Definition of Exploratory Trajectories in Robotics Using Genetic Algorithms

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Abstract

In this paper we address the problem of defining survey trajectories for robotic platforms equipped of short range perception sensors and using dead-reckoning navigation, i.e., that do not have access to external global positioning information. Our work explicitly considers the impact of positioning errors in the execution of mapping-type missions. Assuming that the mapped region is delimited by a set of known objects, each possible exploratory trajectory is evaluated not only with respect to path length and surface coverage (which are the usual criteria for this problem) but also the effective utilization of the border of the explored region by the exploratory trajectory. We formulate the problem as a multi-criteria optimization problem, and apply stochastic optimization tools (genetic algorithms) to find a set of solutions (trajectories) which correspond to distinct trade-offs between the individual criteria. New appropriate reproduction and mutation algorithms have been defined, which must deal with the fact that the solution space is the (in general infinite) union of several finite dimensional spaces. To cope with the multi-criteria nature of the problem, we use an evaluation/selection strategy based on the notion of Pareto set, which instead of a single "optimal" solution, tries to identify the set of non-dominated solutions of the problem. We present results showing the behavior of the solution for ideal and real situations (more precisely, for contour information acquired by a real mini-robotic platform), which show that the genetic algorithms are able to find solutions with present geometric regularities, learning basic local "filling modes," dependent on the geometry of the external contour.

Keywords: Genetic Algorithms, Multi-criteria problems, Mobile robotics, trajectory planning, reasoning under uncertainty.

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1 Introduction

This paper addresses the problem of determining a trajectory for exploration of a closed region delimited by known objects, motivated by robotic mapping missions, where an unknown region must be surveyed (in the framework of underwater robotics this can, for example, correspond to the exploration of the inner region of an harbor). This problem is distinct from the traditional path planning problem in that it is fundamentally dependent on the "empty part" of the environment, i.e., in that it must essentially resort to deliberate motions of the robot, being impossible to formulate it as a search for an optimal chain of go-through points, or of a sequence of perception based behaviors.

The mapping problem has been studied by several researchers in the last years. Our work differs from the majority of these studies in that we explicitly address the effect of navigation errors in the execution of survey missions. In fact, the majority of the mapping algorithms that have been proposed consider ideal perfect positioning of the platform along the exploration mission, being based on purely geometric arguments. This kind of robotic task usually has one of two main objectives: either to make sure that if a given kind of object is present it will be detected – one obvious example is mine-hunting – and thus that *all the surface* will be observed; or to acquire an internal representation of the objects present in the explored region, for instance, to be able to study the evolution of the environment between successive observations. In either case, blind application of algorithms that assume perfect platform positioning to a platform using dead-reckoning navigation will fail to achieve the the mission goal: drifting will create "holes" – areas which are not observed, and that increase the probability of not detecting the objects of interest – and deform the internal representation built with respect to reality. With these considerations in mind, our approach is based on giving the robot the possibility of having a better knowledge of the regions that were effectively surveyed, by using available information about the contour of the explored region. Note that the role of perceptual information in this framework is to provide global positioning information at the borders of the explored region, and can be either pre-existing (for instance if the robot started by learning the contour of its workspace) or installed for mission purposes (it can consist, for instance, on a set of landmarks which can be observed using a vision system or a set of short-range acoustical positioning systems that cover the border of the surveyed region).

Since for robotic platforms using dead-reckoning positioning uncertainty tends to increase most importantly when the vehicle maneuvers, the exploratory trajectory is assumed to be a sequence of straight line segments, minimizing in this way the accumulated uncertainty with respect to the robot position and orientation.

A second constraint considers that the location of the extreme points of these line segments must coincide with one of the delimiting objects, allowing in this way repositioning of the platform at each of these "contact points".

With these two constraints, the exploratory trajectory t can be defined, for a fixed initial position $p(0)$, by the number of linear segments n_t and by the orientation ϕ of each segment with respect to a global frame, see figure 1,

$$t \leftrightarrow (n_t, \{\phi_i(t)\}_{i=1}^{n_t}) .$$

We further assume that the robotic platform has limited range perception sensors, which

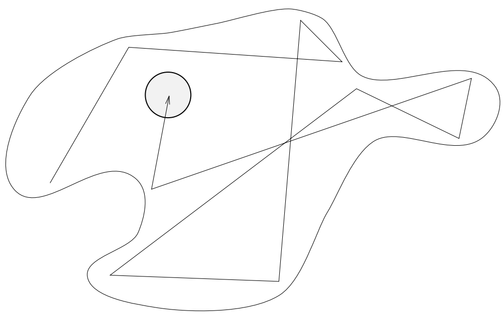

Figure 1: Exploration of a closed region.

define an observed region around each pose of the robot. This region is represented in figure 1 by a gray circle around the robot's position. Our goal is to find a minimal length trajectory which optimizes the use of a priori information, such that the predefined region is completely covered.

2 Problem Formulation

We formalize this problem as a multi-criteria optimization problem, considering the following three criteria :

- the length of the trajectory, $L(t)$;
- the percentage of the complete surface that is effectively observed along trajectory t : $S(t)$;
- the quality of vehicle self-positioning at the vertices of t: $C(t)$.

Our problem can thus be formalized as finding the number n_{t^*}, and the set of orientations $\phi_i(t^*), i = 1, \ldots, n_{t^*}$, such that $S(t^*) \simeq 1$, $L(t^*)$ is minimized, and $C(t^*)$ is maximized. The first two criteria, $L(t)$ and $S(t)$ have an obvious geometric definition, being non-linear functions of the angles that define the geometry of each possible trajectory. They are the two performance indexes considered by the majority of the works on definition of survey trajectories.

The last criterion evaluates the ability of the platform to acquire its position and orientation at the end of each linear segment, and is its explicit consideration is new. We define it using a performance analysis tool based on notions of Statistical Estimation Theory, and which describes the asymptotic properties of Maximum Likelihood parameter estimates, the Cramer-Rao lower bound. Let z be a vector that denotes the available observations, which are probabilistically related to a parameter θ that we whish to determine (estimate), by a known conditionally family of density functions:

$$\{p(z|\theta) \,|\, \theta \in \Theta\}.$$

It is known that the covariance of the estimation error of any unbiased estimator of θ, $\hat{\theta}$, is bounded below by the Cramer-Rao bound $CRB(\theta)$:

$$\mathrm{E}\left\{\left(\theta\hat{\theta}\right)\left(\theta\hat{\theta}\right)^T\right\} \geq CRB(\theta) = J(\theta)^{-1}$$

where $J(\theta)$ is the Fisher information matrix for parameter θ, defined by

$$J(\theta)_{ij} = \mathrm{E}\left\{\frac{\partial \ln p(z|\theta)}{\partial \theta_i}\frac{\partial \ln p(z|\theta)}{\partial \theta_j}\right\}.$$

Denote by p_i the pose (position and orientation) of the robot at the i-th "contact point" of the trajectory. We define criterion $C(t)$ as the sum of the volumes of uncertainty (with respect to the vehicle position and orientation) at all the contact points of the trajectory t:

$$C(t) = \sum_{i=1}^{n_t} \left|\mathrm{CBR}(p_i)\right|. \tag{1}$$

Note that the particular definition of this criterion is strongly depend on the available perceptual sensors and on the geometric characteristics of the delimiting objects (shape, texture, etc.).

As it can be easily seen, criteria $S(t)$ and $C(t)$ are highly non-linear functions of the variables of the problem, i.e., this problem is a non-linear multi-variate multi-criteria problem, with the additional difficulty that the dimension of the solution, i.e., the number of linear segments need to cover the complete surface, is not known. Moreover, there is not, in general, *one optimal* solution to the problem, i.e., there may exist several distinct trajectories that lead to the same value of the three criteria. Standard optimization techniques cannot deal with problems with these characteristics. We applied stochastic optimization tools to this problem (genetic algorithms) in order to determine a *set of trajectories* which correspond to distinct trade-offs between the three criteria involved.

3 Definition of Genetic Operators

Considering each possible trajectory as an individual, genetic mutation and reproduction operators have been defined.

For single criteria problem, it is well known that genetic algorithms are guaranteed to find the set of parameter values that yield the extreme values of the optimizing criteria if the set of probabilistic reproduction and mutation operators cover the complete solution space with probability one, i.e, if given any two points t_1 and t_2 in the solution space, there us a sequence of reproduction and mutation operators that apply bt_1 into t_2. Since the solution space of our problem is composed of several disconnected "layers," each one corresponding to the set of feasible trajectories of a given dimension, the usual set of genetic algorithms had to be increased with operators able to change the dimension of the current set of solutions (number of linear segments).

Three different *mutation* operators were designed : elimination of a randomly chosen contact point; introduction of a randomly chosen contact point at a random location; and random modification of a randomly chosen contact point. The first operator enables to decrease by one the dimension of the trajectory, while the second results in an increase of the number of linear segments. The last mutation operator corresponds to the classical genetic mutation operator, and keeps the dimension fixed, enabling the search inside each layer of the solution space. Figure 2 illustrates the three mutation operators.

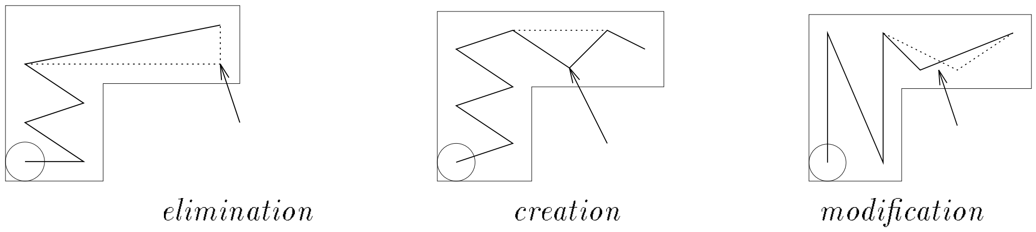

Figure 2: Mutation operators.

The probability that the three mutation operators be applied is changed according to the values of the evaluation criteria, in order to speed up convergence process. The choice of the particular mutation operator that is applied is made randomly, favoring, for instance, the application of creation of line segments for individuals with low values of the covered surface, and the application of elimination operator for very long trajectories.

The *reproduction* operator (applied to a pair of trajectories) randomly selects two points (one in each parent) and builts a new pair of trajectories by joining the original parent trajectories at the selected points. this operator differs from the traditional genetic operator in that the dimension of the resulting "child trajectories" differs in general from the dimension of the parent trajectories, n_{t_1} and n_{t_2}, being comprised in the interval $[2,\ n_{t_1}+n_{t_2}-2]$. Figure 3 illustrates the application of the reproduction operator to two parent trajectories.

The trajectories found by the algorithm must be completely contained in the region to be explored. At each step of the algorithm, a verification is made that the application of the mutation and reproduction operators does not yield invalid solutions. If this happens, another random application of the genetic operators is tried, until an admissible trajectory is generated.

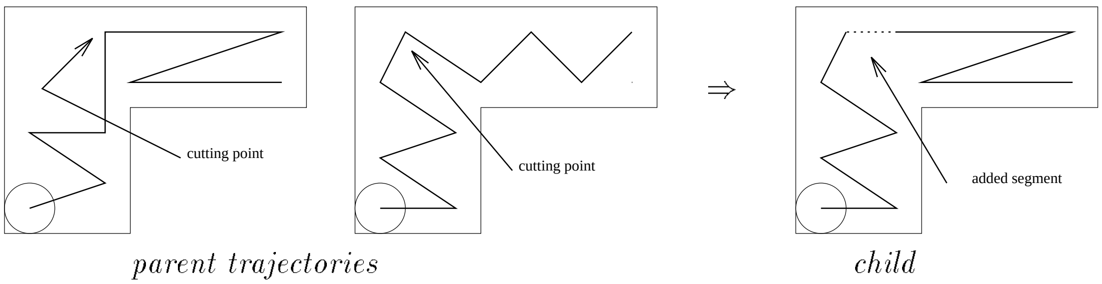

Figure 3: Reproduction operator.

4 Evaluation and Selection

Two approaches to the definition of the selection mechanism for this multi-criteria problem have been studied. The first is based on the total ordering of the population with respect to a single criterion which algebraically combines the values of each separate criterion, and is seen to rapidly lead to strong genetic pressure, leading to strongly homogeneous populations that correspond to one of the possible trade-offs between all criteria.

The second approach uses a selection mechanism based no the notion of Pareto optimality [1], and does not require the total ordering of the population. The individuals in the population are separately evaluated with respect to each of the criteria. For each one, the number of individuals by which it is dominated, i.e., which have better values of *all* the criteria, is counted. The selection process randomly selects the next population, with the probability that a given individual is not selected being proportional to the number of individuals dominating it. This approach has the advantage of identifying a *set* of possible solutions, that correspond to different compromises between the criteria considered. Figure 4 illustrates three snapshots of distribution of the values of percentage of re-covered surface (surface that is covered more than once) and percentage of the total surface that is effectively observed, for three distinct iterations of the algorithm: at the beginning, where a wide spread is observed, at an intermediate step, and after a large number of iterations.

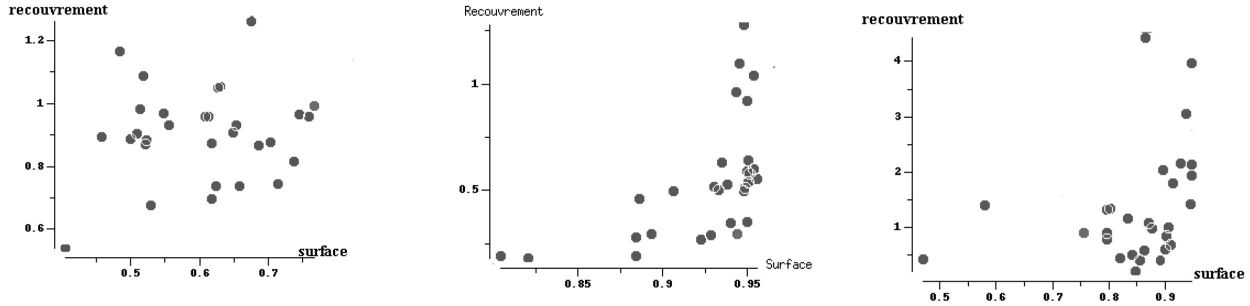

Figure 4: Evolution of re-covered/ observed surface distribution.

Notice the wide spreading of the initial distribution (which is randomly chosen), and the increasing coverage of the trade-off set by the population of trajectories. This figure shows that the algorithm effectively succeeds in identifying the surface of feasible non-dominated solutions for this problem.

5 Results

In the first phase of this work, only the requirements of minimal length and complete coverage, which allow an easier and direct geometric interpretation and analysis of the solutions found, have been considered. The interested reader can find the details of the results presented in [2]. Incorporation of the criteria measuring uncertainty, using (1), presents no conceptual difficulty, implying mainly an increase on computational effort.

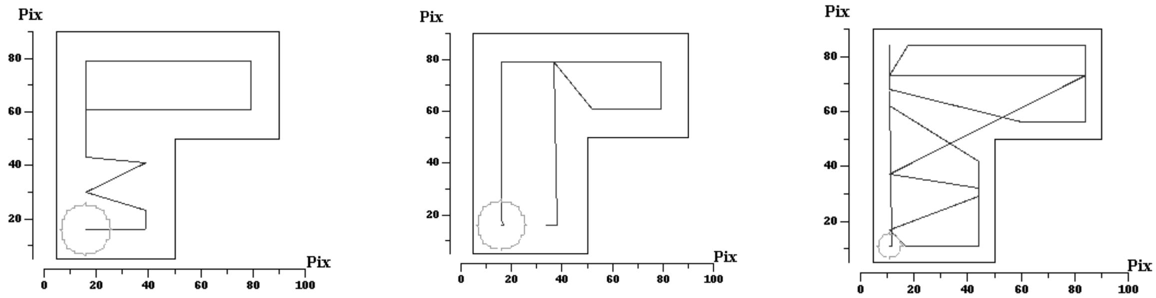

Figure 5: Polygonal contour.

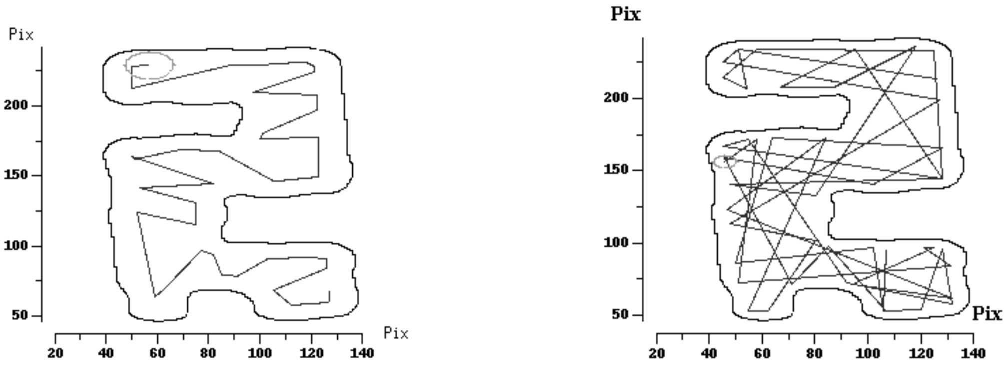

Figure 6: Natural contour.

Our experiments show that the genetic algorithms are able to "discover" regular geometric solutions, using for instance, sets of parallel lines, diagonals, etc. Figure 5 shows examples of trajectories generated by the algorithm for a simple and geometric contour, for two distinct sizes of the region covered by the perceptual sensors of the robot.

The two examples in the left of figure 5, which correspond to a large size of sensing region, show that the algorithm is able to find highly regular trajectories, using parallel lines, and zig-zag behaviors. We note that these two clearly distinct solutions to the problem could not be simultaneously obtained using a simple evaluation/selection method which combines the two criteria considered (trajectory length and observed surface), which cold only be obtained using the Pareto approach. The other example in this figure corresponds to a smaller size of the region covered by the perception sensors. Even if the trajectory shown has a more complex geometric structure, it is still possible to recognize the good use of lines parallel to the contour, and of zig/zaging procedures.

In figure 6 we present two trajectories generated by the algorithm (for a large and small sensing region) for a smoother contour, which has been learned by the robot in a previous step. the trajectory shown in the left of this figure corresponds to a large sensing region of the perception sensors of the robot. Een if the contour is not a simple polygon in this case, the solution provided by the algorithm still presents a strong regular geometry, making again use of lines (approximately) parallel to the contour, and of zig-zig segments. This structure is less clear when a more dense recovering of the surface is needed, because the range of the robot's sensors is smaller, as it is the case for the trajectory on the right hand side. However, even if the same basic constructs (parallel lines and zig-zigging behaviors) can still be identified in this case, the nice local coverage of each of the convex components of the surface, which happens in the previous case, is now lost.

6 Conclusions

The paper presents a new formulation of the problem of definition of exploratory trajectories, appropriate for platforms having no means of global positioning. We show that genetic algorithms can provide meaningful solutions to the problem. We present examples of exploratory trajectories defined by a conveniently defined genetic algorithm, demonstrating the ability of this tool to exploit the geometry of the problem.

Current work integrates the uncertainty criteria in the algorithm, enabling the definition of exploratory trajectories that are "supported" by perceptual knowledge, and whose geometry depends on the local perceptual features of the contour surface, as well as on the global geometrical properties of the surface to be covered.

Acknowledgments

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