A REACTIVE MOTION PLANNER ARCHITECTURE FOR GENERIC MOBILE ROBOTS BASED ON MULTILAYERED CELLULAR AUTOMATA

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Abstract: The aim of this paper is to describe the architecture of a Path Planner for Mobile Robots based on the paradigm of Cellular Automata. The environment representation is distributed, as the robot shape; both and the robot kinematics are parameters for the planner. Hence, it results to be very flexible, handling robots with quite different kinematics (omnidirectional, car-like, asymmetrical, etc.), with generic shapes (even with concavities and holes) and with generic cinematic center positions. Because of these characteristics, it is applicable for the assembly planning in the manufacturing industry, as in the Piano Mover's problems, or in vehicles trajectories generation. It can be applied to flat (Euclidean) Work Space and to natural variable terrains. Considering robots moving with smoothed trajectories, the underlying algorithm is based on a Potential Fields Method, using an anisotropic propagation of potentials on a non-Euclidean manifold. The collision-free trajectories are found following the minimum valley of the potential hypersurface embedded in a 4D space. Thanks to the Multilayered Cellular Automata architecture, it turns out to be very fast, complete and optimal, allowing to react to the wold dynamics (reactive planning), generating new optimal solutions every time the obstacles positions changes.

1 INTRODUCTION

The work presented in this paper concerns Mobile Robots Path-Planning exploiting Multilayered Cellular Automata (MCA). The Path-planning problem is very important to drive mobile robots in environments avoiding collision with obstacles. In our work, we consider robots with different types of kinematics: for example, robots moving thanks to differential drives (moving forward and backward, and rotating in the place), robots moving as cars (car-like kinematics or non-holonomic), robots also translating in any directions and rotating (sphere-like kinematics or omnidirectional), etc. To realize a path-planner able to face with different types of motion is quite problematic. More over, we added other constrains to this problem. When a robot moves between obstacles, its real shape and size must be considered to avoid collisions. It is more difficult to handle robot with asymmetrical shapes, even with concavity, holes, etc. Most of the works in literature treat this problem substituting the real shape with an equivalent cylinder with the same radius, enlarging the space occupancy. This solution is feasible when the robot moves in wide spaces, but it is not when considering narrow spaces, cluttered environments, etc. A further complication derives from the geometry of the world in which the robot is situated. In a flat world, as office-like structured environments, the geometry is quite simple: it is a planar surface (Euclidean 2D Space) on which the robot navigates. We want to face different situations, as motion on natural terrains, where the Euclidean metric is no more applicable. In this work we introduce the architecture of a complete optimal path-planner applicable on robots with different shapes and kinematics operating in a natural world. Because the use of the paradigm of Cellular Automata, the approach is distributed and very fast, even on single-processor computers. During the last twenty years, many authors have proposed different solutions, based on geometrical descriptions of the environment (e.g. (Lozano-Pérez and Wesley, 1979; Lozano-Pérez, 1983)). In the eighties, Khatib in (Kathib, 1985) first introduced a new method for the collision avoidance problem in a continuous space for a 6 DOF manipulator robot. This alternative approach is less precise, but more efficient: the Artificial Potential Fields Methods. Jahanbin and Fallside introduced a Wave Propagation

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algorithm in the discretized Configuration Space ($\mathcal{C}$-*Space*) (*Distance Transform* (Jahanbin and Fallside, 1988)). Barraquand et al. in 1992 (Barraquand et al., 1992) used the Numerical Potential Field technique on the $\mathcal{C}$-*Space* to build a generalized Voronoi Diagram. Zelinsky extended the *Distance Transform* to the *Path Transform* (Zelinsky, 1994). Tzionas et al. in (Tzionas et al., 1997) described an algorithm for a diamond-shaped holonomic robot in a static environment, where they let a CA to build a Voronoi Diagram. Pai and Reissel in (Pai and Reissell, 1998) introduced a Motion Planning algorithm on multiresolution representation of terrains using wavelets. The path finding is based on a variation of Dijkstra's algorithm on a regular 2D lattice. In (Kobilarov and Sukhatme, 2004), the authors presented a Path-Planner for outdoor terrain based on the Control Theory and the technique of random trees (RRT). We used CA as a formalism for merging the Grid Model of the world (Occupancy Grid) with the $\mathcal{C}$-*Space* of a robot and Numerical (Artificial) Potential Field methods, with the task to find a simple and fast solution for the path-planning problem for mobile robots with different kinematics. This method uses a directional (anisotropic) propagation of distance values between adjacent automata to build a potential hypersurface embedded in 4D space. Using a constrained version of the descending gradient on the hypersurface, it is possible to find out all the admissible, equivalent and shortest (for a given metric of the discretized space) trajectories connecting two configurations of the robot $\mathcal{C}$-*Space*.

2 PROBLEM STATEMENTS

A wide variety of world models can be used to describe the interaction between an autonomous agent and its environment. One of the most important is the Configuration Space (Lozano-Pérez, 1983). The $\mathcal{C}$-*Space* $\mathcal{C}$ of a rigid body is the set of all its configurations $\mathbf{q}$ (i.e. poses). If the robot can freely translate and rotate on a 2D surface, the $\mathcal{C}$-*Space* is a 3D manifold ($\mathbb{R}^2 \times \mathbf{SO}(2) \equiv \mathbf{SE}(2)$). It can be modelled using

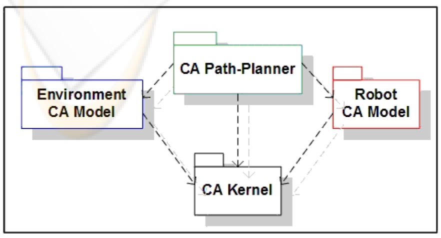


Figure 1: Mobile Robot Path-Planner Architecture

a 3D Bitmap $\mathcal{GC}$ ($\mathcal{C}$-*Space Binary Bitmap*), a regular decomposition in cells of the $\mathcal{C}$-*Space*, represented by the application $\mathcal{GC} : \mathcal{C} \rightarrow \{0, 1\}$, where 0s represent non admissible configurations. The $\mathcal{C}$-*Potential* is a function $\mathbf{U}(\mathbf{q})$ defined over the $\mathcal{C}$-*Space* that "drives" the robot through the sequence of configuration points to reach the goal pose (Barraquand et al., 1992). Let us introduce some other assumptions: 1) space topology is finite and planar; 2) the robot has a lower bound on the steering radius (non-holonomic vehicle). The latter assumption introduces important restrictions on the types of trajectories to be found. In the following section, we will describe each layer and its properties.

3 THE PATH-PLANNER ARCHITECTURE

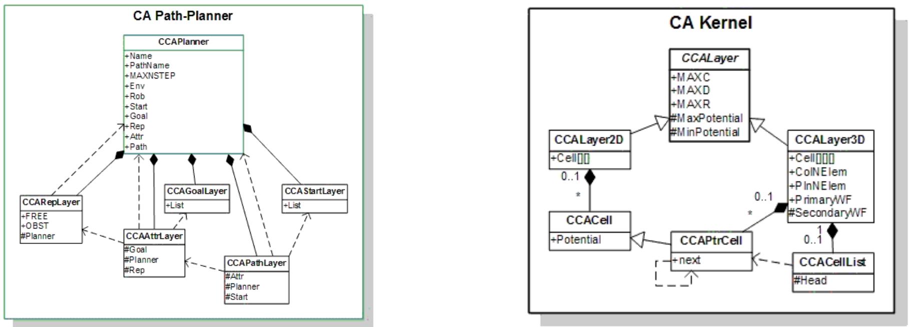
The planner architecture is organized in four main packages (Fig. 1). The main package is the Path-Planner itself: it coordinates the two lateral packages (Environment and Robot Models). It is worth noting that the World Model, the Robot Model and the Path-Planner use the same structure based on Cellular Automata, i.e. there is an isomorphism based on a regular decomposition structure.

3.1 CA Kernel

The CA Kernel realizes the Cellular Automata paradigm (Fig. 2.b). The architecture is organized in layers of cells depending on the underlying topological space. There are bi-dimensional spaces, such as the Work-Space, and 3D spaces (C-Space, Attraction Potential, etc.); some of them are active and are used to make calculations, others are static and are used only to represent specific information. The package makes available the basic structures to represent the information of both types of spaces and the related calculation kernel.

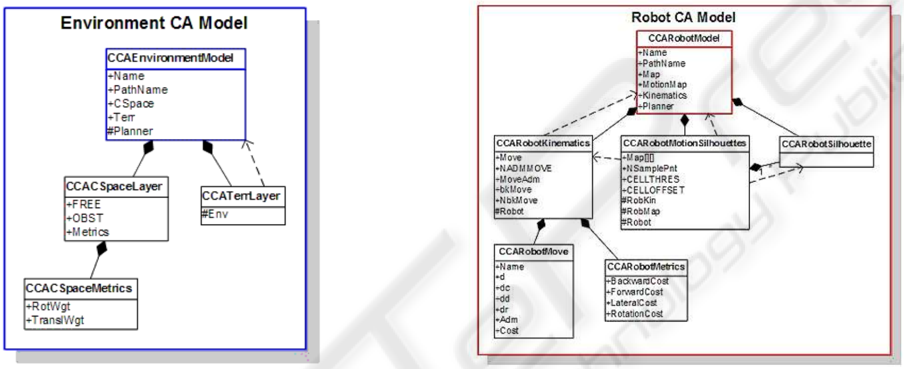
3.2 Environment CA Model

The Environment Model (Fig. 3.a) is subdivided in two parts: the C-Space and the Terrain Elevation Map. The first is a 3D space ($\mathbf{SE}(2)$, i.e. position and orientation) in which are represented both the $\mathcal{C}$-*Obstacles* and the $\mathcal{C}_{free}$-*Space*. The second is a regular 2D manifold representing the elevation map ($z = f(x, y)$) of the terrain on which the robot navigates. In a structured world (e.g. an office-like environment), it is simply as a flat surface ($z = 0$). There is space metric associated to the $\mathcal{C}$-*Space*. Formally, in a continuous space, it is a set of parameters used to define a matrix (fundamental tensor) necessary to evaluate the infinitesimal distance between two neighboring points. In



(a) (b)

Figure 2: Packages inside views (A)



(a) (b)

Figure 3: Packages inside views (B)

our case, the space is discretized in cells (CA), and the set of parameters are slightly different, but the has the same role: the evaluation of the linear distance between two adjacent cells in the 3D $\mathcal{C}$-*Space*.

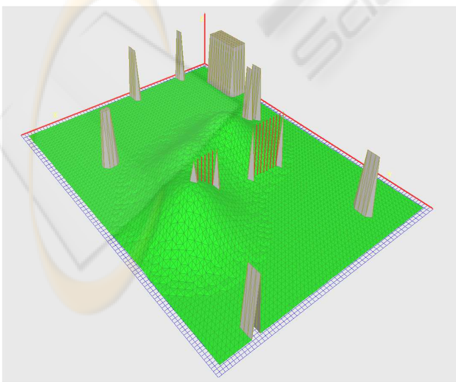
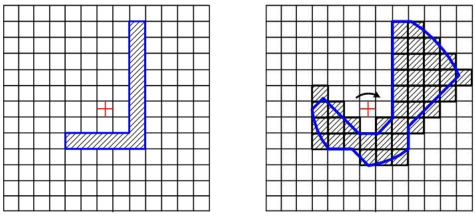


Figure 4: An example of Environment Model as a combination of Terrain and Obstacles Layers

3.3 Robot CA Model

This package is used to model the robot (Fig. 3.b). Two major components are necessary to model the robot: its shape and its kinematics. The shape is defined using a 2D CA (Fig. 5.a): it is a small occupancy map centered on the robot cinematic center. The robot kinematics is defined as a set of available moves. Each move allows the robot to rototranslate from the current cell to an adjacent one. The kinematics definition is completed with a robot metric. This is a set of costs associated to each robot move, to evaluate the cost (in term of energy or time or path length) the robot has to spend to reach a new pose. From this two structures is derived a secondary structure containing the Motion Silhouettes. In Regular Decomposition world models, the obstacles are decomposed in full or empty cells (Occupancy Grids) and the robot is shrunk to a point (the robot cinematic center). The well-known technique of enlarging the obstacles by the robot maximum radius is then used to take into account of its real extension (Lozano-Pérez and Wesley, 1979). An isotropic enlargement with a constant radius would give the same results as using an equivalent cylindrical robot. The consequence is a great loss of space around the obstacles, and many trajectories are lost. An anisotropic enlargement (Lozano-Pérez and Wesley, 1979), i.e. a different obstacles enlargement for each robot orientation, would solve only partially the problem for asymmetric robots. Counter-examples can be shown where the robot still collides with obstacles between two consecutive poses. We adopted a different approach to address this problem, by defining the Motion Silhouettes (e.g. Fig. 5.b) and evaluating cell by cell the set of admissible robot movements that avoid collisions (see *Repulsive Layer* in 3.4.1). The Motion Silhouette is generated by sweeping the basic robot shape during a single move and marking the cells covered. To avoid collisions, there must not be any obstacles cells in the marked cells. The Motion Silhouettes are calculated off-line once for all for any robot orientation, combining the set of movements (robot kinematics) and the basic silhouette (robot shape).



(a) (b)

Figure 5: An example of CA silhouette for a L-shaped robot (red cross: cinematic center): a) basic silhouette (robot shape); b) a motion silhouette obtained sweeping the robot silhouette during a single movement (rotation)

3.4 CA Path-Planner

The Path-Planner of Fig. 2.a is a sort of "bridge" between the Environment Model and the Robot Model. It combines the information from both to generate a set of optimal trajectories. It is organized in two major subsystems: an Input Subsystem and an Output Subsystem (Fig. 6). They are subdivided in five sublayers (3 + 2), some of them are statical and the others evolve during the planning time. The Input Subsystem is an interface toward the outstanding environment. Its layers have to react as fast as possible to the external changes: the robot starting pose, the robot goal pose, the elevation map of the terrain and, the most important, the changes of the environment, i.e. the obstacles movements in a dynamic world. The first two layers (*Starting Pose L.* and *Goal Pose L.* are considered quasi-statical, because they are updated from the outside at a very low frequency (much lower than the internal updating frequency); the *Repulsive L.* is updated externally (by means of a perception system) and it evolves testing the robot movements admissibility to avoid collisions. The Output Subsystem returns the results of the planning, that is the set of complete trajectories from the *Path Extraction L.*, or a single motion step from the *Attraction L.*

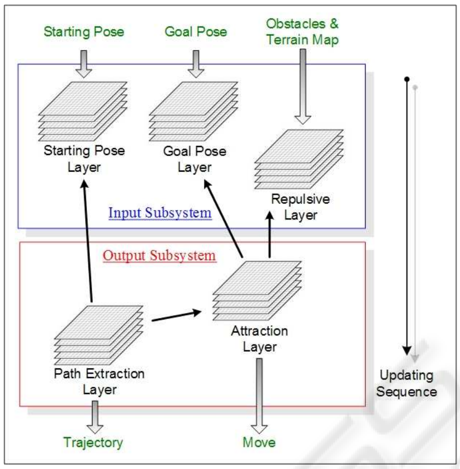
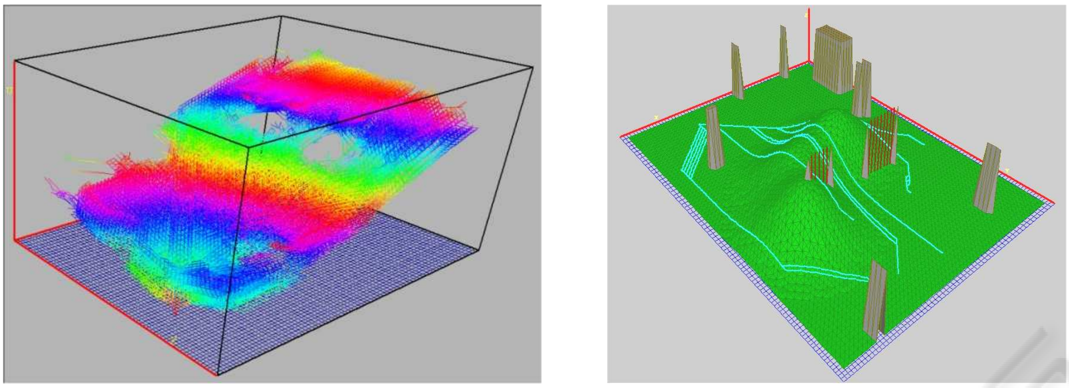


Figure 6: Path-Planner Layers Structure

3.4.1 Repulsive Layer

The Repulsive Layer is the dynamical version of the $\mathcal{C}$*-Space*. It is first initialized with the $\mathcal{C}$*-Obstacles* in the *Environment CA Model*, then it starts evolving to find out cell by cell any admissible move (Collision-free Moves) exploiting the Motion Silhouettes previously determinated. The admissibility of a move is influenced: 1) globally, by the specific robot kinematics; 2) locally, by the vicinity of an obstacle and by the robot shape. This layer is decomposed in sublayers, one for each robot orientation and move: it is itself a Multilayered CA on a 2D domain (the space $\mathbb{R}^2$ of positions). It is a particular type of Cellular Automata also for another reason: the cell neighborhood does not have the standard square shape, but a *non-standard fixed architecture* (Sipper, 1997). Its particular shape reflects the robot Motion Silhouette as shown in the example of Fig. 5.b. In Fig. 7 is shown the result of the evolution of this layer for a rectangular robot using the terrain of Fig. 4.b. The grey level is proportional to the number of admissible moves, ranging from white (all moves admissible) to black (no move).



(a) (b)

Figure 9: An example with a car-like robot: a) Attraction Potentials hypersurface (3D skeleton); b) Trajectories on the elevation map;

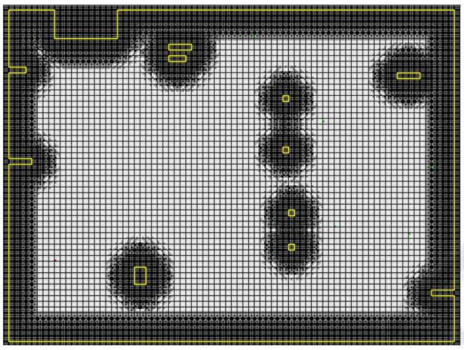


Figure 7: An example of the Obstacles Layer for a rectangular Robot moving in Fig. 4 world

3.4.2 Attraction Layer

This layer is the main part of the entire Path-Planning Algorithm. The *Attraction Layer* is the digitalized representation of the $\mathcal{C}$-*Potential* function **U(q)** defined on the $\mathcal{C}$-*Space Bitmap*: for any position and orientation is calculated a potential value. The $\mathcal{C}$-*Potential* is a potential surface with a global minimum in the goal cell. The potential represents the integer "distance" of the cell c from the Goal cell when the robot moves with an outgoing direction along a collision-free path, or more simply it is the cost to reach the goal from the cell c. To evaluate the path cost, we have introduced the *Robot Metric* as a set of costs for the basic robot movement: (*forward*, *forward_diagonal*, *direction_change*, *stop*, *rotation*, *lateral*, *backward*, *backward_diagonal*). These basic movements are combined in different ways to represent the different robots kinematics. The robot can be subjected also to non-holonomic constraints, therefore not every movement can be done as an omnidirectional robot does. To treat different kinematics, we have introduced a subset of admissible moving directions ($D'(c, d) \subseteq D$) depending on the robot position (cell c) and orientation d compiled off-line on the base of the robot kinematics. Changing the metric, we can realize the kinematics of different robots. For example, the kinematics $(2, 3, 1, 0, \mathit{High}, \mathit{High}, 2, 3)$ emulates a common car-like kinematics (Reed's and Shepp's vehicle), while A robot also translating in any direction (omnidirectional) has a kinematics like: $(2, 3, 1, 0, 1, 2, 2, 3)$. To compute the path length, an *Environment Metric* (3.2) is needed. On a flat environment (Euclidean Space), the distance between cells (the space metric) is invariant with respect to the position. For variable terrains, the cost value must de-

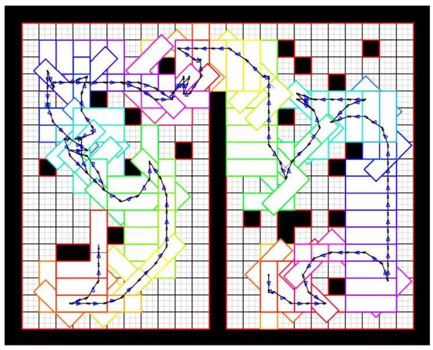


Figure 8: Manoeuvering example for a L-robot in a cluttered world

pend on the 3D distance between points on the surface, on the difference of elevation between two positions, hence the space metric changes from point to point. For this reason, it is necessary to include the surface gradient in the cost function. The over-all path cost results in a combination of robot metric, environment metric and surface gradient (a kind of "path-planner metric"). Two main properties can be demonstrated: the termination of the propagation of the potential values through the $\mathcal{C}$-*Space* and the absence of local minima. The later property ensures to achieve the goal (in the global minimum) just following the negated gradient vector of the $\mathcal{C}$-*Potential* function without stalling in any local minima.

4 EXPERIMENTS AND RESULTS

We have generated some synthetic elevation maps and introduced an obstacle distribution to observe the algorithm behavior. An interesting property of this algorithm is the simultaneous computation of trajectories from more than one starting position. We exploit this property to show multiple problems in the same environment. In the example of Fig. 9, the terrain has a group of three "hills" in the middle, and we consider five different starting points of the robot and one goal (bottom-left). From any position, the robot tries to move around the hills, unless the shortest path is to pass over them (in any case, at the minimum elevation). The performance tests, carried out with an Intel Pentium IV 2.26 GHz PC, gave the following result (mean times over 500 repetitions): 182 ms (Fig. 9), 26.7 ms (Fig. 8). The complexity of a path-planning algorithm is always strictly related to the obstacles distribution. A good upper-bound estimate, in the worst cases without obstacles enlargements, can be done. Considering that the longest paths cover approximatively $1/2$ of the total number of cells N of the 2D *Workspace Bitmap*, and require nearly $2\frac{N}{2}N$ cells updates to be computed, a realistic upper-bound of the complexity is $O(N^2)$. If we take also into account of the obstacles enlargements, the result is even better since the number of free cells is much lower, especially in a cluttered world.

5 CONCLUSION

In this paper we have described an architecture solution for the Path-Planning Problem for mobile robots with generic shapes (user defined) and with generic kinematics on variable (regular) terrains based on (Multilayered) Cellular Automata. Another important property of this algorithm is related to the consistency of the solution found. For a given terrain surface, the solution found (if it exists) is the set of all shortest paths (for the given metric) that connect the starting cell to the goal cell. The CA evolution can be seen as a motion from one point to another point of a global state space until an optimal solution is reached. This is a convergence point for the given problem or a steady global state. If we make some perturbations, such as changing the environment (e.g. adding, deleting or moving one or more obstacles), then the point becomes unstable and the CA starts to evolve again towards a new steady state, finding a new set of optimal trajectories (*Incremental Updating*).

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