an example of a feature-based approach. It uses the extended Kalman filter to estimate the localization of the robot. The essence of this approach is to take actions that maximize the total knowledge about the system in the presence of measurement and navigational uncertainties. This approach was tested successfully in wheeled land robot and autonomous underwater vehicles (AUVs). Yamauchi (39) (40) developed the Frontier-Based Exploration to build maps based on grids. This method uses a concept of frontier, which consists of boundaries that separate the explored free space from the unexplored space. When a frontier is explored, the algorithm detects the nearest unexplored frontier and attempts to navigate towards it by planning an obstacle free path. The planner uses a depth-first search on the grid to reach that frontier. This process continues until all the frontiers are explored. Zelek (42) proposed a hybrid method that combines a local planner based on a harmonic function calculation in a restricted window with a global planning module that performs a search in a graph representation of the environment created from a CAD map. The harmonic function module is employed to generate the best path given the local conditions of the environment. The goal is projected by the global planner in the local windows to direct the robot. Recently, Prestes el al. (28) have investigated the performance of an algorithm for exploration based on partial updates of a harmonic potential in an occupancy grid. They consider that while the robot moves, it carries along an activation window whose size is of the order of the sensors range.

Prestes and coworkers (29) propose an architecture for an autonomous mobile agent that explores while mapping a two-dimensional environment. The map is a discretized model for the localization of obstacles, on top of which a harmonic potential field is computed. The potential field serves as a fundamental link between the modelled (discrete) space and the real (continuous) space where the agent operates.

3.3 Approaches to motion planning

The motion planning method proposed in this chapter can be included in the sensor-based global planner paradigm. It is a potential method but it does not have the typical problems of these methods enumerated by Koren- Borenstein (11): 1) Trap situations due to local minima (cyclic behavior). 2) No passage between closely spaced obstacles. 3) Oscillations in the presence of obstacles. 4) Oscillations in narrow passages. The proposed method is conceptually close to the navigation functions of Rimon-Koditscheck (33), because the potential field has only one local minimum located at the single goal point. This potential and the paths are smooth (the same as the repulsive potential function) and there are no degenerate critical points in the field. These properties are similar to the characteristics of the electromagnetic waves propagation in Geometrical Optics (for monochromatic waves with the approximation that length wave is much smaller than obstacles and without considering reflections nor diffractions).

The Fast Marching Method has been used previously in Path Planning by Sethian (36) (35), but using only an attractive potential. This method has some problems. The most important one that typically arises in mobile robotics is that optimal motion plans may bring robots too close to obstacles (including people), which is not safe. This problem has been dealt with by Latombe (14), and the resulting navigation function is called *NF2*. The Voronoi Method also tries to follow a maximum clearance map (7). Melchior, Poty and Oustaloup (21; 27), present a fractional potential to diminish the obstacle danger level and improve the smoothness of the trajectories, Philippsen (26) introduces an interpolated Navigation Function, but with trajectories too close to obstacles and without smooth properties and Petres

(30), introduces efficient path-planning algorithms for Underwater Vehicles taking advantage of the underwaters currents.

LaValle (15), treats on the feedback motion planning concept. To move in the physical world the actions must be planned depending on the information gathered during execution.

Lindemann and Lavalle (17) (18) present a method in which the vector field globally solves the navigation problem and provides robustness to disturbances in sensing and control. In addition to being globally convergent, the vector field's integral curves (system trajectories) are guaranteed to avoid obstacles and are $\mathcal{C}^\infty$ smooth, except in the changes of cells. They construct a vector field with these properties by using existing geometric algorithms to partition the space into simple cells; they then define local vector fields for each cell, and smoothly interpolate between them to obtain a global vector field that can be used as a feedback control for the robot.

Yang and Lavalle (41) presented a randomized framework motion strategies, by defining a global navigation function over a collection of spherical balls in the configuration space. Their key idea is to fill the collision free subset of the configuration space with overlapping spherical balls, and define collision free potential functions on each ball. A similar idea has been developed for collision detection in (31) and (32).

The proposed method constructs a vectorial field as in the work by Lindemann, but the field is done in the global map instead of having local cells maps with the problem of having trajectories that are not $\mathcal{C}^\infty$ in the union between cells. The method has also similitudes with the Yang and Lavalle method. They proposed a series of balls with a Lyapunov potential associated to each of them. These potentials are connected in such a way that it is possible to find the trajectory using in each ball the gradient method. The method that we propose, has a unique global Lyapunov potential associated with the vectorial field that permits build the $\mathcal{C}^\infty$ trajectory in a single pass with the gradient method.

To achieve a smooth and safe path,it is necessary to have smooth attractive and repulsive potentials, connected in such a way that the resulting potential and the trajectories have no local minima and curvature continuity to facilitate path tracking design. The main improvement of the proposed method are these good properties of smoothness and safety of the trajectory. Moreover, the associated vector field allows the introduction of nonholonomic constraints.

It is important to note that in the proposed method the important ingredients are the attractive and the repulsive potentials, the way of connecting them describing the attractive potential using the wave equation (or in a simplified way, the eikonal equation). This equation can be solved in other ways: Mauch (20) uses a Marching with Correctness Criterion with a computational complexity that can reduced to $\mathcal{O}(N)$. Covello (5) presents a method that can be used on nodes that are located on highly distorted grids or on nodes that are randomly located.

4. The VFM Motion Planner

Which properties and characteristics are desirable for a Motion Planner of a mobile robot? The first one is that the planner always drives the robot in a smooth and safe way to the goal point. In Nature there are phenomena with the same way of working: electromagnetic waves. If in the goal point, there is an antenna that emits an electromagnetic wave, then the robot could drive itself to the destination following the waves to the source. The concept of the electromagnetic wave is especially interesting because the potential and its associated vector field have all the good properties desired for the trajectory, such as smoothness (it is $\mathcal{C}^\infty$) and the absence of local minima. This attractive potential still has some problems. The

most important one that typically arises in mobile robotics is that optimal motion plans may bring robots too close to obstacles, which is not safe. This problem has been dealt with by Latombe (14), and the resulting navigation function is called *NF2*. The Voronoi Method also tries to follow a maximum clearance map (6). To generate a safe path, it is necessary to add a component that repels the robot away from obstacles. In addition, this repulsive potential and its associated vector field should have good properties such as those of the electrical field. If we consider that the robot has an electrical charge of the same sign as the obstacles, then the robot would be pushed away from obstacles. The properties of this electric field are very good because it is smooth and there are no singular points in the interest space (C_{free}).

The third part of the problem consists in how to mix the two fields together. This union between an attractive and a repulsive field has been the biggest problem for the potential fields in path planning since the works of Khatib (10). In the VFM Method, this problem has been solved in the same way that Nature does so: the electromagnetic waves, such as light, have a propagation velocity that depends on the media. For example, flint glass has a refraction index of 1.6, while in the air it is approximately one. This refraction index of a medium is the quotient between the velocity of light in the vacuum and the velocity in the medium under consideration. That is the slowness index of the front wave propagation in a medium. A light ray follows a straight line if the medium has a constant refraction index (the medium is homogeneous) but refracts when there is a transition of medium (sudden change of refraction index value). In the case of a gradient change in refraction index in a given medium, the light ray follows a curved line. This phenomenon can be seen in nature in hot road mirages. In this phenomenon, the air closer to the road surface is warmer than the higher level layers. The warmer air has lower density and lower refraction index. For this reason, light rays coming from the sun are curved near the road surface and cause what is called the hot road mirage, as illustrated in fig. 1. This is the idea that inspires the way in which the attractive and the repulsive fields are merged in our work.

For this reason, in the *VFM* method, the repulsive potential is used as refraction index of the wave emitted from the goal point. In this way, a unique field is obtained and its associated vector field is attractive to the goal point and repulsive from the obstacles. This method inherits the properties of the electromagnetic field. Intuitively, the *VFM* Method gives the propagation of a front wave in an inhomogeneous media.

In Geometrical Optics, Fermat's *least time principle* for light propagation in a medium with space varying refractive index $\eta(\mathbf{x})$ is equivalent to the eikonal equation and can be written as $||\nabla \Phi(\mathbf{x})|| = \eta(\mathbf{x})$ where the eikonal $\Phi(\mathbf{x})$ is a scalar function whose isolevel contours are normal to the light rays. This equation is also known as the Fundamental Equation of the Geometrical Optics.

The eikonal (from the Greek "eikon", which means "image") is the phase function in a situation for which the phase and amplitude are slowly varying functions of position. Constant values of the eikonal represent surfaces of constant phase, or wavefronts. The normals to these surfaces are rays (the paths of energy flux). Thus the eikonal equation provides a method for "ray tracing" in a medium of slowly varying refractive index (or the equivalent for other kinds of waves).

The theory and the numerical techniques known as Fast Marching Methods are derived from an exposition to describe the movement of interfaces, based on a resolution of the equations on partial differential equations as a boundary condition problem. The Fast Marching Method has been used previously in Path Planning by Sethian(35; 36), but using only an attractive potential.
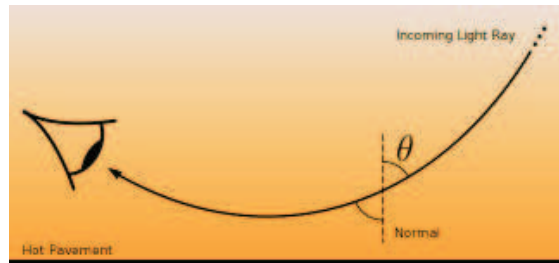
Fig. 1. Light rays bending due to changing refraction index in air with higher temperature near road surface.

The use of the Fast Marching method over a slowness (refraction or inverse of velocity) potential improves the quality of the calculated trajectory considerably. On one hand, the trajectories tend to go close to the Voronoi skeleton because of the optimal conditions of this area for robot motion (6).

An attractive potential used to plan a trajectory bring robots too close to obstacles as shown in fig. 2. For this reason, in the proposed method, the repulsive potential (fig. 3) is used as refraction index of the wave emitted from the goal point. This way a unique field is obtained and its associated vector field is attracted to the goal point and repulsed from the obstacles, as shown in fig. 4. This method inherits the properties of the electromagnetic field, i.e. it is $\mathcal{C}^{\infty}$, if the refraction index is $\mathcal{C}^{\infty}$. Intuitively, the VFM Method gives the propagation of a front wave in an inhomogeneous media.

The solution of the eikonal equation used in the VFM method is given by the solution of the wave equation:

$$\phi = \phi_0 e^{ik_0(\eta x - c_0 t)}$$

As this solution is an exponential, if the potential $\eta(x)$ is $\mathcal{C}^{\infty}$ then the potential ϕ is also $\mathcal{C}^{\infty}$ and therefore the trajectories calculated by the gradient method over this potential would be of the same class.

This smoothness property can be observed in fig. 5, where the trajectory is clearly good, safe and smooth. One advantage of the method is that it not only generates the optimum path, but also the velocity of the robot at each point of the path. The velocity reaches its highest values in the light areas and minimum values in the greyer zones. The VFM Method simultaneously provides the path and maximum allowable velocity for a mobile robot between the current location and the goal.

4.1 Properties

The proposed VFM algorithm has the following key properties:

- *Fast response*. The planner needs to be fast enough to be used reactively and plan new trajectories. To obtain this fast response, a fast planning algorithm and fast and simple treatment of the sensor information is necessary. This requires a low complexity order algorithm for a real time response to unexpected situations. The proposed algorithm has a fast response time to allow its implementation in real time, even in environments with moving obstacles using a normal PC computer.

  The proposed method is highly efficient from a computational point of view because the method operates directly over a 2D image map (without extracting adjacency maps), and due to the fact that Fast Marching complexity is $O(m \times n)$ and the Extended Voronoi Transform is also of complexity $O(m \times n)$, where $m \times n$ is the number of cells in the environment map. In table 1, orientative results of the cost average in time appear
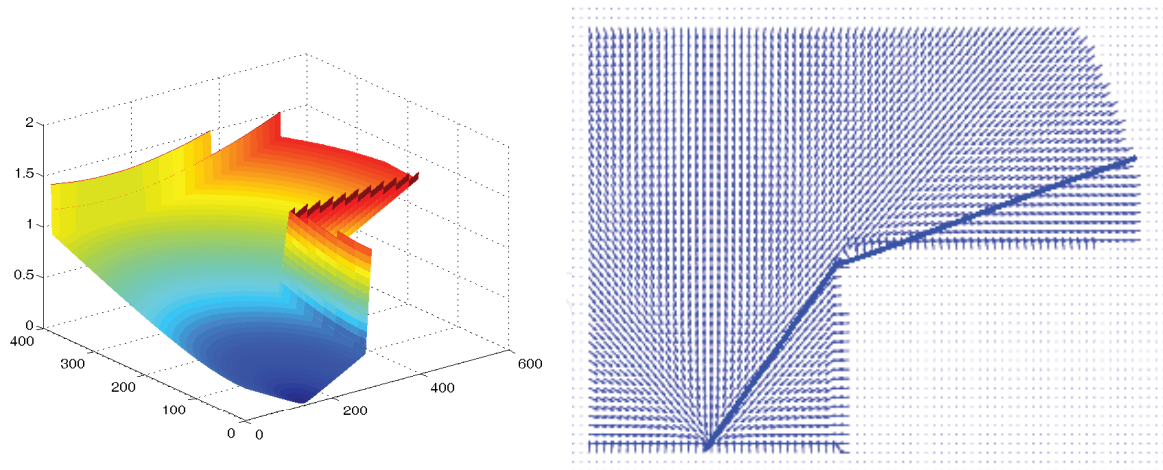
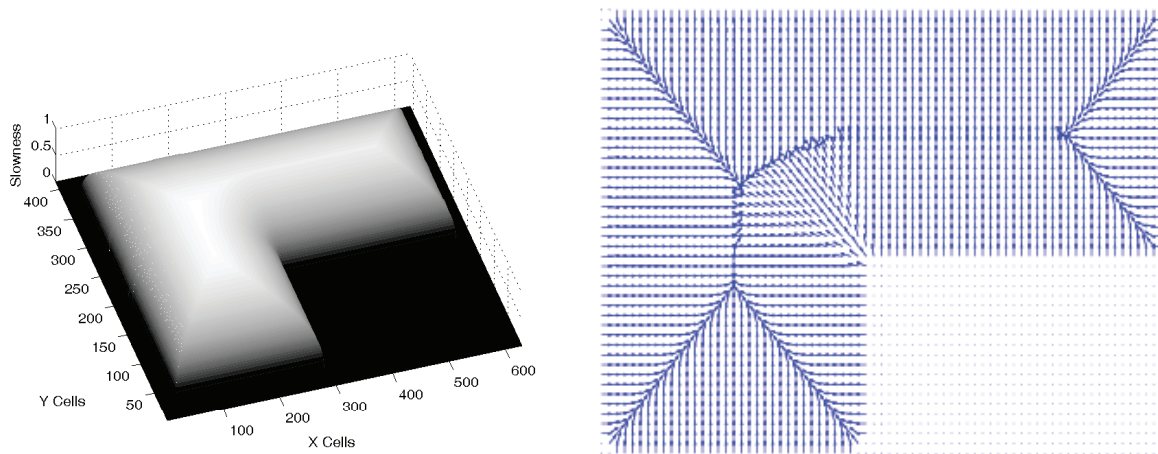Fig. 2. Attractive potential, its associated vector field and a typical trajectory.

Fig. 3. The Fast Marching Method applied to a L-shaped environment gives: the slowness (velocity inverse) or repulsive potential and its associated vector field.

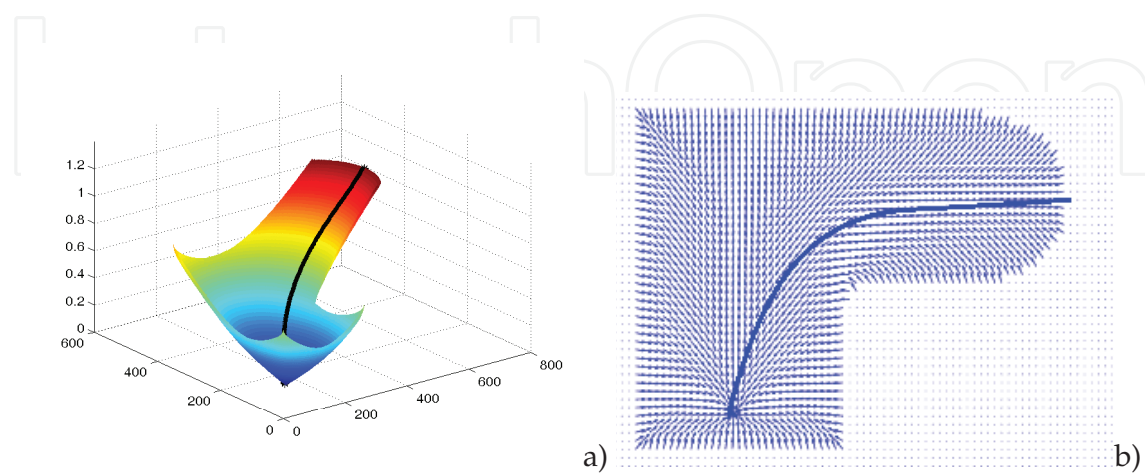a)   b)

Fig. 4. a) Union of the two potentials: the second one having the first one as refractive index. b) Associated vector field and typical trajectories obtained with this method.
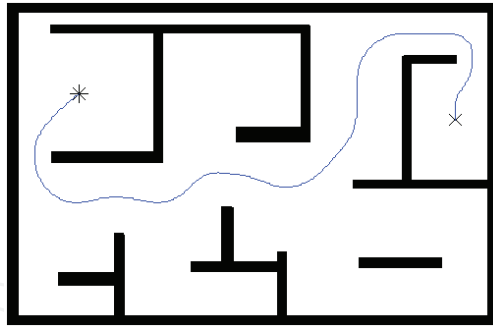
Fig. 5. Trajectories calculated applying the proposed algorithm with Fast Marching over the Logarithm Extended Voronoi Transform.

(measured in seconds), and each step of the algorithm for different trajectory lengths to calculate (the computational cost depends on the number of points of the image).

Alg. Step/Trajectory length	Long	Medium	Short
Obst. Enlarging	0.008	0.008	0.008
Ext. Voronoi Transf.	0.039	0.039	0.039
FM Exploration	0.172	0.078	0.031
Path Extraction	0.125	0.065	0.035
Total time	0.344	0.190	0.113

Table 1. Computational cost (seconds) for the room environment (966x120 pixels)

- *Smooth trajectories.* The planner must be able to provide a smooth motion plan which can be executed by the robot motion controller. In other words, the plan does not need to be refined, avoiding the need for a local refinement of the trajectory. The solution of the eikonal equation used in the proposed method is given by the solution of the wave equation:

$$\phi = \phi_0 e^{ik_0(\eta x - c_0 t)}$$

As this solution is an exponential, if the potential $\eta(x)$ is $\mathcal{C}^\infty$ then the potential ϕ is also $\mathcal{C}^\infty$ and therefore the trajectories calculated by the gradient method over this potential would be of the same class.

This smoothness property can be observed in fig. 5, where the trajectory is clearly good, safe and smooth. One advantage of the method is that it not only generates the optimum path, but also the velocity of the robot at each point of the path. The velocity reaches its highest values in the light areas and minimum values in the greyer zones. The VFM Method simultaneously provides the path and maximum allowable velocity for a mobile robot between the current location and the goal.

- *Reliable trajectories.* The proposed planner provides a safe (reasonably far from detected obstacles) and reliable trajectory (free from local traps). This is due to the refraction index, which causes higher velocities far from obstacles.

- *Completeness.* As the method consists of the propagation of a wave, if there is a path from the the initial position to the objective, the method is capable of finding it.

5. Differential evolution approach to the SLAM

Localization and map building are key components in robot navigation and are required to successfully execute the path generated by the VFM planner in the exploration method proposed in this work. Both problems are closely linked, and learning maps are required to solve both problems simultaneously; this is the SLAM problem. Uncertainty in sensor measures and uncertainty in robot pose estimates make the use of a SLAM method necessary to create a consistent map of the explored environment.

The SLAM algorithm used in this work is described in (23). It is based on the stochastic search of solutions in the state space to the localization problem by means of a differential evolution algorithm. A non linear evolutive filter, called Evolutive Localization Filter (ELF), searches stochastically along the state space for the best robot pose estimate. The proposed SLAM algorithm operates in two steps: in the first step the ELF filter is used at a local level to re-localize the robot based on the robot odometry, the laser scan at a given position and a local map where only a low number of the last scans have been integrated. In a second step, the aligned laser measures, together with the corrected robot poses, are used to detect when the robot is revisiting a previously crossed area. Once a cycle is detected, the Evolutive Localization Filter is used again to reestimate the robot position and orientation in order to integrate the sensor measures in the global map of the environment.

This approach uses a differential evolution method to perturb the possible pose estimates contained in a given set until the optimum is obtained. By properly choosing the cost function, a maximum a posteriori estimate is obtained. This method is applied at a local level to re-localize the robot and at a global level to solve the data association problem. The method proposed integrates sensor information in the map only when cycles are detected and the residual errors are eliminated, avoiding a high number of modifications in the map or the existence of multiple maps, thus decreasing the computational cost compared to other solutions.

6. Implementation of the explorer

In order to solve the problem of the exploration of an unknown environment, our algorithm can work in two different ways. First, the exploration process can be directed giving to the algorithm one or several successive goal points in the environment which the robot must drive to during the exploration process. Second, that is the second form to work of our algorithm, the exploration can be carried out without having any previously fixed objective point. In such case, the algorithm must automatically determine towards where the robot must drive in order to complete the exploration process.

6.1 Case I

In the first one, the initial information is the localization of the final goal. In this way, the robot has a general direction of movement towards the goal. In each movement of the robot, information about the environment is used to build a binary image distinguishing occupied space represented by value 0 (obstacles and walls) from free space, with value 1. The Extended Voronoi Transform of the known map at that moment gives a grey scale that is darker near the obstacles and walls and lighter far from them. The Voronoi Fast Marching Method gives the trajectory from the pose of the robot to the goal point using the known information. In this first way of working, the SLAM algorithm described in (23) is used to avoid localization errors being translated into the map built during the exploration process.
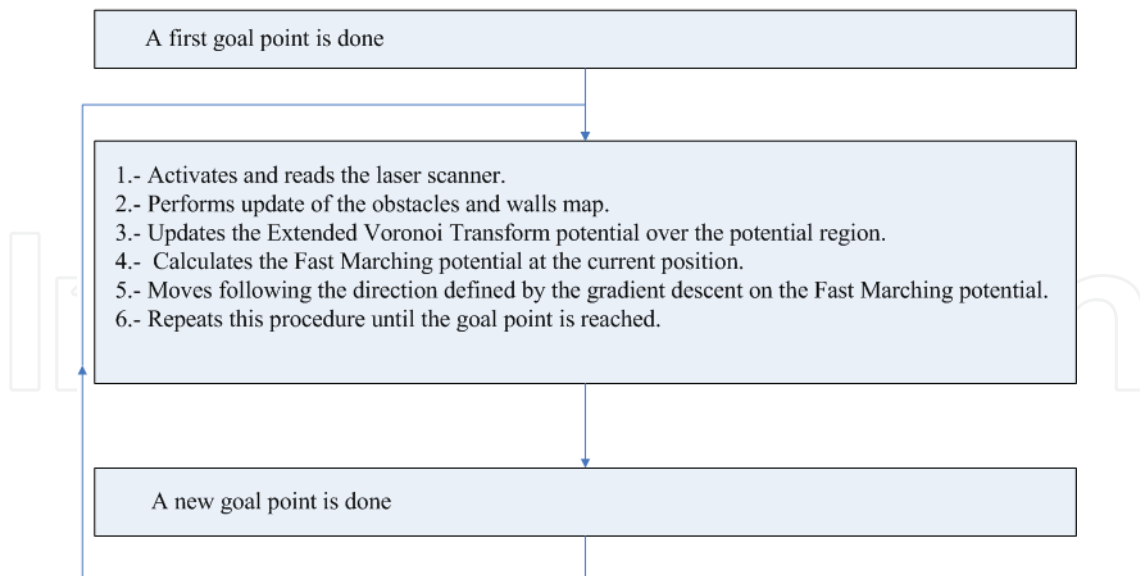
Fig. 6. Flowchart of case 1.

In this first case, the robot has a final goal: the exploration process the robot performs in the algorithm described in the flowchart of fig. 6.

6.2 Case II

In the second way of working of the algorithm, the goal location is unknown and robot behavior is truly exploratory. We propose an approach based on the incremental calculation of a map for path planning.

We define a neighborhood window, which travels with the robot, roughly the size of its laser sensor range. This window indicates the new grid cells that are recruited for update, i.e., if a cell was in the neighborhood window at a given time, it becomes part of the explored space by participating in the EVT and Fast Marching Method calculation for all times. The set of activated cells that compose the explored space is called the neighborhood region. Cells that were never inside the neighborhood window indicate unexplored regions. Their potential values are set to zero and define the knowledge frontier of the state space, the real space in our case. The detection of the nearest unexplored frontier comes naturally from the Extended Voronoi Transform calculation. It can also be understood from the physical analogy with electrical potentials that obstacles repel while frontiers attract.

Consider that the robot starts from a given position in an initially unknown environment. In this second method, there is no direction of the place where the robot must go.

A initial matrix with zeros in the obstacles and value 1 in the free zones is considered. This first matrix is built using the information provided by sensors and represents a binary image of the environment detected by sensors. The first step consists of calculating the EVT of the obstacles in this image. A value that represent the distance to the nearest obstacle is associated to each cell of the matrix. A matrix W of grays with values between 0 (obstacles) and 1 is obtained. This W matrix gives us the EVT of the obstacles found up until that moment.

A second matrix is built darkening the zones that the robot has already visited. Then, the EVT of this image is calculated and the result is the VT matrix.

Finally, matrix WV is the sum of the matrices VT and W, with weights 0.5 and 1 respectively.
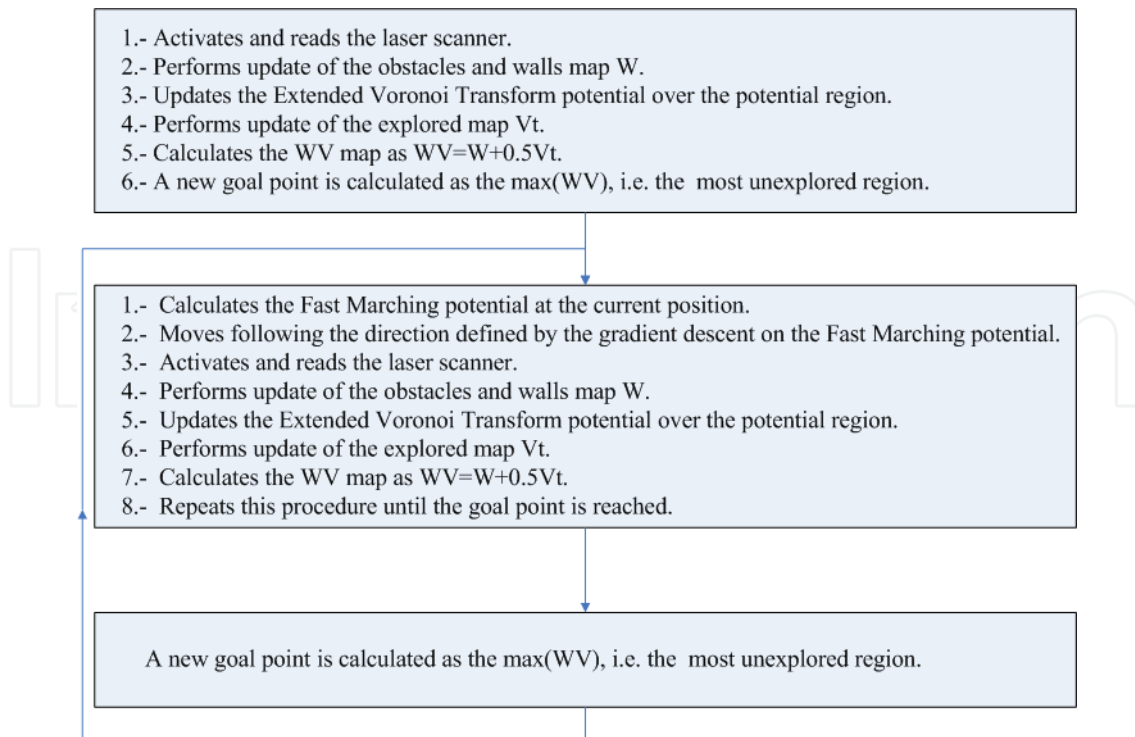
$$WV = 0.5 * VT + W$$

1.- Activates and reads the laser scanner.
2.- Performs update of the obstacles and walls map W.
3.- Updates the Extended Voronoi Transform potential over the potential region.
4.- Performs update of the explored map Vt.
5.- Calculates the WV map as WV=W+0.5Vt.
6.- A new goal point is calculated as the max(WV), i.e. the most unexplored region.

1.- Calculates the Fast Marching potential at the current position.
2.- Moves following the direction defined by the gradient descent on the Fast Marching potential.
3.- Activates and reads the laser scanner.
4.- Performs update of the obstacles and walls map W.
5.- Updates the Extended Voronoi Transform potential over the potential region.
6.- Performs update of the explored map Vt.
7.- Calculates the WV map as WV=W+0.5Vt.
8.- Repeats this procedure until the goal point is reached.

A new goal point is calculated as the max(WV), i.e. the most unexplored region.

Fig. 7. Flowchart of algorithm 2.

In this way, it is possible to darken the zones already visited by the robot and impel it to go to the unexplored zones. The whitest point of matrix WV is calculated as $max(WV)$, that is, the most unexplored region that is in a free space. This is the point chosen as the new goal point. Applying the Fast Marching method on WV, the trajectory towards that goal is calculated. The robot moves following this trajectory. In the following steps, the trajectory to follow is computed, calculating first W and VT at every moment, and therefore WV, but without changing the objective point. Once the robot has been arrived at the objective, (that is to say, that path calculated is very small), a new objective is selected as $max(WV)$.

Therefore, the robot moves maximizing knowledge gain. In this case or in any other situation where there is no gradient to guide the robot, it simply follows the forward direction. The exploration process the robot performs in the second method described is summarized in the flowchart of fig. 7.

The algorithms laid out in fig. 6 (flowchart of case 1) can be inefficient in very large environments. To increase speed it is possible to pick a goal point, put a neighborhood window the size of the sensor range, run into the goal point, then look at the maximal initial boundary, and recast and terminate when one reaches the boundary of the computed region. Similar improvements can be made to algorithm 2.

7. Results

The proposed method, has been tested using the manipulator robot Manfred, see website: roboticslab.uc3m.es. It has a coordinated control of all degree of freedom in the system (the mobile base has 2 DOF and the manipulator has 6 DOF) to achieve smooth movement. This mobile manipulator use a sensorial system based on vision and 3-D laser telemetry to perceive and model 3-D environments. The mobile manipulator will include all the capabilities needed to navigate, localize and avoid obstacles safely through out the environment.

To illustrate the performance of the exploration method based on the VFM motion planner proposed, a test in a typical office indoor environment as shown in fig. 8, has been carried out. The dimensions of the environment are 116x14 meters (the cell resolution is 12 cm), that is the image has 966x120 pixels.

The VFM motion planning method provides smooth trajectories that can be used at low control levels without any additional smooth interpolation process. Some of the steps of the planning process between two defined points are shown in fig. 9. In this figure, the trajectory computed by the VFM planner is represented (the red line represents the crossed path, and the blue one represents the calculated trajectory from the present position to the destination point). This figure shows also the map built in each step using the SLAM algorithm.
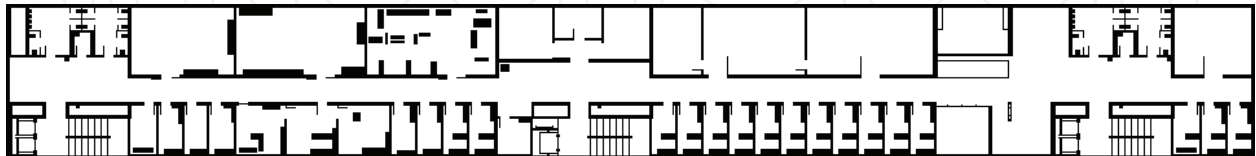
Fig. 8. Environment map of the Robotics Lab.

The results of two different tests are presented to illustrate both cases of exploration that this work contemplates in the same environment. In this case the size of image is 628x412 pixels.

Figs. 10 and 11 represent the first case for implementing the exploration method (directed exploration) on the Environment map shown in fig. 5. A final goal is provided for the robot, which is located with respect to a global reference system; the starting point of the robot movement is also known with respect to that reference system. The algorithm allows calculating the trajectory towards that final goal with the updated information of the surroundings that the sensors obtain in each step of the movement. When the robot reaches the defined goal, a new destination in an unexplored zone is defined, as can be seen in the third image of the figure.

The results of one of the tests done for the second case of exploration described are shown in figs. 12 and 13. Any final goal is defined. The algorithm leads the robot towards the zones that are free of obstacles and unexplored simultaneously (undirected exploration).
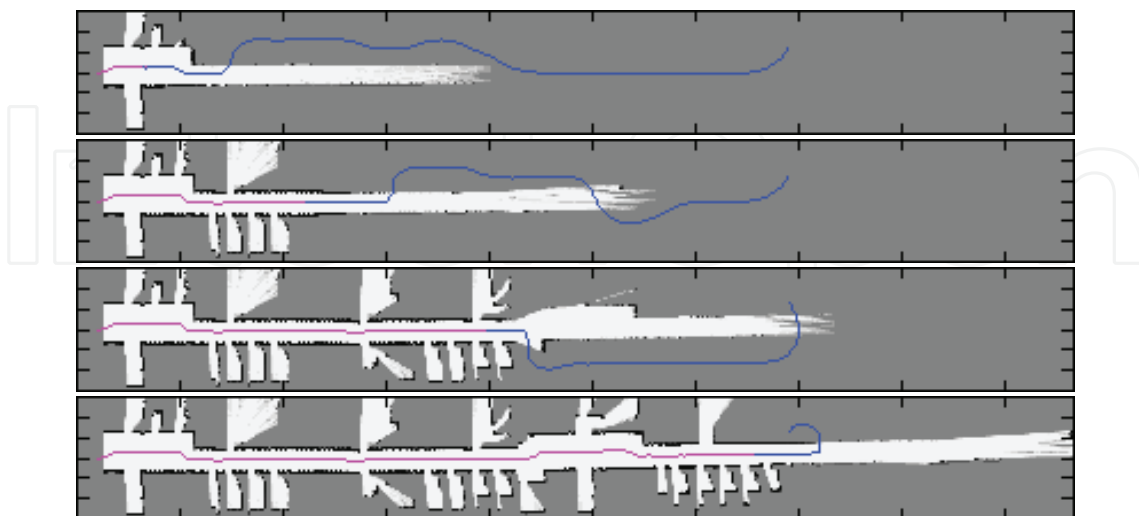

Fig. 9. Consecutive steps of the process using the first case of the exploration algorithm. The red line represents the crossed path and the blue one represents the calculated trajectory from the present position to the destination point.
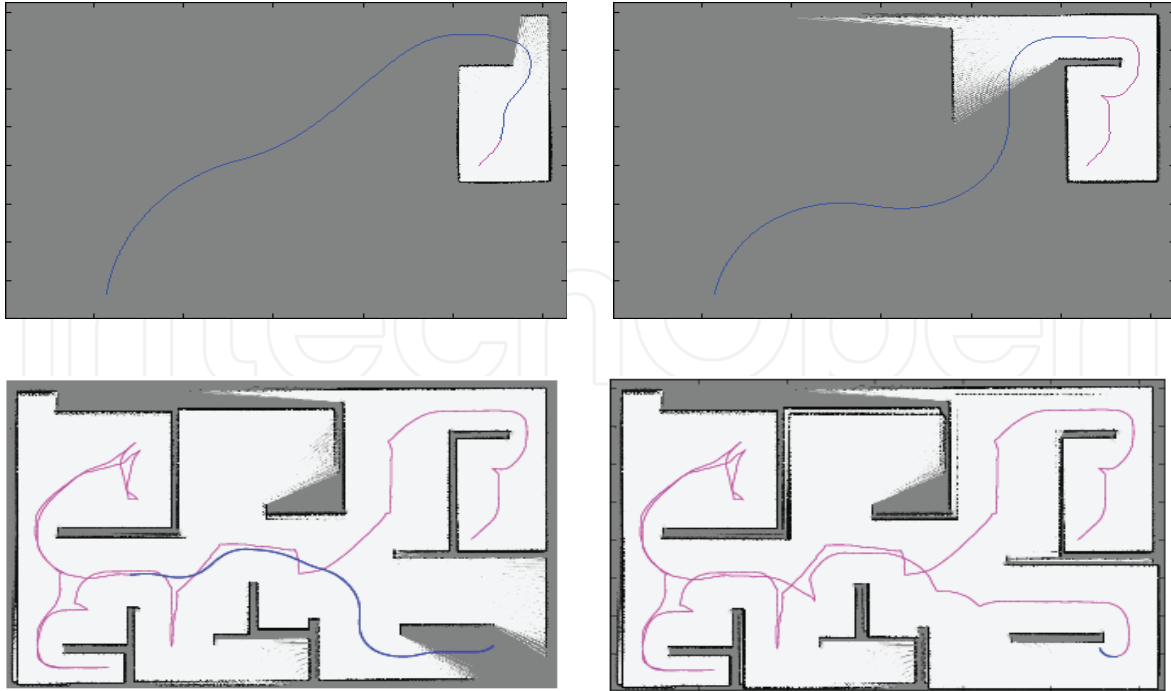
Fig. 10. Simulation results with method 1, with final objective. Trajectory calculated. The red line represents the crossed path and the blue one represents the calculated trajectory from the present position to the destination point.
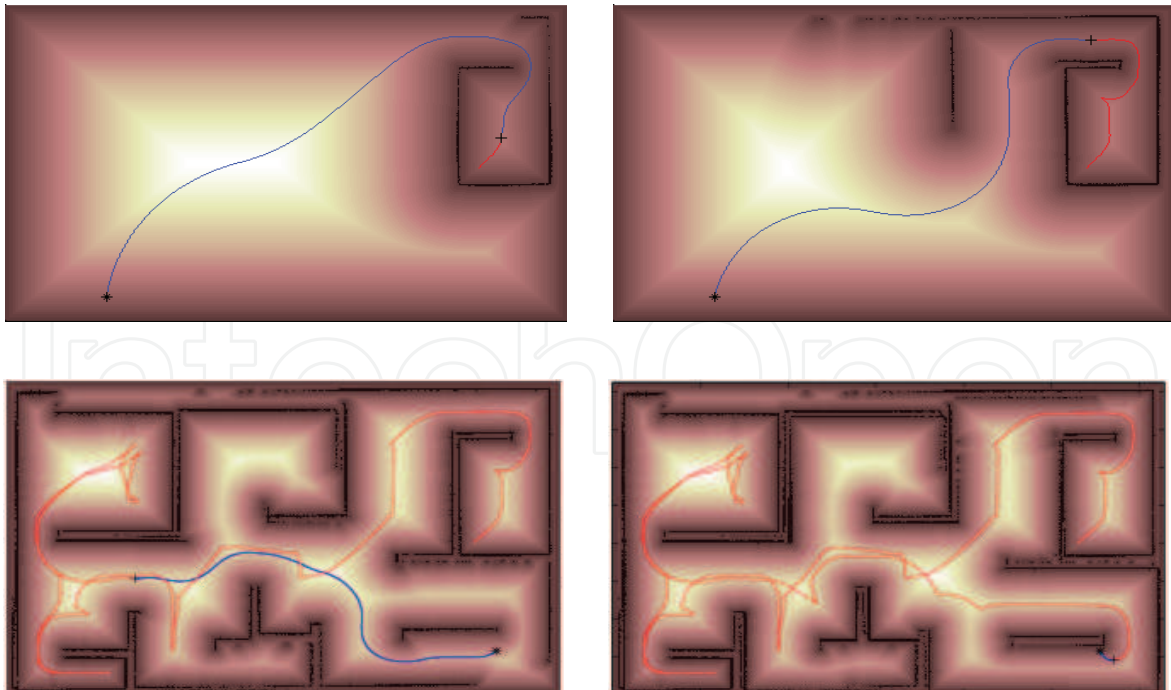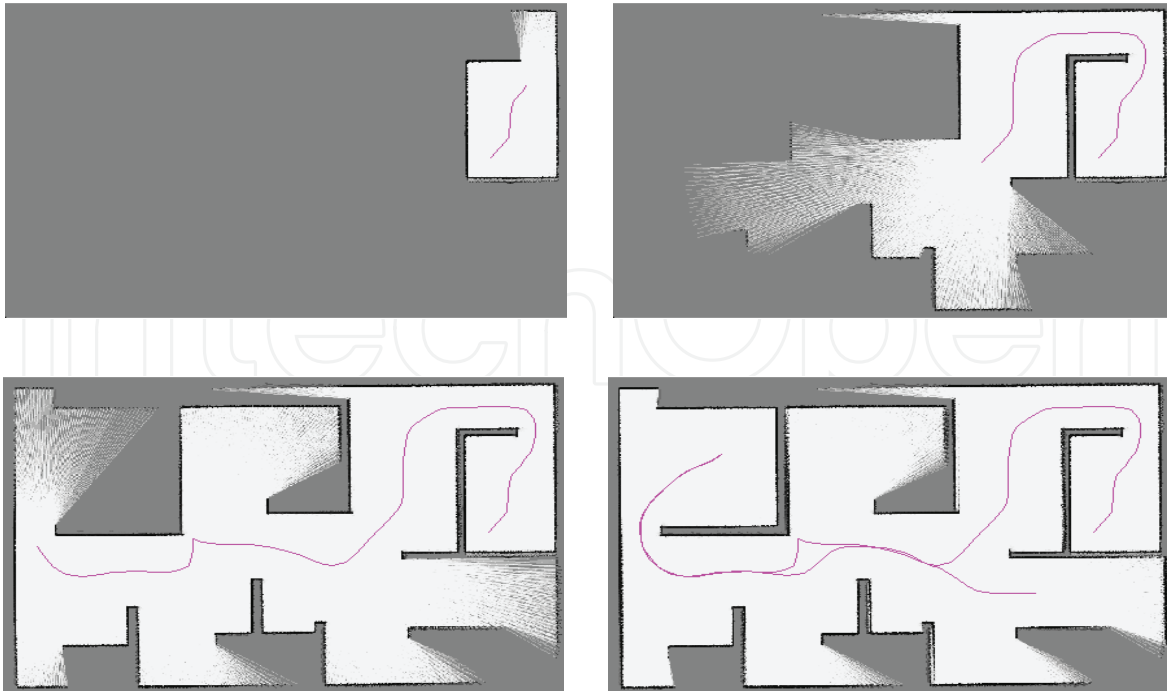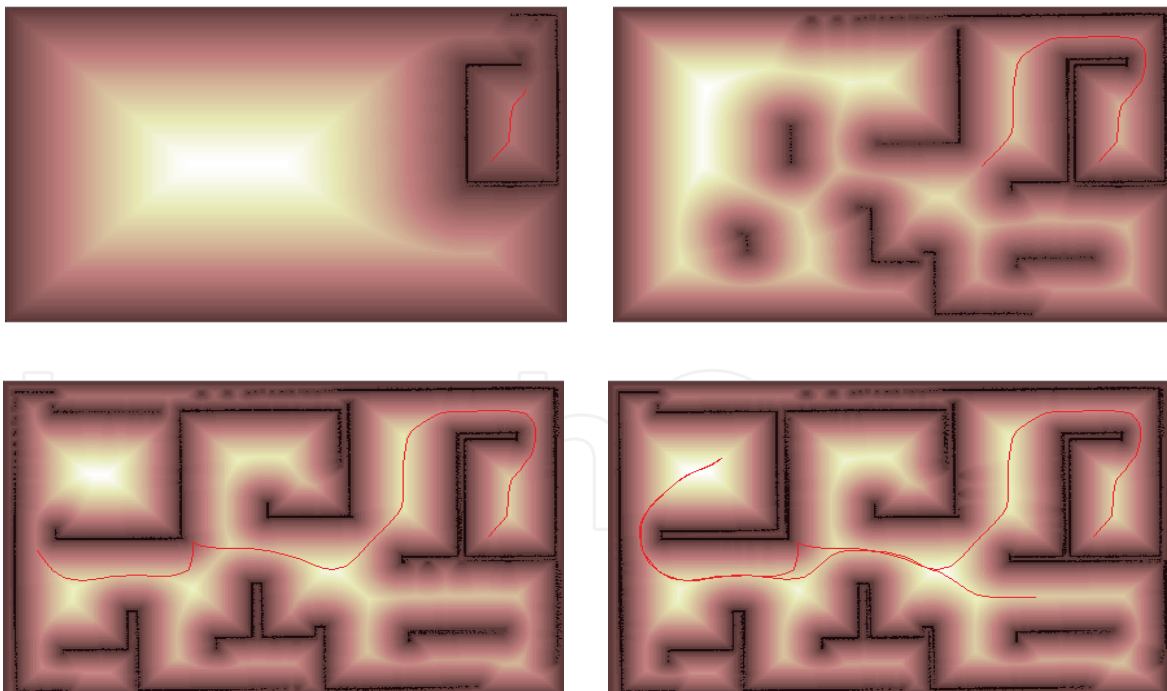

Fig. 11. Simulation results with method 1. Map built. The red line represents the crossed path and the blue one represents the calculated trajectory from the present position to the destination point.

Fig. 12. Simulation results with method 2, without final objective. Trajectory calculated.

Fig. 13. Simulation results with method 2. Map built.

8. Conclusion

This work presents a new autonomous exploration strategy. The essential mechanisms used included the VFM method (8) applied to plan the trajectory towards the goal, a new

exploratory strategy that drives the robot to the most unexplored region and the SLAM algorithm (23) to build a consistent map of the environment. The proposed autonomous exploration algorithm is a combination of the three tools which is able to completely construct consistent maps of unknown indoor environments in an autonomous way.

The results obtained show that the Logarithm of Extended Voronoi Transform can be used to improve the results obtained with the Fast Marching method to implement a sensor based motion planner, providing smooth and safe trajectories.

The algorithm complexity is $O(m \times n)$, where $m \times n$ is the number of cells in the environment map, which lets us use the algorithm on line. Furthermore, the algorithm can be used directly with raw sensor data to implement a sensor based local path planning exploratory module.

9. References

[1] J. Borenstein and Y. Koren, "Histogramic in-motion mapping for mobile robot obstacle avoidance.", *IEEE Journal of Robotics*, vol. 7, no. 4, pp. 535–539, 1991.

[2] A. Elfes, "Sonar-based real world mapping and navigation.", *IEEE Journal of Robotics and Automation*, vol. 3, no. 3, pp. 249–265, 1987.

[3] A. Elfes, "Using occupancy grids for mobile robot perception and navigation.", *Computer Magazine*, pp. 46–57, 1989.

[4] H. Feder, J. Leonard and C. Smith, "Adaptive mobile robot navigation and mapping.", *International Journal of Robotics Research*, vol. 7, no. 18, pp. 650–668, 1999.

[5] P. Covello and G. Rodrigue, "A generalized front marching algorithm for the solution of the eikonal equation.", *J. Comput. Appl. Math.*, vol. 156, no. 2, pp. 371–388, 2003.

[6] S. Garrido, L.Moreno, and D.Blanco, "Voronoi diagram and fast marching applied to path planning." in *2006 IEEE International conference on Robotics and Automation. ICRA 2006.*, pp. 3049–3054.

[7] S. Garrido, L. Moreno, M. Abderrahim, and F. Martin, "Path planning for mobile robot navigation using voronoi diagram and fast marching." in *Proc of IROS'06. Beijing. China.*, 2006, pp. 2376–2381.

[8] S. Garrido, L. Moreno, and D. Blanco, *Sensor-based global planning for mobile robot navigation.*, Robotica 25 (2007), 189–199.

[9] A. Howard and L. Kitchen, "Generating sonar maps in highly specular environments." in *Proceedings of the Fourth International Conference on Control, Automation, Robotics and Vision*, 1996.

[10] M. Khatib and R. Chatila, "An extended potential field approach for mobile robot sensor-based motions." in *Proceedings of the IEEE Int. Conf. on Intelligent Autonomus Systems*, 1995.

[11] Y. Koren and J. Borenstein, "Potential field methods and their inherent limitations for mobile robot navigation" in *Proceedings of the IEEE Int. Conf. on Robotics and Automation*, pp. 1398–1404, 2004.

[12] B. Kuipers and T. Levitt, "Navigation and mapping in large-scale space.", *AI Magazine*, vol. 9, pp. 25–43, 1988.

[13] B. Kuipers and Y. Byun, "A robot exploration and mapping strategy based on a semantic hierarchy of spatial representations.", *Robotics and Autonomous Systems*, vol. 8, pp. 47–63, 1991.

[14] J.-C. Latombe, *Robot motion planning*. Dordrecht, Netherlands: Kluwer Academic Publishers, 1991.

[15] S. M. LaValle, 2006. *Planning Algorithms*, Cambridge University Press, Cambridge, U.K.

[16] W. Lee, "Spatial semantic hierarchy for a physical robot.", Ph.D. dissertation, Department of Computer Sciences, The University of Texas, 1996.

[17] S. R. Lindemann and S. M. LaValle," Simple and efficient algorithms for computing smooth, collision-free feedback laws", *International Journal of Robotics Research*, 2007.

[18] S. R. Lindemann and S. M. LaValle, "Smooth feedback for car-like vehicles in polygonal environments." in *Proceedings IEEE International Conference on Robotics and Automation*, 2007.

[19] M. Mataric, "Integration of representation into goal-driven behavior-based robots.", *IEEE Transaction on Robotics and Automation*, vol. 3, pp. 304–312, 1992.

[20] S. Mauch, "Efficient algorithms for solving static hamilton-jacobi equations.", Ph.D. dissertation, California Inst. of Technology, 2003.

[21] P. Melchior, B. Orsoni, O. Laviale, A. Poty, and A. Oustaloup, "Consideration of obstacle danger level in path planning using A* and Fast Marching optimisation: comparative study.", *Journal of Signal Processing*, vol. 83, no. 11, pp. 2387–2396, 2003.

[22] H. Moravec and A. Elfes, "High resolution maps from wide angle sonar." in *Proceedings of the IEEE International Conference on Robotics and Automation*, March, 1985, pp. 116–121.

[23] L.Moreno, S.Garrido and F.Martin. "E-SLAM solution to the grid-based Localization and Mapping problem", in *2007 IEEE International Symposium on Intelligent Signal Processing (WISP'2007)*. Alcala Henares. Spain. pp.897-903, 2007.

[24] G. Oriolo, M. Vendittelli and G. Ulivi,"On-line map-building and navigation for autonomous mobile robots." in *Proceedings of the IEEE International Conference on Robotics and Automation*, 1995, pp. 2900–2906.

[25] G. Oriolo, G. Ulivi and M. Vendittelli, "Fuzzy maps: A new tool for mobile robot perception and planning.", *Journal of Robotic Systems*, vol. 3, no. 14, pp. 179–197, 1997.

[26] R. Philippsen and R. Siegwart, "An interpolated dynamic navigation function." in *2005 IEEE Int. Conf. on Robotics and Automation*, 2005.

[27] A. Poty, P. Melchior and A. Oustaloup, "Dynamic path planning by fractional potential." in *Second IEEE International Conference on Computational Cybernetics*, 2004.

[28] E. P. Silva., P. Engel, M. Trevisan, and M. Idiart, "Exploration method using harmonic functions.", *Journal of Robotics and Autonomous Systems*, vol. 40, no. 1, pp. 25–42, 2002.

[29] E. P. Silva, P. Engel, M. Trevisan, and M. Idiart, "Autonomous learning architecture for environmental mapping.", *Journal of Intelligent and Robotic Systems*, vol. 39, pp. 243–263, 2004.

[30] C. Petres, Y. Pailhas, P. Patron, Y. Petillot, J. Evans and D. Lane, "Path planning for autonomous underwater vehicles.", *IEEE Trans. on Robotics*, vol. 23, no. 2, pp. 331–341, 2007.

[31] S. Quinlan and O. Khatib. "Elastic bands: Connecting path planning and control. " in *IEEE Int. Conf Robot and Autom.*, pp 802-807, 1993.

[32] S. Quinlan and O. Khatib, "Efficient distance computation between nonconvex objects." in *IEEE Int. Conf Robot and Autom.*, pp. 3324-3329, 1994.

[33] E. Rimon and D.E. Koditschek, "Exact robot navigation using artificial potential functions.", *IEEE Transactions on Robotics and Automation*, vol. 8, no. 5, pp.501–518, 1992.

[34] J. A. Sethian, "A fast marching level set method for monotonically advancing fronts.", *Proc. Nat. Acad Sci. U.S.A.*, vol. 93, no. 4, pp. 1591–1595, 1996.

[35] J. A. Sethian, "Theory, algorithms, and aplications of level set methods for propagating interfaces.", *Acta numerica*, pp. 309–395, Cambridge Univ. Press, 1996.

[36] J. Sethian, *Level set methods*. Cambridge University Press, 1996.

[37] S. Thrun and A. Bücken, "Integrating grid-based and topological maps for mobile robot." in *Proceedings of the 13th National Conference on Artificial Intelligence (AAAI-96)*, 1996, pp. 944–950.

[38] S. Thrun and A. Bücken, "Learning maps or indoor mobile robot navigation." CMU-CS-96-121, Carnegie Mellon University, Pittsburgh, PA, Tech. Rep., 1996.

[39] B. Yamauchi, "A frontier-based exploration for autonomous exploration." in *IEEE International Symposium on Computational Intelligence in Robotics and Automation, Monterey, CA*, 1997, pp. 146–151.

[40] B. Yamauchi, A. Schultz, W. Adams and K. Graves, "Integrating map learning, localization and planning in a mobile robot." in *Proceedings of the IEEE International Symposium on Computational Intelligence in Robotics and Automation, Gaithersburg, MD*, 1998, pp. 331–336.

[41] L. Yang and S. M. LaValle, "A framework for planning feedback motion strategies based on a random neighborhood graph" in Proceedings IEEE International Conference on Robotics and Automation, pages 544–549, 2000.

[42] J. Zelek, "A framework for mobile robot concurrent path planning and execution in incomplete and uncertain environments." in *Proceedings of the AIPS-98 Workshop on Integrating Planning, Scheduling and Execution in Dynamic and Uncertain Environments, Pittsburgh, PA*, 1988.

Advances in Robot Navigation

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Robot navigation includes different interrelated activities such as perception - obtaining and interpreting sensory information; exploration - the strategy that guides the robot to select the next direction to go; mapping - the construction of a spatial representation by using the sensory information perceived; localization - the strategy to estimate the robot position within the spatial map; path planning - the strategy to find a path towards a goal location being optimal or not; and path execution, where motor actions are determined and adapted to environmental changes. This book integrates results from the research work of authors all over the world, addressing the abovementioned activities and analyzing the critical implications of dealing with dynamic environments. Different solutions providing adaptive navigation are taken from nature inspiration, and diverse applications are described in the context of an important field of study: social robotics.

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