A Biologically-Plausible Approach for Mobile Robots Path Planning: The Virtual Lightning Approach

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Abstract

This paper deals with the path planning problem of mobile robots involving in partially known or unknown environments. We describe a biologically-plausible approach of this problem based on the definition of virtual top view images, obtained by the transformation of real frontal images (visual images or proximetric images).

Index terms: Path planning, navigation, collision avoidance, biologically inspired systems.

1 Introduction

Automatic motion planning deals with finding a feasible sequence of motions to take movable object (the 'robot') from a given initial configuration to some specified goal configuration. Research in path planning for robots has traditionally been focused on finding ways to ensure that a fixed arm will not collide with objects in its workspace as it performs its tasks. However, to be truly flexible, manipulators are mounted upon mobile platforms, giving them not just the ability to manipulate objects in a fixed region, but to interact with their environment in more complex ways, much as humans do. The reigning paradigm of path planning has been the piano movers problem, which concerns moving an object through a set of obstacles without any constraints on the type of movements which can be made. But mobile robots are likely to be based upon carts with wheels for steering and locomotion.

To date, motion planning approaches can be classified into three categories [2]: 1) Roadmap methods, 2) Cell decomposition methods, and 3) Potential field methods.

The roadmap approach (or skeleton approach) consists of capturing the connectivity of the robot free configuration space ($\mathcal{C}_f$) in the form of a network of one -dimensional curves -the roadmap- lying in $\mathcal{C}_f$. After a roadmap ρ has been constructed, the path planning is reduced to connecting the start and goal configurations to ρ, and searching ρ for a path. Algorithms based on the visibility graph, the voronoï diagram, and the silhouette (projection of obstacle boundaries) are examples of the roadmap approach. In the cell decomposition approach the free space is represented as a union of cells, and a sequence of cells comprises a solution path. For efficiency, hierarchical trees, e.g., octree, are often used. In the potential field approach, a scalar potential function that has high values near obstacles and the global minimum at the goal is constructed, and the robot moves in the direction of the negative gradient of the potential.

The aim of this paper is to propose a biologically-plausible approach to path planning. By these words, we mean the replacement of symbolic or geometric representation of the world by "imaged" representations, and then use these virtual images as basis for the pre-execution of the future motion [1]. This paper is organized as follows. Section 2 described the Virtual Lightning Approach (VLA). This algorithm allows to obtain safe trajectories for a polygonal holonomic robot and the extension to nonholonomic mobile robot is discussed. In the Section 3, we briefly present control motion, i.e., the problem of coupling VLA algorithm with a reactive controller based on the Deformable Virtual Zone Approach (DVZ). Section 4 present experimental considerations and particularly we describe several simulations that prove the potentiality of our approach.

2 The Virtual Lightning Approach

2.1 Morphological methods in artificial vision

Briefly speaking, the vast subject of mathematical morphology [5, 4] deals with the application settheory for image processing. Numerous topics go from image enhancement to region labelling through parameters and pattern extraction. Mathematical morphology uses two main operations on binary images: *dilatation* and *erosion*.

Dilatation of a binary image $\boldsymbol{I}$ by a “moving” *structuring binary element* $\boldsymbol{B}$ consists in determining the set of image points (center of $\boldsymbol{B}$) such that it exists a non empty intersection with $\boldsymbol{I}$.

Erosion of a binary image $\boldsymbol{I}$ by a “moving” *structuring binary element* $\boldsymbol{B}$ consists in determining the set of image points (center of $\boldsymbol{B}$) such that $\boldsymbol{B}$ is included in $\boldsymbol{I}$. For instance, the dilatation of the image of Figure 1 by the structuring element $\boldsymbol{B} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$ gives the image represented in Figure 2. Its erosion by the same structuring element gives the image represented in Figure 3.

Figure 1: *Original image* $\boldsymbol{I}$.

Figure 2: *Dilatation of image* $\boldsymbol{I}$ *by* $\boldsymbol{B}$.

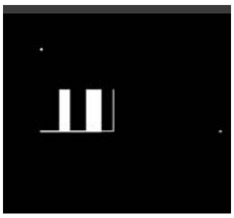

Figure 3: *Erosion of image* $\boldsymbol{I}$ *by* $\boldsymbol{B}$

2.2 Extension to path planning

We have extended this approach of image processing to mobile robot path planning and we have proposed an algorithm by implementing mathematical morphology somehow “biologically-inspired”, and this, along 3 paradigms:

- P1: There is no abstract, nor symbolic nor geometric modeling of the environment in which the robot evolves. The environment representation is a binary image (a top view virtual image) of the world.
- P2: The path planning process is a multi modal simulation of the motion to be carried out by the robot.
- P3: There is a “natural” bridge between the real frontal perception of the world (obtained for instance through distance sensors), and the virtual top view image.

Furthermore, one of the main advantages of this algorithm is to be very fast, property which also could be seen as a biologically plausible result.

2.3 The main algorithm (The Virtual Lightning Approach)

In order to describe the main algorithm, we assume that the mobile is a holonomic point robot, and can sense its environment (it perceives distances field in several directions of its space). We will describe the main algorithm (VLA) in 2 steps: moving in a known environment and moving in an unknown one.

1) Moving in a known environment (P1 and P2) This environment is described as a binary image (a bitmap) $\boldsymbol{I}$ which the ones (1’s) represent various obstacles and the zeros (0’s) the free space in which the robot can move. In the same image, the potential virtual trajectories are also represented as a set $\boldsymbol{P}$ (of pixels) of value $l_i > 1$(one index i for each trajectory). The initial value $\boldsymbol{P_0}$ of $\boldsymbol{P}$ is the initial configuration S of the robot. At each time step, the robot dilates $\boldsymbol{P}$ in direction of the final configuration G(goal), transforming the virtual image $\boldsymbol{I}\cup\boldsymbol{P_t}$ into $\boldsymbol{I}$ $\cup$ $\boldsymbol{P_{t+1}}$, where $\boldsymbol{P_{t+1}}$ is the dilated of $\boldsymbol{P_t}$. In other words, the robot creates an initial “virtual lightning” issued from $\boldsymbol{P_0}$ and consisting of a set of pixels of value $L_0 > 1$“moving” towards the goal.

Unfortunately, this initial virtual lightning can meet obstacles. In this case, it separates in two, creating two secondary virtual lightnings (of the values $10l_0$ and $10l_0 + 1$, respectively) which are dilated parallel to the obstacle until they can move again in the free space (and are therefore dilated toward the goal). At each collision between a Virtual Lightning and an obstacle, there is a creation of two Virtual Lightnings (of the values $10l_i$ and $10l_i + 1$, respectively), and so on. At the end of the process, the image has been augmented by a set of pixels of value $l_j > 1$, representing all the lightnings.

2) Moving in an unknown environment(P3). In this case, the robot builds the environment representation $\boldsymbol{I}$ during its motion.

At time 0, $\boldsymbol{I_0}$ is initialized at 0 (black image). At each time step t, each distance measured by its proximity sensors is transformed into a pixel of value 1, providing an image $\boldsymbol{S_t}$ and the image $\boldsymbol{i_t}$ is obtained by the union of the morphological dilatation of $\boldsymbol{S_t}$ with the structuring element $\boldsymbol{B} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$ and $\boldsymbol{I_{t-1}}$. Therefore, we have: $\boldsymbol{I_t} = \boldsymbol{I_{t-1}} \cup \boldsymbol{S_t}$. The robot generates its virtual lightnings in this partial image, moves in this partially known environment and continues, building and incrementing its environment.

2.4 The filtering algorithm

At the end of the Virtual Lightning generation process (one of them has reach the goal), the robot enters in the filtering stage consisting in keeping only the successful lightning. This operation is done by "thresholding" the image $\boldsymbol{P_{end}}$ with the sequence of threshold values $a_1 = l_{end}$, $a_2 = floor(l_{end}/10)$, $a_3 = floor(a_2/10)$, $\cdots$. Afterwards, it is possible to optimize the process by smoothing the obtained trajectory. This is done by choosing the more distant point M from the successful virtual lightning and running again the process between S and M and between M and G. At this stage, only stays a filtered Virtual Lightning, as an image $\boldsymbol{V}$ mainly composed of 0's and which pixels of value 1's represent the trajectory between S and G.

2.5 Trajectory parameterization

The longest process in this approach consists in transforming the image $\boldsymbol{V}$ in a sequence of positions. This is done by the parameterization of $\boldsymbol{V}$. This process is again based on mathematical morphology. In a first stage, $\boldsymbol{V}$ is slightly dilated in order to ensure its perfect connection (to fill small holes appearing during the VLA phase). In a second stage, the connected components of $\boldsymbol{V}$ (only one here) is extracted. This operation is based on an iterative use of morphological dilatation, starting from S. At each iteration, the difference between the connected component at time t and the connected component at time $t-1$, allows a parameterization of the set of pixels.

2.6 Extension to holonomic non punctual robots

The extension to non punctual robots is a very easy process. Actually, the dilatation operation can simply take into account the size of the robot. In the main algorithm (VLA), the structuring element $\boldsymbol{B}$ can be increased in size to prevent the robot from colliding. This is the same kind of process that is used in cell decomposition methods or in roadmap methods. The transformation of the real robot space into the configuration space is done while taking into account this robot size.

2.7 Extension to real robots: The virtual corridor

A common there for many nonholonomic path planning approaches is to divide the problem into two stages. In the first stage, a holonomic planning method is used by producing a collision-free path that ignores the nonholonomic constraints. In the second stage, an iterative method attempts to replace portions of the holonomic path with portions that satisfy the non-holonomic constraints (for example Reeds & Shepp shortest paths [3]), yet still avoid obstacles. We describe this approach for the case of a car-like robot.

Car-like behavior is described by the following differential system:

$$\begin{cases} \dot{x} = \cos\theta \cdot u_1 \\ \dot{y} = \sin\theta \cdot u_1 \\ \theta = \frac{1}{R} \cdot u_2 \end{cases} \tag{1}$$

with $|u_1(t)| = 1$ and $|u_1(t)| \leq 1$, where u_1 and u_2/R are respectively the linear and angular velocity of the car.

The study of the shortest paths for a car-like robot has an history. It has first been addressed without considering the presence of any obstacle. The pioneering result has been achieved by Dubins who characterized the shape of the shortest paths when $u_1 \equiv 1$ (the robot moves always forward). More recently, Reeds and Shepp have provided a sufficient family of 48 shortest paths for the car-like robot moving forward and backward ($|u1| \equiv 1$). Shortest paths for Dubin's car are a finite sequence of at most 3 pieces consisting of straight line segments or arcs of circle with radius 1. Optimal paths for Reeds & Shepp's car are constituted by a finite sequence of at most five elementary pieces which are either straight line segments or arcs of a circle of radius 1.

Assume that a fast holonomic planning method has been selected for the first stage. Suppose that a path $\tau : [0,1] \rightarrow \mathcal{C}_f$ has been computed. The path can be iteratively improved as follows. Randomly select two real numbers $\xi_1 \in [0,1]$ and $\xi_2 \in [0,1]$. Assuming $\xi_2 > \xi_1$, attempt to replace the portion of τ from $\tau(\xi_1)$ to $\tau(\xi_2)$ with a path segment that satisfies the nonholonomic constraints. This implies that τ is broken into three segments, $\tau_1 : [0, \xi_1] \rightarrow \mathcal{C}_f$, $\tau_2 : [\xi_1, \xi_2] \rightarrow \mathcal{C}_f$, $\tau_3 : [\xi_2, 1] \rightarrow \mathcal{C}_f$. Note that $\tau_1(\xi_1) = \tau_2(\xi_1)$ and $\tau_2(\xi_2) = \tau_3(\xi_2)$. The portions τ_1 and τ_3 remain fixed, but τ_2 is replaced with a new path, $\tau' : [\xi_1, \xi_2] \rightarrow \mathcal{C}_f$,that satisfies the nonholonomic constraints. τ' must also avoid collisions, $\tau'(\xi_1) = \tau_1(\xi_1)$, and $\tau'(\xi_2) = \tau_3(\xi_2)$. This procedure can be iterated multiple times until eventually, the original path is completely transformed into a nonholonomic path. The completeness of the algorithm only depends on the completeness of the geometric planner that computes a first collision-free path.

The combination of this transformation of holonomic trajectories to non holonomic ones and of the VLA approach is very easy. At the end of the parameterization phase, the trajectory can be dilated by a substantial structuring element ($\boldsymbol{B}= I_{25\times25}$ for instance) and from the resulting image is subtracted $\boldsymbol{I}$. The result, is an image of a collision free corridor (the virtual corridor) in which the holonomic trajectory is transformed in a nonholonomic one.

3 The Control Motion

3.1 The control of reactive actions

In previous papers [7, 8], we have defined an algorithm for controlling mobile robots evolving in unknown environments, the Deformable Virtual Zone (DVZ). Let summarize here the principles of this method : the DVZ Ξ represents a deformable zone whose geometry characterizes the interaction between the robot and its environment. The DVZ is the sum of 2 terms:

$$\Xi = \Xi_h + \Delta \tag{2}$$

where Ξ_h is an undeformed protecting zone and Δ represents a deformation of Ξ_h due to the intrusion information in the robot space (denoted by $\mathcal{I}$ and sensed by distance sensors).

The undeformed zone depends on a vector π characterizing the motion capabilities of the robot (its translational and rotational velocities for instance):

$$\Xi_h = \rho(\pi) \tag{3}$$

The deformation Δ depends on the intrusion of proximity information and on the undeformed DVZ:

$$\Delta = \alpha(\Xi_h, \mathcal{I}) \tag{4}$$

By differentiating equations (2) and (3) with respect to time, we get:

$$\dot{\Delta} = \lfloor \nabla_{\Xi_h} \alpha \rfloor [\nabla_\pi \rho] + [\nabla_{\mathcal{I}} \alpha] \psi \tag{5}$$

∇_ζ is the derivation operator with respect to the variable ζ and where

$$\begin{cases} \phi = \nabla_t \pi = \dot{\pi} \\ \psi = \nabla_t \mathcal{I} = \dot{\mathcal{I}} \end{cases}$$

The evolution of Δ is driven by a 2-fold input vector $u = [\phi \ \psi]^T$. The first control vector ϕ tends to minimize the deformation of the DVZ. The second one, ψ, is induced by the environment itself (and could, at most, try to maximize these deformations).

Therefore, the complete evolution of the deformation Δ is modeled by a differential equation of the type:

$$\dot{\Delta} = A\,\phi + B\,\psi \tag{6}$$

The control algorithm consists in choosing the desired evolution of this deformation $\dot{\nabla} = \dot{\Delta}_{des}$. A simple and efficient control law is to choose this desired deformation as proportional to the real deformation and its derivative (Proportional and Derivative gains):

$$\dot{\nabla} = -M\,\Delta - N\,\dot{\Delta} \tag{7}$$

where the two matrices M and N, are heuristically tuned in order to carry out the avoidance task. The control vector at time t is then defined by inverting equation (5) after replacing the derivative of the deformation $\dot{\Delta}$ by the desired evolution $\dot{\nabla}$:

$$\breve{\phi} = A^{\bullet}(\nabla - B\,\hat{\psi}) \tag{8}$$

where $A^{\bullet}$ is the pseudo-inverse of A, and is the previous measured uncontrolled control vector (due to the intrusion of information at time $t-1$ and depending on the unknown behavior of the environment). This control law tends to minimize the function $\|\dot{\nabla} - \dot{\Delta}\|^2$. A vision-based stereo-matching algorithm consisting in a spatial stereo-matching of characteristics points of two images (obtained by a left and a right cameras) allows us to get the distance field in the robot front-space and therefore to build the DVZ [6].

3.2 Coupling the VLA and the DVZ

As an alternative of transforming the holonomic trajectory into a non holonomic one, we can easily couple the DVZ approach of reflex actions to the VLA algorithm. Actually, once the parameterized trajectory has been computed and the virtual corridor been generated, it is possible to run the DVZ from one parameterized point to another and to limit the DVZ protecting zone to the virtual corridor. Therefore, the reflex action will be trigged up if and only if unscheduled obstacles appear in the robot environment.

4 Experimentations

4.1 Real experiments

The DVZ approach for controlling reactive behaviors of a mobile robot has been tested on several robots (mobile wheeled vehicles, AUVs, walking robots).

In the future, this will be tested on a car-like small robot equipped with a stereovision system. The idea, is first to use the couple of images obtained by the left and right cameras in order to build the distance field of the front space robot (for collision avoidance purpose) and second to transform the real images into a virtual top view image (for path planning purposes). However, several simulated experiments have been carried out.

4.2 Simulation results

1) Context

The VLA algorithm has been experimented in simulation with a holonomic polygonal robot. The experiments have been carried out on a PC Pentium IV computer at 1.7GHz. The software has been developed with MATLAB 6.1. The robot environment is a 10m square room . The obstacles are 25cm thick walls. The different stages of the VLA algorithm are illustrated with different figures.

2) First experiment

One room, 3 walls. The robot world is a priori known. Figure 4 shows the robot in its environment. Figure 5 shows the corresponding virtual image and the 2 lightnings that have been generated by the algorithm. Figure 6 shows the virtual image P_{end}. Figure 7 shows the ultimate filtering providing the trajectory $\boldsymbol{V}$. Figure 8 shows the virtual corridor minus the obstacles. Figure 9 shows the parameterized trajectory. Here, we have chosen to parameterize this trajectory with ten intermediate positions. Next table shows the performance data for this experiment.

	Time (sec)
Lightning	0.22
Virtual Lightning	0.06
Corridor	0.06
Parameterization	3.97

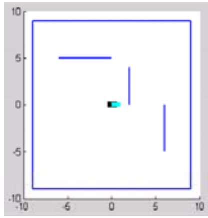

Figure 4: *Original environment.*

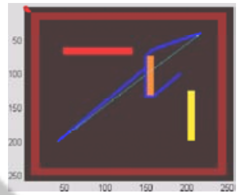

Figure 5: *The virtual image.*

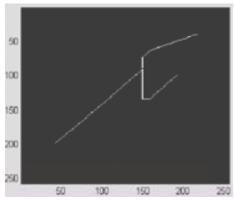

Figure 6: *The resulting lightnings.*

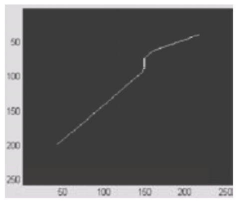

Figure 7: *The trajectory* $\boldsymbol{V}$.

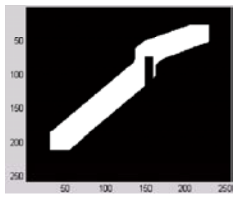

Figure 8: *The virtual corridor.*

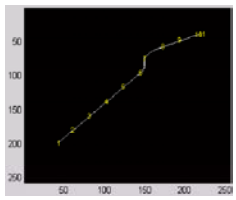

Figure 9: *The parameterized trajectory.*

3) Second experiment

This time we assume that the environment is a priori unknown. In the same world, the robot runs 7 times from different start positions (S) toward the same final position (G) and builds its virtual image, using 32 ultrasonic sensors scanning the whole robot space. See Figures 10 to 17.

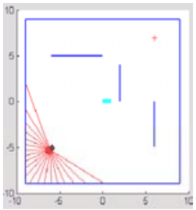

Figure 10: *Original environment and sensor information.*

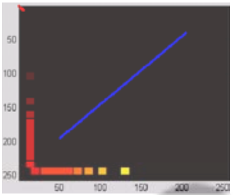

Figure 11: *The virtual image at step 1.*

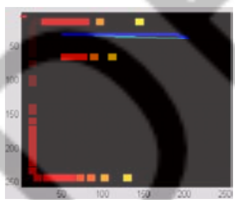

Figure 12: *The virtual image at step 2.*

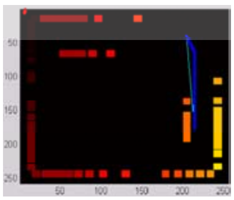

Figure 13: *The virtual image at step 3.*

4) Third experiment

This time, the robot encounters a known complex environment (see figures 18 to 22). Next Table shows the performance data for this experiment.

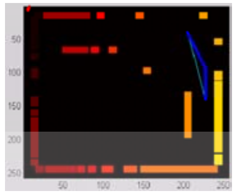

Figure 14: *The virtual image at step 4.*

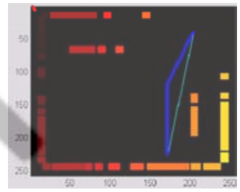

Figure 15: *The virtual image at step 5.*

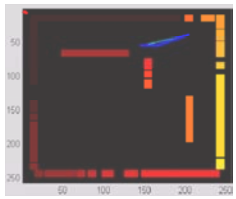

Figure 16: *The virtual image at step 6.*

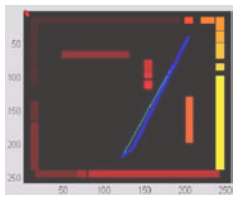

Figure 17: *The virtual image at step 7.*

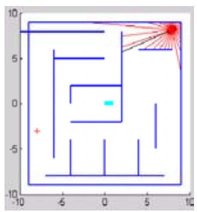

Figure 18: *Initial and final position.*

	Time (sec)
Lightning	2.7
Virtual Lightning	0.09
Corridor	0.04
Parameterization	6.2

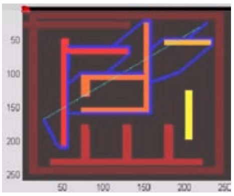

Figure 19: *The virtual image and the lightnings.*

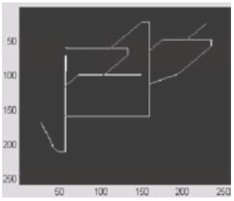

Figure 20: *The virtual lightnings.*

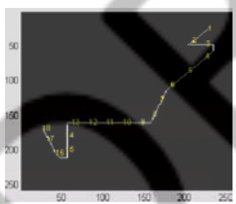

Figure 21: *The parameterized trajectory.*

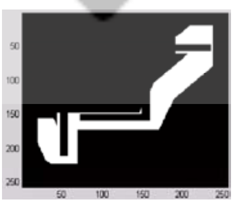

Figure 22: *The virtual corridor.*

5 Conclusion and Perspectives

This paper has presented several aspects of the realization of a biologically-based path planner based on mathematical morphology. This investigation is in development, but the simulations that we have obtained allow us to foresee the applicability of this approach to real mobile robots evolving in partially known environments. The VLA algorithm will be tested in the future on a car-like robot equipped with a stereovision system, and coupled with a collision avoidance algorithm able to generate reactive behaviors in a completely unknown environment. The idea, is to use the couple of images obtained by the left and right cameras in order to build the distance field of the front space robot (for collision avoidance purpose) and second to transform the real images into a virtual top view image (for path planning purposes).

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References

[1] A. Berthoz. Le sens du mouvement, *Editions Odile Jacob [The Brain's sense of movement, Perspectives in Cognitive Neuroscience, Harvard University Press]*.

[2] J.C. Latombe. *Robot motion planning*, Kluwer Academics Publishers, 1991.

[3] J. A. Reeds and R. A. Shepp. Optimal paths for a car that goes both forwards and backwards. *Pacific Journal of Mathematics*, 145(2), pages 367-393, 1990.

[4] J. Serra and P. Soille (Eds). Mathematical Morphology and its Applications to Image Processing, *Proceedings ISMM 94*, Kluwer Academics, 1994.

[5] J. Serra. Cours de Morphologie Mathématique. Available at: http://cmm.ensmp.fr/∼serra/cours/index.htm.

[6] L. Torres, P. Lepinay, R. Zapata, J. Droulez, V. Creuze. Codesign of a vision-based collision avoidance autonomous system, *XIII Symposium on Integrated Circuits and Systems Design, SBCCI2000*, Manaus, Brazil, 2000.

[7] R. Zapata and P. Lepinay. A biologically-plausible vision system for controlling mobile robots, *International Symposium on Robotics and Automation, ISRA98*, pp. 113-120, 2000.

[8] R. Zapata and P. Lepinay. Collision avoidance of a 3D simulated flying robot, *International Symposium on Robotics and Automation, ISRA98*, 1998.